A CREDIT RISK MODEL FOR AGRICULTURAL LOAN PORTFOLIOS UNDER THE NEW BASEL CAPITAL ACCORD

A Dissertation

by

JUNO KIM

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2005

Major Subject: Agricultural Economics

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ABSTRACT

A Credit Risk Model for Agricultural Loan Portfolios

under the New Basel Capital Accord. (May 2005)

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The New Basel Capital Accord (Basel II) provides added emphasis to the development of portfolio credit risk models. An important regulatory change in Basel II is the differentiated treatment in measuring capital requirements for the corporate exposures and retail exposures. Basel II allows agricultural loans to be categorized and treated as the retail exposures. However, portfolio credit risk model for agricultural loans is still in their infancy. Most portfolio credit risk models being used have been developed for corporate exposures, and are not generally applicable to agricultural loan portfolio.

The objective of this study is to develop a credit risk model for agricultural loan portfolios. The model developed in this study reflects characteristics of the agricultural sector, loans and borrowers and designed to be consistent with Basel II, including consideration given to forecasting accuracy and model applicability. This study conceptualizes a theory of loan default for farm borrowers. A theoretical model is developed based on the default theory with several assumptions to simplify the model.

An annual default model is specified using FDIC state level data over the 1985 to 2003. Five state models covering Iowa, Illinois, Indiana, Kansas, and Nebraska are estimated as a logistic function. Explanatory variables for the model are a three-year moving average of net cash income per acre from crops, net cash income per cwt from livestock, government payments per acre, the unemployment rate, and a trend. Net cash income generated by state reflects the five major commodities: corn, soybeans, wheat, fed cattle, and hogs. A simulation model is developed to generate the stochastic default rates by state over the 2004 to 2007 period, providing the probability of default and the loan loss distribution in a pro forma context that facilitates proactive decision making. The model also generates expected loan loss, VaR, and capital requirements.

This study suggests two key conclusions helpful to future credit risk modeling efforts for agricultural loan portfolios: (1) net cash income is a significant leading indicator to default, and (2) the credit risk model should be segmented by commodity and geographical location.

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"I can do all things through Christ which strengtheneth me - Philippians 4:13." I confess what I have achieved was His plan and guided by Him. I give thanks for what God has done for me. I have finished my dissertation by His grace.

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CHAPTER I

INTRODUCTION

Banks face numerous risks affecting performance throughout its business line. Since banks are, in fact, firms balancing risk and return characteristics in alternative management strategies to obtain profit, high risk in banks' management is unavoidable. The success or failure of banks is closely related to their ability to manage risk. Banks face several sources of risks, including credit risk, market risk, operational risk, liquidity risk, legal risk and reputation risk. The Basel Committee on Bank Supervision (The Basel Committee, 2000) defines credit risk as "*the potential that a bank borrower or counterparty will fail to meet its obligation in accordance with agreed term*." Credit risk is mostly associated with loans and securities in banks' balance sheet and is the largest risk confronted by commercial banks in the U.S. Credit risk is regarded as the primary cause of bank failures in recent years, and it is the most visible risk faced by bank management (Fraser et al., 2001).

During the 1980s and 1990s, the banking industry was confronted by the forces of financial deregulation and globalization. Many banks experienced growing competition. Many suffered heavy loan losses during the late-1980s and early-1990s at commercial banks in general, and during the mid-1980s at largely agricultural banks. From these experiences, banks began to realize the importance of managing credit risk

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This dissertation follows the style of *Journal of Banking and Finance*.

and developing analytical tools to evaluate credit risk. In particular, bank concerns shifted from credit risk at the individual transaction level toward credit risk at the portfolio level. Credit risk modeling has been developed rapidly over the past decades to become a key component in the risk management system of the commercial banking industry (Lopez and Saidenberg, 2000).

The New Basel Capital Accord (Basel II) provides the emphasis to the development of portfolio credit risk models. The original Basel Capital Accord was implemented in 1988 and became the world standard for bank capital requirements. It had banks maintain at least an eight percent capital to risk-weighted asset ratio as a cushion against possible credit losses. The Basel II, which was proposed in 2004 and will be implemented in 2006, is more risk sensitive than the initial 1988 Accord, but offers banks a range of options for measuring credit risk: (1) Standard Approach, (2) Foundation Internal Rating Based (IRB) Approach, and (3) Advanced Internal Rating Based Approach. The standard approach is similar to the 1988 Accord. The IRB approaches [1] allow banks to use an internal rating model for portfolio credit risk assessment and required capital calculation. In other words, banks need a portfolio credit risk model to implement the IRB approaches under Basel II.

Another critical implication of Basel II is the differentiated treatment of measuring capital requirements for corporate versus retail exposures. Banks can measure the credit risk for retail portfolio as a whole and can "ignore" credit risk at the exposure level. This differentiated treatment underscores bank interest in credit risk models for

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[1] The differences between the foundation IRB and advanced IRB will be discussed in Chapter II.

retail credit, which includes individual loans, mortgage loans, small business loans, and loans managed on a pooled basis. Survey results reported by the Basel Committee (2003) suggest that the implementation of Basel II can considerably reduce capital requirements for retail exposures, which stimulates interest in credit risk modeling of these exposures. The demand for a portfolio credit risk model for retail exposures will be increasing in the future as well. Basel II implicitly suggests that agricultural loan portfolios can be classified as retail exposure. Agricultural loans are made mostly to farmers (individuals) or small businesses. These exposures often permit pooling of loans.

The portfolio credit risk model methodology requires estimation of the probability of default or probability of loan losses for a loan portfolio over a particular time horizon. This methodology was initially developed in the 1990s for industrial applications. There are several commercial models developed for sale to third parties; these include Portfolio Manager, CreditMetrics, Credit Risk Plus, and CreditPortfolio View. These models were originally designed for corporate loan portfolios. However, it is hard to adapt the models of large corporate loan exposures to retail loan exposures because of cost and data restrictions (Burns, 2002; Dietsch and Petey, 2002; Ieda, et al, 2000). The literature on the theoretical underpinnings for credit risk in retail loan portfolios is relatively sparse.

Credit risk modeling of agricultural loan portfolios is still in the beginning stages. Only two literature citations can be found. Moreover, one can question whether these studies use the appropriate theory or methodology, and if they are applicable to agricultural banks. When modeling credit risk for agricultural loans, one must account for the attributes of agricultural sector and its borrowers. The U.S. agricultural sector typically experiences cash flow stress resulting from relatively low but volatile rates-of-return to production assets. The performance of the sector is also influenced by economic cycles and is highly correlated with farm typology, commodity, and geographical location. Credit risk for agricultural loans is closely related to a farm's net cash flows like other retail loan categories. However, these cash flows exhibit annual cycles. Agricultural banks need a unique credit risk model for their loan portfolio that captures these and other characteristics unique to agriculture.

The objective of this research is to develop a credit risk model for an agricultural loan portfolio. This model takes into account the characteristics of the agricultural sector, attributes of agricultural loans and borrowers, and restrictions faced by agricultural banks. The proposed model is also consistent with Basel II, including consideration given to forecasting accuracy and applicability. The model developed in this study has following characteristics:

(i) It conceptualizes a theory of loan default for farmers, which is based on causal relationship between creditworthiness and economic factors at the micro level. The theoretical model is developed around the theory of loan default and reflects several assumptions introduced to simplify the model.

(ii) It regards net cash income as the key factor affecting credit risk for agricultural loans as opposed to asset value or collateral.

(iii) It specifies credit risk by loan segments (or sub-portfolio level), which can be classified by region and/or primary commodity. As a result, it reduces data requirements for modeling and focuses the applicability of the model.

(iv) The simulation phase of the study uses several macroeconomic variables as risk derivers to capture future trends in the state-of economy, which allows credit risk to be estimated in proactive manner.

(v) The model will generate loss distributions and calculate expected losses, the VaR and associated capital requirements.

The next chapter defines credit risk and its relationship with banking theory. Measures of credit risk are also discussed, and the Basel II Accord is summarized in detail along with its application to agricultural loan portfolios. Chapter III describes existing credit risk models. This includes the literature on stand-alone credit risk models as well as portfolio credit risk models. Recent applications of portfolio credit risk models for retail exposures are discussed, as are portfolio credit risk models for agricultural loan portfolios. Chapter IV develops a theoretical portfolio credit risk model and an empirical default model for an agricultural loan portfolio. Calibration models for simulation are specified, and simulation processes are examined. Chapter V describes the original data source, generated data, and data generation process. Estimation results of the model are tabulated and compared. Chapter VI provides a validation of the default model and simulation model, and presents the simulation results for the default rate, expected losses, VaR, and capital requirements. Chapter VII presents a summary of this study, conclusions reached, and suggestions for future research.

CHAPTER II

CREDIT RISK AND THE BASEL CAPITAL ACCORD

The aim of this chapter is to present an overview of the existing issues surrounding credit risk management in agricultural banking. Basic theories and application processes for credit risk management in agricultural portfolios are similar to those for commercial loans in general. This chapter first discusses the definition and the role of credit risk management in banking in the context of banking theory. Several measures of credit risk used in the banking industry are explained. The New Basel Capital Accord, which is expected to change bank credit risk management, is summarized. Its implications for credit risk management for agricultural loan portfolios are discussed.

Credit Risk in Banking

There is a substantial literature on models explaining the behavior of banking firms using neoclassical microeconomic theory. Early work by Klein (1971) represents a corner stone in the theory of the banking firm, and was followed by Monti (1972), Baltensperger (1980), Santomero (1984), and Dermine (1986). These models assume that the bank is operated to maximize expected profit, and incorporates the role of a bank as a financial intermediary that performs both a brokerage and a risk transformation function (O'Hara, 1983). As such, the bank is viewed as a firm accepting and managing risks to earn profit.

Adopting the assumption of a profit maximizing banking firm, we can define banking risks as the adverse impact on profitability of several distinct sources of uncertainty (Bessis, 2002). The major role of banking in an economy is to bring together borrowers and lenders of funds. Since the bank is subject to credit and market risks on the funds it lends and to withdrawal risk on the funds it borrows, it must contend with risk associated with both its assets and its liabilities (O'Hara, 1983). In fact, banks face numerous risks affecting profitability throughout its business line. The management of these risks has always been a major component of bank management. Banks can also be defined as firms balancing risk/return characteristics of alternative opportunities with the goal of maximizing profit. By offering depositors financial instruments with desirable risk/return characteristics, banks encourage savings. By discriminating credit requests, banks channel funds into socially productive and profitable uses (Fraser et al., 2001).

The major sources of banking risks are classified into four categories: (1) credit risk, (2) market risk, (3) operational risk and (4) performance risk. Credit risk is the change in asset value due to changes in the perceived ability of counterparties to meet their contractual obligation.[2] Market risk is the change in asset value due to changes in underlying economic factors such as interest rates, exchange rates, and equity and commodity prices. Operational risk comes from costs incurred through mistakes made in

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[2] This definition reflects the theory of asset value model proposed by Merton. This model is discussed in Chapter III.

carrying out transactions such as settlement failures, failures to meet regulatory requirements, and untimely collections. Performance risk encompasses losses resulting from the failure to properly monitor employees or to use appropriate methods (Pyle, 1997).

The classification of banking risks, however, differs by researcher or supervisory agency. The Basel Committee (1997) lists the key risks faced by banks as credit risk, country and transfer risk, market risk, interest rate risk, liquidity risk, operational risk, legal risk, and reputation risk. The Office of the Comptroller of the Currency (OCC, 2001)[3] has defined nine categories of risk for bank supervision purposes. These risks are: credit, interest rate, liquidity, price, foreign currency translation, transaction, compliance, strategic, and reputation. Bessis (2002) summarizes the financial risks faced by banks as credit risk, interest risk market risk, liquidity risk, operational risk, foreign exchange risk, and other risk.

Credit risk, which is the focus of this research, is defined by the Basel Committee (2000) as "*the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms*." It is usually associated with loans and securities, which by generating interest income, are the primary source of bank revenue. Credit risk is the largest risk faced by commercial banks in the U.S. Loans made up 56.87% of total banking assets at year-end 2003, while securities made up an additional 21.89% (See Table 1). Loans are the major and most obvious source of credit risk to

[3] The Office of the Comptroller of the Currency (OCC) is the regulator of national banks. It charters, regulates, and supervises all national banks and also supervises the federal branches and agencies of foreign banks.

banks. However, other sources of credit risk exist throughout the activities of a bank, including in the banking book, the trading book,[4] and both on and off the balance sheet[5]. Banks are increasingly facing credit risk (or counterparty risk) in various financial instruments other than loans, including acceptances, inter-bank transactions, trade financing, foreign exchange transactions, financial futures, swaps, bonds, equities, options, in the extension of commitments and guarantees and in the settlement of transactions (The Basel Committee, 2000).

Table 1 Asset Portfolio Composition of U.S. Bank, 2003

Asset Portfolios			%
Interest Earning Asset			86.06
	Loan and Leases		56.87
		Commercial and industrial	12.20
		Consumer	9.06
		Real estate	29.91
		Other loans	3.58
		Lease	2.12
	Securities		21.98
		Investment Account	18.96
		Trading Account	3.02
	Other interest-earning assets		7.21
Non-interest-earning Assets			13.94
Sum			100.00

Source: Carlson and Perli (2004)

[4] A bank's trading book includes equities and fixed income securities held for dealing or proprietary trading. It also includes equity and fixed income derivatives, repurchase agreement, certain forms of securities lending and exposures due to unsettled transactions.

[5] Off-balance sheet credits in banks do not appear on balance sheets. Usually, they represent financing from sources other than debt and equity offerings, such as joint ventures, R&D partnerships, and operating leases.

The primary effect of high credit risk on a bank is loss in assets and interest income. This reduces the bank's profit, depletes its capital, and might at the extreme lead bank failure. Liang (1989) shows empirically that credit risk reduces bank profit because a bank recognizes expected costs associated with high risk, such as higher premiums on uninsured deposits demanded by risk averse investors. Berger and DeYoung (1997) examine the inter-temporal relationship between loan quality and cost efficiency using the Granger causality concept. Their empirical results suggest that high levels of problem loans cause banks to increase spending on monitoring, working out, and/or selling off these loans, and possibly become more diligent in administering the portion of their existing loan portfolio that is currently performing. Credit risk is regarded as the primary cause of bank failures in recent years, and it is the most visible risk faced by bank management (Fraser et al., 2001).

During 1980s and 1990s, the banking industry was confronted by the forces of financial deregulation and globalization. Many banks suffered during this period for a multitude of reasons, including the heavy loan losses emerging during late-1980s and early-1990s. There have been other drivers of change the industry, such as a worldwide structural increase in the number of bankruptcies, a trend towards disintermediation by the highest quality and largest borrowers, more competitive margins on loans, a declining value of real assets, and a dramatic growth of off-balance sheet instruments with inherent default risk exposure (Altman and Saunders, 1998). These worldwide phenomena have led to the development of modern credit risk management techniques.

Credit risk modeling has been developed rapidly over the past decades to become a key component in the risk management system of the banking industry. Credit risk models help bank management measure the credit risk associated with individual loans as well as their asset portfolio. They enable a bank to forecast possible credit losses over the coming year, to differentiate loan price over lenders having different risk, to determine the loan loss reserves and risk-based capital requirements, to evaluate credit concentration and set concentrate limits, and to measure risk-adjusted profitability (Lopez and Saidenberg, 2000).

The goal of credit risk management is to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions. Banks should also consider the relationships between credit risk and other risks. The effective management of credit risk is a critical element of a comprehensive approach to risk management and essential to the long-term success of any banking organization (Basel Committee, 2000).

Measure of Credit Risk

Most credit risk models consider two sources of credit risk: default risk and migration risk. Default risk is the risk that counterparties default, meaning that they fail to meet their debt obligation. Default triggers a total or partial loss of any amount lent to the counterparty. Migration risk is the risk that obligors' credit rating goes down into a lower loan classification. The deterioration of credit rating doesn't imply default but it does imply that the probability of default increased (Bessis, 2002).

There have been various arguments about the definition of default. They vary by models and by banks, and depend on the philosophy and/or data available to each model builder. Liquidation, bankruptcy filing, loan loss (or charge off), non-performing loan, or loan delayed in payment obligation are used at many banks as proxies of loan default. The Basel II suggests, in the §452, a conservative definition of default for a bank to use when calculating the capital requirement (The Basel Committee, 2004):

"A default is considered to have occurred with regard to a particular obligor when either or both of the two following events have taken place.

- *The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held).*
- *The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstanding."*

Default risk can be measured at individual loan level, which is called stand-alone credit risk, and at portfolio level, which is called portfolio credit risk. The most direct and common measure of default risk is the probability of default (PD), which is the likelihood that a loan falls into default. It captures the volatility of default risk and is usually expressed as a distribution and its parameters, probability density function (PDF) or cumulative distribution function (CDF). It is calculated for an individual borrower as well as for entire bank portfolio.

When calculating default risk at the portfolio level, Value at Risk or simply VaR has become the industry standard measure.[6] It is defined as the loss exceeding expected loss (or unexpected loss) at some given fraction of occurrences (the confidence interval) if a portfolio is held for a particular time (holding period). When estimating credit risk facing a bank, common practice is to employ a long holding period (one year or more) and a small confidence level, usually one percent or less (Jackson and Perraudin, 1999). VaR is a theoretical measure of the potential loss for a portfolio capturing downside risk. Its concept is favored for three major reasons, which are providing a complete view of portfolio risk, measuring economic capital, and assigning a fungible value to risk (Bessis, 2002).

VaR is usually measured by the probability distribution function of loan losses and requires two more risk measures: (1) exposure at default (EAD), which, for loan commitments measures the amount of the facility that is likely to be drawn if a default occurs, and (2) loss given default (LGD), which measures the proportion of the exposure that will be lost if a default occurs. The probability (or distribution) of loan loss is measured by following formula:

$$\text{(2.1)} \qquad \textit{Probability of Loan Loss} = \textit{Total} \quad \textit{Loan} \times PD \times EAD \times LGD\,.$$

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[6] VaR was initiated to measure market risk in trading portfolios. It has roots in Modern Portfolio Theory and a crude VaR measure was published by Leavens in 1945. VaR becomes a proprietary risk measure in 1990s after the Basel Committee authorized the utilization of VaR when banks calculate capital requirement (Holton, 2002).

Figure 1 illustrates the VaR concept for a distribution of loan loss. There are two critical points on the graph; (1) expected loss and (2) maximum loss (or 99th or more percentiles). VaR at a given confidence interval is the maximum loan loss less expected loss, which is the same to unexpected loss, or

(2.2) Value at Risk (Unexpected Loss) = Maximum Loan Loss – Expected Loss.

VaR represents the required capital in excess of expected losses necessary for absorbing deviations from average losses.

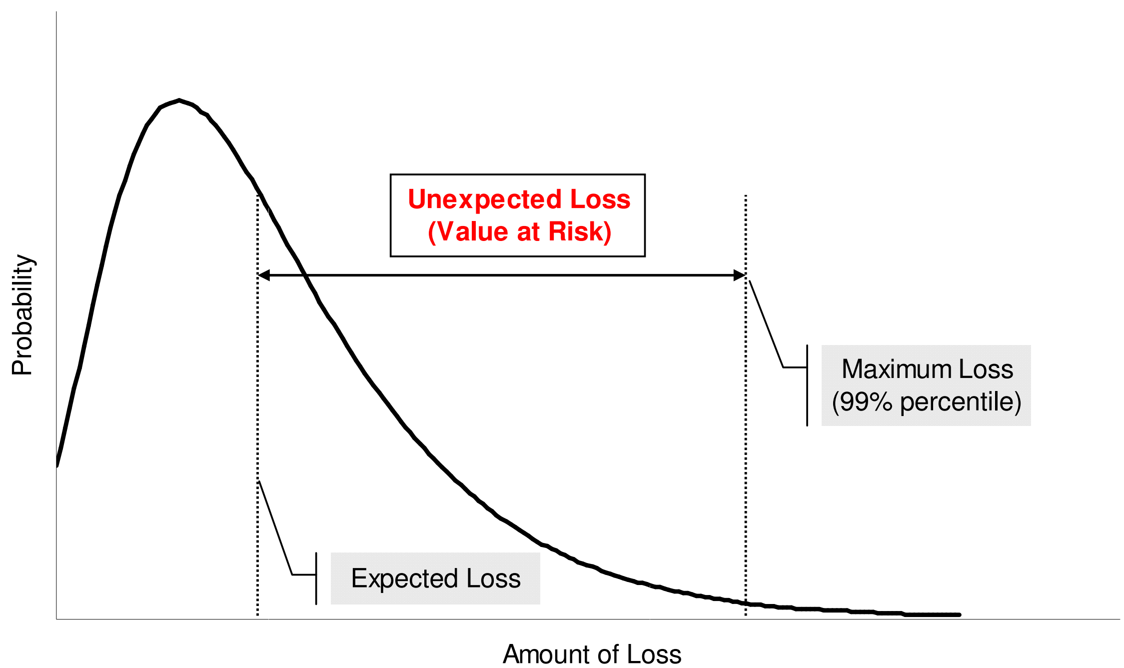

Figure 1 Measure of Value at Risk on Loss Distribution

The Basel Capital Accords

The Bank for International Settlements (BIS) is an international organization, which assists central banks of member countries by regulating international banking standards and promoting international monetary and financial cooperation. In 1974, central bank supervisors from ten industrialized countries established the Basel Committee on Banking Supervision.[7] The Basel Committee does not have formal supervisory authority and legal force against its members, but it formulates broad supervisory standards and guidelines that each country's government can use to determine the best policy for their own national systems. The Basel Committee developed several sets of standards such as the Capital Accord (The Basel Committee, 1988) and the Core Principals (The Basel Committee, 1997). These standards have been gradually introduced and received powerful backing not only in member countries but also in all countries with active international banks.

The Basel Committee introduced regulations for capital in 1988 known as the Basel Capital Accord. The Accord was enforced for internationally active banks in the G10 countries, which meant they had to maintain at least an eight percent of capital to risk-weighted assets[8] ratio as a cushion against possible credit losses. This requirement

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[7] The committee consists of senior supervisory representatives from Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, Netherlands, Sweden, Switzerland, United Kingdom and United States. It meets every three months at BIS in Basel, Switzerland.

[8] The capital ratio of a bank is total capital divided by risk-weighted asset. The Accord standardizes the credit risk of each asset according to its characteristics, and uses the standardized risks to calculate risk-weighted assets. For example, the risk weight of cash is 0%, that of a loan fully secured by mortgage is 50%, and that of private loan is 100%. Accordingly, the denominator of the capital ratio is the sum of risk-weighted assets.

became a world standard during the 1990s. Over 100 countries have since applied the Basel framework to their banking system (The Basel Committee, 2001).

In June 1999, the Committee issued a proposal for a New Capital Adequacy Framework (First Consultative Package on the New Basel Capital Accord) to replace the 1988 Accord and had published two more Consultative Documents in January 2001 and April 2003. After extensive interactions with banks and industry groups, the Basel Committee published the final document, "International Convergence of Capital Measurement and Capital Standard, a Revised Framework," which is widely known "Basel II" in June 2004. Basel II will affect bank risk management and financial markets much like the 1988 Accord. The central bank in each country will force banks to adopt Basel II. Even small banks might face the same situation. Those interested in credit risk and its modeling, from academic researchers to practitioners in banks, should understand the new regulation because compatibility with Basel II will be required for any credit risk model. The balance of this chapter discusses detail regulations for credit risk in the Basel II and issues related to agricultural loan portfolios.

Basel II is more risk sensitive than the 1988 Capital Accord. It offers banks a range of new options for measuring both credit and operational risk. It is built on three pillars, which are (1) minimum capital requirements, (2) supervisory review process and (3) market discipline. The first pillar sets out the calculation of the total minimum capital requirements for credit, market, and operational risk. The minimum capital requirement is calculated using three fundamental elements: (1) regulatory capital, (2) risk weighted assets and (3) minimum ratio of capital to risk-weighted assets (no lower than 8%), which is the same as the past definitions, or:

(2.3) Capital ratio = regulatory capital / total risk weighted assets.

The major innovation of Basel II is the introduction of three distinct options for the calculation of credit risk and three others for operational risk, while the market risk measures remain unchanged. The standardized approach for credit risk is similar to the 1988 Capital Accord. Banks are required to allot their credit exposures into supervisory categories based on observable characteristics of exposure. Basel II establishes fixed risk weights by external credit assessments for each supervisory category. The Internal Rating Based (IRB) approach is different from the standardized approach in that banks can apply the internal rating or model for credit risk assessment for their loan exposure and, can use the results as primary inputs to calculate their own capital requirement. The IRB calculation of risk-weighted assets relies on four risk components, which include (1) measures of probability of default or PD, (2) loss given default or LGD, (3) the exposure at default or EAD, and (4) effective maturity or M. Basel II suggests two IRB approaches, foundation and advanced IRB, which differ in terms of the risk components estimated by the bank. Banks using advanced IRB must provide their own estimates of all risk components, but foundation IRB bank can use supervisory values given for LGD, EAD, and M. Figure 2 illustrates the basic structure of the Basel II.

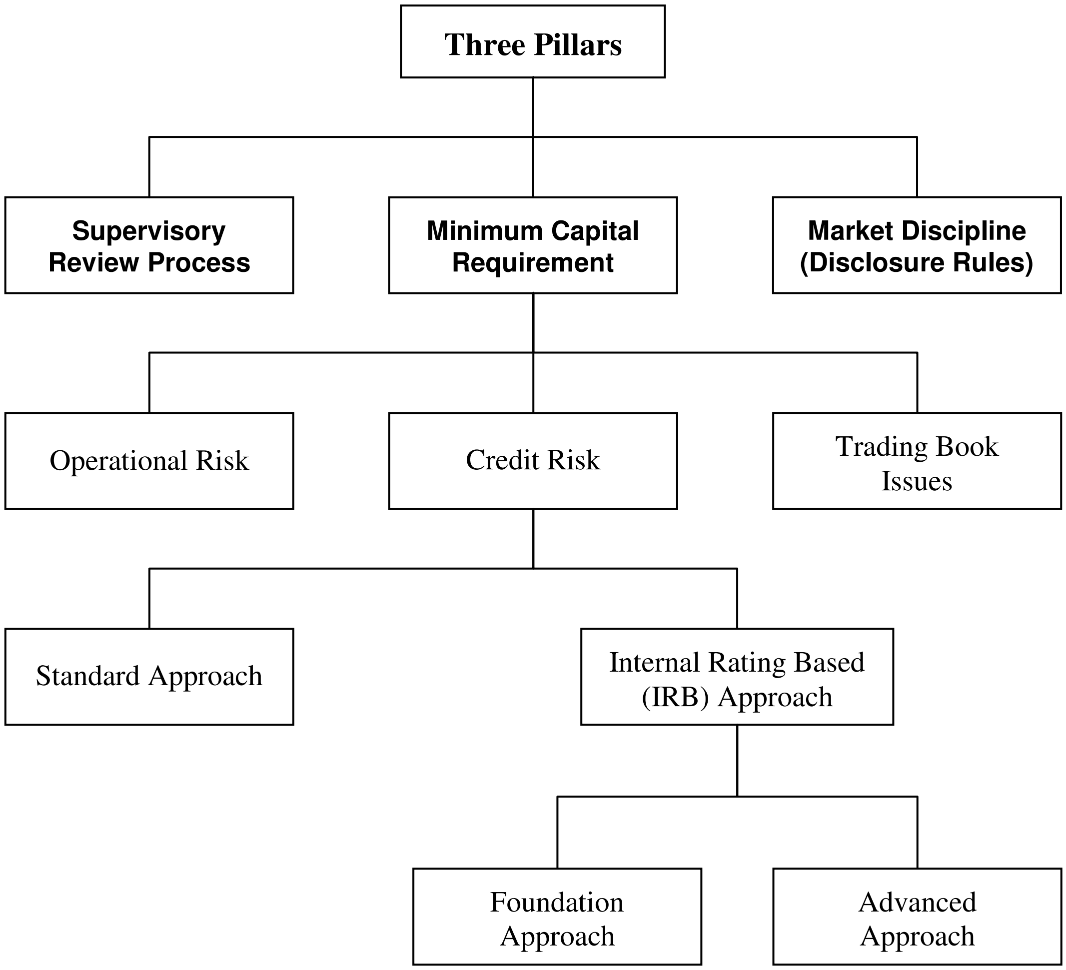

Figure 2 Structure of New Basel Capital Accord

Basel II and Agricultural Loan Portfolio

We cannot find the word "Agriculture" in the Basel II document, and there is no explicit regulation pertaining to agricultural loan portfolios. Under the IRB approach, banks must categorize banking-book exposures into broad classes of assets with different underlying risk characteristics. The classes of assets are corporate, sovereign, bank, retail and equity. Corporate exposure is defined as a debt obligation of a corporation, partnership, or proprietorship. Within the corporate asset class, five sub-classes of specialized lending are identified and regulated separately: (1) project finance, (2) object finance, (3) commodities finance, (4) income-producing real estate and (5) high-volatility commercial real estate.

Agricultural loans could be categorized as a corporate exposure. However, it is more fitting that they be classified as retail exposures since agricultural loans are mostly loans to farmers (individuals) or small businesses; a number of these exposures can make a pool. According to the definition of retail exposure in Basel II, an exposure can be categorized as a retail exposure if it meets all of the following criteria: (1) nature of borrower or low value of individual exposure, (2) exposure to individuals, personal term loan and leases, (3) residential mortgage loans, (4) small business loan managed as retail exposures and less than one million euro, and (5) one of a large pool of exposures managed by the bank on a pooled basis. Although agricultural loans are not a retail exposure by the general definition of 'retail exposure', according to the definitions of Basel II, agricultural exposures should be categorized and treated as retail exposures when estimating risk components and calculate risk-weighted assets in agricultural loan portfolios.

Banks typically manage retail exposures on a portfolio or pool basis, where each portfolio contains exposures with similar risk characteristics. One of the most significant differences between the corporate and retail categories in the IRB approach is that the risk inputs (PD, LGD, EAD, and M) for retail exposures do not have to be assigned at the level of an individual exposure. Therefore, a key characteristic of the retail IRB framework is that the risk inputs for retail exposures would be assigned to portfolios or pools of exposures rather than to individual exposures. There is no distinction between a foundation and advanced IRB approach for the retail exposure, so banks must provide their own estimates of PD, LGD, and EAD. Before banks apply the IRB approach to retail exposures, they must assign each exposure in the retail portfolio into a particular pool or segment. In determining how to group their retail exposures into portfolio segments for the purpose of assigning IRB risk inputs, banks should use a segmentation approach that is consistent with their approach for internal risk assessment purposes and that classifies exposures according to predominant risk characteristics (OCC et. al., 2004).

Summary

This chapter presented an overview of the key issues in credit risk management of agricultural loan portfolios. Since banks are firms balancing risk and return characteristics among alternative opportunities, banks cannot avoid risks. There are several categories of banking risks, but credit risk is the largest risk faced by banks. Credit risk management has been widely applied in the banking industry after the 1990s. Environments around the banking industry became riskier, increasing bank concerns about the credit risk management. Effective credit risk management has become an important factor of bank success.

Credit risk can be measured at the exposure level and the portfolio level. VaR is the industry standard for portfolio credit risk. Basel II shares the VaR concept in its regulation and provides the emphasis to the portfolio credit risk. An important implication of Basel II is differentiated treatment of measuring capital requirements for corporate exposure and retail exposure.

The most important implication of this chapter is the argument that agricultural loans should be categorized and treated as retail exposures. The reason is agricultural exposures are typically managed on a portfolio basis, and many exposures in the same portfolio have similar risk characteristics. In the next chapter, an extensive review of the literature on the credit risk models at the exposure level and portfolio level is provided. The review makes clear the differences between the stand-alone credit risk model and portfolio credit risk model as well as the differences between the corporate and retail portfolio credit risk models. Modeling issues on portfolio credit risk for the retail exposures will be discussed further, and recent models developed for retail loans and agricultural loans are detailed.

CHAPTER III

CREDIT RISK MODELS

Credit risk models initiated by financial institutions arise from a question that is simple to ask but hard to answer: which is a good credit and which is a bad credit? Banks have devoted considerable resources addressing this question, and research in the field of credit risk modeling has developed rapidly over the past decades. A credit risk model helps bank management evaluate the credit risk of individual loans as well as its whole portfolio. It also enables a bank to forecast possible credit losses over the coming years, to differentiate loan price over borrowers exhibiting different risk, to determine the loan loss reserves and the risk based capital requirements, to evaluate credit concentration and set concentrate limits, and to measure risk-adjusted profitability (Lopez and Saidenberg, 2000).

There have been two lines of research in this area. The first one is a stand-alone credit risk model, which attempts to evaluate credibility at the transaction or account level such as a firm or individual borrower. The other is a portfolio credit risk model, which measures credit risk at the portfolio level. The portfolio credit risk modeling began later but has been the focus of more attention recently. Banks are increasingly measuring and managing credit risk at the portfolio level in addition to the transaction level. This has occurred for a number of reasons. First, banks realize that traditional classifications of good and bad loans are not sufficient to properly manage their credit risk because all credits could potentially default under a particular extraordinary economic scenario. Second, possible errors in selecting and pricing individual loans are decreasing, but diversification and timing impacts on bank credit risk is increasing. Bank management needs more proactive risk measures for loan exposure after the loan has been originated (Wilson, 1998).

This chapter reviews the literature for credit risk models. The following section reviews existing models for stand-alone and portfolio credit risk. This literature includes journal articles, research papers, and commercial models developed by consulting firms. The literature on portfolio credit risk models for retail exposures is reviewed. Finally, recent research in the literature on portfolio credit risk for agricultural loans is discussed.

Stand-alone Credit Risk Model

As discussed in Chapter II, banks have made wide use of the probability of default (PD) as a proxy of the risk inherent in an individual credit.[9] There have been three broad categories of traditional models used to estimate the credit risk at individual loan level: (1) expert systems, (2) internal and external credit rating, and (3) credit scoring models.

Expert Systems

About 20 years ago, most financial institutions relied virtually exclusively on subjective analysis or the so-called banker expert system to assess the credit risk of

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[9] Loss given default (LGD) may be more accurate measure of credit risk, but the use of DP is common practically since banks appear to have greater difficulty in estimating LGD (The Basel Committee, 2000).

borrowers. Bank loan officers used information on various borrower characteristics, which are called as the “5 Cs” of credit. They are (1) character of borrower (reputation), (2) capital (leverage), (3) capacity (volatility of earnings), (4) collateral, and (5) condition (macroeconomic cycle). Because human experts have evaluated the “5 Cs” subjectively, they might be inconsistent. Moreover, expert systems specify no weighting scheme that would order the “5 Cs” in terms of their relative importance in forecasting default probability (Allen et al., 2004; Altman and Saunders, 1998; Tomas, 2000).

Credit Rating

A credit rating is a summary indicator of risk for banks’ individual credit exposures (Treacy and Carey, 2000). In general, they depend on a number of factors, quantitative financial ratios and qualitative variables. The credit rating usually includes from six to ten different ranks,[10] but they are not quantitative measures of risk but rather a qualitative ordering (Bessis, 2002). External credit ratings refer to the rating system or ratings from the system independently made outside the banks or creditors, while internal credit ratings are those constructed in the banks for their own use. Moody’s first offered external credit ratings of the U.S. firm in 1909. Now, banks can use many external credit ratings to apply for their credit risk management process. Moody’s and Standard & Poor’s are the leading companies in the market, and there are many public and commercial rating agencies.

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[10] Ratings are usually expressed as numbers (1, 2, 3, …) or characters (AAA, AA, BBB, BB, CC, …).

Internal credit ratings have become more and more critical for credit risk management in large U.S. banks. Bank internal rating systems differ from external ratings in architecture and operating design as well as in the uses to which ratings are applied, because they are designed by bank personnel and are usually not revealed to outsiders. Internal rating systems across banks are also considerably diversified. The number of grades and the risk associated with each grade vary across institutions because differences exist in who assigns ratings and how rating assignments are reviewed (Treacy and Carey, 2000). Internal credit rating systems has also been enforced by regulators and examiners of banks. The Office of the Comptroller of the Currency has long required banks to implement a rating system (Allen et al., 2004). The Basel II is the most powerful driving force in this area today. Banks should have an internal rating system when calculating their capital requirements. Basel II also regulates the detail in the design of an internal rating system such as rating dimension, system structure, rating criteria, assessment horizon, use of model, and documentation of rating system design.

Banks usually use credit ratings in the lending process, credit monitoring, loan pricing, management decision-making, and in calculating inputs for portfolio credit risk model. Banks typically utilize the credit ratings for business and institutional loans, but not for consumer loans. In the U.S., credit ratings are used for large companies while credit scoring models are used for small business loans and consumer credit (ERisk, 2002).

While credit ratings themselves do not represent the default probability of a borrower, they are transformed into the probability of default for use in portfolio credit risk models. Commercial rating companies offer probabilities of default for each rating from historical data for their client banks. Banks can also map internal ratings to the external ratings with pre-measured probability of default, or estimate the probability of default directly from own historical data by internal ratings.

Credit Scoring

Credit scoring began as a tool for banks to decide whether or not to grant credit to consumers (Thomas, 2000). Durand (1941) was the first paper that employed statistical methods in discriminating good and bad loans. Since then, many researchers have made efforts to develop better theoretical and empirical models. New statistical methodologies have been utilized in this area, and remarkable development in computer systems enables banks to apply a variety of new models. Today, many banks are implementing credit scoring models in their credit decision-making. Credit scoring models are widely used in credit card approval, mortgage loans, and consumer loans and are increasingly used for business loan applications (Mester, 1997).[11] When constructing a credit scoring model, banks are confronted by two critical issues, (1) the functional form and (2) choice of explanatory variables. Table 2 summarizes the advantages and disadvantages of current credit scoring models by functional form.

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[11] 97% of banks use credit scoring model to approve credit card applications and 70% of banks use credit scoring in their small business lending.

Table 2 Comparison of Credit Scoring Models

			Advantages	Disadvantages
Parametric Model	Linear	Discriminant Analysis	• Good performance in large sample • Technical convenience in estimation and maintenance	• Statistical problems and inefficient estimator • Don’t produce default probability
		Linear Probability Model	• Good performance in large sample • Suggest default probability • Easily interpretable parameters	• Inefficient estimator • Estimated probability might lie outside the interval (0, 1)
	Non-linear	Logit Model	• Good statistical properties and no strict assumption on data • Show the probability of default • Good performance	• Hard to interpret parameters
		Probit Model	• Good statistical properties and no strict assumption on data • Show the probability of default	• Hard to interpret parameters • Relatively complicated estimation process
Non-parametric Model		Linear Programming	• Deal with a lot of variables • High flexibility in modeling • Don’t need pre-specification of model	• No default probability and parameters • Low comprehensibility • Low prediction accuracy
		Neural Network	• Good prediction in small sample • High flexibility in modeling • Don’t need pre-specification of model	• No default probability and parameters • Low comprehensibility
		Recursive Partitioning Technique	• Best performance in many papers • High flexibility in modeling • Don’t need pre-specification of model	• No default probability and parameters • Low comprehensibility

There is no common consensus on which variables should be included in a credit scoring model because economic theory hardly supports the issue. As a practical matter, the choice of the explanatory variables largely relies on data availability. There are four methodological forms of parametric models in the credit scoring literature: (1) discriminant analysis (DA), (2) linear probability models (LPM), (3) logit models and (4) probit models. DA assumes that there are two groups of loans, good and bad, and finds the best linear combination of explanatory variables, i.e. characteristics of borrower, that can discriminate each group (Betubiza and Leatham, 1990).

There is a great deal of literature on discriminant analysis in 1970s and 1980s, including studies by Altman et al. (1977), Sexton (1977), and Reichert et al. (1983). LPM, logit models and probit models employ standard statistical techniques and provide banks with the probability of default for a borrower. LPM use a least square regression approach, where the dependent variable is 1, if a borrower is in default, or 0, otherwise. The regression equation is expressed as a linear function of explanatory variables (Orgler, 1970). Logit and probit models are different from LPM in that they assume the probability of default is logistic or normal distribution. Application of logit and probit models in credit scoring began in the 1980s under the background development of quantitative choice model in 1970. After Wiginton (1980), and Grablowsky and Talley (1981), numerous papers have been published, and logit and probit analysis became the most preferred models in credit scoring research.

It has been pointed that a weakness of DA is that the method doesn't produce a probability of default. Furthermore, when DA models are estimated, the OLS estimator used is not efficient because it basically assumes that explanatory variables of two groups are normally distributed and have the same variance-covariance matrix (Turvey, 1991). Since the DA approach exhibited good performance in large samples in spite of statistical problems, and because it has the advantage of technical convenience in estimation and maintenance, it was widely used in the 1960s and 1970s.

LPM has similar statistical problems to DA. Its biggest problem is that the estimated probability of default might exist outside the interval (0, 1). LPM has the advantage in that it can suggest default probability and its estimated parameters can be easily interpretable. It also has the advantage of technical convenience. Logit and probit models were developed to solve the statistical problems existing in DA and LPM. Estimators of logit and probit model are efficient and consistent. These methods don't need the strict assumptions on data. Loan officers can conveniently calculate the default probability of a borrower with the logit or probit model, but the parameters estimated are more difficult to understand because of their nonlinear characteristics (Green, 2000; Maddala, 1983).

Since the 1980s, there have been many attempts to use non-parametric statistics or artificial intelligence techniques such as neural networks, recursive partitioning algorithms, expert systems, and nearest neighbor methods. These models are highly flexible in modeling because they don’t have distributional assumptions on data and/or don't require pre-specification of the model (Chhikara, 1989). Much attention has been given recently on new methodologies. Some argue that new techniques can improve the predictive accuracy of credit scoring models. (Desai et al., 1996; Freed and Glover, 1981; Frydman et al, 1985; Henley and Hand, 1996; Srinivasan and Kim, 1987). Many consulting institutions are applying these new statistical techniques. In spite of their statistical advantages and good performance, these models have as many limitations as non-parametric models. Most of all, they cannot provide the probability of default and informative parameters useful in loan pricing, management policy decisions, and portfolio credit risk modeling.

Model accuracy has been a critical argument in research on credit scoring model.[12] There have been many papers arguing a specific model represents the best accuracy, but generally there were no major differences in performance among these models. Thomas (2003) argued that there is no conclusive evidence on model accuracy and there is no agreement on which statistical technique should be preferred. No matter what model banks use, the application of credit scoring can cut operating costs by making the loan process simple, reduce potential loan losses, and focus attention more on problem loans. Banks are expending the application of credit scoring over their credit line. For example, recent modifications of credit scoring models have given banks the opportunity to treat small business loans as retail credit (Allen et al., 2004; Longenecker et al., 1997; Mester, 1997).

[12] Type I error and type II error are used for statistical measure of model accuracy that represent how well a model can predict good or bad loan. In credit scoring model, type I error, classifying bad loan as good, is more important than type II error, classifying good loan as bad.

Portfolio Credit Risk Model

The portfolio credit risk model is a methodology that estimates the probability of default and loan loss for a loan portfolio over a particular time horizon. It usually combines the probabilities of default for individual loans and estimates the probability of default at portfolio level by aggregation (Lopez, 2001). Portfolio credit risk modeling is a process to find specific solutions to the two main problems: (1) the modeling of the probability of default for individual loans, and (2) the construction of the joint distribution (or probability) of default by taking into account the correlations between defaults in the portfolio (Dietsch and Petey, 2002). Therefore, the key inputs to a portfolio credit risk model are: (1) stand-alone credit risk measure for each loan, (2) its weight in the loan portfolio and (3) the correlation of default between each pair of loans.

Portfolio credit risk models were initially developed for commercial use in the 1990s. These models include proprietary applications constructed for internal use by financial institutions as well as others intended for sale or distribution to third parties. There are four leading portfolio credit risk or “vender” models: (1) Portfolio Manager by Moody’s KMV, (2) CreditMetrics by the CreditMetrics Group, (3) Credit Risk Plus by Credit Suisse Financial Products and (4) CreditPortfolio View by McKinsey. The underlying assumptions, theoretical background, mathematical structure and solution of these models are summarized in technical documents published by these companies, which include Crosbie and Bohn (2002), Gupton et al. (1997), Credit Suisse (1997), and Wilson (1997a, 1997b). Current portfolio credit risk models can be traced to three alternative forms: (1) option-based structursal models, (2) reduced form (actuarial) models, and (3) multi-factor econometric model. The following comparative description is summarized from available technical documents, and by Koyluoglu and Hickman (1999), Crouhy et al. (2000), and Gordy (2000).

Option-based Structural Model

The option-based structural model consists of two parts: (1) default model[13] and (2) correlation model. The default model relies on an asset value model proposed by Black and Scholes (1973) for option pricing and discussed in detail by Merton (1974). It specifies unconditional probabilities of default for individual loans. The Black-Scholes model assumes the market value of the firm's underlying assets follows the following stochastic process:

(3.1) $$dV_A = \mu V_A dt + \sigma_A V_A dz\ ,$$

where V_A is firm's asset value, μ is firm's asset value drift rate, σ_A is asset volatility, and dz is Wiener process, which assumes z ~ N(0, 1). The asset value at time t, V^t_A, given the initial asset value, V^0_A, can be written as follows:

(3.2) $$\ln V^t{}_A = \ln V^0{}_A + (\mu - \frac{\sigma^2{}_A}{2})t + \sigma^2{}_A \sqrt{t}\varepsilon\ ,$$

[13] Default models are a category of models to assess the probability of default by an obligor. They differ from credit scoring models in two ways: (1) Credit scoring is usually applied to individual or small business, but default models are applied more to larger credits such as corporate. (2) Credit scoring models are statistical, regressing instances of default against various risk indicators. Default models directly model the default process, and are typically calibrated to market variables such as the obligor's stock price. (www.riskglossary.com/articles/portfolio_credit_risk.htm)

where μ is expected return on the firm's asset and ε is the random component of the firm's return.

The value of equity can be viewed as a call option on the value of a firm's assets. Thus the equity value can be calculated by the Black-Scholes' option price formula. The firm's equity and its volatility can be valued as a function of the asset value at time t (V^t_A), maturity value of debt (Debt), asset volatility (σ_A), and risk-free interest rate (r), or:

(3.3) $V^t_E \;\; or \;\; \sigma_E = f(V^t_A,\;\; Debt,\;\; \sigma_A,\;\; r)$.

Asset value and volatility are the only unknown variables in these relationships, and thus two equations can be solved to estimate asset value and its volatility. The Merton model regards a firm in default when the value of a firm's assets falls below its outstanding debt obligations.

To estimate credit risk at the portfolio level from probability of default or loan loss of each loan, which aggregates individual credit risk, correlations must be accounted for as illustrated by the Modern Portfolio Theory (MPT) of Markowitz (1952). If correlations or diversification effects in a loan portfolio are ignored, portfolio credit risk could be over estimated unless the correlations are equal to one. The multi-factor structural model is the general specification for the correlations which assigns default correlations to pairs of obligations.

Portfolio Manager, which was the first portfolio credit risk model, was developed by KMV[14] in 1993. It implements the Merton model in its commercial credit risk model for loan portfolios. Based on the option price model, KMV estimates expected asset value and asset volatility as a function of the existing capital structure of the firm, equity value (or stock price), and its volatility. It measures the number of standard deviations between the mean of the future distribution of the asset and a critical threshold, the default point, which is called distance-to-default (DD). The probability of default (or expected default frequency, EDF) for each individual loan is directly calculated by the predetermined relationship between the distance-to-default and historical default or bankruptcy frequencies. The relationship[15] is developed from the database managed by KMV, which contains the firm's stock price and balance sheet.

To estimate credit risk at the portfolio level, Portfolio Manager uses asset return correlations between all pairs of obligors as a proxy of asset correlation, which takes the effect of portfolio diversification into account. It is derived from a multi-factor structural model[16] to avoid computational problems expected from a huge correlation matrix in a large loan portfolio. In the multi-factor model, asset return is assumed to be generated by systematic factors and idiosyncratic factors, and its correlations between two borrowers are only explained by the common systematic factors to all firms. Finally, Monte Carlo

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[14] KMV was merged by Moody's Corporation and formed Moody's KMV in 2002.

[15] The relationship is made based on the U.S. data and its derivation is not thoroughly explained

[16] For this reason, option-based structural model is also called as 'factor model' or 'conditionally independent credit risk model.

simulation provides a loss distribution for the loan portfolio, and VaR is used to measure portfolio credit risk.

CreditMetrics, which was developed by RiskMetrics Group[17], has similarities with Portfolio Manager in several aspects. This model uses the Merton's asset value model for the calculation of individual credit risk, a multi-factor model for correlation, and Monte Carlo simulation for the portfolio loss distribution. However, the CreditMetrics approach is based on credit migration analysis. It assumes that all borrowers can be assigned to rating classes, and all borrowers within a same rating class are credit-homogeneous with the same probability of default and the same transition probabilities. Modeling begins with specification of a rating system and calculation of a transition matrix, which represents the average annual frequencies of migration among credit classes. Banks can use a commercial rating system and its transition matrix constructed by Moody's or Standard & Poor's, or a proprietary internal rating system. Once a firm is assigned to a rating class, the probabilities of migration from one rating class to the other rating class are decided by the transition matrix. CreditMetrics estimates expected asset values and their volatilities of a firm by credit ratings to which migration is supposed to be taken place. Asset value distribution of individual exposure is estimated by asset pricing model over a chosen time horizon from the transition matrix, asset values and asset volatilities. CreditMetrics use equity prices (or stock prices) of publicly traded firms as a proxy to calculate asset correlation.

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[17] RiskMetrics Group was established in 1994 as a division of JP Morgan, and become an independent company in 1998.

Reduced Form Model

The reduced form model was originally introduced by Jarrow and Turnbull (1992) and subsequent research includes Jarrow and Turnbull (1995), Jarrow et al. (1997) and Duffie and Singleton (1999). It uses a mathematical technique common in loss distribution modeling developed in the insurance industry, the so called actuarial model.[18] Credit Suisse Financial Products developed a commercial reduced form model named Credit Risk Plus in 1997.

Credit Risk Plus only models default risk, not migration risk. In other words, it is assumed that at the end of the risk horizon the borrower is in one of two states, default or non-default. Contrary to the option-based structural model, this model doesn't make any assumptions on timing and causality between default and other variables. The influence of systematic factors on the default rate is supposed to be captured through default rate volatilities instead of default correlation between borrowers. It further assumes that the probability of default for a loan is constant over time.

Credit Risk Plus first assigns each loan to a credit rating category (or segment) and calculates key inputs for each loan: (1) credit exposure, (2) obligor default rate, and (3) obligor default rate volatilities. Default rates for each loan are usually estimated by mapping of default rate to its credit rating.[19] Default rate volatility is defined as the historical standard deviation of the default rate. Loans are assumed to be mutually independent of each other, and each rating category consists of homogeneous loans with

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[18] It is also called as intensity model or mortality models of default.

[19] This implies that banks already have rating system or can use agency ratings. Banks also should have historical default rates by rating category.

identical credit risk characteristics such as default rate and volatility. If there are a large number of loans in a portfolio, the effect of a loan exposure on the probability of default to the portfolio is very small, and the default frequency in any given period is independent of default frequency in any other period. Under those conditions, the probability distribution for the number of defaults at the portfolio level during a given period of time can be represented by the following Poisson distribution:

(3.4) $$P(n) = \frac{\mu^n e^{-\mu}}{n!},$$

where n is average number of defaults per year and μ stands for the expected number of defaults in the portfolio.

To estimate the loss distribution for a loan portfolio, the joint default behavior of loans is captured by treating the default rate of a portfolio as a continuous random variable with volatility, which incorporates uncertainty about the future state of loans. The default rate for each segment, X, is supposed to follow a gamma distribution and can be expressed as:

(3.5) $X_k \sim \Gamma(\alpha_k, \beta_k)$, where $\alpha_k = \dfrac{\mu_k{}^2}{\sigma_k{}^2}$ and $\beta = \dfrac{\sigma_k{}^2}{\mu_k}$.

The default rate at the portfolio level is calculated by a probability generating function of a gamma distribution and a probability generating function for the entire portfolio derived by the multiplication of probability generating function for each segment. Finally, the distribution of the credit loss is estimated by the probability generating function, and depends on distributional assumptions, the default rate for each loan, the standard deviation of the default rate, and weight of each loan.

Multi-factor Econometric Model

The multi-factor econometric model evaluates systemic credit risk of a country, an industry or a portfolio segment as opposed to an individual exposure. This model assumes a homogenous credit standing for firms within a portfolio segment and the existence of causal relationship between credit risk of a portfolio segment and economic conditions associated with the loan portfolio (Bessis, 2002). The econometric model begins with the intuitive theory that credit cycles follow business cycle closely, but its behavior is different from industries. Since the state of nature is, to a large extent, driven by macroeconomic factors, the econometric approach proposes a methodology to link the macroeconomic factors to the probability of default of a loan.

CreditPortfolio View (CPV), which was the first multi-factor econometric model, was developed by Wilson (1997a, 1997b) of McKinsey. It focuses on the default rate and the migration rate. CPV consists of two model blocks: (1) the default block and (2) the time series block. In default block, default rate for a portfolio is formulated as a logit specification. The index variable (or default rate) is expressed as a linear function of macroeconomic variables (multi-factor model) and is assumed to follow logistic distribution as shown below:

(3.6) $$Y_{it} = \frac{1}{1+\exp(Z_{it})}$$

(3.7) $$Z_{it} = \alpha_0 + \sum_{j=1}^{n} \alpha_j X_{jt} + e_t ,$$

where Y_{it} is conditional probability of default in period t for i^{th} segment, Z_{it} is the index value from the multi-factor model, X_{jt} macroeconomic variables, αs are unknown parameters and e_t is error term. Each macroeconomic variable is supposed to follow a univariate autoregressive process of order 2, or:

$$X_{jt} = \gamma_{j0} + \sum_{k=1}^{2} \alpha_{jk} X_{j,t-k} + v_t \,. \quad (3.8)$$

This model simulates the joint distribution of default rate conditional on the macroeconomic factors like unemployment rate, rate of economic growth, government expenditure and aggregate savings rate.

To estimate the distribution of default probabilities for a loan portfolio, the model first determines the stochastic macroeconomic state. This is accomplished by simulating the relevant macroeconomic variables over several years more than 1,000 times. The conditional defaults probability is then estimated by country or by industry segment. It is also assumed that all default correlations are caused by the correlated segment-specific default. This means there is no further information beyond country, industry, the state of nature, and the state of economy used for predicting the default correlation between borrowers. Finally the model estimates the default distribution for a portfolio from the relevant segment default distributions.

Comparison of Models and Model Selection

Portfolio credit risk models have developed under divergent theoretical backgrounds and are distinct in their assumptions, data requirements, individual credit risk measures, mathematical structure, and aggregation. First of all, option-based structural models apply an asset price model to estimate stand-alone credit risk, but the other two types of models are built on an intensity model and econometric model, respectively. CreditMetrics and CreditPortfolio View take both migration and default risk into account, while the other two models deal with only default risk. Option-based structural models explicitly specify correlation with asset return to measure the joint probability of default. However, without explicit specification, Credit Risk Plus utilizes default rate volatilities and sub-portfolio weights. CreditPortfolio View uses dependencies on macroeconomic factors. For all those differences on the surface, Koyluoglu and Hickman (1999), and Gordy (2000) argue that the underlying mathematical structures are similar.

An essential inquiry, "Which class of model is the best for our bank?" is based on bank risk management strategies. Unfortunately, professional and academic literatures still debate this issue, and set forth different answers without common consensus. Speaking in principle, the best model for one bank may be different from other banks, and is highly dependent on the structure and characteristic of its loan portfolio. For example, a big international bank and a small community bank might have quite different loan portfolios and demand different types of classes. The final selection criteria rest upon: (1) forecasting accuracy and (2) applicability.

There is just a handful of studies on forecasting accuracy of portfolio credit risk models. Crouhy et al. (2000) and Gordy (2000) demonstrate the similarity of those models by showing that they give homogenous results if the input data is consistent. The empirical results of Rösch (2005), and Catarineu-Rabell et al. (2003) demonstrate CreditMetrics is more stable than Portfolio Manager. Sobhart et al. (2000) develops several indicators[20] to evaluate forecasting accuracy of credit risk models and argue that Portfolio Manager outperforms CreditMetrics, reduced-form models or simple z-score models. Jarrow and Protter (2004) suggest the reduced form model is the preferred approach if the bank is interested in pricing a firm's risky debt or related credit derivatives. Since Basel II will be implemented beginning in 2006 and requires validation of the IRB approach, more discussion and research will be expected in the future.

Applicability is a prerequisite condition for model selection. No matter how accurate a portfolio credit risk model is in forecasting, banks cannot choose any model for its loan portfolio unless it is applicable to the bank's existing conditions. First, data required for the model should be available (data availability). One of the key data required for CreditMetrics model is historical asset prices for individual borrowers. If this data or its equivalent is not attainable, banks cannot use the model. Second, the model must be manageable by the bank (manageability). If a model is sound theoretically but is too complicated to be applied by a bank's management, it cannot be a candidate model for adoption. Finally, cost efficiency of a model should be taken into account (cost efficiency). In Chapter II, the bank's objective function was assumed to be profit maximization. Therefore, the cost of implementation and maintenance should be considered when banks make a decision on model selection.

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[20] They include Cumulative Accuracy Profiles (CAPs), Accuracy Ratios (ARs), Conditional Information Entropy Ratio (CIER), and Mutual Information Entropy (MIE). See the working papers for the details.

In terms of data availability, CreditMetrics has big handicap because it might be the most data demanding model. It needs huge cross-sectional data with enough length in number of years. The rating system, transition matrix, and stock price data are the essential inputs for this model. Portfolio Manager also needs historical capital and debt structure data for individual firms, which is hard to obtain in small-to-medium enterprise (SME) or retail loan portfolio. Reduced form models demand relatively small amounts of data, which include the size of exposures and their default probabilities for individual exposures. CreditPortfolio Views has an advantage in this regard. It needs aggregated data at segment level such as historical default rate, migration rate and macroeconomic variable. However, this model requires time series modeling for the macroeconomic variables and assumptions on the error terms in the time series models.

Portfolio Credit Risk Models for Retail Loans

There are a number of attributes that differentiate retail loan portfolios from corporate loan portfolios. Retail loan portfolios usually consist of a large number of small size exposures, and the proportion of a loan in bank portfolio is relatively small. The banking industry and its regulators have viewed expected credit losses of retail loans is relatively higher but predictable, and unexpected credit losses are relatively low. On the other hand, corporate loan portfolios are regarded as having almost the opposite characteristics, especially having large unexpected losses that could often threaten bank solvency (Burns, 2002). Data availability in retail exposures is also a challenge. Corporate credit risk models use rich information such as firm financial statements and market data, but they are usually not available in retail loans or are too costly to obtain. It is difficult to measure the asset value of a borrower, and there is no continuously available market price because the market mechanism for continuously trading in retail loans doesn't exist. In consumer loans and small business loans, default is more closely related to their cash flows and the fact that their income becomes insufficient to service the loan, but the information is also not easy to acquire. The relevant information is reduced to a credit score and a behavioral score, but these scores are known only to the lender, not to the whole market. (Allen et al., 2004; Dietsch and Petey, 2002; Thomas, 2003).

In this sense, it is not surprising that both regulators and risk management have paid less attention to retail portfolio credit risk. After the first consultative document for Basel II was proposed in 1999, the need to develop an accurate credit risk model for a retail loan portfolio and to develop segmentation method for a loan portfolio in an optimal way is of more interest to bank management. Interest in retail portfolio credit risk modeling is inspired by the fact that the new Basel II proposal begins to apply different regulations to retail exposures from corporate exposures, and that its implementation can reduce the capital requirements.[21] Nevertheless, there is still very little literature on the theoretical underpinnings for capturing credit risk in retail loan

[21] The Basel Committee launched a comprehensive field test for banks, referred to as the third quantitative impact study, or QIS 3. The study focused on the impact of the Basel II proposals on minimum capital requirements (i.e. pillar one) before finalization of the third consultative paper (CP3), and it was published on October 2002 and updated on May, 2003. The paper reports that total credit risk will decrease 14% under the advanced IRB compare to current regulation and banks can reduce required capital for retail loan exposure up to 50%.

portfolios. Moreover, there have been only a few attempts to implement credit risk models developed in retail loan portfolios. Current portfolio credit risk models were originally designed and developed for corporate loan portfolios, and most applications of these models in the literature have focused on bonds or corporate loans (Carey, 1998; Crouhy et al., 2000; Bucay and Rosen, 2001; Thomas, 2003; Wilson, 1997a, 1997b). Now, banks are facing two important decisions: (1) should they develop an appropriate model specifically designed for their retail loan portfolio or (2) should they pick one of the current corporate models and modify it? In the latter case, what kind of model should they adopt?

The general principles and theory of current portfolio credit risk models could be applicable to retail loans, but several studies question their applicability and appropriateness. As discussed above, the characteristics of a retail loan portfolio are quite different from a corporate loan portfolio. This restricts the application of current models to retail market. Limited information, especially lack of equity price data and credit ratings, hinders banks from applying an option-based structural model such as Portfolio Manager and CreditMetrics. It is hard to directly adopt the methodological choices being used in models for large corporate loan portfolios because they might require extensive resources to estimate credit risk at the individual level (Burns, 2002; Dietsch and Petey, 2004; Ieda et al., 2000). The Risk Management Association (RMA, 2000) demonstrates that risk characteristics such as the probability of default, loss given default, exposure at default, and default correlations differ from the corporate loan market, and their parameters used for the corporate loan market cannot be used directly in the retail market. For these reasons, just transposing the corporate default models to retail default models can lead to some aspects of consumer default being missed (de Andrade and Thomas, 2004). Thomas (2003) asserts a skeptical view of the claim that existing corporate credit risk models can be modified to model retail loan portfolios.

A recent series of papers[22] focused on the application of current portfolio credit risk models to small business or retail loan portfolios. First, a simplified form of option-based structural model, proposed by Vasicek (1997) called "firm value model", is one of the leading applications. This model assumes a very simplified homogenous asymptotic portfolio: (1) a portfolio consisting of a large number of exposures, (2) the exposures are of identical size and have identical recovery rates, (3) default of the obligors happen independently of each other, and (4) the probability of default for each obligor is the same. Schönbucher (2000) specifies a simplified firm value model resembling CreditMetrics. The model uses the same concept for default as an asset pricing model. A firm is in default if its asset value, $V_n(T)$, which is distributed standard normal, falls below a pre-specified barrier, K_n: $V_n(T) \leq K_n$. The probability of default of n^{th} firm can therefore be represented as:

(3.9) $$K_n = \Phi^{-1}(p_n)\,.$$

The value of the firm's assets is driven by a common, standard normally distributed factor Y and an idiosyncratic standard normal noise component ε_n expressed as:

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[22] Some of them are published as a special edition of Journal of Banking and Finance in 2004, which is focused on credit risk of retail credit and consisted of eight papers. They were presented at the Conference on Retail Credit Risk Management in 2003, sponsored by the Research Department of the Federal Reserve Bank of Philadelphia in association with Journal of Banking and Finance.

(3.10) $V_n(T) = \sqrt{\rho}Y + \sqrt{1-\rho}\varepsilon_n$.[23]

Using the homogenous asymptotic portfolio assumption, an individual conditional default probability p(y) can be expressed, given the systematic factor Y takes the value y, as:

(3.11) $$p(y) = \Phi\left(\frac{K - \sqrt{\rho}y}{\sqrt{1-\rho}}\right).$$

The model derives the following distribution function of credit loss, which is a function of the probability of default (*p*) and common asset value correlation (AVC) among all consumers (*ρ*):

(3.12) $$F(x) = \Phi\left[\frac{1}{\sqrt{\rho}}\left(\sqrt{1-\rho}\Phi^{-1}(x) - \Phi^{-1}(p)\right)\right],$$

where *x* is a random variable indicating the fraction of defaulted loan, F(·) is a cumulative distribution function, Φ(·) and $\Phi^{-1}(\cdot)$ are standard normal CDF and inverse standard normal CDF. Basel II uses this formula for retail credit regulation along with a fixed correlation of 15% for mortgages exposures and 4% for revolving exposures. For other retail exposures, the correlation is specified as a weighted average of two extreme values.[24]

Vasicek (1997) and Schönbucher (2000) suggest banks apply an option-based structural model for a corporate loan portfolio to their retail loan portfolio. This suggestion is followed by Dietsch and Petey (2002, 2004) for SME loans, and Perli and

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[23] This is an example for one-factor version model. See Schönbucher for multi-factor model in detail
[24] See the Basel Committee (2004), §330, page 70.

Nayda (2004) for revolving retail exposures. de Andrade and Thomas (2004) develop a theory for consumer default on the basis of option theory and suggest a way of generalizing corporate credit models to retail credit by substituting the firm's asset value with a behavioral score that is a proxy of the individual's creditworthiness.

Another application is implementing reduced form models to retail exposures based on the theoretical underpinnings of an intensity-based model. Credit Risk Plus by itself can be applied to retail exposures because of its small data requirement and simple distributional assumptions discussed previously. Calem and LaCour-Little (2004, 2001) develop and implement a reduced form model for mortgage loans. They assume that a loan is subject to transitions from one segment to the other, and explicitly specify the conditional probability of transitions. To generate the distribution of loan loss, they apply Carey's non-parametric simulation procedure, which is done by Monte-Carlo re-sampling from historical data. An important finding of this research is that credit risk and economic capital depend on the degree of geographic diversification in a mortgage portfolio, while Basel II ignores it. Schmit (2004) developed a credit risk model for the leasing industry using non-parametric re-sampling method without any distributional assumptions.

RMA (2003) surveys portfolio credit risk models for retail loans that are being used in twelve banks of the RMA Capital Working Group. Three approaches were identified: (1) the EL-Sigma (ELS) approach, (2) the Asset-Value-Correlation (AVC) Approach and (3) the Loan-Default-Correlation (LDC) approach. Among the twelve banks, five banks employ AVC, three banks employ LDC, and four banks use ELS. One common aspect for all banks is the loss distribution estimated by loan segments, which is a prerequisite for classifying retail loan portfolios into individual segments. Segmentation of a retail loan portfolio is done by product, probability of default bands, multi-dimensional matrix of risk characteristics such as credit scores, and delinquency status. Segmentation also reflects geographic regions and type of business. Within each segment, the implicit assumption is that loans are homogenous with same probability of default and other risk characteristics.

The ELS approach, which is similar to the simplified reduced form model, calculates two parameters: (1) the mean and (2) the standard deviation of the default rate for each loan segment from bank historical performance data. The true underlying loss distribution is assumed to have a particular shape that can be characterized by the parameters such as a beta distribution. The basic assumption within this method is that the true underlying loss distribution for the bank's portfolio has been unchanged over time, and will remain so in the future. Distributional stability is also often assumed in the structural models (AVC and LDC), but this is problematic because it does not hold in the real credit market. The precision of the model is associated with (1) segmentation with realistic homogeneity, (2) fitness and flexibility when choosing a distribution from historical data and (3) available cross-sectional data.

The AVC approach is consistent with option-based structural model and Basel II, and it is the most widely used internal model among the RMA survey banks. It requires three critical inputs: (1) probability of default (PD), (2) loss given default (LGD), and obligor asset value correlation (AVC). There are several ways to estimate PDs for the use in the structural model: (1) simple historical average, (2) observed loss rates with in a segment,[25] (3) PD estimation model, which estimates PD as a function of several risk characteristics such as delinquency status, payment history, absolute balance, and (4) using credit migration data. Banks typically estimate PD at segment level, even those banks using a PD estimation model that can be carried out at the individual loan. LGD estimates are assigned at segment level as a constant, which is computed from the historical average loss rate on defaulted loans within a segment. AVC is estimated by one-factor or multi-factor models. Some banks use industry benchmarks. A more popular and simple way is backing into the implied AVC from the estimate of loss distribution, which is obtained from the same way one would estimate ELS, economic capital, PD and LGD.

The LDC model requires three inputs: (1) PD, (2) LGD and (3) loan default correlation (LDC) instead of AVC. This model shares the same methodologies for estimating PDs and LGDs as those used in AVC, and the estimation of LDC can be also accomplished using similar processes to AVC model.

Portfolio Credit Risk Model for Agricultural Loans

As discussed in Chapter II, agricultural loans can be viewed as retail exposures. Research on portfolio credit risk models for agricultural loan portfolios is in its infancy. Lyubov (2003) developed the first portfolio credit model applied to agricultural lending.

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[25] Banks first estimate expected loss (EL) and LGD, and then EL is divided by LGD to estimate PD.

The model is a reduced form model rooted along the lines of Credit Risk Plus, but addresses a disadvantage of this approach by incorporating recent research on sector relationships using a more stable algorithm. The model was applied to a representative Farm Credit System association in Minnesota, AgStar Financial Services. The model output is a loan loss distribution which is used to calculate the expected and unexpected loan losses for the overall portfolio and to estimate required capital.

Katchova and Barry (2005) specify an option based structural model much like the CreditMetrics and Portfolio Manager models. This represents the first attempt at applying the structure model to agricultural loans. However, this approach is difficult for agricultural banks because it requires extensive data. Agricultural banks need a more simplified and practical model. The theory and methodology developed recently for retail exposures discussed in previous section should be considered.

When modeling portfolio credit risk for agricultural loans, one must account for the attributes of the agricultural sector and its borrowers, which is substantially different from the other retail exposures. The U.S. agricultural sector, which is capital-intensive, has a history of liquidity problems.[26] It experiences chronic cash flow pressures resulting from relatively low but volatile returns to production assets. These characteristics contribute to the aggregate debt-servicing capacity and credit worthiness during downward swings in farm income and reductions in asset value, as happened in 1980s (Barry et al., 2002). Credit risk in agricultural loans is closely tied to a farm's net cash

[26] 87.4% of U.S. farm assets in 2002 consist of real estate, machinery, and motor vehicles. Farm business balance sheet data, ERS, USDA.

flow just as it is for other retail loan categories. Expected net cash flows is a good leading indicator for the eventual credit worthiness of an agricultural borrower. The utilization of the expected net cash flow information in credit risk modeling makes the model more proactive. Asset values can be evaluated as a lagging indicator of credit worthiness in the agricultural sector because of their illiquidity and lags in market valuation. Thus, application of an asset value model for agricultural loans is questionable.

Volatile performance of farm businesses stems mainly from fluctuating commodity prices and weather conditions, which are highly correlated, especially for farms with similar typology, commodity, and geographical region (Bliss, 2002). This phenomenon implies that segmentation of an agricultural loan portfolio should consider commodity and regional differences. Economic performance in the agricultural sector is also widely influenced by events in both the domestic and international economy. Capturing the state of these economies is critical in credit risk modeling for agricultural sector.

Net cash flows in the agricultural sector typically exhibit cycles within the year. However, term debt repayment is typically annual in nature. These characteristics restrict more frequent periodicity in model specification. In addition, monthly and quarterly data is difficult to obtain. When an agricultural bank chooses a model among several candidates, applicability of the model becomes one of the essential considerations since data availability is more problematic in agricultural sector.

Summary

This chapter provided an extensive review of literature on approaches to credit risk modeling. There are three categories of stand-alone credit risk models: expert systems, credit ratings and credit scoring models. These models are used as an input to portfolio credit risk modeling. Portfolio credit risk models were initially developed for commercial use. There are several types of portfolio credit risk model: option-based structural models, reduced form models, and multi-factor econometric model. Portfolio credit risk models for retail exposures have received recent attention from banks, but there have been only a few attempts to model credit risk for retail exposures, including agricultural loans.

This chapter argued that a model for bank portfolio credit risk should be chosen based upon forecasting accuracy and applicability. In this sense, portfolio credit models developed for corporate exposures may not be a candidate for retail exposures because of applicability problem accompanied with intensive data requirement. Retail exposures have unique characteristics and modeling need to take those into account. One of the most important implications from the literature review is that default is closely related to their net cash flows. The consideration of net cash flows in credit risk modeling is more important in agricultural loan because agricultural sector is known to have liquidity problem and chronic cash flow pressures. Expected net cash flows is thought to be a good leading indicator for credit worthiness.

CHAPTER IV

A PORTFOLIO CREDIT RISK MODEL

This chapter proposes a portfolio credit risk model for agricultural loans. A theory of loan default for farm borrowers is conceptualized first. Then, a theoretical model is developed that takes into account the characteristics of the agricultural sector, farm loans, and farm borrowers to insure the applicability of the model. Consistency with Basel II is addressed. For empirical application, a default model is specified by state. Simulation is used to project the probability of default and the other outputs for 2004 to 2007 period. The six steps involved in this simulation processes are explained.

Theoretical Model

This study proposes a simplified default model based on intuitive theory that a default event occurs when the borrower incurs negative net cash flows. This model therefore specifies creditworthiness in a more direct manner rather than the indirect manner common in asset value models. The default of an individual borrower is specified first. A portfolio default rate is then formulated by aggregation with assumptions about the loan portfolio and specific segments.

Assumption 1 (Definition of Default): *An individual borrower (i) defaults if available cash at t is not enough to service the loan obligation (K_{it}). Available cash at t is the sum of net cash income (NCI_{it}), cash reserves (CR_{it}), and available credit (AC_{it}).*

The condition of default for each borrower is denoted as:

(4.1) $W_{it} = NCI_{it} + CR_{it} + AC_{it} - K_{it} < 0$.

W_{it} is the difference between available cash or cash equivalents and the cash requirements for the loan obligation. This default condition is similar to distance-to-default in KMV model.

Assumption 2 (Credit worthiness of individual borrower): *There is an unobservable stochastic variable Z_{it}^{*}, which is the index variable representing credit worthiness of borrower i at time t. Since the default of each borrower is triggered by net cash flows, W_{it} can be used as a proxy variable for the credit worthiness.*

The borrower's credit worthiness can therefore be represented by the following relationship with disturbance term, ζ_{it}:

(4.2) $Z_{it}^{*} = NCI_{it} + CR_{it} + AC_{it} - K_{it} + \zeta_{it}$.

The credit worthiness, Z_{it}^{*}, is increasing as net cash income, credit reserves or available credit increases, but is decreasing as the amount of the periodic loan obligations increase.

Assumption 3 (Net cash income and the others): *There exists causal relationship between the net cash income (NCI_{it}) and specific economic variables. NCI_{it} is generated by a set of systematic factors (Y_t), which is common to each borrower, and idiosyncratic factors (I_{it}). The values for CR_{it}, AC_{it}, and K_{it} are the same over all borrowers in a particular pool or segment.*

The credit worthiness, Z_{it}^{*}, can be therefore expressed as the following regression relationship:

(4.3) $\quad Z_{it}^{*} = C^{*} + \mathrm{A}'Y_t + \mathrm{B}'I_{it} + \varepsilon_{it}$,

where $C^{*} = CR_{it} + AC_{it} + K_{it}$, A and B are vector of unknown parameters, and ε_{it} is error term.

In practice, Z_{it}^{*} is unobservable variable, but banks can monitor the default (or non-default) of each borrower. So, the credit index variable, Z_{it}, can be written out as a binary variable defined by

(4.4) $$\begin{cases} Z_{it} = 1, & if \quad borrower \quad i \quad default \\ Z_{it} = 0, & otherwise \end{cases}.$$

By assuming the cumulative distribution of ε_{it} is logistic, this study specifies a binary choice logit model for the credit index variable (Z_{it}):

(4.5) $\quad Z_{it} = C^{*} + \mathrm{A}'Y_t + \mathrm{B}'I_{it} + \varepsilon_{it}$

(4.6) $$\Pr(Z_{it} = 1) = \frac{1}{1 + \exp(-\hat{Z}_{it})}.$$

Equation (4.5) and (4.6) represent the credit risk models for individual borrower. In this specification, $\hat{\mathrm{Z}}_{\mathrm{it}}$ is interpreted as the probability of default of borrower i at time t.

To estimate credit risk at portfolio level, this study makes the following assumptions regarding the bank loan portfolios:

Assumption 4 (Homogenous asymptotic loan portfolio): [27]

(i) The portfolio has a significantly large number (N) of exposures: $N \rightarrow \infty$,

(ii) Each exposure is homogenous and identical in size: $L_i = 1$ *and* $\Sigma L_i = N$,

(iii) Default event occur independently conditional on the realization of systematic factors (Y).

Let Z_t denote the fraction of the defaulted loan (or default rate) in the portfolio at time t. One can derive following equation:

$$
\begin{aligned}
(4.7)\qquad Z_t &= \frac{Loan \quad Loss_t}{Total \quad Loan_t} \\
&= \frac{\sum_{i=1}^{N}(1 \times Z_{it})}{N_t} \\
&= \frac{\sum_{i=1}^{N}(C^* + \mathrm{A}'Y_t + \mathrm{B}'I_{it} + \varepsilon_{it})}{N_t} \\
&= C^* + \mathrm{A}'Y_t + E(\mathrm{B}'I_{it}) + E(\varepsilon_i) \\
&= C^* + \mathrm{A}'Y_t + \mathrm{B}'E(I_{it}).
\end{aligned}
$$

To simplify equation (4.7), segmentation of the loan portfolio and their attributes of each segment are assumed as follows:

Assumption 5 (Homogenous segments): *Bank loan portfolios can be classified into finite number (k) of segments or sub-portfolios. Even though entries and exits of loans*

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[27] This study takes the almost same assumptions to the simplified retail portfolio credit risk model such as Schönbucher (2000), Dietsch and Petey (2004), and Perli and Nayda (2004)

are continuously taken place in each loan segment, the average value of idiosyncratic factors in a segment is stationary over time.

Based on this assumption, $B'E(I_{it})$ in equation (4.7), the expected value of idiosyncratic factor at time t, can be divided into two terms; a constant value and stochastic error, e_t. Accordingly, one can rewrite equation (4.7) as:

(4.8) $$Z_t = C + A'Y_t + e_t .$$

Default model for p^{th} loan segment can be expressed as follows:

(4.9) $$Z_{p,t} = \alpha_{p,0} + \sum_{k=1}^{m} \alpha_{p,k} Y_{p,k,t} + e_{p,t}$$

(4.10) $$DR_{p,t} = \frac{1}{1 + \exp(-\hat{Z}_{p,t})},$$

where $Z_{p,t}$ is the credit index for p^{th} loan segment at time t, $Y_{p,k,t}$ is k^{th} systematic factor for p^{th} loan segment at time t, $DR_{p,t}$ is default rate of p^{th} loan segment at time t, α's are unknown parameters, and $e_{p,t}$ is error term. These equations can be simply transformed into a logistic functional form as follows:

(4.11) $$DR_{p,t} = \frac{1}{1 + \exp\left[-\left(\alpha_{p,0} + \sum_{k=1}^{m} \alpha_{p,k} Y_{p,k,t} + e_{p,t}\right)\right]}.$$

The systematic factors capturing the state of economy in each segment are determined by following multiple regression model:

(4.12) $$Y_{p,k,t} = f(X_{p,k,t}) + \mu_{p,k,t} ,$$

where X is the vector of factor specific, segment specific, or macroeconomic variables, and $\mu_{p,k,t}$ is the error term.

After estimating equation (4.11) and (4.12), one can formulate a stochastic simulation model. By the nature of correlation among the economic factors in this model, the probability of default is a function of weighted average of systematic risk factor Y conditioned on state-of-the-economy X. This gives us a joint conditional distribution of default for each loan segment through simulation analysis as follows:

$$(4.13)\quad D\tilde{R}_{p,t} = \frac{1}{1+\exp\left[-\left(\hat{\alpha}_{p,0}+\sum_{k=1}^{m}\hat{\alpha}_{p,k}\left(\tilde{Y}_{p,k,t} \mid \tilde{X}\right)+\tilde{e}_{p,k,t}\right)\right]}$$ [28]

$$(4.14)\quad \tilde{Y}_{p,k,t} = f(\tilde{X}_{p,k,t}) + \tilde{\mu}_{p,k,t}\,.$$

Empirical Model

The discussion of the empirical model in this study is disaggregated in two parts; (1) the default model and (2) simulation model.

Default Model

The theoretical model reflected in equation (4.11) assumes that the default rate of a loan segment can be expressed as a function of the systematic factors, and that they should be segment-specific and cash-flow-related variables if the default model is specified by sub-portfolio or loan segment. For example, if an agricultural bank segments its loan portfolio by commodity and by state (or region), i.e. loans to corn farmers in Iowa, Illinois, and so on, the explanatory variable of the default model should

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[28] "~" on the variables represents that the variable is stochastic.

be associated with cash flows of the borrowers in the specific loan segment. However, this study specifies a default model by state, not by commodity because of data availability at the time of this study.[29] As discussed in more detail in the next chapter, default rate data available in this study is disaggregated down to state level, and so this study collected state-specific data.

This study creates three indicator variables by state to capture the robustness of net farm cash income; (1) net cash income per acre from crops or *NCIC*, (2) net cash income per hundred pounds (cwt) from livestock or *NCIL*, and (3) government payments per acre or *GPMT*. The two net cash income indicators, *NCIC* and *NCIL*, are selected because they are the major sources of cash income to U.S. farmers. Since government payments are also an important cash income source, *GPMT* is as an additive variable to the *NCIC*. The summation of *NCIC* and *GPMT* represents the total net cash income per acre from crops. The state rate of unemployment (*UEMP*) is introduced as a proxy indicator to capture the availability of off-farm income. A trend variable (*TREND*) is not a variable directly associated with net cash flows. However, at portfolio level, credit risk at agricultural banks has been decreasing due to the development of credit risk management technology such as credit scoring, improved loan approval process, and more extensive data availability. The trend variable can eliminate the effect of technological advances and enable the model to capture the impact of net cash income on the bank's credit risk.

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[29] Attempts to secure enterprise-level default information from the Farm Credit System were unsuccessful within the time frame of this study.

The default rate in each state is modeled based on equation (4.11) in the theoretical model. A three-year moving average of the indicator variables (*NCIC, NCIL, GPMT,* and *UEMP*) is used as explanatory variables with the trend variable (*TREND*). The use of a moving average is employed because the default event in a specific year is determined not only by concurrent net cash flows but also by past net cash flows. In other words, cash flow deficiencies cause default events in cumulative manner. The empirical default model for the agricultural loan segment in i^{th} state is specified based as follows:

$$(4.15)\quad DR_{i,t} = 1\Big/\left[1+\exp\left\{-\Big(\alpha_{0,i}+\alpha_{1,i}movav(NCIC_{i,t}+GPMT_{i,t})+\alpha_{2,i}movav(NCIL_{i,t}) + \alpha_{3,i}movav(UEMP_{i,t})+\alpha_{4,i}TREND_t+\varepsilon_{i,t}\Big)\right\}\right],$$

where $DR_{i,t}$ is the default rate for agricultural loans in i^{th} state at the end of year t. The term *movav*( ) represents moving average of the variable(s) in the parenthesis ( ). $NCIC_{i,t}$ is net cash farm income per acre from crops in i^{th} state at time t, $NCIL_{i,t}$ is net cash farm income per cwt from livestock, $GPMT_{i,t}$ is government payments per acre, $UEMP_{i,t}$ is state rate of unemployment, and *TREND* is trend variable representing technological advances in bank risk management.

Since *NCIC*, *NCIL*, and *GPMT* cannot be directly collected from secondary data, this study creates them. Net cash farm income from crops (*NCIC*) is calculated as a weighted average of net cash farm incomes from three major crops (corn, soybeans and wheat), and the weights are determined by their percentage of cash receipts:

$$(4.16)\quad NCIC_{i,t} = \sum_{m=1}^{3} NCIC_{i,m,t} \times CRW_{i,m,t}$$

$$(4.17)\quad CRW_{i,m,t} = \frac{CREC_{i,m,t}}{\sum_{P=1}^{3} CREC_{i,p,t}},$$

where $NCIC_{i,m,t}$ is net cash income per acre of mth crop in ith state at time t, $CRW_{i,m,t}$ is the percentage of state cash receipts from mth crop among total state cash receipts from the three crops, and $CREC_{i,m,t}$ is state cash receipts from mth crop.

Net cash income by crop is calculated from the state level yield, commodity price and cash cost of production:

$$(4.18)\quad NCIC_{i,m,t} = YIELD_{i,m,t} \times PRICE_{i,m,t} - CCOST_{i,m,t},$$

where $YIELD_{i,m,t}$ is yield of mth crop in ith state at time t, $PRICE_{i,m,t}$ is price received by farmers for mth crop, and $CCOST_{m,i,t}$ is cash cost of production of mth crop.

Net cash farm income from livestock (*NCIL*) is generated by weighted average of net cash farm incomes from fed beef cattle and market hogs, and it is calculated by following equations:

$$(4.19)\quad NCIL_{i,t} = \sum_{n=1}^{2} NCIL_{i,n,t} \times CRW_{i,n,t}$$

$$(4.20)\quad CRW_{i,n,t} = \frac{CREC_{i,n,t}}{\sum_{q=1}^{2} CREC_{i,q,t}}$$

$$(4.21)\quad NCIL_{i,n,t} = PRICE_{i,n,t} - CCOST_{i,n,t},$$

where $NCIL_{i,n,t}$ is net cash income per cwt of nth livestock in ith state at time t, $CRW_{i,n,t}$ is the percentage of state cash receipt from nth livestock among total state cash receipt from the two livestock, $CREC_{i,n,t}$ is state cash receipt from nth livestock, $PRICE_{i,n,t}$ is price received by farmers for nth livestock, and $CCOST_{i,n,t}$ is cash cost of production for nth livestock.

These three crops and two livestock represent 88.5% of total cash receipts in the states covered by this study. More details will be discussed in the next chapter.

Simulation Model

The objective of the simulation model developed in this study is to project the distribution of default rate and loan losses from 2004 to 2007, where 2007 is the last year of current U.S. farm bill. The objective is achieved through six steps of following simulation procedures:

Step 1: Generating stochastic exogenous variables

Step 2: Solve the COMGEM[30] econometric model for national prices and cash costs

Step 3: Estimate state prices and cash cost of production

Step 4: Calculate exogenous variables for the default model

Step 5: Estimate the probability of default and loan loss distribution

Step 6: Generate model outputs.

Figure 3 illustrates the structure and processes of simulation model. This is followed by a detailed discussion of each step.

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[30] COMGEM is a multi-sector macroeconomic model containing a fully simultaneous agricultural sector. A description of its design can be found in Penson and Taylor (1992). This model over time has been used for numerous analyses of government policy and agricultural issues. Taylor et al. (1991) is one of the applications of the model.

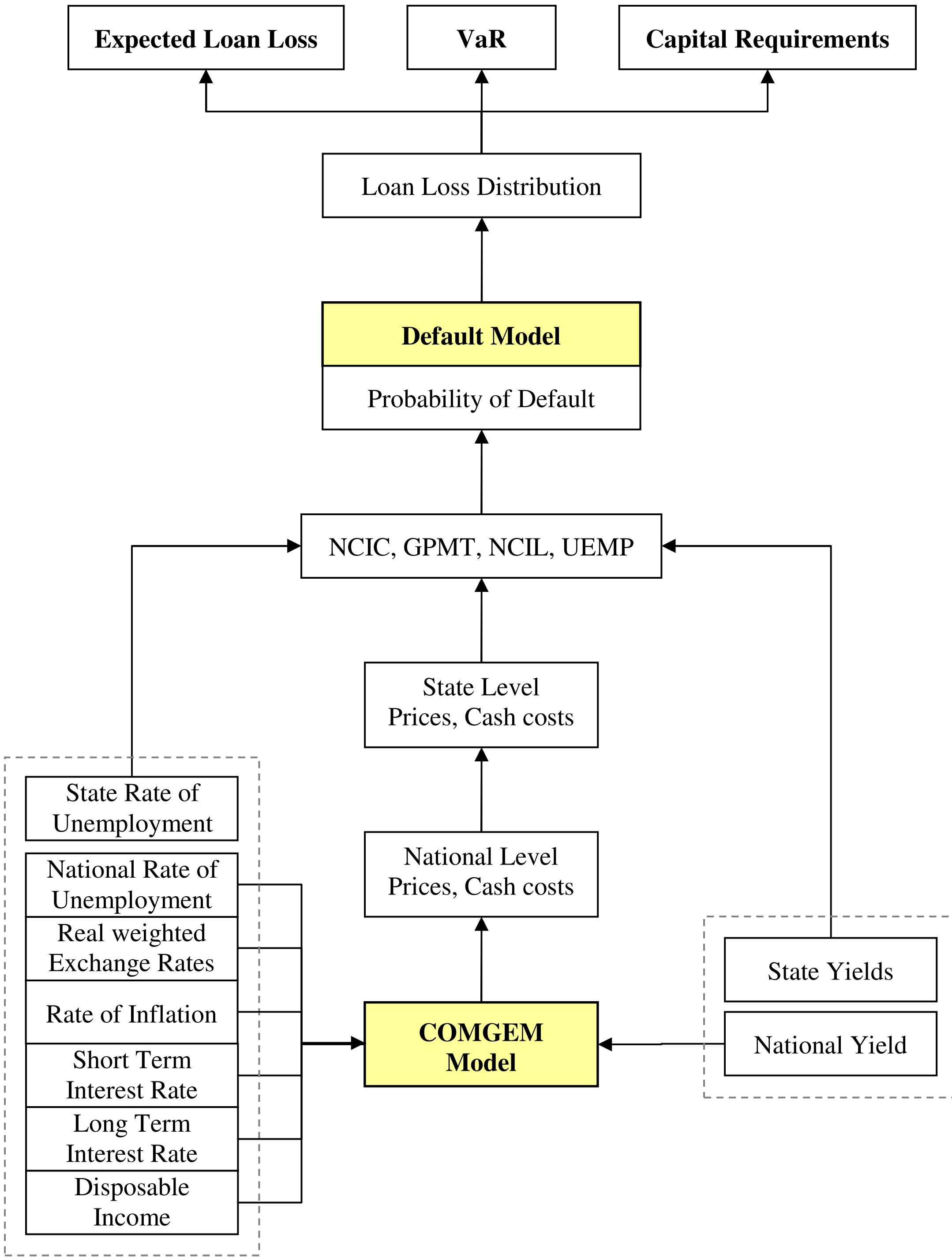

Figure 3 Structure of Simulation Model and Outputs

Step 1: This model identified nine exogenous variables and generated 100 iterations using Simetar[31] for each of these stochastic variables to capture the states of the economy. The exogenous variables are divided into two groups. The first group includes (1) state rate of unemployment (*UEMP*), (2) national rate of unemployment (*USUEMP*), (3) real weighted exchange rates for corn, soybeans, wheat and meats (*CER*), (4) rate of inflation (*PGDP*), (5) short term interest rate (*RS*), (6) long term interest rate (*RL*), and (7) consumer disposable income (*YD*). The second group includes (8) the national yields for corn, soybeans and wheat (*USYIELD*), and (9) the state yields for these crops (*YIELD*). It is assumed that stochastic exogenous variables take a multivariate empirical distribution[32] within a group, but they are not correlated inter-temporarily or between groups.

The empirical distributions consist of two components, deterministic forecasted means and stochastic deviations. The stochastic deviations are selected randomly from historical deviations. Forecasted mean values are generated from the COMGEM model, and the state rate of unemployment (*UEMP*) and state yields (*YIELD*) are estimated from the following regression models as follows:

(4.22) $$UEMP_{i,t} = \hat{\beta}_{0i} + \hat{\beta}_{1i} USUEMP_t .$$

[31] Simetar is simulation software developed by Richardson (2003), which is used in Microsoft Excel as add-in program. 100 iterations for this simulation model are enough because Simetar uses Latin Hypercube technique.

[32] Empirical distribution is a non-parametric distribution generated from historical data. It is useful when there are too small observations to estimate the parameters for the true distribution or when a parametric distribution assumption is not appropriate for data, i.e. crop yield typically having two peaks. See Richardson (2003) for the formula and calculation of multivariate empirical distribution (MVE) in detail.

(4.23) $YIELD_{i,m,t} = \hat{\delta}_{0i,m} + \hat{\delta}_{1i,m} USYIELD_{m,t}$,

where the subscript *i*, *m*, and *t* denote the state, commodity, and year, respectively. From the forecasted values and empirical distributions,[33] stochastic exogenous variables are calculated for $UEM\tilde{P}_i$, $USUEM\tilde{P}$, $CE\tilde{R}$, $PGD\tilde{P}$, $L\tilde{R}$, $S\tilde{R}$, $Y\tilde{D}$, $USYIEL\tilde{D}$, and $YIEL\tilde{D}_i$.

<u>Step 2</u>: Generated random exogenous values are used as inputs to simulation of the COMGEM model. The model is solved to generate stochastic output variables; namely, national commodity prices ($USPRIC\tilde{E}$) and unit cash cost of production ($USCCOS\tilde{T}$) for corn, soybeans, wheat, beef cattle, and hogs.

<u>Step 3</u>: The stochastic national prices and costs from the COMGEM model are used to estimate state prices and costs. State commodity prices ($PRIC\tilde{E}$) and cash costs ($CCOS\tilde{T}$) are specified as a function of national commodity prices and cash cost of production as follows:

(4.24) $PRIC\tilde{E}_{i,m,t} = \hat{\phi}_{0i,m} + \hat{\phi}_{1i,m} USPRIC\tilde{E}_{m,t} + \tilde{\upsilon}_{i,m,t}$

(4.25) $CCOS\tilde{T}_{i,m,t} = \hat{\lambda}_{0i,m} + \hat{\lambda}_{1i,m} USCCOS\tilde{T}_{m,t} + \tilde{\varpi}_{i,m,t}$,

where $\tilde{\upsilon}$ and $\tilde{\varpi}$ are error terms assumed to follow a multivariate empirical distribution.

<u>Step 4</u>: In this step, stochastic exogenous variables for the default model, $NCI\tilde{C}_i$, $NCI\tilde{L}_i$, $GPM\tilde{T}_i$, and $UEM\tilde{P}_i$ are calculated. Stochastic net cash incomes ($NCI\tilde{C}_i$

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[33] Empirical distributions are generated as percentage deviations from mean, percentage deviations from trend, or actual data of the regression error terms in equation (4.23) and (4.24).

and $NCI\tilde{L}_i$) are generated by equation (4.16) through (4.21) with the stochastic commodity prices, cash cost of production, and yields at state level. The percentage of cash receipts for a commodity among total cash receipt (*CRW*) is assumed to be constant, which equal to the average contribution over the five most recent years, or:

(4.26) $CRW_{i,m,t} = Average(CRW_{i,m,1999-2003})$.

Stochastic state rates of unemployment ($UEM\tilde{P}_i$), which are simulated in step 1, are utilized directly.

Simulating government payment per acre, $GPM\tilde{T}_i$ out to 2007 is problematic because of the data restrictions at the state level and potential changes in government policy prior to a new farm bill in 2008. Historical *GPMT* data is calculated by dividing state total direct payment by total planted acres for the three crops from 1985 to 2003. During this period, the farm bill has changed three times. Thus, the historical data represents four different crop policies. Estimating future *GPMT* through historical information, therefore, is not done. Instead, this study measures government payment per base acre using the formulas contained in the 2002 Farm Bill. Government payment (*GPMT*) is the sum of direct payments (*DP*), loan deficiency payments (*LDP*), and counter-cyclical payments (*CCP*), or:

(4.27) $GPM\tilde{T}_{i,t} = \sum_{m=1}^{3}(DP_m + LD\tilde{P}_{i,m,t} + CC\tilde{P}_{m,t})$.

DP is calculated as a fixed payment by state and by commodity, and is expressed as a multiplication of direct payment rate (DPR), farm program yield (*FPY*) and a constant number 0.85, or:

(4.28) $DP_{i,m} = DPR_m \times 0.85 \times FPY_{i,m}$.

LDP is a function of Loan Rate (*LR*) given by commodity, state price and state yield, or:

(4.29) $LD\tilde{P}_{i,m,t} = (LR - PRIC\tilde{E}_{i,m,t}) \times YIEL\tilde{D}_{i,m,t}$.

Finally, CCP is calculated by following two equations:

(4.30) $CC\tilde{P}_{m,t} = (TP_m - Effective\ PRIC\tilde{E}_{m,t}) \times 0.85 \times Updated\ FPY$

(4.31) $Effective\ PRIC\tilde{E}_{m,t} = Max\ (USPRIC\tilde{E}_{m,t}, LR_m + DP_{i,m}),$

where *TP* is target price. *TP*, and *LR* are fixed by commodity over the time period covered by this study, and *Updated FPY* is determined by state and by commodity. As a whole, *GPMT* is predetermined by the values for *DPR, FPY, LR, TP, and Updated FPY*, and by stochastic state and national commodity prices and yields.

An inconsistency exists between historical and simulated *GPMT* since they are calculated by different approaches. The former is generated on a planted acre basis while the later is calculated on a base acre basis. To connect the two data series, this paper collects national average of government payment data per base acre (*USGPMT*). The data set is developed by Outlaw et al. (2004), and includes both crop year and fiscal year data from 1990 to 2002. Simulated *GPMT* by state is adjusted by the relationship between historical *GPMT* and *USGPMT* as followed:

(4.32) $GPMT_{i,t} = \hat{\gamma}_{0i} + \hat{\gamma}_{1i} USGPM\tilde{T}_t$.

<u>Step 5</u>: Stochastic default rates (*DR*) are calculated by the equation (4.15), and simulation model generates the probability of default or PDF for the default rate. The default model for simulation can be expressed as follows:

$$(4.33)\quad D\tilde{R}_{i,t} = 1\Big/\left[1+\exp\left\{-\left(\hat{\alpha}_{0,i} + \hat{\alpha}_{1,i} movav(NCI\tilde{C}_{i,t} + GPM\tilde{T}_{i,t}) + \hat{\alpha}_{2,i} movav(N\,CI\tilde{L}_{i,t}) + \hat{\alpha}_{3,i} movav(UEM\tilde{P}_{i,t}) + \hat{\alpha}_{4,i} TREND_t + \tilde{\varepsilon}_{i,t}\right)\right\}\right],$$

where $\tilde{\varepsilon}_{i,t}$ is assumed to follow empirical distribution.

Step 6: The final step of the simulation model is to generate the loan loss distribution and calculate management variables such as expected loan loss, VaR, and capital requirements. The loan loss distribution can be generated by following formula, which is identical to equation (2.1):

$$(4.34)\quad L\tilde{L}_{i,t} = Total\quad Loan_{i,t} \times D\tilde{R}_{i,t} \times EAD_{i,t} \times LGD_{i,t},$$

where $L\tilde{L}_{i,t}$ is stochastic loan loss in the ith state at time t, EAD is the exposure at default, and LGD is loss given default. Since the data used in this study is not bank level data but FDIC data aggregated by state as explained in Chapter V, the total loan, EAD, and LGD is not attainable. Therefore, this study makes assumptions about the variables, and develops the processes for generating loan loss distribution and calculating expected loan loss, VaR, and capital requirements from the loss distribution at the state level as discussed in Chapter V.

The Basel II formula for capital requirements in retail exposures is based on the work of Vasicek (1997), where an analytical solution for distribution of default rate of a corporate loan portfolio was derived. Basel II applies this formula to retail exposures as well. The capital requirements formula for other retail exposure[34] is expressed as the multiplication of 99.9% percentile of the distribution of default rate and LGD, or:

$$(4.35)\quad K = LGD \times \Phi\left(\frac{1}{\sqrt{1-R}}\Phi^{-1}(DR) + \sqrt{\frac{R}{1-R}}\Phi^{-1}(0.999)\right),$$

where K represent capital requirement as a percentage of total loans outstanding, Φ and Φ^{-1} are the cumulative standard normal distribution function and its inverse function respectively, DR is expected value of the default rate, and R is correlation between asset value of borrower.[35]

In retail exposures, the asset correlation cannot be observed. Basel II suggests a formula for indirect measure of the correlation from the default rate. The correlation was given by the following equation as a weighted average of minimum R (0.03) and maximum R (0.16):

$$(4.36)\quad R = 0.03 \times \left(\frac{1-\exp(-35 * DR)}{1-\exp(-35)}\right) + 0.16 \times \left(1 - \frac{1-\exp(-35 * DR)}{1-\exp(-35)}\right).$$

Summary

This chapter presented the theoretical model proposed in this study and developed a default model and a simulation model based on this theoretical model conditioned by data availability. The empirical default model was developed as a logistic

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[34] Basel II suggests three different formulas for retail exposures, which include residential mortgage exposures, revolving exposures, and other retail exposures. Agricultural exposures are fitting to the other retail exposures.

[35] This formula includes asset correlation because Basel II simply introduced the formula from the asset value model designed for corporate exposures.

specification to evaluate loan portfolio credit risk by loan segment. The simulation model generated stochastic exogenous variables associated with the state of the economy, and were used as an input to the COMGEM econometric model. The COMGEM model generated national level variables, which were transformed into state level variables for use in the default model. This model is designed to generate probability of default in a proactive manner. The processes to generate loan loss distribution, expected default, VaR, and capital requirements was based on the Basel II regulation.

CHAPTER V

DATA AND ESTIMATION

The purpose of this chapter is to give a detailed description of data used in this study and to show the results from model estimation. Quantitative analysis is as good as the quality of data. The default rate and macroeconomic variables are described with the aid of both tables and graphs. The processes generating net cash income and associated variables are also explained, and details are tabulated in Appendix. The next section of this chapter presents econometric estimation results, which include equations for default rate, state rate of unemployment, state yields, state price, and state cash cost of production.

Data

Default Rate

The default rates used in the development of the default model were graciously provided by the Federal Deposit Insurance Corporation (FDIC).[36] This data contained requested series on loan performance for all agricultural loans at the state level from their Call Report[37] database. The data was collected from commercial banks and

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[36] FDIC is an organization that insures deposits held by about 98% of all U.S. commercial banks.

[37] All FDIC-insured institutions are required to file consolidated Reports of Condition and Income (Call Report) as of the close of business on the last day of each calendar quarter. FDIC constructed a database from the Call Report, and the database is publicly available on the web site from 1998.

aggregated at the state level for the 1985 to 2003 period. The data consists of (1) total loans outstanding, (2) loans past due greater than 30 days and less than 90 days but still accrual, (3) loans past due over 90 days but still accrual, (4) non-accrual loans, and (5) charge offs. The data was available quarterly, but this study uses only the fourth quarter balance to estimate annual default model. The sum of loans past due greater than 90 days but still accrual and non-accrual loans are considered as defaulted loans, or:

(5.1) $Default\ Loan_{i,t} = Loan\ past\ due\ over\ 90\ days,\ accrual_{i,t} + Non\text{-}accrual\ loan_{i,t}$,

where i and t indicate state and year, respectively.

This formula is consistent with the Basel II definition of default. The default rate is calculated by the fraction of default loans to total loans outstanding, or:

(5.2) $$Default\ \ Rate_{i,t} = \frac{Default\ \ Loans_{i,t}}{Total\ \ Loan\ \ Outstanding_{i,t}}.$$

This study models default rates for five states: Iowa, Illinois, Indiana, Kansas, and Nebraska. These are located in the USDA's Corn Belt and Northern Plains production regions. These states were chosen because the bulk of farm cash receipts come from the major commodities covered in this study. The following table shows cash receipts by state by commodity. Cash receipts for five major commodities (corn, soybeans, wheat, fed cattle and hogs) represent an average of 88.5% of total cash receipts in these states. The percentage of cash receipts from five major commodities is 92.6% in Nebraska, followed by Iowa (89.2%), Kansas (88.9%), Illinois (88.8%) and Indiana (77.7%). Cash receipts in Iowa, Illinois and Indiana come primarily from crops, while cash receipts in Kansas and Nebraska come primarily from livestock.

Table 3 Cash Receipts by State, 2000-2003 Average

Unit: million Dollars

State	Total Cash Receipt (a)	Cash Receipts by commodity						% (b/a)
		Corn	Soybeans	Wheat	Fed Cattle	Hogs	Sum (b)	
IA	11,376,288	3,135,676	2,236,461	2,723	1,969,281	2,805,124	10,149,264	89.2
IL	7,581,468	2,991,317	2,258,059	126,608	543,743	810,923	6,730,651	88.8
IN	4,864,499	1,432,689	1,241,391	69,948	813,939	220,579	3,778,545	77.7
KS	8,294,277	703,204	314,296	1,015,588	5,072,684	271,217	7,376,989	88.9
NE	9,557,588	1,874,317	917,512	188,418	5,217,601	649,480	8,847,327	92.6
Sum	41,674,120	10,137,203	6,967,719	1,403,284	13,617,248	4,757,322	36,882,775	88.5

Source: Farm Income Data, ERS / USDA: www.ers.usda.gov/Data/FarmIncome/Finfidmu.htm#receipts

Historical data for loan performance status and default rates for the five states are tabulated in the Appendix 1. Figure 4 shows the historical trend for the default rate in the five states, while Table 4 presents summary statistics for these default rates. From the highest point in 1985, default rates have decreased to around 1% in 2003. Kansas represents the highest average default rate (1.75%), followed by Nebraska (1.68%), Indiana (1.60%), Illinois (1.53%), and Iowa (1.46%). Iowa recorded the highest and lowest default rates in history, 6.64% and 0.48%, and so it shows biggest standard deviation (1.71). Volatility represented by standard deviation is 0.96 in Indiana, which is the lowest, and followed by Illinois (1.15), Kansas (1.17), and Nebraska (1.39).

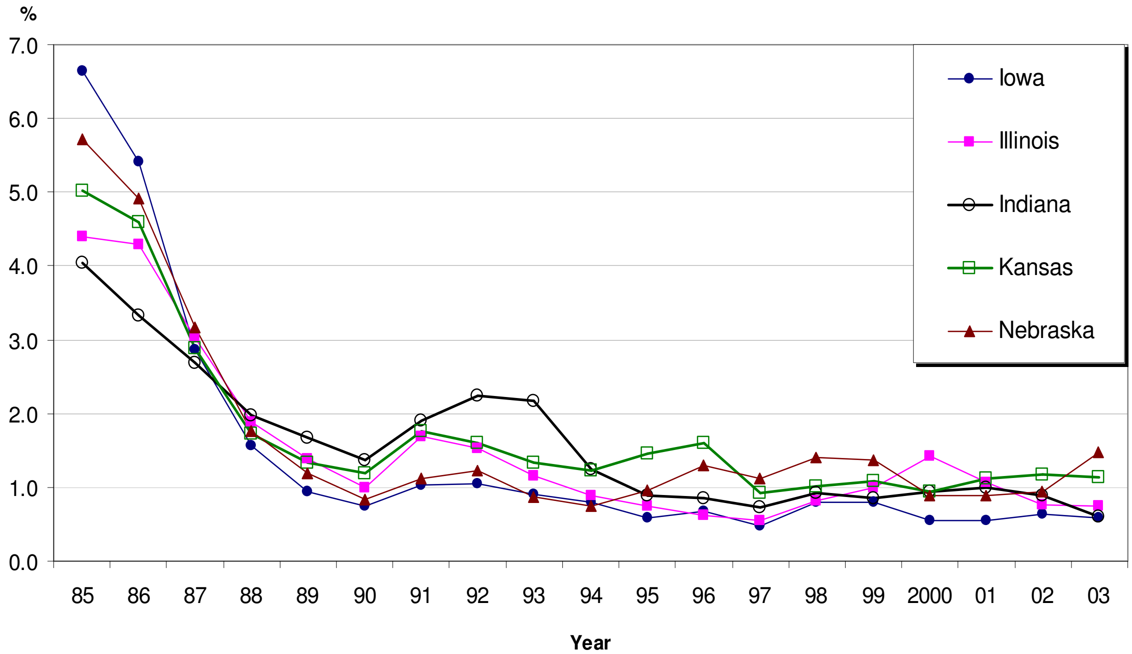


Figure 4 Historical Default Rate by State, 1985-2003

Table 4 Summary Statistics of Default Rate

	Iowa	Illinois	Indiana	Kansas	Nebraska
Mean	1.46	1.53	1.60	1.75	1.68
St. Dev.	1.71	1.15	0.96	1.17	1.39
95 % LCI	0.69	1.01	1.17	1.22	1.05
95 % UCI	2.22	2.04	2.02	2.27	2.31
Min	0.48	0.55	0.60	0.93	0.74
Median	0.81	1.07	1.24	1.33	1.20
Max	6.64	4.40	4.04	5.02	5.71

LCI and UCL represent lower and upper confidence interval

The default rates in each state are highly correlated with each other as illustrated in Table 5. The correlation coefficients are greater than 0.9 except for those of Iowa-Indiana and Indiana-Nebraska, and the coefficients are all statistically significant.

Table 5 Correlation Matrix of Default Rate between States

Correlation Coefficient

	Iowa	Illinois	Indiana	Kansas	Nebraska
Iowa	1	0.96	0.89	0.99	0.98
Illinois		1	0.93	0.96	0.94
Indiana			1	0.90	0.84
Kansas				1	0.97
Nebraska					1

Correlation Coefficient t-values

	Iowa	Illinois	Indiana	Kansas	Nebraska
Iowa		14.25	8.24	24.46	23.06
Illinois			10.46	13.76	11.38
Indiana				8.37	6.31
Kansas					16.99

Critical value of t-state is 2.11 at 95% significance level

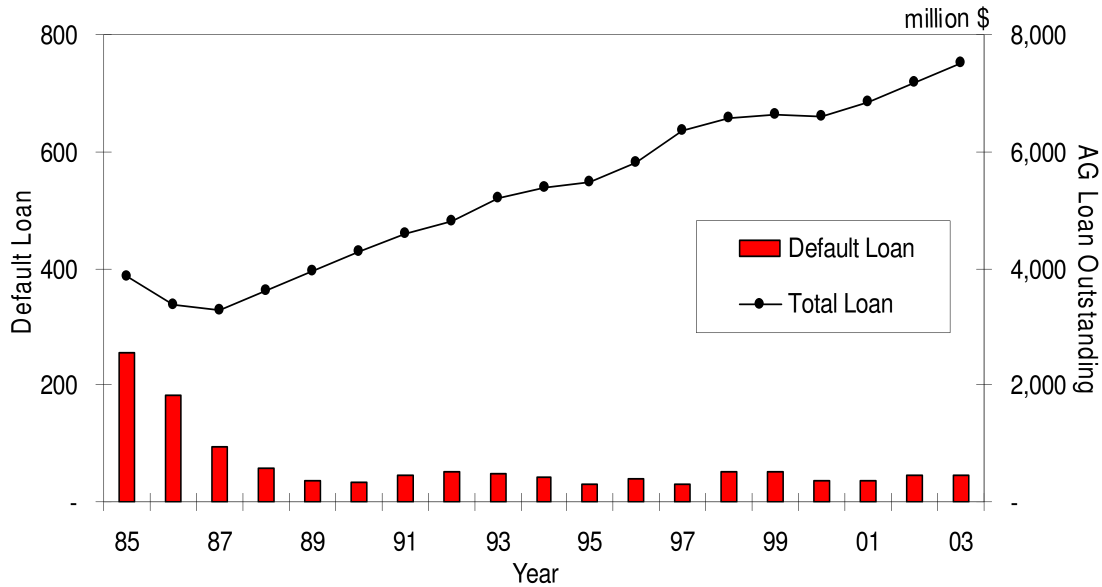
As shown Table 6, the default rates in all five states had fallen from previous year in 1986 through 1990, 1993, 1994, and 1997. On the other hand, the default rates in all five states had been increased from the previous year in only two years, 1991 and 1998. After 1999, the default rates don’t represent any trend over states and they are relatively stable.

Table 6 Changes in Default Rates

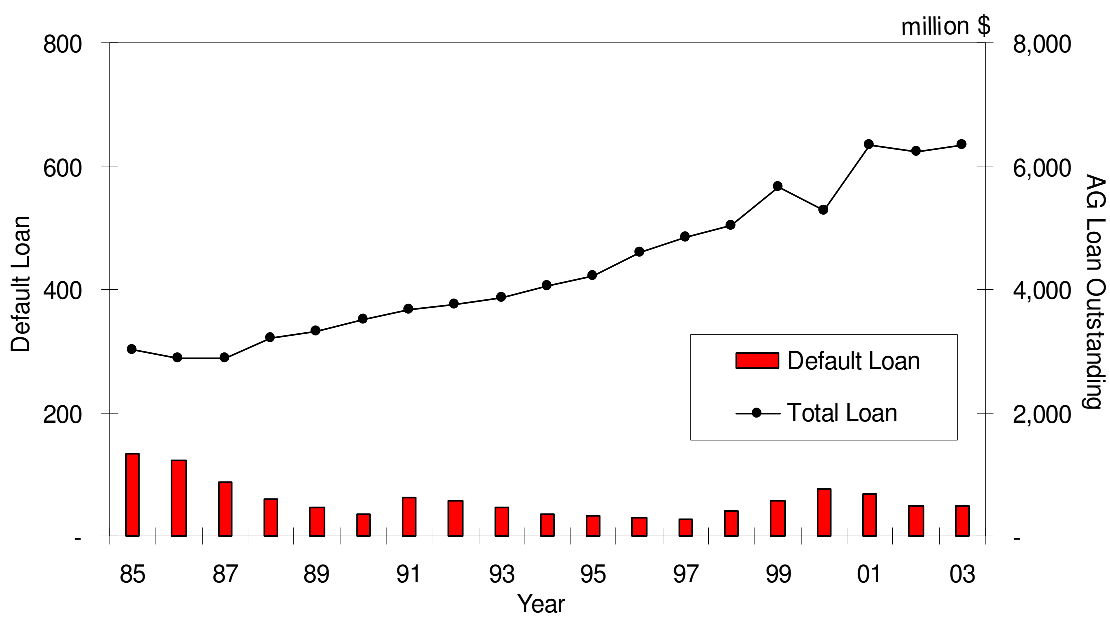
unit: % point

Year	Iowa	Illinois	Indiana	Kansas	Nebraska
1986	-1.23	-0.11	-0.71	-0.42	-0.79
1987	-2.54	-1.26	-0.64	-1.72	-1.76
1988	-1.31	-1.14	-0.70	-1.14	-1.40
1989	-0.62	-0.49	-0.31	-0.40	-0.57
1990	-0.20	-0.39	-0.30	-0.13	-0.35
1991	0.28	0.70	0.54	0.55	0.28
1992	0.03	-0.16	0.33	-0.15	0.10
1993	-0.14	-0.37	-0.07	-0.27	-0.36
1994	-0.10	-0.27	-0.93	-0.10	-0.12
1995	-0.23	-0.15	-0.35	0.23	0.21
1996	0.10	-0.12	-0.04	0.14	0.35
1997	-0.20	-0.08	-0.13	-0.67	-0.19
1998	0.33	0.28	0.21	0.08	0.29
1999	-0.01	0.18	-0.07	0.08	-0.05
2000	-0.25	0.43	0.08	-0.14	-0.48
2001	0.00	-0.35	0.06	0.18	0.01
2002	0.10	-0.31	-0.12	0.05	0.06
2003	-0.05	-0.01	-0.28	-0.03	0.53

Figure 5 illustrates the trend of total agricultural loan outstanding and default loan by states. Total agricultural loan outstanding in Iowa have increased sharply from 1987 and records the highest in 2003, followed by Illinois, Nebraska, and Kansas. Indiana represents the lowest total agricultural loan outstanding in 2003 and shows a gentle slope throughout the sample period.

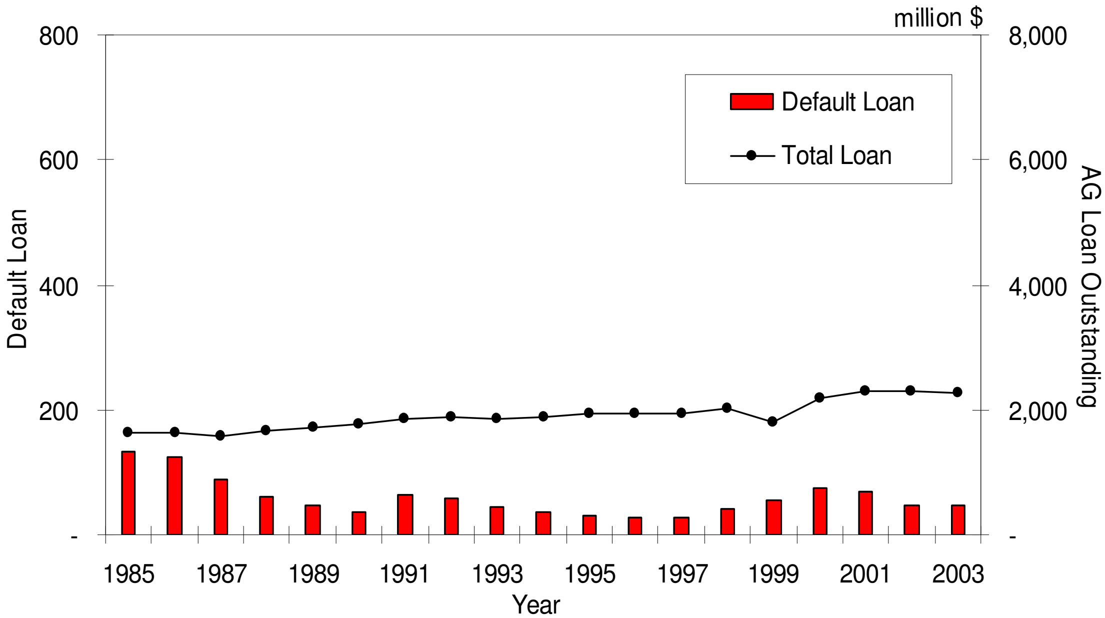


Iowa

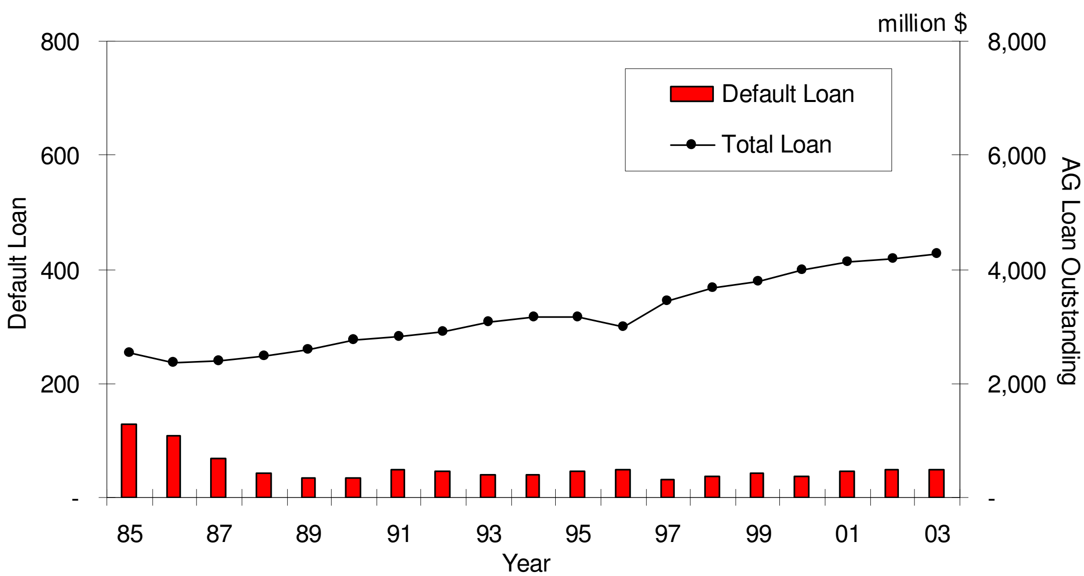


Illinois

Figure 5 Default Loans and Total Agricultural Loans Outstanding

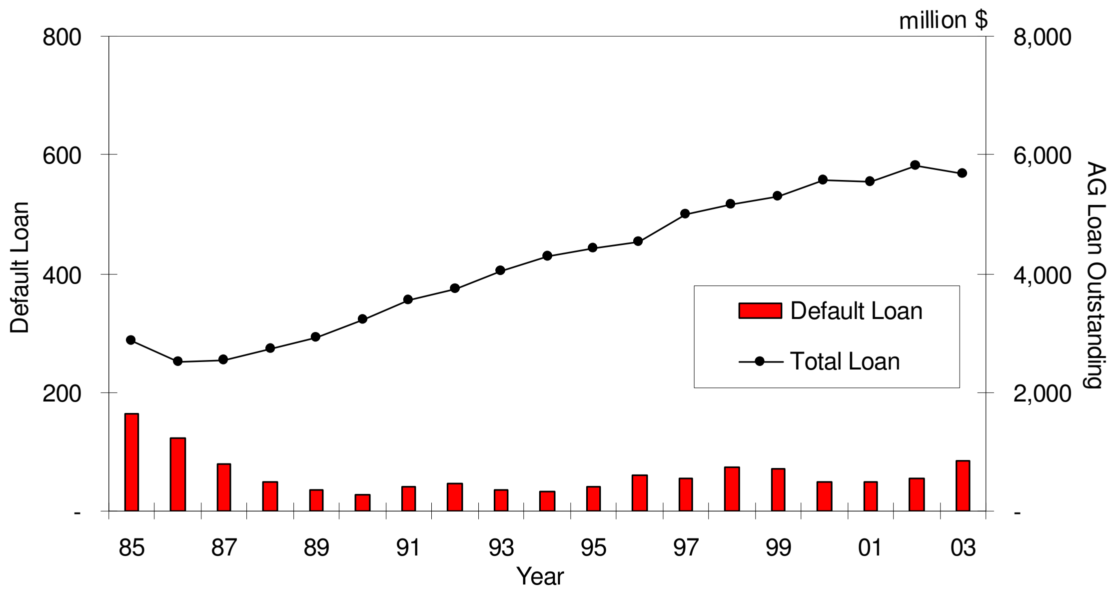


Indiana



Kansas

Figure 5 Continued



Nebraska

Figure 5 Continued

Net Cash Income and Associated Variables

Crop yields (*YIELD*) are measured on a planted acre basis and the price of crops (*PRICE*) is measured by marketing year average prices received by farmers. These variables are collected by state and by commodity from Ag Statistic Database on the web site of the National Agricultural Statistics Service (NASS), an agency of the U.S. Department of Agriculture (USDA). The price of livestock commodities is measured by average price per cwt received by farmers and is gathered from several state web sites. Appendix 2 provides more details on the sources of data.

The cash cost of production (*CCOST*) is calculated in several steps. First, state budget data is collected for crops and livestock for 2003 from state web sites. This represents the base year for the total production costs data, which consists of cash costs and non-cash costs. Appendix 3 addresses the total cost of production in the base year, provides a data description, and indicates web sites where the data was collected. *CCOST* at time t is estimated by combining the base year cash cost of production with production cost index (*PCI*) as follows:

(5.3) $CCOST_{i,m,t} = CCOST_{i,m,t-1} \times (PCI_{i,m,t} / PCI_{i,m,t-1})$,

where $CCOST_{i.m.t}$ is cash cost of mth commodity in state i at t and $PCI_{i.m.t}$ is production cost index of mth commodity in state i at t (1982=100). The production cost index by state relates cash cost of production at a regional level with the U.S. cash cost of production data, both of which are available from ERS, USDA. Appendix 4 and 5 provide more details on the measurement of production cost index and estimates of the cash cost of production by state.

Net cash income by commodity is calculated using equation (4.18) and (4.21). The estimates of net cash income from crops (*NCIC*) and livestock (*NCIL*) are based on equation (4.16) and (4.19), and listed in Appendix 7. *NCIC* and *NCIL* are weighted average net cash income for each commodity, where the weight is derived from historical cash receipts presented in Appendix 6. For the estimates for government payment per acre (*GPMT*), government payments aggregated by state are collected, and then divided by the sum of planted acres to corn, soybeans and wheat. Appendix 8 details this calculation and the results. Parameters and data required to simulate government payments in equation (4.27) to equation (4.32) are provided in Appendix 9

Macroeconomic Variables

Rate of unemployment data at the state level and national level are collected from the Bureau of Labor Statistics, U.S. Department of Labor for 1982 to 2003 period. Other exogenous macroeconomic variables, such as real weighted exchange rates for corn, soybeans, wheat and meat, the rate of inflation, short term and long term interest rates, and real consumer disposable income were collected from the COMGEM database, which was also available from ERS, USDA, and are tabulated in Appendix 10.

Estimation Results

The default model and simulation models for the state rate of unemployment, state yields, prices, and cash cost of production were estimated by EView 3.1 econometric software. Data series utilized in the estimation of the default model cover the 1985 to 2003 period. Other estimated equations were based upon data beginning in 1982 with the same end point with the exception of the price equations, which have severe serial correlation problem with the extended data back to the early 1980s.

The default rate equations were estimated with a nonlinear least squares (NLS) estimator because the models exhibit a nonlinear functional form as seen in equation (4.15). The other equations were estimated using either the OLS or NLS estimator with the application of the first or second-order autoregressive (AR(1) or AR(2)) model to correct serial correlation problem. Each model utilizes the Durbin-Watson (DW) test and Breusch-Godfrey Lagrange multiplier test (or serial correlation LM test) to test for the existence of serial correlation common in the regression analysis with time series data.

The DW statistic is a test for first-order serial correlation and measures the linear relationship between adjacent residuals for regression. The DW statistic sometimes cannot reach a conclusion when the statistic value is located between upper and lower bound. The LM test can be used for high-order serial correlation. The null hypothesis of the test is "There is no correlation in the residuals up to the specified order." EViews generates "Obs*R-squared" statistic and its probability, which has an asymptotic Chi-square distribution under the null hypothesis. If the statistic, which is represented as LM (p) in the result tables, is smaller than the critical value with high probability, the null hypothesis cannot be rejected and no correlation is implied. This paper pursues first to fourth order LM tests but shows only the LM (2) statistic under the result tables.

In case of the existence of serial correlation problem, this paper specifies AR (1) or AR (2) model for regression residuals. To estimate an AR (1) model, following two models are specified first:

(5.4) $y_t = X_t \mathrm{B} + \mu_t$

(5.5) $\mu_t = \rho\mu_{t-1} + v_t$,

and then transform the linear model in the nonlinear model:

(5.6) $y_t = \rho y_{t-1} + (X_t - \rho X_{t-1})\mathrm{B} + v_t$,

by substituting (5.5) into the first equation and rearranging term. Equation (5.6) is estimated using a nonlinear regression technique. NLS estimates are asymptotically equivalent to maximum likelihood estimates and are asymptotically efficient. AR (2) specifications are handled analogously. The nonlinear model estimates the coefficients using the Gauss-Newton algorithm in EViews (Quantitative Micro Software, 1998).

Default Model Estimation

Estimation results for the default model are tabulated in Table 7. The default rate is a function of a three-year moving average of (1) total net cash income from crops (*NCIC+GPMT*), (2) net cash income from livestock (*NCIL*), and (3) rate of unemployment (*UEMP*), and (4) *TREND*. A two-year moving average value is used for *UEMP* in Illinois. In Nebraska, a two-year moving average of *NCIC* and *GPMT* are used since it is more significant statistically and explains well the variability of default rate in these states. The variables *NCIL* in Indiana and *UEMP* in Kansas were deleted during estimation process because significant parameters could not be attained. Different model specifications for the default model suggest that each state has unique economic structures at the micro and macro level, and demonstrates that default model should be specified by state or by region.

The signs on the estimated coefficients for movav (*NCIC+GPMT*) and movav (*NCIL*) are negative as expected since an increase in net cash income should, *ceteris paribus*, decrease the default rate. An increase in the rate of unemployment implies lower off-farm income level, and so movav (*UEMP*) and default rate are expected to have a positive relationship. The sign on the *TREND* parameter is anticipated to be negative because the variable is introduced to capture technical advances in bank risk management. The estimation results show the signs of coefficients expected and are consistent with theoretical model without exception as shown in Table 7.

Table 7 Estimation Results of Default Rate Equations

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	-4.058	-1.583	-3.567	-0.242	-3.938
	(-5.09)	(-1.41)	(1.07)	(-0.95)	(-6.51)
movav (*NCIC*+*GPMT*)	-0.005	-0.013	-0.007	-0.022	-0.007
	(-4.29)	(-2.95)	(-3.19)	(-8.33)	(-4.18)
movav (*NCIL*)	-0.058	-0.035		-0.048	-0.045
	(-5.33)	(-2.53)		(-5.06)	(-2.64)
movav (*UEMP*)	0.406	0.090	0.130		0.490
	(6.04)	(1.07)	(3.41)		(5.83)
TREND	-0.035	-0.055	-0.029	-0.088	-0.017
	(-1.54)	(-2.13)	(-2.04)	(-12.50)	(-1.06)
Adj. R^2	0.992	0.917	0.942	0.956	0.955
DW	1.542	1.510	1.330	1.750	1.916
LM (2)	2.510	0.880	2.125	0.120	2.536
(Prob)	(0.28)	(0.64)	(0.35)	(0.94)	(0.28)

The t-statistics for each parameter indicate the explanatory variables are statistically significant at 5% significance level with the exception of *TREND* in Iowa, movav (*UEMP*) in Illinois, and *TREND* in Nebraska. The DW statistics and Lagrange multiply (LM) test verify there is no correlation problem with the error terms of the estimated equations. The estimated models show high adjusted R^2, meaning that the model explains 99.2% of variability of default rate in Iowa, and followed by Kansas (95.6%), Nebraska (95.5%), Indiana (94.2%), and Illinois (91.7%). In the theoretical model, it was assumed that default of each borrower is associated with net cash income (assumption 2 and 3). Therefore, empirical results support the assumptions and justify the theoretical model specification for default rate in equation (4.9) and (4.10).

Simulation Model Estimation

Four groups of equations are estimated for inclusion in the simulation model: (1) state rate of unemployment, (2) state yield, (3) state price and (4) state cash cost of production. The first two groups of equations project forecasts and are used to generate random numbers for simulation analysis. The five state rates of unemployment are expressed as a function of US rate of unemployment with an AR (1) term except for Kansas to correct autocorrelation problem. Estimation results are tabulated in Table 8. The estimated coefficients are statistically significant at the 1% level except for *USUEMP* in Nebraska. The adjusted R^2 for the Indiana rate of unemployment equation is the highest (0.972), followed by Illinois (0.953), Iowa (0.914), Nebraska (0.758), and Kansas (0.680). The DW statistics and LM test show no equation has serial correlation in its error terms.

Table 8 Estimation Results of State Rate of Unemployment Equations

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	0.784	0.418	-0.400	1.996	1.317
	(0.65)	(0.48)	(-0.56)	(4.87)	(1.17)
USUEMP	0.536	0.995	0.884	0.435	0.337
	(3.15)	(7.13)	(7.37)	(6.76)	(1.84)
AR(1)	0.852	0.814	0.764		0.768
	(9.36)	(17.04)	(11.87)		(5.84)
Adj. R^2	0.914	0.953	0.972	0.680	0.758
D.W.	1.674	2.286	2.610	1.339	2.134
LM (2)	1.405	1.380	2.494	1.734	4.152
(Prob)	(0.50)	(0.50)	(0.29)	(0.42)	(0.13)

State yields are regressed on the U.S. yield as specified in equation (4.26). The estimation results are summarized by commodity in Table 9. Estimated parameters for the U.S. yield are all significant at 1% significance level, and are all positive as expected. Test results report no serial correlation problem. Yield equations for major crops in a state (i.e. corn and soybean in Iowa and Illinois) result in high adjusted R^2, but minor crops (i.e. wheat in Iowa) result in low adjusted R^2.

Table 9 Estimation Results of State Yield Equations

Corn

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	-19.218	-10.448	9.442	33.792	47.651
	(-1.53)	(-0.85)	(0.57)	(2.14)	(3.60)
USYIELD	1.337	1.276	1.039	0.803	0.681
	(11.62)	(11.28)	(6.80)	(5.43)	(5.61)
DM0103				-29.356	
				(-4.27)	
Adj. R^2	0.865	0.857	0.683	0.615	0.592
DW	2.212	1.450	2.068	1.870	2.164
LM (2)	1.693	3.056	2.613	0.047	1.115
(Prob)	(0.43)	(0.22)	(0.27)	(0.98)	(0.57)

Soybeans

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	-1.214	3.043	5.350	-5.188	-4.683
	(-0.21)	(0.73)	(0.94)	(-0.55)	(-0.93)
USYIELD	1.228	1.067	1.008	0.935	1.218
	(7.43)	(8.78)	(6.07)	(3.38)	(8.30)
Adj. R^2	0.721	0.784	0.630	0.332	0.775
DW	2.081	2.064	1.776	1.481	2.834
LM (2)	2.203	4.818	1.051	1.537	5.777
(Prob)	(0.33)	(0.09)	(0.59)	(0.46)	(0.06)

Table 9 Continued

Wheat

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	-0.229	9.397	3.785	-23.414	-1.316
	(-0.01)	(0.46)	(0.19)	(-2.59)	(-0.13)
USYIELD	0.977	1.123	1.369	1.754	1.078
	(1.40)	(1.79)	(2.22)	(6.32)	(3.51)
Adj. R^2	0.044	0.095	0.157	0.650	0.351
DW	1.313	1.574	1.327	2.111	1.717
LM(2)	4.031	1.274	1.916	2.306	0.812
(Prob)	(0.13)	(0.53)	(0.38)	(0.32)	(0.67)

State prices were estimated based on equation (4.24) with the addition of AR (1) for beef cattle and hogs in Illinois and Indiana, and AR (2) for hogs in Iowa to correct first order or second order autocorrelation problem in the error terms. These state prices are specified as a function of the U.S. price. The estimation results are summarized by commodity in Table 10. The estimated coefficients for the U.S. price in the state price equations are close to positive one, and show high t-values and adjusted R^2 values except for a few equations, which suggest that national price movements explain the movement at the state level. The DW and LM test demonstrate no serial correlation problems existed in the estimated models.

Estimated parameters and test statistics for fed cattle and hogs in Indiana are the same to those in Illinois because Indiana beef cattle data was not available, and Illinois data was therefore used as a proxy. The results for Nebraska and Kansas are same for the same reason.

Table 10 Estimation Results of State Price Equations

Corn

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	-0.121	0.045	-0.012	0.059	0.052
	(-2.26)	(1.17)	(-0.15)	(0.56)	(0.80)
US Price	1.017	1.006	1.034	0.998	0.970
	(43.54)	(60.04)	(30.74)	(21.47)	(34.25)
Adj. R^2	0.991	0.995	0.981	0.962	0.985
DW	1.297	1.238	1.480	1.776	1.264
LM(2)	0.996	4.116	0.729	0.262	3.597
(Prob)	(0.61)	(0.13)	(0.69)	(0.88)	(0.16)

Soybeans

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	-0.121	0.134	0.039	-0.314	-0.177
	(-1.40)	(2.36)	(0.46)	(-1.48)	(-2.48)
US Price	1.012	0.997	1.002	1.039	1.004
	(68.47)	(102.59)	(68.50)	(28.47)	(82.09)
Adj. R^2	0.996	0.998	0.996	0.978	0.997
DW	1.619	1.598	1.415	1.181	2.311
LM(2)	0.826	1.870	2.002	2.012	2.474
(Prob)	(0.66)	(0.39)	(0.37)	(0.37)	(0.29)

Wheat

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	0.169	0.071	-0.031	-0.482	-0.335
	(0.38)	(0.25)	(-0.12)	(-3.16)	(-2.87)
US Price	0.865	0.901	0.933	1.117	1.076
	(6.25)	(10.13)	(11.67)	(23.78)	(29.98)
Adj. R^2	0.679	0.850	0.882	0.969	0.980
DW	1.578	1.613	1.188	2.274	1.574
LM (2)	4.154	2.261	3.674	0.901	0.197
(Prob.)	(0.13)	(0.32)	(0.16)	(0.64)	(0.91)

Table 10 Continued

Fed Cattle

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	-1.756	-1.912	-1.912	-2.500	-2.500
	(-0.69)	(-0.69)	(-0.69)	(-1.11)	(-1.11)
USPRICE	1.015	1.014	1.014	1.044	1.044
	(27.80)	(26.83)	(26.83)	(32.29)	(32.29)
AR(1)		0.467	0.467		
		(2.56)	(2.56)		
Adj. R^2	0.977	0.986	0.986	0.983	0.983
DW	1.124	1.771	1.771	1.189	1.189
LM (2)	2.061	0.145	0.145	2.556	2.556
(Prob.)	(0.36)	(0.93)	(0.93)	(0.28)	(0.28)

Hogs

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	7.941	-5.873	-5.873	5.088	5.088
	(3.34)	(-0.22)	(-0.22)	(2.15)	(2.15)
USPRICE	0.796	0.968	0.968	0.864	0.864
	(15.83)	(42.43)	(42.43)	(17.17)	(17.17)
AR(1)		1.040	1.040		
		(4.66)	(4.66)		
AR(2)	-0.636				
	(-2.68)				
Adj. R^2	0.954	0.986	0.986	0.942	0.942
DW	1.135	1.860	1.860	1.391	1.391
LM (2)	4.417	2.922	2.922	4.251	4.251
(Prob.)	(0.11)	(0.23)	(0.23)	(0.12)	(0.12)

State cash cost of production are estimated by equation (4.25) specified in previous chapter. AR (1) terms were added as an explanatory variable for each equation except wheat to eliminate first order serial correlation problems. For the corn and soybeans equations, a dummy variable was used for the period after 2002.[38] The variable is introduced to correct for a data inconsistency problem. The USDA data for cash cost of production for corn and soybeans were surveyed and calculated differently before and after 2002. The dummy variable is also included in simulation analysis for 2004 to 2007.

State cash cost of production are modeled as a function of U.S. cash cost of production (*USCCOST*). The estimation results are tabulated in Table 11. The results for Illinois and Indiana are identical because both data are the same as explained before. All estimated parameters and statistics are very similar each other within a commodity. This stems from the fact that cash cost of production data are directly observed only in 2003, while historical data series are calculated using a production cost index constructed by region, not by state. With respect to the production cost index for crops, Iowa, Illinois, Indiana, and Nebraska all belong to the same USDA's production region. Thus, the data series for the four states have same fluctuation. The production cost indexes for meat are all the same. As shown in the Table 11, coefficients are all significant statistically at 5% significance level, and there is no serial correlation problem. However, adjusted R^2 is somewhat different by commodity.

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[38] The dummy variable, DM(02-07), is denoted to one during the period from 2002 to 2007, otherwise, equals to zero.

Table 11 Estimation Results of State Cash Cost of Production Equations

Corn

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	-6.525	-6.543	-6.543	-41.930	-6.576
	(-0.07)	(-0.07)	(-0.07)	(-1.13)	(-0.07)
USCCOST	1.096	1.099	1.099	1.216	1.105
	(3.12)	(3.12)	(3.12)	(5.12)	(3.12)
DM (02-07)	-27.687	-27.762	-27.762	-27.138	-27.904
	(-2.85)	(-2.85)	(-2.85)	(-2.44)	(-2.85)
AR(1)	0.899	0.899	0.899	0.709	0.899
	(7.50)	(7.50)	(7.50)	(4.05)	(7.50)
Adj. R^2	0.608	0.608	0.608	0.882	0.608
DW	2.396	2.396	2.396	1.503	2.396
LM (2)	3.177	3.177	3.177	1.707	3.177
(Prob.)	(0.20)	(0.20)	(0.20)	(0.43)	(0.20)

Soybeans

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	49.362	61.312	61.312	49.023	70.529
	(4.61)	(4.61)	(4.61)	(3.87)	(4.61)
USCCOST	0.669	0.830	0.830	0.783	0.955
	(4.60)	(4.60)	(4.60)	(4.58)	(4.60)
DM (02-07)	-16.502	-20.497	-20.497	-14.947	-23.578
	(-2.95)	(-2.95)	(-2.95)	(-2.40)	(-2.95)
AR(1)	0.402	0.402	0.402	0.473	0.402
	(1.80)	(1.80)	(1.80)	(2.18)	(1.80)
Adj. R^2	0.687	0.687	0.687	0.728	0.687
DW	1.334	1.334	1.334	1.344	1.334
LM (2)	4.571	4.571	4.571	4.514	4.571
(Prob.)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)

Table 11 Continued

Wheat

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	46.741	46.741	46.741	-1.239	44.343
	(5.41)	(5.41)	(5.41)	(-0.32)	(5.41)
USCCOST	0.622	0.622	0.622	1.060	0.590
	(4.43)	(4.43)	(4.43)	(16.96)	(4.43)
Adj. R^2	0.470	0.470	0.470	0.932	0.470
DW	1.613	1.613	1.613	2.116	1.613
LM (2)	2.170	2.170	2.170	1.451	2.170
(Prob.)	(0.34)	(0.34)	(0.34)	(0.48)	(0.34)

Fed Cattle

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	38.527	34.487	34.487	47.287	37.103
	(4.88)	(4.88)	(4.88)	(4.88)	(4.88)
USCCOST	0.288	0.258	0.258	0.353	0.277
	(2.51)	(2.51)	(2.51)	(2.51)	(2.51)
AR(1)	0.805	0.805	0.805	0.805	0.805
	(6.16)	(6.16)	(6.16)	(6.16)	(6.16)
Adj. R^2	0.780	0.780	0.780	0.780	0.780
DW	1.479	1.479	1.479	1.479	1.479
LM (2)	2.752	2.752	2.752	2.752	2.752
(Prob.)	(0.25)	(0.25)	(0.25)	(0.25)	(0.25)

Hogs

	Iowa	Illinois	Indiana	Kansas	Nebraska
Intercept	9.219	9.882	9.882	7.982	8.732
	(2.68)	(2.68)	(2.68)	(2.68)	(2.68)
USCCOST	0.393	0.422	0.422	0.341	0.373
	(4.99)	(4.99)	(4.99)	(4.99)	(4.99)
AR(1)	0.742	0.742	0.742	0.742	0.742
	(5.56)	(5.56)	(5.56)	(5.56)	(5.56)
Adj. R^2	0.838	0.838	0.838	0.838	0.838
DW	1.895	1.895	1.895	1.895	1.895
LM (2)	0.722	0.722	0.722	0.722	0.722
(Prob.)	(0.70)	(0.70)	(0.70)	(0.70)	(0.70)

Summary

Default rate data was provided by the FDIC while other variables are collected from selected government web sites or generated from the original data for the purpose of modeling. Fourth quarter balances in the loan performance data from FDIC are used by state to estimate an annual model from 1985 to 2003. This study covers five states: Iowa, Illinois, Indiana, Kansas, and Nebraska. Five state models are specified and estimated separately. The key input of the default model, net cash income, was generated by state for the five major commodities in these states: corn, soybeans, wheat, fed cattle, and hogs.

Estimation results show strong statistical attributes. Signs and magnitudes of the estimated parameters are consistent with theory or intuitive expectation. The t-statistics for estimated parameters are significance with a few exceptions. The magnitudes of the adjusted R^2 differ by equation, but gave overall satisfaction. Importantly, the default model results high adjusted R^2. The DW statistics and LM test results demonstrate there are no serial correlation problems. The results of the default model gave important implications to portfolio credit risk modeling. The results supported the assumption in the theoretical model that default of borrower is associated with net cash income, and that net cash income can be used as a leading indicator of default in agricultural loans. Different model specification suggests that default model should be specified by state and/or by region.

CHAPTER VI

MODEL VALIDATION AND SIMULATION

This chapter has three objectives: (1) to verify whether or not estimated models are appropriate to forecast the probability of default, (2) to present an application of the model, and (3) to discuss the interpretation and implication of the simulation results to bank credit risk management. Model validation of the default model is conducted within-sample and out-of-sample simulation. For validation of the simulation model, t-statistics and F-statistics are used to test if the simulated exogenous variables are invariant to the historical data. Simulation analysis is used to project the probability of default and loss distribution. This is then used to calculate expected loan losses, maximum loan losses, Value at Risk, and capital requirements

Model Validation

Model validation refers the processes by which the model builder tests the completeness, accuracy and forecasting ability (Richardson, 2003). Several statistical tests, including t-statistics for estimated coefficients, adjusted R^2, DW and LM statistics for serial correlation, and theoretical hypothesis tests, have already been presented in Chapter V. In this chapter, model validation is examined for both the default model and the simulation model.

Default Model

Ex post and ex ante simulations are used to evaluate the forecasting accuracy of the default model. Ex post simulation generates forecasted values within the sample period, and the actual values and forecasted values are then compared. The Rood Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Theil U are calculated to evaluate the forecasting error.[39] The first two statistics capture the scale value of the forecasted error, while the other two statistics are scale invariant and lie between zero and one. The smaller the statistic, the greater the forecasting power of the model. The Theil U, or Theil inequality coefficient, is comprised of three components: bias, variance and covariance. The bias (or variation) proportion indicates how far the mean (or variation) of the forecasted value is from the actual mean (or variation). The covariance portion captures the remaining unsystematic forecasting errors. The bias, variance, and covariance proportions add up to one. A good forecast should have a small bias and variance component so that most of the bias comes from the unsystematic proportion (Pindyck and Rubinfeld, 1991).

Table 12 presents these the statistics by state. The default model for Iowa has the smallest RMSE (0.134), which means that average forecasting error for the default rate is a 0.134% point during sample period, followed by Indiana (0.204), Kansas (0.216), Nebraska (0.245), and Illinois (0.283). The default model for Iowa also has the smallest MAPE (13.1%); the historical forecast by the model achieved an error of 13.1%. This is followed by Indiana (13.2%), Kansas (13.3%), Illinois (18.1%), and Nebraska (19.6%).

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[39] See Green (2000) for detail formula of these statistics

The Theil U statistic for each model is below 10 percent level. The components show a small bias and variation, but a covariance of almost one.

Table 12 In-Sample Model Validation Statistics for Default Model

	Iowa	Illinois	Indiana	Kansas	Nebraska
RMSE	0.134	0.283	0.204	0.216	0.245
MAE	0.111	0.220	0.165	0.195	0.232
MAPE	13.1%	18.1%	13.2%	13.3%	19.6%
Theil U	0.030	0.075	0.055	0.052	0.059
Bias	0.005	0.000	0.002	0.002	0.001
Var	0.000	0.023	0.038	0.000	0.003
Cov	0.995	0.977	0.960	0.998	0.996

Ex ante simulation analysis is used to evaluate the forecasting accuracy of the model beyond the sample period. The default models are estimated again with the data covering 1985 to 2001, and then used to forecast the annual default rate for 2002 and 2003. The forecasted default rates are then compared with the actual default rates to calculate RMSE, MAE, and MAPE. Validation statistics from this out-of-sample simulation are reported in Table 13. RMSE and MAE statistics are close with-in-sample statistics except for Nebraska. The forecasted default rate for Nebraska however was considerably different from the actual default rate in 2003. The smallest MAPE is recorded for Iowa (12.2%) and followed by Kansas (15.4%), Illinois (24.3%), Indiana (28.0%), and Nebraska (28.7%). The MAPE is bigger than the in-sample simulation MAPE except for Iowa. This result stems from the fact that the default rates in 2002 and 2003 were so small, mostly less than one, that percentage error is bigger.

Table 13 Out-of-Sample Model Validation Statistics for Default Model

	Iowa	Illinois	Indiana	Kansas	Nebraska
RMSE	0.077	0.205	0.218	0.183	0.565
MAE	0.076	0.184	0.175	0.178	0.416
MAPE	12.2%	24.3%	28.0%	15.4%	28.7%

Simulation Model

Model validation for the simulation model is examined for the stochastic component of the model. The stochastic exogenous variables were simulated with 100 iterations to determine whether the simulated series are statistically equal to historical series or whether the distributions from the two series are the same. Three statistics are used in the validation process: (1) t-test for mean, (2) F-test for standard deviation, and (3) t-test for correlation coefficient. These tests determine whether (1) the means from simulated variables are equal to the forecasted means, which are given by COMGEM or regression models, (2) the simulated variances are equal to the historical variance, and (3) the correlation coefficients among simulated variables are statistically the same as those among historical series.

The t and F statistics and their p-values are summarized in the Table 14 to test the means and standard deviations of macro economic variables and crop yields. All the p-values in the table are greater than 0.05, which means the null hypothesis, which is a test parameters of simulated values and historical (or forecasted) values are the same, can not be rejected at 5% significance level. For example, the p-values in the t-test for the rate of unemployment are ranged from 0.8 to 0.99, and those in the F-test for the rate of unemployment rate are distributed from 0.51 to 0.99.

Table 15 represents the p-values of the t-test for comparing the correlation coefficients between correlation matrix from the original data series and that from the simulated values. The null hypothesis is that the correlation coefficients are the same. The critical value of the test is 3.75. If looking at the p-values on the table for both macroeconomic variables and national and state yields, they are all smaller than the critical value, meaning that the null hypothesis cannot be rejected and correlation coefficients from the original data series and the simulated values are statistically the same.

Table 14 Model Validation Statistics for Stochastic Variables

Macroeconomic Variables

		Rate of Unemployment						PGDP
		US	Iowa	Illinois	Indiana	Kansas	Nebraska	
t-test for Mean	Test Value	0.12	0.08	-0.01	0.03	-0.06	-0.02	0.26
	P-Value	0.91	0.93	0.99	0.97	0.95	0.98	0.80
F-test for S.D.	Test Value	98.08	89.35	102.65	104.72	101.55	96.45	93.17
	P-Value	0.99	0.51	0.76	0.66	0.82	0.89	0.71

		Real Weighted Exchange Rate				RS	RM	YD
		Corn	Soybean	Wheat	Meat			
t-test for mean	Test Value	0.62	0.62	-0.15	0.46	1.05	0.90	0.37
	P-Value	0.54	0.54	0.88	0.65	0.30	0.37	0.71
F-test for S.D.	Test Value	94.90	98.24	105.05	95.13	75.90	76.18	109.49
	P-Value	0.80	0.99	0.64	0.82	0.08	0.09	0.44

Corn Yield

		US	Iowa	Illinois	Indiana	Kansas	Nebraska
t-test for mean	Test Value	0.42	-0.38	0.03	0.16	-0.13	-0.24
	P-Value	0.67	0.70	0.97	0.87	0.90	0.81
F-test for S.D.	Test Value	85.73	85.16	95.43	94.41	109.77	123.67
	P-Value	0.35	0.32	0.83	0.78	0.43	0.09

Soybean Yield

		US	Iowa	Illinois	Indiana	Kansas	Nebraska
t-test for mean	Test Value	-0.21	-0.31	-0.03	0.23	-0.07	-0.01
	P-Value	0.83	0.75	0.98	0.82	0.95	0.99
F-test for S.D.	Test Value	99.04	112.91	91.43	105.11	102.34	100.94
	P-Value	0.96	0.32	0.61	0.64	0.78	0.85

Wheat Yield

		US	Iowa	Illinois	Indiana	Kansas	Nebraska
t-test for mean	Test Value	-0.08	0.08	-0.09	0.08	0.14	-0.04
	P-Value	0.93	0.93	0.93	0.94	0.89	0.97
F-test for S.D.	Test Value	111.31	104.59	106.24	94.62	100.21	99.44
	P-Value	0.37	0.66	0.58	0.79	0.89	0.94

Table 15 Model Validation Statistics for Correlation Coefficients

Macroeconomic Variable

	CER			US UEMP	PGDP	RS	RL	YD	UEMP				
	Corn	SB	Meat						IA	IL	IN	KS	NE
CER_W	1.38	1.50	1.84	0.45	0.44	0.15	1.21	0.97	0.84	1.71	0.22	1.97	0.51
CER_C		1.01	0.88	0.87	0.57	1.79	0.65	0.68	1.01	0.72	0.05	2.08	0.96
CER_S			0.74	0.55	0.34	1.94	1.15	0.06	1.07	0.77	0.44	2.33	0.70
CER_M				0.59	0.03	2.47	0.93	0.30	1.09	0.39	0.06	3.11	0.31
USUEMP					0.97	0.22	0.89	0.07	0.79	1.42	0.40	0.66	1.25
PGDP						0.13	0.66	0.29	1.82	0.39	0.12	0.33	0.94
RS							1.68	1.33	0.24	2.37	2.14	1.63	0.51
RL								0.49	0.02	1.22	0.57	2.46	0.12
YD									0.22	0.18	0.05	2.49	0.13
UEMP_IA										1.33	0.95	2.01	1.11
UEMP_IL											0.67	0.82	0.38
UEMP_IN												0.16	1.11
UEMP_KS													0.35

Critical value of this test is 3.75.

Table 15 Continued

Yields

	Y2US	Y3US	Y1IA	Y1IL	Y1IN	Y1KS	Y1NE	Y2IA	Y2IL	Y2IN	Y2KS	Y2NE	Y3IA	Y3IL	Y3IN	Y3KS	Y3NE
Y1US	1.33	0.33	0.53	0.70	0.12	0.01	0.64	1.42	0.23	0.93	0.98	0.67	1.08	0.42	0.76	1.03	0.04
Y2US		0.23	0.34	0.84	0.89	0.38	0.95	0.38	0.55	0.99	0.16	0.77	1.24	0.14	0.13	0.07	0.15
Y3US			1.55	0.73	0.68	1.15	0.17	1.05	0.24	0.26	0.19	1.60	0.43	0.58	0.68	0.66	1.24
Y1IA				0.67	0.44	0.71	0.90	0.84	1.05	0.41	0.65	1.54	0.11	1.08	1.65	1.23	0.74
Y1IL					1.13	0.14	0.37	0.46	0.24	0.46	0.12	0.05	1.02	0.39	0.47	0.82	1.52
Y1IN						1.08	0.99	0.82	0.27	0.68	0.55	0.53	0.64	0.74	0.30	0.94	0.38
Y1KS							0.19	0.07	0.37	0.80	0.03	0.04	0.70	0.23	1.35	0.84	2.03
Y1NE								0.03	1.07	0.77	0.32	0.15	1.76	0.26	0.98	0.03	0.68
Y2IA									0.24	0.26	0.88	0.01	0.92	0.05	0.01	1.05	0.74
Y2IL										0.50	0.87	0.80	0.91	0.79	0.50	0.82	0.23
Y2IN											0.80	0.92	1.22	0.06	0.45	0.97	0.39
Y2KS												0.18	0.82	0.37	0.16	0.92	0.67
Y2NE													1.77	0.78	1.12	0.01	0.25
Y3IA														0.25	0.69	0.55	0.34
Y3IL															0.16	1.13	0.01
Y3IN																0.98	0.48
Y3KS																	0.48

Critical value of this test is 3.75.
Y1, Y2, and Y3 represent corn, soybeans, and wheat yield, respectively.

Simulation Results

The key output of the default model and simulation model is the probability of default (or default distribution). The probability of default is measured using the simulated stochastic default rate, which is simulated for the 2004 to 2007 period with 100 iterations. The probability of default can be represented graphically as a PDF or a CDF, and statistically by the mean, standard deviation, maximum and minimum. The loss distribution is measured by equation (4.35) with the default distribution. Finally, the loss distribution is used to calculate the expected loan loss, Value at Risk, and capital requirements.

Probability of Default

Figure 6 illustrates the projected expected default rates simulated for 2004 to 2007 period with historical default rates from 2000 to 2003. The graph illustrates the recent trend and projected default rate for each state. The overall trend for the expected default rates in agricultural loans suggests a decrease in 2004 and 2005 and an increase in 2006 and 2007. This result is tied to good economic conditions in the agricultural sector in 2003 and 2004. During this period, U.S. farmers experienced good yields and high prices. Furthermore, program commodity producers continued to receive direct payments from the federal government, resulting in even higher net cash income. In 2004, the expected default rates are expected to be below 1% in five states. These rates could represent a historical minimum or near historical minimum default rate. Nebraska is anticipated to have the highest default rate throughout the forecasting horizon, meaning that agricultural banks in Nebraska could be exposed to the highest risk of the five states over this period. The default rates in Kansas are forecasted to increase sharply after 2005 and will be more than double the 2005 default rate by 2007.

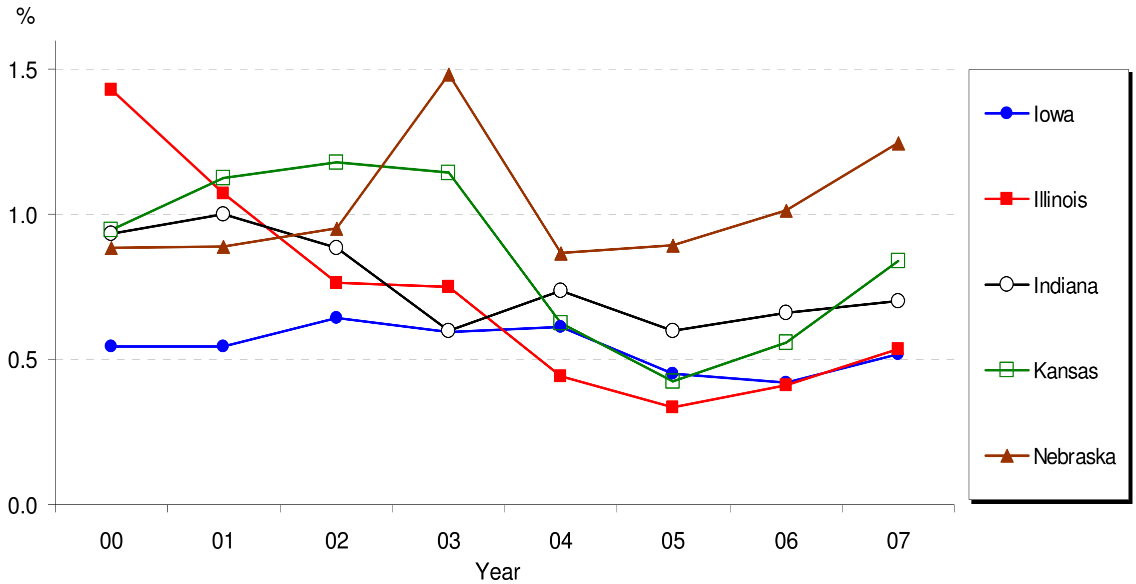


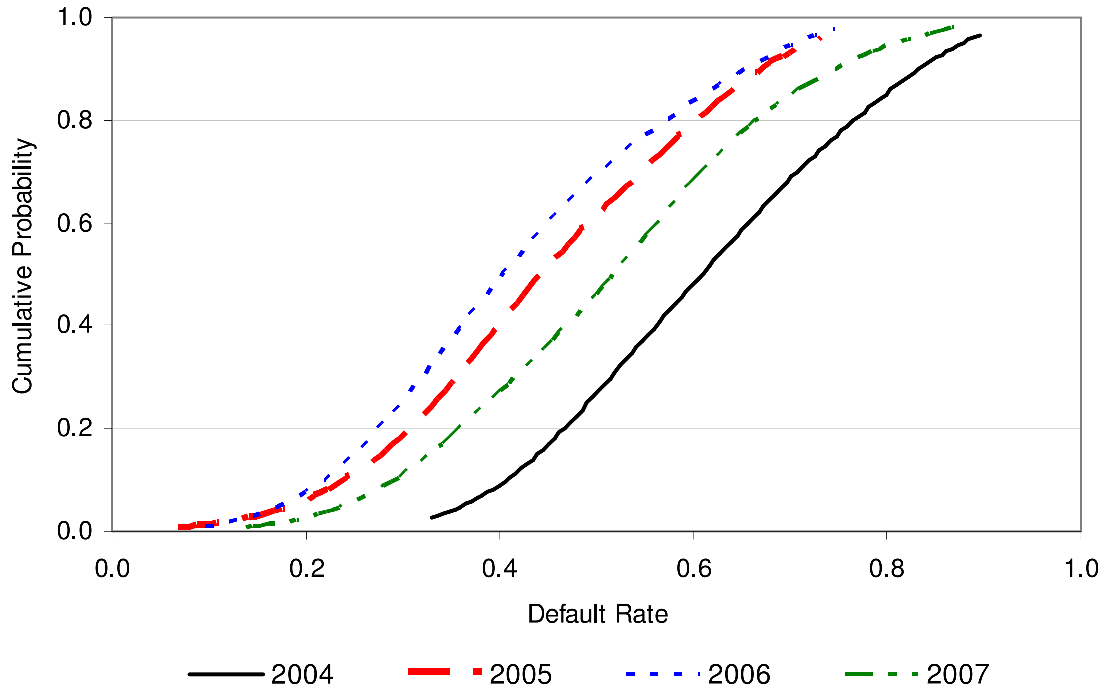
Figure 6 Expected Default Rates by State

Table 16 lists the mean, standard deviation, minimum and maximum, for the simulated default rate in detail. In 2004, the default rate in Nebraska was 0.87%, the highest value among states, followed by Indiana (0.74%), Kansas (0.63%), Iowa (0.61%), and Illinois (0.44%). Nebraska is expected to have the widest default rate distribution with standard deviation of 0.28 and followed by Kansas (0.25), Illinois (0.23), Indiana (0.20), and Iowa (0.15). In 2007, the default rates are expected to be higher than those in 2004 except for Iowa and Indiana. Nebraska still has the highest expected default rate with 1.25, followed by Kansas (0.84%), Indiana (0.70%), Illinois (0.54%), and Iowa (0.52%).

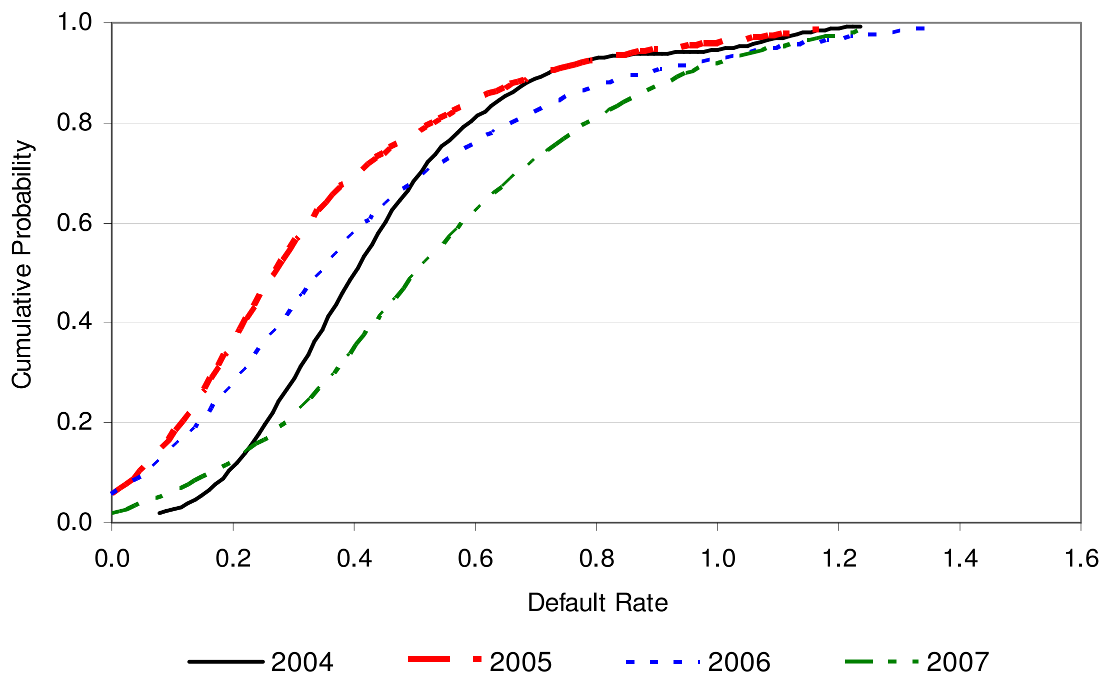
Table 16 Summary Statistics for Simulated Default Rate, 2004-2007

		2004	2005	2006	2007
Iowa	Mean	0.61	0.45	0.42	0.52
	St. Dev.	0.15	0.15	0.15	0.16
	Min	0.33	0.07	0.10	0.14
	Max	0.90	0.73	0.75	0.88
Illinois	Mean	0.44	0.33	0.41	0.54
	St. Dev.	0.23	0.27	0.31	0.28
	Min	0.08	0.00	0.00	0.00
	Max	1.24	1.17	1.36	1.25
Indiana	Mean	0.74	0.60	0.66	0.70
	St. Dev.	0.20	0.23	0.26	0.21
	Min	0.42	0.21	0.22	0.26
	Max	1.36	1.39	1.37	1.34
Kansas	Mean	0.63	0.42	0.56	0.84
	St. Dev.	0.25	0.24	0.23	0.32
	Min	0.15	0.01	0.03	0.11
	Max	1.12	0.88	1.04	1.64
Nebraska	Mean	0.87	0.89	1.01	1.25
	St. Dev.	0.28	0.35	0.34	0.38
	Min	0.30	0.08	0.37	0.47
	Max	1.75	2.02	1.87	2.20

The cumulative distribution function (CDF) shows the probability of the default rate, and provides valuable information to bank management. Figure 7 illustrates the CDF by state by year.

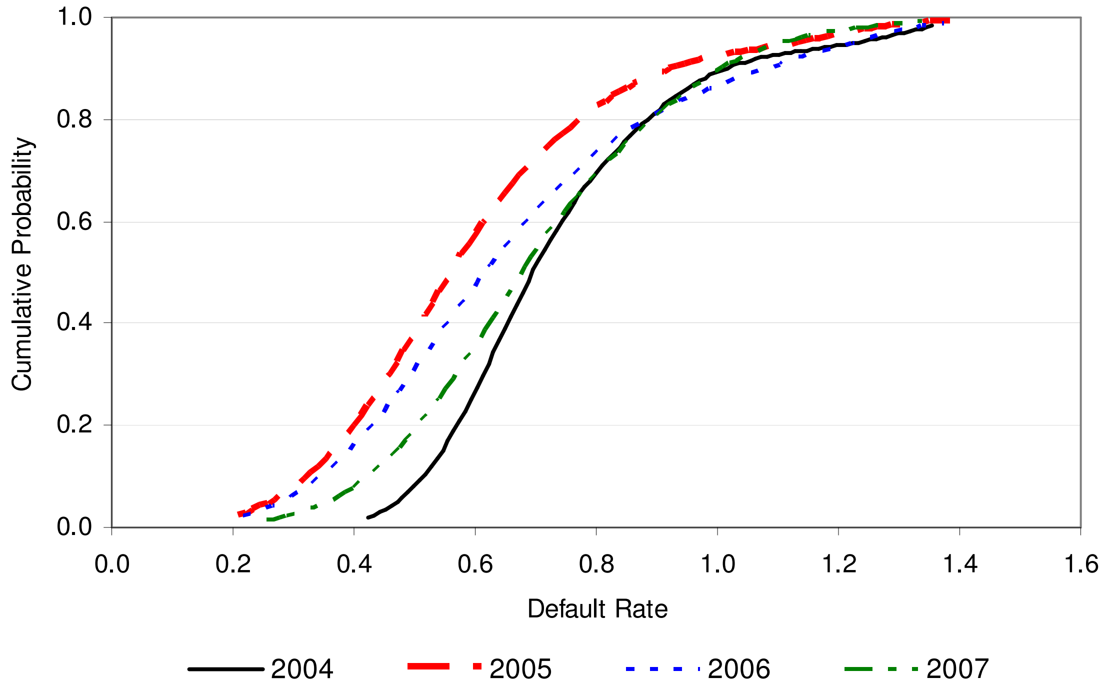


Iowa

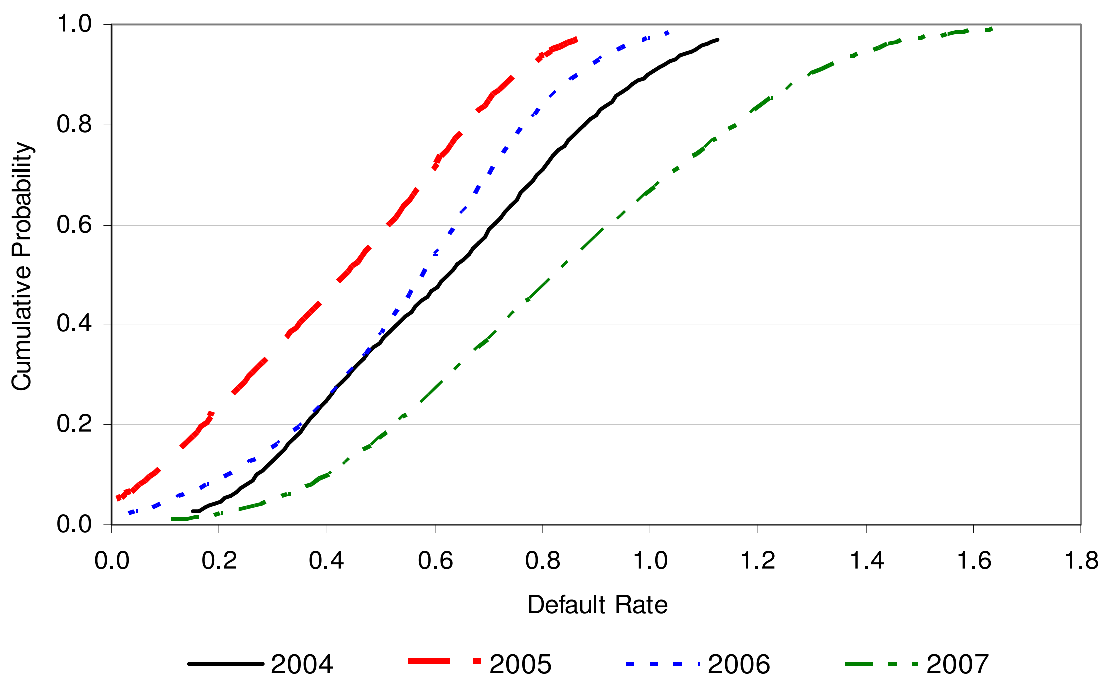


Illinois

Figure 7 CDF for Projected Default Rate, 2004-2007

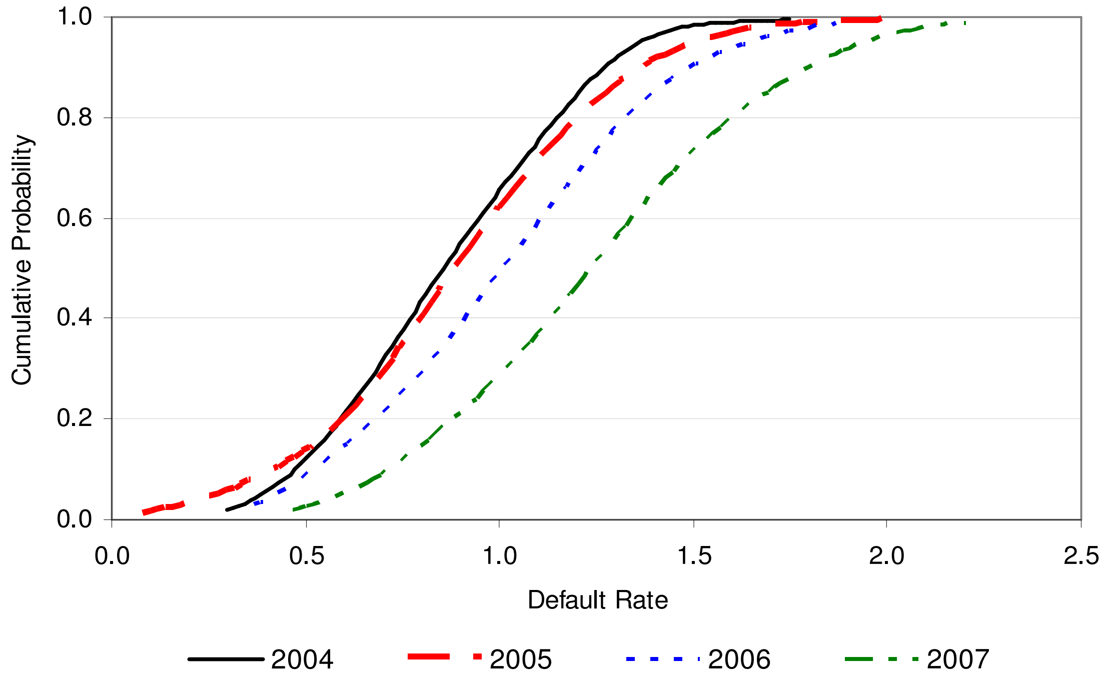


Indiana



Kansas

Figure 7 Continued



Nebraska

Figure 7 Continued

Assume a bank serving farmers in Iowa has a risk management goal of maintaining the default rate under 0.5%. As illustrated in Figure 8, the bank has only 27% of chance to achieve the goal in 2004. The possibility of accomplishing the goal will be increased up to 61% in 2005 and 72% in 2006, and then fall to 46% in 2007. If the bank uses a projected default rate exceeding a threshold as "a high credit risk condition," the CDF can be used as early warning indicator of future loan defaults. Let's suppose the bank in Iowa has 0.8% of threshold, meaning the bank regards its credit risk as a high level if projected default rate is greater than 0.8%. The probability of the bank being exposed to high credit risk conditions based upon this threshold is 17% in 2004.

During 2005 to 2006, the probability of exceeding this threshold is 0%, while there is 4% possibility in 2007.

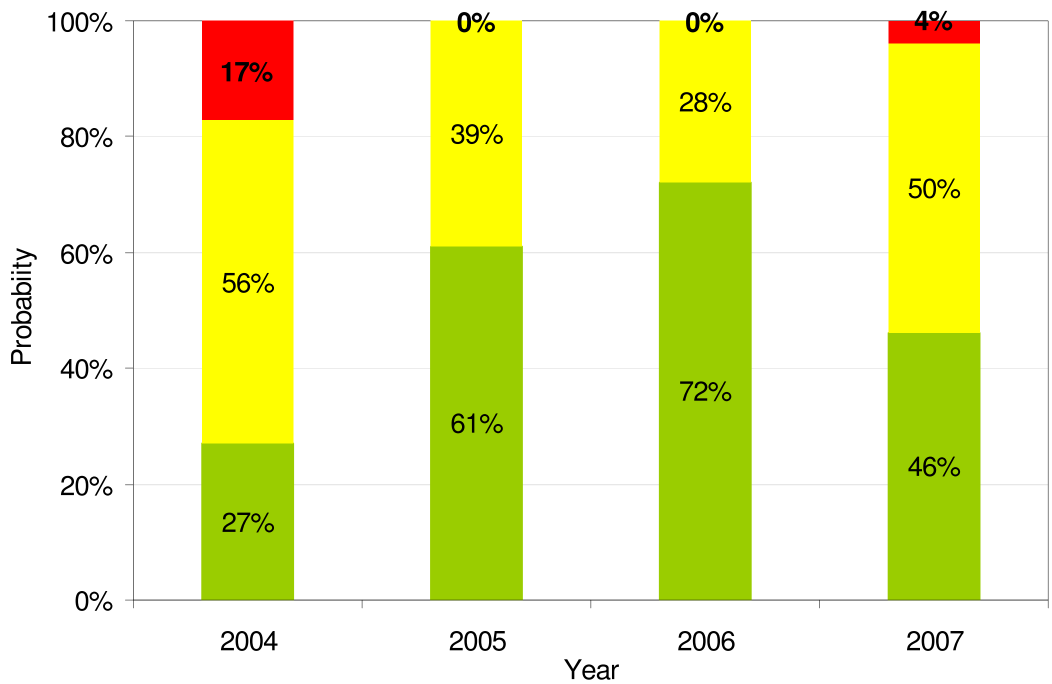


Figure 8 Stoplight Chart for Default Probabilities of Iowa with Two Cut-off Values of 0.5% and 0.8%

Loan Losses Distribution and VaR

The stochastic loan loss is calculated using (1) the default rate, (2) total loans outstanding, (3) the exposure at default and (4) the loss given default as discussed in Chapter IV. Since this study did not have access to bank level data, the calculation of loan loss distribution cannot be directly calculated. Instead, this study develops a process for generating the loan loss distribution and the other risk management variables based upon a set of assumptions.

Let's first assume each state represents a bank.[40] Each "state bank" can estimate total loans outstanding for coming year (2004) and ahead. Total loans outstanding in the future are decided by bank loan policy, available funds, and loan demand. Let's further assume that total loans outstanding can be represented by a simple trend model with the forecasts listed in Table 17. Exposure at default and loss given default can be estimated from historical data. However, this study simply assumes that exposure at default is equal to one[41] and loss given default is equal to 0.5.[42] For sensitivity analysis, loss given default can be varied parametrically within a range of a policy value.

Each default rate generated from the 100 iterations of the simulation model is multiplied by the forecasted value of total loans outstanding, EAD (1.0), and LGD (0.5). The corresponding 100 number of loan losses can then be generated, and used to calculate expected loan loss, maximum loan loss, and VaR as shown in Table 17. This table shows the results only for 2004. The results for the other years can be obtained using same procedure. Forecasted total loans outstanding for Iowa in 2004 is $7,724 million, followed by Illinois ($6,404 million), Nebraska ($6,205 million), Kansas ($4,309 million), and Indiana ($2,270 million). Nebraska is anticipated to have the

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[40] Since this study uses the loan performance data for agricultural loan obtained from the FDIC, loan portfolio of the banks are assumed to consist of agricultural loans in the commercial banks in a state. Loan performance data at other lenders serving farms in these states was not included in this study.

[41] EAD value is less than the current balance. EAD is generally taken to be equal to one for non-revolving loans. Banks typically ignore the EAD when they calculate VaR, which is equivalent to assuming EAD is equal to one (RMA, 2003).

[42] LGD is quiet different by bank and even by loan portfolio segment within a bank. It is known that LGD of mortgage loan is usually low (10-20%) but that of credit card is high, more than 80% (RMA, 2003). However, survey data about LGD for an agricultural loan portfolio is not available. This study assumes the median of possible LGD range (0% ~ 100%).

highest expected loan losses at $27.0 million, followed by Iowa ($23.7 million), Illinois ($14.1 million), Kansas ($13.5 million), and Indiana ($8.4 million).

Table 17 Projections for Loan Loss Distribution and VaR, 2004

Unit: million dollars

	Iowa	Illinois	Indiana	Kansas	Nebraska
Total Loan Forecasts	7724	6404	2270	4309	6205
Expected Loan Loss	23.7	14.1	8.4	13.5	27.0
Maximum Loan Loss	34.6	39.5	15.4	24.2	54.2
Value at Risk	10.9	25.4	7.0	10.8	27.3

Maximum loan loss is influenced by expected loan loss as well as dispersion of the loan loss distribution. Nebraska has the highest expected loan losses and widest loan loss distribution as seen in Figure 8. As a result, Nebraska has the highest maximum loan losses ($54.2 million) and VaR ($27.3 million). VaR is calculated by subtracting the expected loan loss from the maximum loan loss.[43] Illinois also has a relatively wide loan loss distribution, which results in the second highest maximum loan losses ($39.5 million) and VaR ($25.4 million). Beside these two states, Iowa has high maximum loan losses ($34.6 million), and followed by Kansas ($24.2 million), and Indiana ($15.4

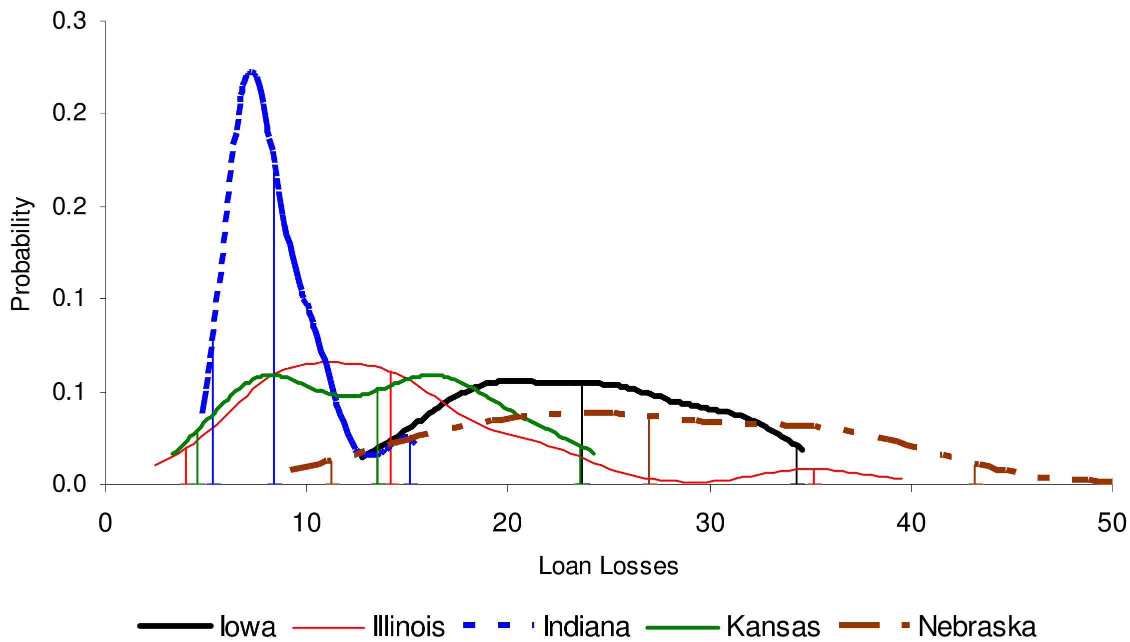
[43] VaR also can be measured on the PDF graph of loan loss distribution. Figure 9 could be manipulated just like Figure 1 in Chapter II.

million). VaR of Iowa and Kansas is $10.9 million and $10.8 million respectively, and Indiana shows the lowest VaR in 2004.

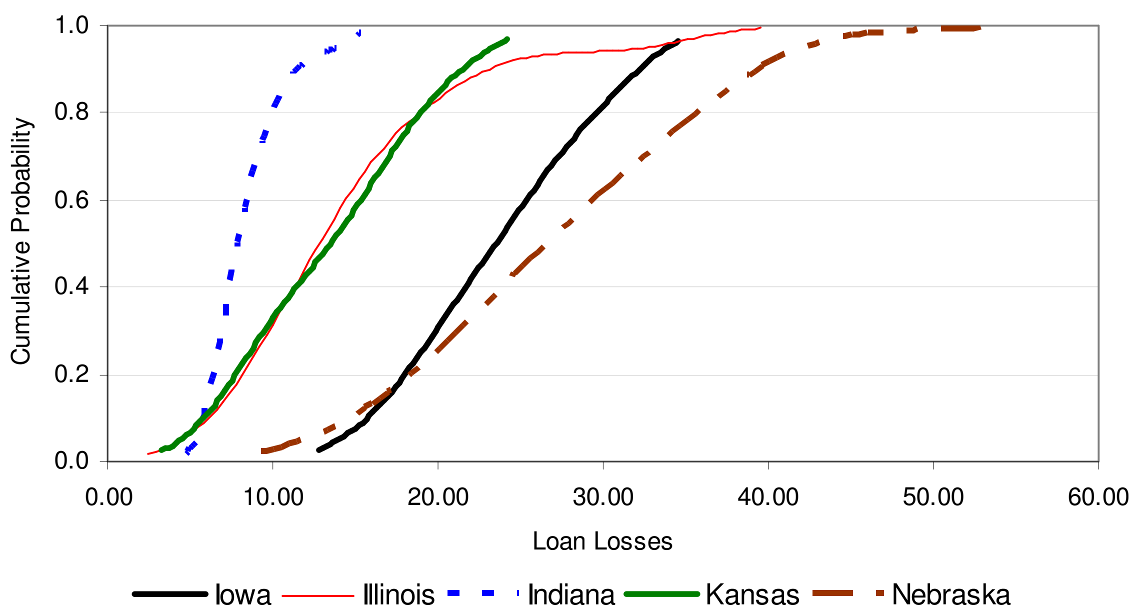
Figure 9 illustrates the PDF and CDF for loan losses in 2004 by state. The graph provides valuable management information and can also be used in risk management by banks the same way as the CDF was used for the default rate. Bank management is surely interested in right hand side of the loan loss distribution. Illinois and Kansas has almost same value of expected loan loss, and the shape of the loan loss distribution is similar except for long right-hand-side of the tail in Illinois. The long tail to the right in Illinois means that Illinois has more risk in spite of the almost same expected loan losses. The big difference in VaR values between Illinois ($28.5 million) and Kansas Illinois ($10.1 million) stems from the difference in loan loss distributions. This gives banks an important implication that bank management should trace expected loan loss (or risk) as well as the distribution of the loan loss (or risk) for coming years.

Banks can also compare loan loss distribution by year.[44] The riskiness of a bank's portfolio can be reviewed through the distributions by year. The results enable banks to prepare a proactive policy to future credit risk.

[44] The loan loss distribution by year is not presented.



Probability Density Function



Cumulative Distribution Function

Figure 9 PDF and CDF for Stochastic Loan Loss Projection, 2004

The loan loss distribution can be interpreted as an early warning indicator to bank management as well as to bank examiners and regulator. For example, let's suppose the OCC classifies a bank with more than 15% of probability that loan losses are greater than $30 million, into as "a risky bank." Figure 10 illustrates the probability that each bank could belong to a risky bank class. In term of the OCC threshold, Iowa with 18% of probability and Nebraska with 36% of probability in 2004 might require close attention from the OCC. Illinois has a long tail in loss distribution and greater maximum losses than Iowa, but the probability that loan losses are greater than $30 million is just 5.5%. Indiana and Kansas are projected to have zero percent of probability that they are classified into a risky bank in 2004. If agricultural banks develop a default model by commodity, the stoplight chart can be used to detect risky commodity segments.

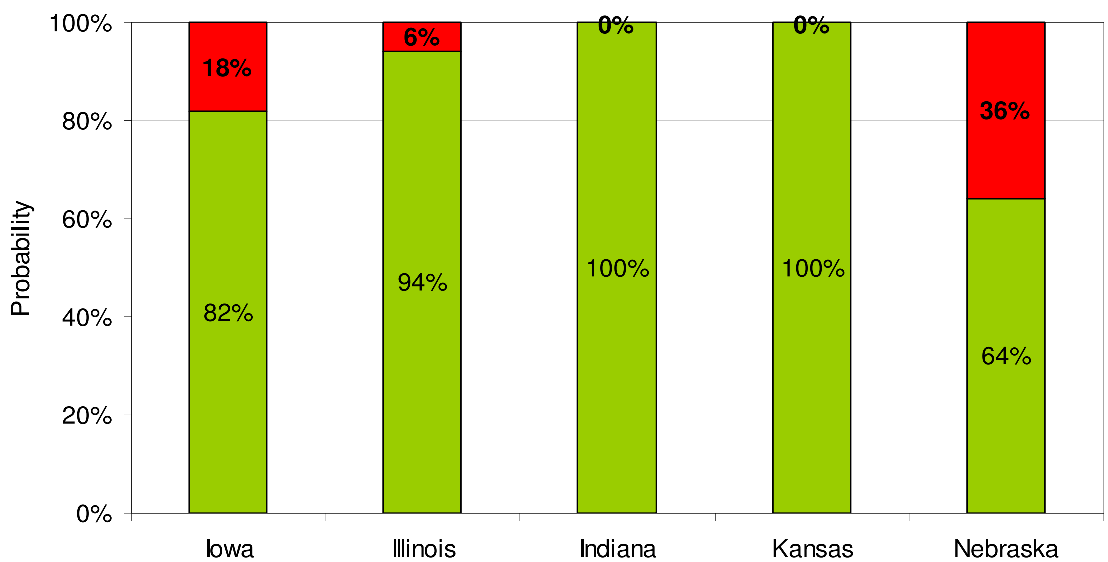


Figure 10 Stoplight Chart Illustrating the Probability that Loan Losses are greater than $30 million in 2004

Capital Requirements

Capital requirements are estimated based on the Basel II formula presented in equations (4.35) and (4.36). Table 18 summarized the capital requirement by state for 2004. Correlations ranged from 0.123 to 0.140. Nebraska has the smallest R value (0.123), followed by Indiana (0.128), Kansas (0.132), Iowa (0.133) and Illinois (0.140). Since the correlation is a decreasing function of the default rate, the state order for the size of correlations is the reverse of the size of the default rates.

Table 18 Calculation Results for Capital Requirements, 2004

	Iowa	Illinois	Indiana	Kansas	Nebraska
Expected default rate (DR)	0.61%	0.44%	0.74%	0.63%	0.87%
Correlation (R)	0.133	0.140	0.128	0.132	0.123
Capital requirement (K)	3.48%	2.87%	3.85%	3.51%	4.18%

Capital requirements are calculated using the expected default rate and the assumption of a normally distributed default rate.[45] Under the normality assumption, the 99.9% percentile of the default distribution is far away from the expected default rate, resulting conservative capital requirements. The Basel II formula also ignores uniqueness of the distribution for each loan portfolio. As shown in Figure 7 and 9, the default distributions and loan loss distributions are quite different by state, but the Basel

[45] Basel II formula for capital requirements assumes normality of the default rate since the formula stems from an option-based structural model such as CreditMetrics, which is detailed in Chapter III.

II assumes the distributions are the same. Capital requirements for Illinois is 2.87% of total loans outstanding in 2004, and followed by Iowa (3.48%), Kansas (3.51%), Indiana (3.85%), and Nebraska (4.18%). The capital requirements can be interpreted as the amount of required capital out of unit dollar of total loans outstanding. For example, Illinois is required to have more than 2.87 cents of capital out of one dollar of loans to fulfill the capital requirements regulated by Basel Capital Accord.

Summary

Model validation for the default model is examined through in-sample and out-of-sample simulation to measure the forecasting error. Four statistics, RMSE, MAE, MAPE, and Theil U, were used for this purpose. The maximum forecasting errors are 19.6% in in-sample simulation and 28.7% in out-of-sample simulation. For validation of the simulation model, t-statistics and F-statistics are used, and the results verify that the simulated exogenous variables are invariant from the historical data.

This chapter simulated the default rate by state from 2004 to 2007. The over all tendencies of the expected default rates suggests a decrease in 2004 and 2005, and an increase in 2006 and 2007. Nebraska would be exposed to the highest risk over the period. This chapter provides the statistics and CDF for the default rates, and suggests, with Iowa sample, how CDF graphs could be used to evaluate riskiness of a bank portfolio example. This chapter explained how the loss distribution could be generated and how the loss distribution could be used to calculate the expected loan loss, maximum loan loss and VaR. Nebraska, which has the highest expected and maximum loan loss, is projected to have the highest VaR in 2004. The calculation for capital requirements was performed using the Basel II formula. Nebraska was projected to have the highest capital requirement, and followed by Indiana, Kansas, Iowa and Illinois.

CHAPTER VII

SUMMARY AND CONCLUSION

Summary

After the heavy loan losses and riskier environments experienced in the 1980s and 1990s, banks became believers in the importance of credit risk management. Credit risk models are widely applied in banks today. Effective credit risk management has become an important factor of bank success. The New Basel Capital Accord (Basel II) provides added emphasis to the development of portfolio credit risk models. However, credit risk models for agricultural loan portfolios are still in the infancy. The general objective of this study was to develop a credit risk model for agricultural loan portfolio.

This study initially reviewed the key issues in bank credit risk management. Since a bank is a firm balancing risk and return characteristics among alternative opportunities, it cannot avoid risks to fulfill its objective. There are several categories of banking risks, but credit risk is the most predominant. Credit risk is regarded as the primary cause of bank failure in recent years. Credit risk can be measured at the exposure level and the portfolio level. VaR is the industry standard measure of the portfolio credit risk. Basel II incorporates the VaR concept in its regulations, providing emphasis to modeling portfolio credit risk. An important regulatory change in Basel II is the differentiated treatment in measuring capital requirements for the corporate exposures and retail exposures, which has important implication to agricultural loan portfolios. Basel II allows agricultural loans should be categorized and treated as the retail exposures, because agricultural exposures are typically managed on a portfolio basis and have similar risk characteristics to other types of retail exposures.

Chapter III presented an extensive review of literature on credit risk models. The review provided a historical perspective, citing existing arguments, directions, and credit risk modeling. There are three categories of stand-alone credit risk models: expert systems, credit ratings, and credit scoring models. These models are used as an input to portfolio credit risk modeling. Portfolio credit risk models were initially developed for commercial use. There are various types of portfolio credit risk models: option-based structural models, reduced form models, and multi-factor econometric models. Portfolio credit risk models for retail exposures have been developed by banks recently. However, little has been done to model credit risk for the retail exposures or agricultural loans.

A model for bank portfolio credit risk should be chosen based upon forecasting accuracy and applicability. In this sense, portfolio credit models developed for the corporate exposures have disadvantages if applied to the retail exposures due to their intensive data requirements. Retail exposures have unique characteristics that need to be taken into account. One of the most important implications from the literature review is that, in consumer loans or small business loans, default is closely related to cash flow and the fact that their income may become insufficient to make scheduled loan payments. Consideration of the cash flow effect in credit risk modeling is important in agricultural loan since the agricultural sector is known to have liquidity problems and chronic cash flow pressures. Net cash flows are a good leading indicator for credit worthiness and provide the basis for making a credit risk model proactive.

A theoretical model and empirical model for an agricultural loan portfolio credit risk were developed in Chapter IV. A theory of loan default for farm borrowers was conceptualized based on causal relationship between creditworthiness and economic factors at the micro level. Several assumptions, such as homogenous asymptotic loan portfolio and homogenous segments, are introduced to make the model simple. The theoretical model emphasizes the applicability to agricultural loan portfolios where data availability is an issue. The empirical default model reflects a logistic specification that evaluates loan portfolio credit risk by loan segment. The simulation model generates stochastic exogenous variables associated with the state of the national economy, which are used as an input to the COMGEM econometric model. The COMGEM model generates national level variables, and they are transformed into state level variables used as explanatory variables (*NCIC*, *NCIL*, *GPMT*, and *UEMP*) in the default model. This model is designed to generate the probability of default in a proactive manner. The procedures to generate the loan loss distribution, expected default, VaR, and capital requirements, based on Basel II, are explained in detail.

Default rate data was provided by the Federal Deposit Insurance Corporation (FDIC). Other variables are collected from the government web sites or generated from the original data for modeling purposes. Fourth quarter balances in the loan performance data provided by the FDIC are used by state to estimate the annual model over the 1985 to 2003 period. This study covers five states: Iowa, Illinois, Indiana, Kansas, and

Nebraska. Five state models are specified and estimated separately. The key input to the default model, net cash income, generated by state reflects the five major commodities: corn, soybeans, wheat, fed cattle and hogs.

The estimation results from the default model and simulation model show strong statistical attributes. The signs and magnitudes of the estimated parameters are consistent with theory or intuitive expectation. The t-statistics for the estimated parameters are significant with few exceptions. The magnitudes of adjusted R^2 differ by equation, but are overall satisfactory. The default model reflects an exceptionally high adjusted R^2. The DW statistics and LM test results demonstrate that there is no serial correlation problem. The results of the default model supported the assumption in the theoretical model that default by the borrower is associated with net cash income, and that net cash income can be used as a leading indicator for default in agricultural loans. Different model specification suggests that default models should be specified by state and/or by region.

Chapter VI has three goals: (1) to verify whether or not the estimated models are appropriate for forecasting the probability of default, (2) to present an application of the model, and (3) to discusses the interpretation and implication of the simulation results to bank credit risk management. Model validation for the default model was examined through in-sample and out-of-sample simulation to measure the forecasting error. Four statistics, RMSE, MAE, MAPE, and Theil U, are used for this purpose. The maximum forecasting errors are 19.6% in the in-sample simulation and 28.7% in the out-of-sample simulation. For validation of the simulation model, t-statistics and F-statistics were used.

The results verify that the simulated exogenous variables are invariant from the historical data.

The default rates are simulated by state over 2004 to 2007 period, providing the probability of default or the default rate distribution. The over all tendencies for the expected default rates in agricultural loans suggest a decrease in 2004 and 2005, and an increase in 2006 and 2007. Nebraska was shown to have the highest risk over this period. Statistics and CDF graphs for simulated default rates are provided by state and by year. The CDF can be used as a means of illustrating potential stress. The loss distribution was generated through multiplication of default rate by total loans outstanding, EAD and LGD. The calculation results for expected loan loss, maximum loan loss, and VaR were presented. Nebraska, which has the highest expected and maximum loan loss, is anticipated to have the highest VaR in 2004. This paper also provides the PDF and CDF for loan loss, illustrating differences in the loss distributions by state. The distribution can be used as a risk indicator for bank management as well as for bank examiners and regulators. The last section of Chapter VI was devoted to the calculation of capital requirements. The calculation was performed based upon the Basel II formula, and capital requirement were presented by percentage terms among the total loan outstanding. Nebraska is expected to have the highest capital requirement (4.18%), and followed by Indiana, Kansas, Iowa and Illinois.

Conclusion

This research was motivated by the recent observations in the banking industry that portfolio credit risk modeling has become a key component in bank management. Basel II provides a new emphasis for bank credit risk management. Basel II proposed a differentiated treatment of measuring capital requirements for corporate exposures and retail exposures, and induces more focus on retail exposures. Agricultural lenders need to pay attention to the new regulations because agricultural loans should be classified as the retail exposures. Credit risk models for agricultural loan portfolios are still in their infancy, while existing portfolio credit risk models developed for corporate exposures lack applicability.

The objective of this study was to develop a credit risk model for agricultural loan portfolios. The objective was accomplished by conceptualizing a theory of loan default for farm borrowers, deriving a theoretical model, and presenting the estimation and simulation results for default model by state. The essential testable hypothesizes of this model are (1) net cash income is a key factor affecting credit risk for agricultural loans, and (2) risk characteristics are different from loan segments classified by region and primary commodity. Therefore, portfolio credit risk models should be specified to consider loans at the segment level.

The first hypothesis is proven by the estimation results in chapter V. A moving average of net cash income, separately measured by commodity groups, government payment, and a proxy of off-farm income does a good job of explaining the default rate. Parameters are statistically significant and consistent with theory. The default model explains more than 90% of variability of the default rate. The use of net cash income in a default model is very important because it is a leading indicator for the credit risk for agricultural loans and it provides the basis for making the model proactive. The main stream of existing portfolio credit risk model for corporate loans captures the credit risk based on asset value, which can be seen as a lagging indicator in agricultural sector because of its illiquidity and lags in market valuation.

The second hypothesis was not fully tested because of data restrictions. Different model specifications for the default model during the estimation process suggest that each state has a unique economic structure at the micro and macro level, making the attributes of the credit risk diverse by state. The simulation results for the default rate distribution and loan loss distribution support the importance of regional considerations in credit risk modeling.

This study could not specify a portfolio credit risk model by primary commodity for reasons of data availability. Net cash flows for a farm enterprise differ by the primary commodity managed by the farmer. Naturally, credit risk of a farmer is influenced by the commodity, and the commodity consideration in loan segmentation for an agricultural bank is conceptually acceptable. This study left the commodity default model for future research as data become available.

The default model developed in this study has several advantages, and has implications for further research. As discussed in Chapter II, the applicability of a model is not an optional condition but a prerequisite. This model reduces data requirements for modeling and focuses the applicability of the model. This is accomplished by developing a segment specific credit risk model. An agricultural lender interested in this model will be required to develop a segmentation process and data base to support the segmentation. This model can provide valuable management variables such as the probability of default, loan loss distribution, expected loan loss, VaR and capital requirements. This information can be used for the internal management of a bank as well as for oversight reasons by regulators.

Implication for Future Research

Suggestions for the future research are closely associated with further data availability. Once a bank level default data is accessible and the loan portfolio is segmented by commodity, primary commodity specific default models can be specified. The model give more testable hypothesizes and applications as followed:

(i) The first hypothesis in the previous section, "net cash income is a key factor affecting credit risk for agricultural loans," can be fully evaluated in the commodity specific default model.

(ii) More research is required to find appropriate economic variables to capture the commodity specific cash flow such as off-farm income. If data is gathered from less aggregated variable, i.e. cash cost of production at a county level, the model accuracy will increase, but modeling cost will also increase. Researchers have to balance data accuracy with modeling cost.

(iii) The commodity specific default model would give loan loss distribution by commodity segment in a bank portfolio. Then the information can be use to solve an optimal loan portfolio, expressed as a percentage share of each commodity segment. For example, a bank can estimate an optimal share of loans to major commodity minimizing the loan losses over a specific time period. For this analysis, a mathematical programming model, such as the Markowiz (1952) EV model or the MOTAD model, needs to be combined with the default model.

(iv) The commodity specific default model can also be applied to evaluating alternative internal management policies in a bank and external policies given by government or regulator. If a bank has several alternative loan policies, projections of loan loss distribution by policy can be calculated and the result can be use to decide a preferred policy.

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APPENDIX

Appendix 1 Loan Performance Status Data

Iowa

(1000 dollars)

Year	Total Loan Outstanding (A)	Past Due > 90 Days, still Accrual (B)	Non-accrual (C)	Charge Offs (D)	Default Loan (E=B+C)	Default Rate (%) (E/A)
1985	3,858,979	44,869	211,501	216,214	256,370	6.64
1986	3,372,177	33,288	149,387	181,071	182,675	5.42
1987	3,285,179	19,934	74,484	33,573	94,418	2.87
1988	3,628,342	15,722	41,041	6,465	56,763	1.56
1989	3,950,725	11,098	26,059	1,596	37,157	0.94
1990	4,297,847	9,696	22,259	675	31,955	0.74
1991	4,578,905	15,747	31,287	6,939	47,034	1.03
1992	4,816,072	17,950	32,889	7,150	50,839	1.06
1993	5,195,324	17,916	29,461	2,465	47,377	0.91
1994	5,375,771	12,909	30,532	4,536	43,441	0.81
1995	5,477,507	11,277	20,447	3,373	31,724	0.58
1996	5,796,362	15,255	23,854	2,350	39,109	0.67
1997	6,359,203	14,817	15,512	861	30,329	0.48
1998	6,574,755	21,012	32,088	7,839	53,100	0.81
1999	6,632,990	21,592	31,310	13,875	52,902	0.80
2000	6,606,385	13,489	22,479	4,702	35,968	0.54
2001	6,857,874	14,283	23,109	13,363	37,392	0.55
2002	7,164,452	20,138	25,813	9,069	45,951	0.64
2003	7,515,551	16,508	28,145	7,206	44,653	0.59

Appendix 1 Continued

Illinois

(1000 dollars)

Year	Total Loan Outstanding (A)	Past Due > 90 Days, still Accrual (B)	Non-accrual (C)	Charge Offs (D)	Default Loan (E=B+C)	Default Rate (%) (E/A)
1985	3,015,472	29,966	102,706	88,973	132,672	4.40
1986	2,886,532	19,374	104,419	84,065	123,793	4.29
1987	2,889,780	12,443	74,961	35,057	87,404	3.02
1988	3,207,571	9,620	50,730	11,520	60,350	1.88
1989	3,332,733	10,574	35,772	4,947	46,346	1.39
1990	3,503,958	7,544	27,500	3,863	35,044	1.00
1991	3,677,847	17,150	45,274	7,619	62,424	1.70
1992	3,763,594	14,160	43,774	5,245	57,934	1.54
1993	3,866,089	11,293	33,753	1,965	45,046	1.17
1994	4,060,074	12,190	24,234	0	36,424	0.90
1995	4,228,193	9,454	22,131	116	31,585	0.75
1996	4,602,772	10,296	18,472	2,303	28,768	0.63
1997	4,829,950	9,674	16,719	3,916	26,393	0.55
1998	5,041,931	14,643	26,798	4,028	41,441	0.82
1999	5,650,496	16,692	39,845	6,191	56,537	1.00
2000	5,288,209	12,549	62,985	13,809	75,534	1.43
2001	6,339,430	9,394	58,723	30,256	68,117	1.07
2002	6,238,046	9,233	38,539	26,151	47,772	0.77
2003	6,352,654	8,899	38,906	4,750	47,805	0.75

Appendix 1 Continued

Indiana

(1000 dollars)

Year	Total Loan Outstanding (A)	Past Due > 90 Days, still Accrual (B)	Non-accrual (C)	Charge Offs (D)	Default Loan (E=B+C)	Default Rate (%) (E/A)
1985	1,638,388	19,404	46,749	41,061	66,153	4.04
1986	1,620,832	11,335	42,579	34,172	53,914	3.33
1987	1,580,724	9,110	33,342	19,403	42,452	2.69
1988	1,673,875	4,404	28,773	4,907	33,177	1.98
1989	1,725,818	4,372	24,530	5,159	28,902	1.67
1990	1,770,229	4,752	19,528	5,175	24,280	1.37
1991	1,846,702	6,794	28,453	7,332	35,247	1.91
1992	1,871,875	4,777	37,205	9,816	41,982	2.24
1993	1,862,525	4,499	35,899	3,737	40,398	2.17
1994	1,888,843	2,322	21,149	3,144	23,471	1.24
1995	1,946,978	2,381	14,956	596	17,337	0.89
1996	1,935,556	2,056	14,390	829	16,446	0.85
1997	1,950,602	3,129	10,958	- 117	14,087	0.72
1998	2,028,527	4,899	13,977	- 2,221	18,876	0.93
1999	1,801,621	3,938	11,511	2,231	15,449	0.86
2000	2,182,989	2,772	17,666	1,199	20,438	0.94
2001	2,284,033	2,710	20,138	2,555	22,848	1.00
2002	2,294,822	3,598	16,661	954	20,259	0.88
2003	2,257,373	2,191	11,336	428	13,527	0.60

Appendix 1 Continued

Kansas

(1000 dollars)

Year	Total Loan Outstanding (A)	Past Due > 90 Days, still Accrual (B)	Non-accrual (C)	Charge Offs (D)	Default Loan (E=B+C)	Default Rate (%) (E/A)
1985	2,545,481	27,477	100,317	83,550	127,794	5.02
1986	2,353,310	17,645	90,615	72,441	108,260	4.60
1987	2,388,884	13,540	55,179	40,177	68,719	2.88
1988	2,465,513	7,467	35,330	15,380	42,797	1.74
1989	2,591,999	7,487	27,080	5,257	34,567	1.33
1990	2,764,871	8,166	25,055	3,640	33,221	1.20
1991	2,823,464	8,642	40,924	4,972	49,566	1.76
1992	2,911,058	8,929	37,702	3,604	46,631	1.60
1993	3,065,193	8,474	32,330	1,217	40,804	1.33
1994	3,159,650	7,180	31,834	508	39,014	1.23
1995	3,153,519	10,304	35,931	5,143	46,235	1.47
1996	2,990,883	13,528	34,370	4,395	47,898	1.60
1997	3,441,612	8,583	23,488	812	32,071	0.93
1998	3,684,634	11,493	25,656	4,677	37,149	1.01
1999	3,780,370	10,144	31,150	3,683	41,294	1.09
2000	3,999,823	10,949	26,975	3,279	37,924	0.95
2001	4,130,891	10,909	35,622	6,019	46,531	1.13
2002	4,186,634	7,979	41,331	14,583	49,310	1.18
2003	4,283,670	8,271	40,824	5,002	49,095	1.15

Appedix 1 Continued

Nebraska

(1000 dollars)

Year	Total Loan Outstanding (A)	Past Due > 90 Days, still Accrual (B)	Non-accrual (C)	Charge Offs (D)	Default Loan (E=B+C)	Default Rate (%) (E/A)
1985	2,860,207	24,298	139,104	143,282	163,402	5.71
1986	2,514,607	16,531	107,271	102,213	123,802	4.92
1987	2,534,768	11,535	68,768	29,739	80,303	3.17
1988	2,735,070	8,166	40,251	617	48,417	1.77
1989	2,924,791	4,800	30,165	- 982	34,965	1.20
1990	3,223,019	4,934	22,221	- 1,872	27,155	0.84
1991	3,555,188	8,608	31,465	- 1,775	40,073	1.13
1992	3,747,551	13,519	32,309	818	45,828	1.22
1993	4,034,495	6,493	28,426	493	34,919	0.87
1994	4,289,264	8,001	23,798	3,906	31,799	0.74
1995	4,420,028	13,493	28,750	2,161	42,243	0.96
1996	4,534,052	14,152	45,125	5,460	59,277	1.31
1997	4,987,209	14,856	41,004	5,799	55,860	1.12
1998	5,169,929	17,815	55,294	8,307	73,109	1.41
1999	5,285,182	17,073	55,144	8,217	72,217	1.37
2000	5,558,834	16,205	32,904	3,938	49,109	0.88
2001	5,543,183	14,144	35,165	52,964	49,309	0.89
2002	5,806,768	12,825	42,435	6,771	55,260	0.95
2003	5,670,630	16,100	67,934	10,307	84,034	1.48

Appendix 2 Yield and Price

Crop Yields per Planted Acre

(Bushel / acre)

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Corn										
Iowa	122.8	132.3	126.9	79.5	114.7	122.1	114.2	144.2	73.3	148.5
Illinois	132.3	132.5	129.9	70.8	121.3	124.6	105.1	147.0	123.8	154.0
Indiana	120.1	118.9	131.8	79.8	129.3	125.5	89.6	143.9	128.4	140.7
Kansas	117.0	125.2	109.3	115.0	113.1	117.8	114.6	140.3	108.0	130.6
Nebraska	122.3	122.7	125.0	118.6	114.5	121.4	120.8	128.5	98.2	133.3
U.S.	106.4	107.4	107.7	72.8	104.1	107.0	98.4	119.5	86.5	127.3
Soybeans										
Iowa	37.8	41.3	43.2	30.8	38.9	41.0	40.2	43.8	29.9	50.3
Illinois	42.0	39.8	37.6	26.7	39.8	38.6	37.1	42.7	41.6	45.2
Indiana	41.1	36.6	39.5	26.9	36.1	40.8	38.6	42.7	45.5	46.8
Kansas	29.1	31.5	31.4	22.4	26.3	23.4	21.9	36.0	26.6	34.2
Nebraska	35.4	37.2	34.8	29.5	31.5	33.9	33.0	41.3	34.6	46.4
U.S.	33.2	32.2	33.3	26.3	31.6	33.3	33.6	37.0	31.1	40.8
Wheat										
Iowa	44.8	18.7	12.7	20.4	41.1	42.2	22.7	22.3	10.4	38.5
Illinois	43.2	27.8	51.0	51.9	56.8	43.3	27.2	42.8	41.3	43.8
Indiana	48.2	33.4	46.4	41.7	55.2	48.0	33.9	31.3	48.4	56.5
Kansas	34.9	29.3	34.2	31.7	17.2	38.1	30.8	30.3	32.1	36.4
Nebraska	34.5	33.0	39.0	31.3	21.7	34.9	28.6	23.6	31.3	32.5
U.S.	32.1	29.0	32.0	27.7	26.6	35.4	28.3	34.2	33.2	33.0

Appendix 2 Continued

(Bushel / acre)

	1995	1996	1997	1998	1999	2000	2001	2002	2003
Corn									
Iowa	119.9	134.7	134.6	141.5	145.3	140.5	142.3	158.3	151.9
Illinois	110.8	133.5	127.3	139.0	138.1	149.0	149.9	132.6	161.8
Indiana	110.9	119.7	118.9	131.1	129.0	142.2	152.5	117.0	140.5
Kansas	113.6	142.9	135.2	139.7	133.4	119.4	112.3	92.8	103.4
Nebraska	106.8	138.8	127.6	140.9	134.2	119.3	140.6	112.0	138.8
U.S	103.5	116.5	115.8	121.7	121.9	124.6	125.5	113.7	128.5
Soybeans									
Iowa	43.8	43.8	45.6	47.8	44.3	43.4	43.7	47.8	32.3
Illinois	38.8	40.3	42.8	43.8	41.8	43.8	44.7	42.8	36.9
Indiana	39.3	37.7	43.1	41.3	38.7	45.8	48.9	41.3	37.4
Kansas	24.4	36.1	36.2	29.4	28.5	16.9	30.7	21.2	21.9
Nebraska	32.6	44.4	39.9	43.4	42.0	37.4	45.0	37.5	40.1
U.S.	34.8	37.1	38.4	38.1	36.0	37.1	39.0	37.3	33.4
Wheat									
Iowa	24.5	26.9	38.9	35.2	33.3	42.3	38.9	42.4	51.2
Illinois	46.0	25.3	57.8	46.1	57.7	55.2	58.6	46.8	61.9
Indiana	56.6	32.2	52.2	51.1	61.2	64.0	62.7	48.3	64.5
Kansas	24.4	21.6	44.0	46.3	43.2	35.5	33.5	27.9	45.7
Nebraska	40.0	32.0	35.2	43.6	42.9	33.9	33.8	30.4	44.1
U.S.	31.6	30.3	35.2	38.7	36.6	35.6	32.8	26.6	37.7

Source: Ag Statistics Data Base, NASS, USDA (www.nass.usda.gov:81/ipedb/main.htm)

Appendix 2 Continued

Marketing Year Average Prices Received by Farmers

(dollar / bushel)

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Corn										
Iowa	2.02	1.41	1.89	2.45	2.29	2.21	2.30	2.00	2.44	2.22
Illinois	2.27	1.54	1.96	2.59	2.40	2.36	2.46	2.11	2.57	2.27
Indiana	2.20	1.53	2.08	2.65	2.47	2.31	2.45	2.09	2.51	2.25
Kansas	2.37	1.60	1.84	2.60	2.28	2.25	2.42	2.15	2.61	2.32
Nebraska	2.22	1.52	1.96	2.48	2.30	2.28	2.34	2.09	2.52	2.33
U.S.	2.23	1.50	1.94	2.54	2.36	2.28	2.37	2.07	2.50	2.26
Soybeans										
Iowa	4.99	4.73	5.97	7.33	5.62	5.63	5.51	5.54	6.34	5.43
Illinois	5.17	4.91	6.00	7.45	5.76	5.85	5.70	5.69	6.49	5.61
Indiana	5.04	4.76	5.94	7.55	5.79	5.81	5.68	5.61	6.31	5.53
Kansas	4.95	4.60	5.49	7.26	5.45	5.67	5.55	5.42	6.41	5.32
Nebraska	4.86	4.56	5.82	7.31	5.45	5.59	5.47	5.37	6.20	5.29
U.S.	5.05	4.78	5.88	7.42	5.69	5.74	5.58	5.56	6.40	5.48
Wheat										
Iowa	2.95	2.30	2.75	3.82	3.80	2.74	2.40	3.05	2.00	3.15
Illinois	3.02	2.41	2.51	3.50	3.80	2.75	2.56	3.28	2.81	3.04
Indiana	2.91	2.25	2.43	3.49	3.83	2.84	2.72	3.19	2.78	3.04
Kansas	2.86	2.25	2.43	3.58	3.74	2.51	2.81	3.13	3.00	3.32
Nebraska	2.79	2.23	2.45	3.66	3.75	2.53	3.01	3.16	3.04	3.39
U.S.	3.08	2.42	2.57	3.72	3.72	2.61	3.00	3.24	3.26	3.45

Appendix 2 Continued

(dollar / bushel)

	1995	1996	1997	1998	1999	2000	2001	2002	2003
Corn									
Iowa	3.20	2.60	2.33	1.86	1.72	1.75	1.90	2.22	2.40
Illinois	3.30	2.79	2.53	2.04	1.91	1.91	2.04	2.35	2.50
Indiana	3.38	2.78	2.53	2.11	1.88	1.90	1.98	2.41	2.50
Kansas	3.24	2.83	2.47	1.96	1.81	2.00	2.03	2.48	2.55
Nebraska	3.22	2.64	2.32	1.88	1.75	1.90	1.94	2.32	2.45
U.S.	3.24	2.71	2.43	1.94	1.82	1.85	1.97	2.32	2.45
Soybeans									
Iowa	6.65	7.36	6.33	4.79	4.53	4.49	4.35	5.54	7.30
Illinois	6.88	7.55	6.56	5.01	4.75	4.62	4.55	5.66	7.35
Indiana	6.73	7.34	6.59	5.05	4.71	4.61	4.42	5.55	7.35
Kansas	6.69	7.17	6.42	4.98	4.53	4.50	4.16	5.49	7.60
Nebraska	6.56	7.19	6.28	4.83	4.47	4.44	4.19	5.43	7.02
U.S.	6.72	7.35	6.47	4.93	4.63	4.54	4.38	5.53	7.25
Wheat									
Iowa	4.05	4.10	3.16	2.73	2.38	2.15	2.50	2.85	2.85
Illinois	3.89	4.12	3.14	2.35	2.11	2.09	2.49	3.01	3.20
Indiana	3.96	4.06	3.18	2.36	2.13	2.11	2.41	3.18	3.20
Kansas	4.59	4.63	3.16	2.53	2.25	2.65	2.69	3.41	3.15
Nebraska	4.56	4.29	3.20	2.54	2.20	2.61	2.75	3.60	3.25
U.S.	4.55	4.30	3.38	2.65	2.48	2.62	2.78	3.56	3.35

Source: Ag Statistics Data Base, NASS, USDA (www.nass.usda.gov:81/ipedb/main.htm)

Appendix 2 Continued

(dollar / cwt)

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Fed Cattle										
Iowa	57.50	57.00	64.40	70.20	73.40	78.10	75.10	73.90	76.10	68.90
Illinois	57.56	57.18	64.08	69.57	72.58	76.63	73.43	73.19	74.57	67.65
Indiana*	57.56	57.18	64.08	69.57	72.58	76.63	73.43	73.19	74.57	67.65
Kansas*	58.60	58.20	65.40	71.30	74.80	80.00	76.50	75.90	76.40	69.60
Nebraska	58.60	58.20	65.40	71.30	74.80	80.00	76.50	75.90	76.40	69.60
U.S.**	59.75	59.25	66.28	71.19	73.86	78.56	74.21	75.35	76.36	68.84
Hogs										
Iowa	44.70	50.00	52.50	43.90	43.80	55.40	50.90	42.90	46.50	41.20
Illinois	44.72	50.69	51.69	43.76	44.41	54.77	49.28	42.89	45.43	39.60
Indiana*	44.72	50.69	51.69	43.76	44.41	54.77	49.28	42.89	45.43	39.60
Kansas*	44.70	50.80	52.50	43.60	43.90	55.30	49.90	42.40	46.60	41.40
Nebraska	44.70	50.80	52.50	43.60	43.90	55.30	49.90	42.40	46.60	41.40
U.S.***	47.82	54.46	54.81	46.07	46.75	57.75	51.79	44.87	48.17	42.00

Appendix 2 Continued

(dollar / cwt)

	1995	1996	1997	1998	1999	2000	2001	2002	2003
Fed Cattle									
Iowa	65.50	63.70	66.70	61.90	65.10	70.00	73.10	66.40	82.40
Illinois	64.87	63.44	65.04	60.70	63.87	68.43	73.70	67.50	85.54
Indiana*	64.87	63.44	65.04	60.70	63.87	68.43	73.70	67.50	85.54
Kansas*	66.80	65.90	67.60	62.70	66.30	70.00	73.60	69.10	85.00
Nebraska	66.80	65.90	67.60	62.70	66.30	70.00	73.60	69.10	85.00
U.S.**	66.26	65.05	66.32	61.47	65.56	69.65	72.71	67.04	84.69
Hogs									
Iowa	41.80	53.80	55.10	36.50	32.50	44.70	46.50	34.30	36.50
Illinois	41.08	52.48	50.95	31.45	31.04	41.59	44.93	34.64	40.41
Indiana*	41.08	52.48	50.95	31.45	31.04	41.59	44.93	34.64	40.41
Kansas*	42.30	54.10	55.50	37.30	32.40	44.40	46.60	36.90	39.60
Nebraska	42.30	54.10	55.50	37.30	32.40	44.40	46.60	36.90	39.60
U.S.***	44.62	56.53	54.30	34.72	34.00	44.69	45.81	34.91	39.45

Source: Iowa Agricultural Statistics, NASS, USDA (www.nass.usda.gov/ia)
Illinois Average Farm Price Received Database (www.farmdoc.uiuc.edu/manage/pricehistory/price_history.html)
Nebraska Historic Price Data, NASS, USDA (www.nass.usda.gov/ne/nebhist.htm)
USDA/AMS (http://www.ers.usda.gov/data/sdp/view.asp?f=livestock/94006/)

* Indiana uses Illinois data, and Kansas uses Nebraska data.

** U.S. cattle price: Slaughter Steer Price, Choice 2-4, Nebraska Direct, 1100-1300 lb.

*** U.S. hog price: Price of market barrows and gilts (Iowa, South Minnesota).

Appendix 3 Total Cost of Production, 2003 (Base Year)

	Total Cost (dollar / ac or cwt)			State / Region	Data Descriptions and Web Sites
	Cash	Non-cash	Sum		
Iowa					www.extension.iastate.edu/agdm/
Corn	187.5	191.3	378.8	State	Corn following corn, 135 bu/ac
Soybeans	101.4	183.5	284.9	State	Soybeans following corn, Non-GMO, 45 bu/ac
Wheat	100.0	174.0	274.0	Illinois	Use Illinois data
Fed Cattle	55.8	16.2	72.1	State	Finishing yearling steers, 1250lb
Hogs	29.4	15.9	45.4	State	Finishing feeder pigs, 250lb
Illinois					www.farmdoc.uiuc.edu/manage/enterprisecost_index.html
Corn	188.0	219.0	407.0	Central	Grain farms, no livestock
Soybeans	126.0	207.0	333.0	Central	Grain farms, no livestock
Wheat	100.0	174.0	274.0	State	Estimated cost for both 03 & 04, 60 bushel / ac
Fed Cattle	50.0	7.3	57.2	State	Beef feeding enterprises, per cwt
Hogs	31.5	7.4	38.9	State	Farrow-to-finish hog enterprise
Indiana	Illinois	Illinois	Illinois	Illinois	Use Illinois data
Kansas					www.agmanager.info/
Corn	172.4	44.5	216.9	State	Non-irrigated
Soybeans	114.1	38.3	152.4	State	Non-irrigated
Wheat	88.3	29.5	117.7	State	Non-irrigated
Fed Cattle	68.5	11.3	79.8	State	Beef finishing
Hogs	25.5	6.1	31.6	State	Swine fattening
Nebraska					www.nfbi.net/2003AnnualReportwithcover.pdf
Corn	189.0	54.3	243.2	State	Dry land corn on owned land
Soybeans	144.9	54.1	199.1	State	Dry land soybean on owned land
Wheat	94.9	17.8	112.7	State	All tenures and by tenure type
Fed Cattle	53.8	0.7	54.5	State	Beef finishing beef calf
Hogs	27.9	3.0	30.9	State	Feeder pig finishing

Appendix 4 Production Cost Index

Cash Cost of production by Region

(dollar / acre or cwt)

	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992
Corn											
North Central	213.0	200.8	212.2	199.1	172.9	164.8	168.9	180.1	184.3	172.5	173.4
Heartland	-	-	-	-	-	-	-	-	-	-	-
Plains	203	207	207.5	195.9	147.7	141.6	146.3	155.3	160.9	218.4	217.7
Prairie Gateway	-	-	-	-	-	-	-	-	-	-	-
Soybeans											
North Central	110.5	124.4	128.8	101.1	93.8	100.2	105.0	112.3	111.1	119.4	115.7
Heartland	-	-	-	-	-	-	-	-	-	-	-
Plains	-	-	-	-	-	-	-	94.0	90.7	96.4	94.6
Prairie Gateway	-	-	-	-	-	-	-	-	-	-	-
Wheat											
North Central	102.0	121	123.5	93.8	78.8	88.0	101.2	115.0	106.7	115.8	112.9
Heartland	-	-	-	-	-	-	-	-	-	-	-
S. Plains	75.8	73.3	72.4	67.6	61.6	56.9	61.9	62.2	65.3	63.0	62.0
Prairie Gateway	-	-	-	-	-	-	-	-	-	-	-
Cow-Calf											
North Central	259	279	285.2	261.6	250.9	265.9	302.3	301.4	324.0	323.6	317.6
Heartland	-	-	-	-	-	-	-	-	-	-	-
Hogs (Farrow-to-Finish)											
North Central	43.9	46.0	46.5	39.1	38.2	34.3	33.0	34.0	32.7	32.3	36.9
Heartland	-	-	-	-	-	-	-	-	-	-	-

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Corn											
North Central	166.0	184.9	193.3	-	-	-	-	-	-	-	-
Heartland	-	-	-	176.4	179.2	175.0	173.1	181.0	169.7	152.9	168.8
Plains	215.1	236.8	252.5	-	-	-	-	-	-	-	-
Prairie Gateway	-	-	-	209.4	212.2	204.0	201.1	213.8	218.7	199.7	220.3
Soybeans											
North Central	116.7	123.0	126.1	131.6	-	-	-	-	-	-	-
Heartland	-	-	-	-	100.0	99.0	96.9	97.9	102.3	89.0	94.6
Plains	96.6	100.9	103.0	108.6	-	-	-	-	-	-	-
Prairie Gateway	-	-	-	-	104.4	104.0	103.9	107.4	112.6	100.2	104.0
Wheat											
North Central	117.4	103.4	116.6	118.2	123.9	-	-	-	-	-	-
Heartland	-	-	-	-	-	87.0	83.4	86.0	95.8	82.9	97.2
S. Plains	65.2	76.0	85.9	86.1	93.4						
Prairie Gateway	-	-	-	-	-	58.4	57.0	60.3	68.1	60.7	70.8
Cow-Calf											
North Central	346.1	340.5	345.4	-	-	-	-	-	-	-	-
Heartland	-	-	-	659.8	662.2	622.0	615.0	631.8	649.0	641.8	641.3
Hogs (Farrow-to-Finish)											
North Central	38.9	38.4	38.5	47.8	45.3	-	-	-	-	-	-
Heartland	-	-	-	-	-	33.3	30.2	31.7	33.0	34.2	34.9

Source: Commodity Costs and Returns, ERS, USDA (www.ers.usda.gov/data/costsandreturns/testpick.htm)

Appendix 4 Continued

U.S. Cash Cost of production

(dollar / acre or cwt)

	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992
Corn	133.5	128.3	132.8	136.8	120.4	117.4	122.8	133.4	134.2	137.9	139.5
Soybeans	61.4	59.6	61.1	56.7	49.1	50.8	54.1	71.3	69.7	72.8	73.3
Wheat	56.0	56.8	55.0	51.1	45.7	44.2	46.3	53.0	52.6	52.3	53.3
Fed Cattle	41.7	44.6	44.4	41.4	38.2	41.8	48.5	50.3	52.6	53.0	48.9
Hogs	32.6	37.5	36.9	31.3	28.2	25.1	33.5	35.1	33.7	33.1	37.1

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Corn	138.9	147.1	158.1	158.9	160.4	164.4	168.5	176.1	184.0	192.3	201.0
Soybeans	73.0	75.8	75.9	80.0	80.2	82.2	84.3	88.1	92.0	96.2	100.5
Wheat	53.9	60.0	65.3	70.0	70.5	67.6	69.3	72.4	75.7	79.1	82.6
Fed Cattle	51.2	47.3	43.3	40.4	46.6	45.2	47.1	52.2	53.8	51.0	55.9
Hogs	39.0	34.2	33.7	43.4	40.1	41.1	42.1	44.0	46.0	48.1	50.2

Appendix 4 Continued

Production Cost Index by Region (1982=100)

	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992
Corn											
IA, IL, IN, NE	100.0	94.2	99.6	93.5	81.2	77.3	79.3	84.5	86.5	81.0	81.4
KA	100.0	101.9	102.4	96.7	72.9	69.9	72.2	76.7	79.4	107.8	107.4
Soybeans											
IA, IL, IN, NE	100.0	112.6	116.6	91.5	84.9	90.7	95.1	101.7	100.6	108.1	104.7
KA	100.0	112.6	116.6	91.5	84.9	90.7	95.1	101.7	98.2	104.3	102.4
Wheat											
IA, IL, IN, NE	100.0	119.1	121.1	92.0	77.2	86.3	99.2	112.7	104.6	113.6	110.7
KA	100.0	96.8	95.6	89.2	81.3	75.1	81.7	82.0	86.2	83.2	81.8
Fed Cattle											
All State	100.0	107.5	110.0	100.9	96.8	102.6	116.6	116.3	125.0	124.9	122.6
Hogs											
All State	100.0	104.7	105.9	89.0	87.0	78.2	75.1	77.5	74.4	73.5	84.0

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Corn											
IA, IL, IN, NE	77.9	86.8	90.7	91.1	92.6	90.4	89.4	93.5	87.7	79.0	87.2
KA	106.2	116.9	124.6	125.2	126.9	122.0	120.2	127.8	130.8	119.4	131.7
Soybeans											
IA, IL, IN, NE	105.6	111.4	114.1	119.1	119.4	118.2	115.8	116.9	122.2	106.3	113.0
KA	104.6	109.2	111.4	117.5	117.8	117.4	117.3	121.2	127.2	113.2	117.4
Wheat											
IA, IL, IN, NE	115.1	101.4	114.3	115.9	121.5	116.5	111.8	115.2	128.2	111.0	130.1
KA	86.1	100.3	113.4	113.6	123.2	118.1	115.3	122.1	137.9	122.9	143.2
Fed Cattle											
All State	133.6	131.4	133.3	123.5	123.9	116.4	115.1	118.2	121.4	120.1	120.0
Hogs											
All State	88.6	87.4	87.6	108.8	103.1	105.7	95.9	100.6	104.9	108.6	111.0

Index is made by the % change of production cost by region.
At the break point of the data series, % change in national cost is used.

Appendix 5 Estimates of Cash Cost of production

(Dollar / acre or cwt)

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Iowa										
Corn	200.9	174.5	166.3	170.4	181.7	186.0	174.1	174.9	167.5	186.6
Soybeans	82.1	76.2	81.4	85.3	91.3	90.3	97.0	94.0	94.8	100.0
Wheat	70.7	59.4	66.3	76.3	86.6	80.4	87.3	85.0	88.4	77.9
Fed Cattle	46.9	45.0	47.7	54.3	54.1	58.1	58.1	57.0	62.1	61.1
Hogs	23.6	23.0	20.7	19.9	20.5	19.7	19.5	22.3	23.5	23.2
Illinois										
Corn	201.4	175.0	166.7	170.9	182.2	186.5	174.5	175.4	168.0	187.1
Soybeans	102.0	94.7	101.1	106.0	113.4	112.2	120.5	116.7	117.7	124.2
Wheat	70.7	59.4	66.3	76.3	86.6	80.4	87.3	85.0	88.4	77.9
Fed Cattle	42.0	40.3	42.7	48.6	48.4	52.0	52.0	51.0	55.6	54.7
Hogs	25.3	24.7	22.2	21.3	22.0	21.1	20.9	23.9	25.2	24.8
Indiana										
Corn	201.4	175.0	166.7	170.9	182.2	186.5	174.5	175.4	168.0	187.1
Soybeans	102.0	94.7	101.1	106.0	113.4	112.2	120.5	116.7	117.7	124.2
Wheat	70.7	59.4	66.3	76.3	86.6	80.4	87.3	85.0	88.4	77.9
Fed Cattle	42.0	40.3	42.7	48.6	48.4	52.0	52.0	51.0	55.6	54.7
Hogs	25.3	24.7	22.2	21.3	22.0	21.1	20.9	23.9	25.2	24.8
Kansas										
Corn	126.6	95.4	91.5	94.5	100.4	104.0	141.1	140.7	139.0	153.0
Soybeans	88.9	82.5	88.2	92.4	98.9	95.4	101.4	99.5	101.6	106.1
Wheat	55.0	50.1	46.3	50.3	50.6	53.1	51.3	50.4	53.1	61.8
Fed Cattle	57.6	55.3	58.6	66.6	66.4	71.4	71.3	70.0	76.2	75.0
Hogs	20.4	20.0	17.9	17.2	17.8	17.1	16.9	19.3	20.3	20.1
Nebraska										
Corn	202.5	175.9	167.6	171.8	183.1	187.4	175.4	176.3	168.9	188.0
Soybeans	117.3	108.9	116.3	121.9	130.4	129.0	138.6	134.3	135.4	142.9
Wheat	67.0	56.3	62.9	72.3	82.2	76.3	82.8	80.7	83.9	73.9
Fed Cattle	45.2	43.4	46.0	52.2	52.1	56.0	55.9	54.9	59.8	58.8
Hogs	22.3	21.8	19.6	18.8	19.4	18.7	18.4	21.1	22.2	21.9

Appendix 5 Continued

(dollar / acre or cwt)

	1995	1996	1997	1998	1999	2000	2001	2002	2003
Iowa									
Corn	195.0	195.9	199.0	194.3	192.3	201.0	188.5	169.8	187.5
Soybeans	102.4	106.9	107.2	106.1	103.9	104.9	109.7	95.4	101.4
Wheat	87.8	89.1	93.3	89.5	85.9	88.5	98.5	85.3	100.0
Fed Cattle	62.0	57.4	57.6	54.1	53.5	55.0	56.5	55.9	55.8
Hogs	23.2	28.8	27.3	28.0	25.4	26.7	27.8	28.8	29.4
Illinois									
Corn	195.5	196.5	199.5	194.8	192.8	201.6	189.0	170.3	188.0
Soybeans	127.2	132.8	133.2	131.8	129.1	130.3	136.2	118.5	126.0
Wheat	87.8	89.1	93.3	89.5	85.9	88.5	98.5	85.3	100.0
Fed Cattle	55.5	51.4	51.6	48.5	47.9	49.2	50.6	50.0	50.0
Hogs	24.9	30.9	29.3	30.0	27.2	28.6	29.8	30.8	31.5
Indiana									
Corn	195.5	196.5	199.5	194.8	192.8	201.6	189.0	170.3	188.0
Soybeans	127.2	132.8	133.2	131.8	129.1	130.3	136.2	118.5	126.0
Wheat	87.8	89.1	93.3	89.5	85.9	88.5	98.5	85.3	100.0
Fed Cattle	55.5	51.4	51.6	48.5	47.9	49.2	50.6	50.0	50.0
Hogs	24.9	30.9	29.3	30.0	27.2	28.6	29.8	30.8	31.5
Kansas									
Corn	163.2	164.0	166.1	159.7	157.4	167.3	171.2	156.3	172.4
Soybeans	108.3	114.2	114.5	114.1	114.1	117.8	123.6	110.0	114.1
Wheat	69.9	70.0	75.9	72.8	71.1	75.2	85.0	75.7	88.3
Fed Cattle	76.1	70.5	70.7	66.4	65.7	67.5	69.3	68.6	68.5
Hog	20.1	25.0	23.6	24.3	22.0	23.1	24.1	24.9	25.5
Nebraska									
Corn	196.5	197.5	200.6	195.8	193.8	202.6	190.0	171.2	189.0
Soybeans	146.4	152.8	153.2	151.6	148.5	149.9	156.7	136.4	144.9
Wheat	83.3	84.5	88.6	84.9	81.5	84.0	93.5	81.0	94.9
Fed Cattle	59.7	55.3	55.5	52.1	51.5	52.9	54.4	53.8	53.8
Hogs	22.0	27.3	25.9	26.5	24.1	25.3	26.3	27.3	27.9

Appendix 6 Cash Receipts

Cash Receipts by State and by Commodity

(1000 dollars)

State	Commodity	1985	1986	1987	1988	1989
Iowa	Corn	2,811,561	2,269,852	1,893,485	1,531,604	1,781,850
	Soybeans	1,629,572	1,485,215	1,771,631	2,011,335	1,724,807
	Wheat	13,528	5,488	2,629	3,805	9,330
	Cattle & Calves	1,644,732	1,647,057	1,904,168	1,996,671	2,030,861
	Hogs	2,474,317	2,629,449	2,700,822	2,407,457	2,420,996
	Sum	8,573,710	8,037,061	8,272,735	7,950,872	7,967,844
	(% out of S. Total)	(91.3%)	(91.1%)	(91.2%)	(90.2%)	(88.8%)
	State Total	9,391,051	8,818,474	9,066,506	8,810,933	8,974,921
Illinois	Corn	3,545,577	2,500,588	2,034,452	1,558,337	2,072,369
	Soybeans	2,007,424	1,770,316	1,752,786	1,907,584	1,865,731
	Wheat	122,902	83,783	123,068	217,534	395,210
	Cattle & Calves	668,451	757,077	798,392	906,925	807,547
	Hogs	992,810	1,008,098	1,049,157	1,023,498	984,086
	Sum	7,337,164	6,119,862	5,757,855	5,613,878	6,124,943
	(% out of S. Total)	(92.3%)	(89.4%)	(88.7%)	(88.1%)	(87.7%)
	State Total	7,948,850	6,845,541	6,494,751	6,373,401	6,984,999
Indiana	Corn	2,811,561	2,269,852	1,893,485	1,531,604	1,781,850
	Soybeans	956,061	820,372	772,128	1,028,004	870,315
	Wheat	103,401	69,842	78,773	114,791	192,008
	Cattle & Calves	304,755	322,248	365,703	364,081	291,874
	Hogs	705,372	778,932	823,275	717,189	708,401
	Sum	4,881,150	4,261,246	3,933,364	3,755,669	3,844,448
	(% out of S. Total)	(102.9%)	(105.5%)	(99.5%)	(92.7%)	(89.9%)
	State Total	4,741,452	4,040,240	3,952,978	4,051,506	4,275,720
Kansas	Corn	293,437	296,713	225,792	202,084	356,775
	Soybeans	170,651	240,567	361,331	316,273	327,428
	Wheat	1,386,322	772,037	853,295	1,075,084	840,050
	Cattle & Calves	2,826,717	2,946,126	3,559,053	3,874,471	3,937,423
	Hogs	278,469	295,809	288,616	269,144	269,304
	Sum	4,955,596	4,551,252	5,288,087	5,737,056	5,730,980
	(% out of S. Total)	(84.3%)	(85.6%)	(87.2%)	(88.0%)	(87.2%)
	State Total	5,881,675	5,317,543	6,062,433	6,518,106	6,569,010
Nebraska	Corn	1,980,357	1,517,672	1,192,253	1,188,540	1,717,525
	Soybeans	462,143	410,069	394,282	533,052	493,560
	Wheat	273,342	146,075	193,855	229,485	255,835
	Cattle & Calves	3,360,428	3,286,713	3,912,898	4,468,106	4,633,788
	Hogs	560,094	699,392	768,762	667,776	723,211
	Sum	6,636,364	6,059,921	6,462,050	7,086,959	7,823,919
	(% out of S. Total)	(89.8%)	(89.6%)	(90.5%)	(90.8%)	(89.7%)
	State Total	7,388,600	6,761,065	7,139,132	7,801,045	8,724,692

Appendix 6 Continued

(1000 dollars)

State	Commodity	1990	1991	1992	1993	1994
Iowa	Corn	2,414,654	2,619,206	2,913,217	2,643,774	2,500,924
	Soybeans	1,786,226	1,832,031	2,026,912	1,784,586	2,055,438
	Wheat	7,886	4,808	5,004	2,405	5,768
	Cattle & Calves	2,295,123	1,906,341	2,144,651	2,162,749	1,796,604
	Hogs	2,989,051	2,916,499	2,732,215	2,818,155	2,579,925
	Sum	9,492,940	9,278,885	9,821,999	9,411,669	8,938,659
	(% out of S.Total)	(90.4%)	(91.0%)	(91.0%)	(90.5%)	(89.8%)
	State Total	10,504,432	10,194,360	10,797,093	10,396,940	9,956,047
Illinois	Corn	2,691,187	2,654,527	2,492,739	2,892,700	2,849,442
	Soybeans	2,023,274	1,918,286	2,103,622	2,378,341	2,384,976
	Wheat	229,715	145,978	177,836	170,238	179,244
	Cattle & Calves	799,657	733,242	707,872	779,520	704,655
	Hogs	1,206,275	1,174,896	1,037,381	1,125,981	939,362
	Sum	6,950,108	6,626,929	6,519,450	7,346,780	7,057,679
	(% out of S.Total)	(89.3%)	(88.7%)	(87.7%)	(89.3%)	(88.7%)
	State Total	7,779,756	7,468,593	7,435,276	8,231,446	7,959,523
Indiana	Corn	2,414,654	2,619,206	2,913,217	2,643,774	2,500,924
	Soybeans	987,202	963,135	1,018,174	1,322,329	1,174,001
	Wheat	139,659	81,565	76,983	95,245	103,647
	Cattle & Calves	330,813	307,403	320,881	331,549	305,953
	Hogs	885,696	826,421	732,307	822,088	678,459
	Sum	4,758,024	4,797,730	5,061,562	5,214,985	4,762,984
	(% out of S.Total)	(97.0%)	(107.3%)	(113.9%)	(97.9%)	(101.6%)
	State Total	4,904,615	4,471,651	4,443,234	5,326,688	4,686,308
Kansas	Corn	334,678	389,830	454,139	399,075	522,082
	Soybeans	265,532	225,075	322,913	327,289	405,278
	Wheat	945,885	1,160,885	1,051,783	1,144,263	1,373,980
	Cattle & Calves	4,416,126	4,228,441	4,306,486	4,371,940	4,294,531
	Hogs	320,920	321,341	271,867	280,374	254,059
	Sum	6,283,141	6,325,572	6,407,188	6,522,941	6,849,930
	(% out of S.Total)	(89.8%)	(90.1%)	(89.3%)	(88.9%)	(89.8%)
	State Total	6,993,039	7,021,362	7,173,331	7,334,715	7,624,853
Nebraska	Corn	1,521,792	1,879,148	1,857,517	1,776,979	1,734,881
	Soybeans	421,205	476,545	498,451	538,562	630,145
	Wheat	180,688	218,052	176,823	213,191	235,609
	Cattle & Calves	4,879,882	4,783,085	4,619,794	4,706,951	4,380,389
	Hogs	899,524	878,134	778,068	857,546	751,851
	Sum	7,903,091	8,234,964	7,930,653	8,093,229	7,732,875
	(% out of S.Total)	(90.6%)	(91.5%)	(91.3%)	(91.2%)	(90.9%)
	State Total	8,718,506	8,999,359	8,685,604	8,871,543	8,509,617

Appendix 6 Continued

(1000 dollars)

State	Commodity	1995	1996	1997	1998	1999
Iowa	Corn	3,630,136	3,869,920	3,828,383	3,186,534	2,672,726
	Soybeans	2,425,006	2,603,442	3,287,303	2,854,681	2,059,389
	Wheat	5,515	6,279	3,809	3,469	3,096
	Cattle & Calves	1,798,250	1,467,234	1,711,836	1,386,143	1,640,243
	Hogs	2,493,239	2,946,643	3,007,488	2,413,704	2,205,658
	Sum	10,352,146	10,893,518	11,838,488	9,844,531	8,581,112
	(% out of S. Total)	(90.9%)	(90.0%)	(91.3%)	(89.2%)	(89.1%)
	State Total	11,388,284	12,101,465	12,966,773	11,035,205	9,632,167
Illinois	Corn	3,410,014	3,274,141	3,359,023	3,034,194	2,443,353
	Soybeans	2,447,663	2,533,994	3,031,421	2,782,398	2,049,141
	Wheat	250,708	169,881	182,284	158,674	96,596
	Cattle & Calves	608,736	536,144	506,618	473,818	487,166
	Hogs	892,042	1,054,898	1,014,474	682,706	619,902
	Sum	7,609,163	7,569,058	8,093,820	7,131,790	5,696,158
	(% out of S. Total)	(89.7%)	(89.2%)	(89.9%)	(89.1%)	(87.1%)
	State Total	8,480,201	8,481,824	8,999,278	8,004,148	6,538,555
Indiana	Corn	3,630,136	3,869,920	3,828,383	3,186,534	2,672,726
	Soybeans	1,304,531	1,392,497	1,653,332	1,165,293	1,002,542
	Wheat	164,392	108,078	114,328	74,853	71,988
	Cattle & Calves	284,136	192,472	276,774	190,340	200,949
	Hogs	710,692	819,923	797,545	559,591	513,177
	Sum	6,093,887	6,382,890	6,670,362	5,176,611	4,461,382
	(% out of S. Total)	(117.1%)	(115.4%)	(115.4%)	(114.9%)	(102.2%)
	State Total	5,205,613	5,531,270	5,777,954	4,506,297	4,365,044
Kansas	Corn	681,858	753,410	819,185	770,372	593,330
	Soybeans	366,074	361,287	551,610	523,707	333,838
	Wheat	1,323,850	1,058,710	1,390,509	1,367,764	939,673
	Cattle & Calves	4,080,676	3,965,635	4,285,479	4,025,903	4,520,982
	Hogs	236,600	330,828	414,835	249,282	227,040
	Sum	6,689,058	6,469,870	7,461,618	6,937,028	6,614,863
	(% out of S. Total)	(87.9%)	(86.1%)	(86.5%)	(87.2%)	(88.2%)
	State Total	7,609,837	7,510,882	8,624,258	7,956,634	7,496,940
Nebraska	Corn	2,320,296	2,481,231	2,493,458	2,231,480	1,733,530
	Soybeans	696,618	652,985	984,672	966,916	686,940
	Wheat	336,243	299,135	241,353	238,510	145,387
	Cattle & Calves	4,125,873	4,135,208	4,403,133	4,267,526	4,583,159
	Hogs	744,898	860,485	805,808	553,336	527,073
	Sum	8,223,928	8,429,044	8,928,424	8,257,768	7,676,089
	(% out of S. Total)	(91.5%)	(91.2%)	(91.1%)	(91.6%)	(91.7%)
	State Total	8,983,526	9,242,132	9,805,771	9,018,091	8,374,336

Appendix 6 Continued

(1000 dollars)

State	Commodity	2000	2001	2002	2003
Iowa	Corn	2,632,991	2,589,019	3,612,084	3,708,608
	Soybeans	2,102,622	1,889,300	2,353,508	2,600,412
	Wheat	2,199	2,554	2,799	3,340
	Cattle & Calves	1,908,548	1,824,202	1,809,823	2,334,551
	Hogs	3,072,456	3,121,306	2,424,512	2,602,223
	Sum	9,718,816	9,426,381	10,202,726	11,249,134
	(% out of S. Total)	(90.2%)	(88.1%)	(89.5%)	(89.0%)
	State Total	10,733,264	10,705,165	11,393,524	12,633,200
Illinois	Corn	2,649,369	2,827,873	3,229,174	3,258,853
	Soybeans	2,080,876	2,047,787	2,343,887	2,557,704
	Wheat	135,138	97,957	115,980	157,356
	Cattle & Calves	532,016	527,954	505,762	609,241
	Hogs	787,693	913,067	709,833	833,100
	Sum	6,185,092	6,414,638	6,904,636	7,416,254
	(% out of S. Total)	(88.4%)	(87.8%)	(89.3%)	(89.5%)
	State Total	6,996,356	7,307,508	7,732,048	8,289,958
Indiana	Corn	2,632,991	2,589,019	3,612,084	3,708,608
	Soybeans	1,110,111	1,204,893	1,260,243	1,390,317
	Wheat	69,172	66,726	53,905	89,987
	Cattle & Calves	238,604	215,717	203,538	224,456
	Hogs	580,979	662,297	500,510	619,626
	Sum	4,631,857	4,738,652	5,630,280	6,032,994
	(% out of S. Total)	(102.5%)	(93.7%)	(119.3%)	(116.9%)
	State Total	4,517,714	5,059,721	4,718,953	5,161,609
Kansas	Corn	786,401	667,326	722,405	636,683
	Soybeans	254,342	301,481	333,856	367,506
	Wheat	909,524	858,407	1,000,533	1,293,888
	Cattle & Calves	4,947,707	4,915,470	4,809,880	5,617,679
	Hogs	310,000	294,135	228,721	252,010
	Sum	7,207,974	7,036,819	7,095,395	8,167,766
	(% out of S. Total)	(89.6%)	(87.7%)	(87.9%)	(90.3%)
	State Total	8,040,160	8,020,702	8,070,149	9,046,096
Nebraska	Corn	1,722,187	1,691,224	2,043,200	2,040,658
	Soybeans	794,070	869,283	917,104	1,089,591
	Wheat	183,404	145,303	200,117	224,846
	Cattle & Calves	4,941,090	5,066,786	4,958,569	5,903,957
	Hogs	682,204	712,715	591,011	611,988
	Sum	8,322,955	8,485,311	8,710,001	9,871,040
	(% out of S. Total)	(92.9%)	(91.9%)	(92.4%)	(92.9%)
	State Total	8,956,360	9,230,640	9,422,076	10,621,275

Appendix 6 Continued

Fraction of State Cash Receipts from Each Crop

State	Comm.	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Iowa	Corn	0.63	0.60	0.52	0.43	0.51	0.57	0.59	0.59	0.60	0.55
	Soybeans	0.37	0.39	0.48	0.57	0.49	0.42	0.41	0.41	0.40	0.45
	Wheat	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Illinois	Corn	0.62	0.57	0.52	0.42	0.48	0.54	0.56	0.52	0.53	0.53
	Soybeans	0.35	0.41	0.45	0.52	0.43	0.41	0.41	0.44	0.44	0.44
	Wheat	0.02	0.02	0.03	0.06	0.09	0.05	0.03	0.04	0.03	0.03
Indiana	Corn	0.73	0.72	0.69	0.57	0.63	0.68	0.71	0.73	0.65	0.66
	Soybeans	0.25	0.26	0.28	0.38	0.31	0.28	0.26	0.25	0.33	0.31
	Wheat	0.03	0.02	0.03	0.04	0.07	0.04	0.02	0.02	0.02	0.03
Kansas	Corn	0.16	0.23	0.16	0.13	0.23	0.22	0.22	0.25	0.21	0.23
	Soybeans	0.09	0.18	0.25	0.20	0.21	0.17	0.13	0.18	0.17	0.18
	Wheat	0.75	0.59	0.59	0.67	0.55	0.61	0.65	0.58	0.61	0.60
Nebraska	Corn	0.73	0.73	0.67	0.61	0.70	0.72	0.73	0.73	0.70	0.67
	Soybeans	0.17	0.20	0.22	0.27	0.20	0.20	0.19	0.20	0.21	0.24
	Wheat	0.10	0.07	0.11	0.12	0.10	0.09	0.08	0.07	0.08	0.09

State	Comm.	1995	1996	1997	1998	1999	2000	2001	2002	2003
Iowa	Corn	0.60	0.60	0.54	0.53	0.56	0.56	0.58	0.61	0.59
	Soybeans	0.40	0.40	0.46	0.47	0.43	0.44	0.42	0.39	0.41
	Wheat	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Illinois	Corn	0.56	0.55	0.51	0.51	0.53	0.54	0.57	0.57	0.55
	Soybeans	0.40	0.42	0.46	0.47	0.45	0.43	0.41	0.41	0.43
	Wheat	0.04	0.03	0.03	0.03	0.02	0.03	0.02	0.02	0.03
Indiana	Corn	0.71	0.72	0.68	0.72	0.71	0.69	0.67	0.73	0.71
	Soybeans	0.26	0.26	0.30	0.26	0.27	0.29	0.31	0.26	0.27
	Wheat	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02
Kansas	Corn	0.29	0.35	0.30	0.29	0.32	0.40	0.37	0.35	0.28
	Soybeans	0.15	0.17	0.20	0.20	0.18	0.13	0.16	0.16	0.16
	Wheat	0.56	0.49	0.50	0.51	0.50	0.47	0.47	0.49	0.56
Nebraska	Corn	0.69	0.72	0.67	0.65	0.68	0.64	0.63	0.65	0.61
	Soybeans	0.21	0.19	0.26	0.28	0.27	0.29	0.32	0.29	0.32
	Wheat	0.10	0.09	0.06	0.07	0.06	0.07	0.05	0.06	0.07

This table is calculated from the state cash receipts

Appendix 6 Continued

Fraction of State Cash Receipts from Livestock

State	Comm.	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Iowa	Cattle	0.40	0.39	0.41	0.45	0.46	0.43	0.40	0.44	0.43	0.41
	Hogs	0.60	0.61	0.59	0.55	0.54	0.57	0.60	0.56	0.57	0.59
Illinois	Cattle	0.40	0.43	0.43	0.47	0.45	0.40	0.38	0.41	0.41	0.43
	Hogs	0.60	0.57	0.57	0.53	0.55	0.60	0.62	0.59	0.59	0.57
Indiana	Cattle	0.30	0.29	0.31	0.34	0.29	0.27	0.27	0.30	0.29	0.31
	Hogs	0.70	0.71	0.69	0.66	0.71	0.73	0.73	0.70	0.71	0.69
Kansas	Cattle	0.91	0.91	0.92	0.94	0.94	0.93	0.93	0.94	0.94	0.94
	Hogs	0.09	0.09	0.08	0.06	0.06	0.07	0.07	0.06	0.06	0.06
Nebraska	Cattle	0.86	0.82	0.84	0.87	0.86	0.84	0.84	0.86	0.85	0.85
	Hogs	0.14	0.18	0.16	0.13	0.14	0.16	0.16	0.14	0.15	0.15

State	Comm.	1995	1996	1997	1998	1999	2000	2001	2002	2003
Iowa	Cattle	0.42	0.33	0.36	0.36	0.43	0.38	0.37	0.43	0.47
	Hogs	0.58	0.67	0.64	0.64	0.57	0.62	0.63	0.57	0.53
Illinois	Cattle	0.41	0.34	0.33	0.41	0.44	0.40	0.37	0.42	0.42
	Hogs	0.59	0.66	0.67	0.59	0.56	0.60	0.63	0.58	0.58
Indiana	Cattle	0.29	0.19	0.26	0.25	0.28	0.29	0.25	0.29	0.27
	Hogs	0.71	0.81	0.74	0.75	0.72	0.71	0.75	0.71	0.73
Kansas	Cattle	0.95	0.92	0.91	0.94	0.95	0.94	0.94	0.95	0.96
	Hogs	0.05	0.08	0.09	0.06	0.05	0.06	0.06	0.05	0.04
Nebraska	Cattle	0.85	0.83	0.85	0.89	0.90	0.88	0.88	0.89	0.91
	Hogs	0.15	0.17	0.15	0.11	0.10	0.12	0.12	0.11	0.09

This table is calculated from the state cash receipts

Appendix 7 Estimates of Net Cash Income

(dollar / acre or cwt)

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Iowa										
NCIC	68.9	54.2	123.2	90.2	103.7	107.7	103.1	127.9	45.0	156.5
NCIL	16.9	21.2	25.5	20.4	21.5	28.9	25.7	19.0	19.1	13.8
Illinois										
NCIC	103.9	57.7	103.3	59.6	113.7	106.8	83.6	128.0	147.3	144.3
NCIL	17.9	22.1	26.0	21.8	23.2	30.0	25.7	20.3	19.7	14.0
Indiana										
NCIC	73.4	25.9	113.0	63.4	123.6	107.6	58.1	122.5	156.8	130.1
NCIL	18.3	23.3	27.0	22.0	22.9	31.2	26.5	20.0	19.9	14.2
Kansas										
NCIC	62.7	44.5	60.2	82.4	54.1	67.2	55.4	82.4	69.0	82.6
NCIL	3.1	5.5	8.9	6.1	9.5	10.6	7.2	7.0	1.7	-3.9
Nebraska										
NCIC	62.5	21.1	74.4	105.1	64.0	77.0	86.3	84.5	73.0	109.9
NCIL	14.7	17.3	21.7	19.8	22.9	26.0	22.3	21.0	17.8	12.0

	1995	1996	1997	1998	1999	2000	2001	2002	2003
Iowa									
NCIC	188.6	178.7	145.3	94.3	74.6	64.9	81.1	176.7	159.6
NCIL	12.3	18.8	21.0	8.2	9.0	16.9	17.9	7.7	16.3
Illinois									
NCIC	154.6	169.5	133.1	86.3	69.5	76.7	94.9	132.3	182.7
NCIL	13.4	18.4	18.9	5.9	9.1	15.5	18.1	9.5	20.2
Indiana									
NCIC	167.2	136.4	115.3	79.5	50.6	71.7	101.6	110.9	158.5
NCIL	14.2	19.8	19.6	4.2	7.2	14.8	17.1	7.8	16.0
Kansas									
NCIC	91.0	122.0	105.1	62.1	42.6	32.2	23.7	36.4	65.1
NCIL	-7.6	-2.0	0.0	-2.8	1.1	3.6	5.3	1.1	16.4
Nebraska									
NCIC	126.0	158.4	91.3	62.9	39.0	20.4	62.1	78.7	139.4
NCIL	9.1	13.4	14.8	10.6	14.1	17.3	19.3	14.7	29.4

Appendix 8 Government Payments

Total Government Payments by State

(1000 dollar)

State	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Iowa	691,136	1,161,181	1,987,685	1,664,991	981,206	753,732	644,955	662,278	1,229,544	732,429
	(9.0%)	(9.8%)	(11.9%)	(11.5%)	(9.0%)	(8.1%)	(7.9%)	(7.2%)	(9.2%)	(9.3%)
Illinois	491,492	882,519	1,477,640	1,373,972	725,941	506,603	441,408	480,651	851,190	302,915
	(6.4%)	(7.5%)	(8.8%)	(9.5%)	(6.7%)	(5.4%)	(5.4%)	(5.2%)	(6.4%)	(3.8%)
Indiana	218,300	411,275	670,244	616,336	333,691	244,172	210,055	232,518	378,953	136,806
	(2.8%)	(3.5%)	(4.0%)	(4.3%)	(3.1%)	(2.6%)	(2.6%)	(2.5%)	(2.8%)	(1.7%)
Kansas	482,151	870,760	966,320	847,994	588,446	834,745	697,895	592,145	783,963	467,531
	(6.3%)	(7.4%)	(5.8%)	(5.9%)	(5.4%)	(9.0%)	(8.5%)	(6.5%)	(5.8%)	(5.9%)
Nebraska	518,369	858,412	1,274,843	1,091,521	542,306	624,643	490,658	478,729	806,273	348,246
	(6.7%)	(7.3%)	(7.6%)	(7.5%)	(5.0%)	(6.7%)	(6.0%)	(5.2%)	(6.0%)	(4.4%)
Sum	2,401,448	4,184,147	6,376,732	5,594,814	3,171,590	2,963,895	2,484,971	2,446,322	4,049,923	1,987,928
	(31.2%)	(35.4%)	(38.1%)	(38.6%)	(29.1%)	(31.9%)	(30.3%)	(26.7%)	(30.2%)	(25.2%)
U.S.	7,704,154	11,813,351	16,746,732	14,479,808	10,886,702	9,298,030	8,214,399	9,168,920	13,402,015	7,879,129

Appendix 8 Continued

(1000 dollar)

State	1995	1996	1997	1998	1999	2000	2001	2002	2003
Iowa	786,652	508,278	712,839	1,168,724	2,061,881	2,302,094	1,971,677	737,107	1,050,621
	(10.8%)	(6.9%)	(9.5%)	(9.4%)	(9.6%)	(10.1%)	(9.5%)	(6.7%)	(6.6%)
Illinois	543,753	386,706	552,452	944,879	1,798,822	1,943,916	1,849,769	612,706	865,813
	(7.5%)	(5.3%)	(7.4%)	(7.6%)	(8.4%)	(8.5%)	(8.9%)	(5.6%)	(5.4%)
Indiana	246,026	213,649	265,132	468,917	852,051	938,464	925,278	332,782	446,374
	(3.4%)	(2.9%)	(3.5%)	(3.8%)	(4.0%)	(4.1%)	(4.5%)	(3.0%)	(2.8%)
Kansas	422,226	554,988	529,786	879,853	1,401,286	1,231,923	1,068,706	452,680	807,739
	(5.8%)	(7.6%)	(7.1%)	(7.1%)	(6.5%)	(5.4%)	(5.2%)	(4.1%)	(5.1%)
Nebraska	507,302	388,738	454,549	814,690	1,411,884	1,406,971	1,297,623	485,091	725,799
	(7.0%)	(5.3%)	(6.1%)	(6.6%)	(6.6%)	(6.1%)	(6.3%)	(4.4%)	(4.6%)
Sum	2,505,958	2,052,359	2,514,758	4,277,063	7,525,925	7,823,368	7,113,054	2,620,366	3,896,347
	(34.4%)	(28.0%)	(33.6%)	(34.5%)	(35.0%)	(34.2%)	(34.3%)	(23.9%)	(24.4%)
U.S.	7,279,451	7,339,570	7,495,294	12,380,016	21,513,119	22,896,433	20,727,496	10,961,465	15,949,402

Source: Farm Income, ERS, USDA (www.ers.usda.gov/data/FarmIncome/finfidmu.htm)
( ) represents the percentage among total U.S. government payments

Appendix 8 Continued

Government Payments per Planted Crop Acre

(dollar / acre)

State	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Iowa	31.10	55.59	107.79	85.34	46.77	36.10	30.32	30.85	59.51	33.67
Illinois	22.81	42.13	76.76	68.70	33.53	23.19	20.02	21.70	39.68	13.61
Indiana	18.87	37.22	66.03	59.61	30.64	22.50	19.10	20.31	33.93	12.02
Kansas	31.72	58.84	68.05	62.81	37.55	52.17	44.74	37.60	48.69	28.60
Nebraska	40.50	70.94	114.85	94.10	43.21	49.77	37.60	36.41	62.26	25.42

State	1995	1996	1997	1998	1999	2000	2001	2002	2003
Iowa	37.02	22.84	31.37	50.95	89.88	100.00	86.76	32.51	45.63
Illinois	25.37	17.15	24.72	42.09	80.13	85.82	82.40	27.40	38.74
Indiana	22.16	18.03	22.19	38.75	71.30	79.87	78.41	28.84	38.78
Kansas	26.47	33.94	32.01	54.14	87.58	76.04	66.38	28.83	50.48
Nebraska	38.29	28.07	31.35	56.19	95.40	94.43	87.68	32.89	49.88

Government payment per acre = State GPMT / Sum of planted area of corn, soybeans and wheat

Appendix 8 Continued

Sum of Planted Area of corn, soybeans, and wheat

(1000 acres)

State	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Iowa	22220	20890	18440	19510	20980	20880	21275	21470	20660	21755
Illinois	21550	20950	19250	20000	21650	21850	22050	22150	21450	22250
Indiana	11570	11050	10150	10340	10890	10850	11000	11450	11170	11380
Kansas	15200	14800	14200	13500	15670	16000	15600	15750	16100	16350
Nebraska	12800	12100	11100	11600	12550	12550	13050	13150	12950	13700

State	1995	1996	1997	1998	1999	2000	2001	2002	2003
Iowa	21250	22252	22727	22940	22940	23020	22725	22670	23025
Illinois	21430	22550	22350	22450	22450	22650	22450	22360	22350
Indiana	11100	11850	11950	12100	11950	11750	11800	11540	11510
Kansas	15950	16350	16550	16250	16000	16200	16100	15700	16000
Nebraska	13250	13850	14500	14500	14800	14900	14800	14750	14550

Appendix 9 Parameters and Data for GPMT Calculation

Direct Payment Rate, Loan Rate and Target Price

	Corn	Soybean	Wheat
DP Rate	0.28	0.52	0.44
Loan Rate	1.95	5.00	2.75
Target Price	2.63	5.80	3.92

Direct Payment Yield

	IA	IL	IN	KS	NE
Corn	116.1	115.3	108.9	102.1	105.8
Soybean	35.7	34.9	35.2	22.1	32.9
Wheat	36.5	44.3	45.4	34.1	36.3

Counter-Cyclical Payment Yield

	IA	IL	IN	KS	NE
Corn	122.1	127.4	120.6	123.0	118.2
Soybean	38.5	39.0	39.1	24.2	36.6
Wheat	36.5	47.0	49.7	35.6	37.0

Source: Farm Service Agency, USDA, "2003 Direct and Counter-Cyclical Program Final Enrollment Report": www.fsa.usda.gov/pas/farmbill/2002_2003_enroll.htm

Crop Year Support per Base Acre

Year	Dollar
1990	84.12
1991	69.45
1992	80.93
1993	62.82
1994	66.50
1995	9.45
1996	51.21
1997	63.09
1998	124.13
1999	201.24
2000	201.14
2001	170.60
2002	80.63

Source: Outlaw et al. (2004)

Appendix 10 Macroeconomic Variables, 1982-2003

Rate of Unemployment (%)

	Iowa	Illinois	Indiana	Kansas	Nebraska	U.S.
1982	8.5	11.3	11.9	6.3	6.1	9.7
1983	8.1	11.4	11.1	6.1	5.7	9.6
1984	7.0	9.1	8.6	5.2	4.4	7.5
1985	8.0	9.0	7.9	5.0	5.5	7.2
1986	7.0	8.1	6.7	5.4	5.0	7.0
1987	5.5	7.4	6.4	4.9	4.9	6.2
1988	4.5	6.8	5.3	4.8	3.6	5.5
1989	4.3	6.0	4.7	4.0	3.1	5.3
1990	4.3	6.2	5.3	4.5	2.2	5.6
1991	4.6	7.2	6.0	4.5	2.8	6.8
1992	4.7	7.6	6.6	4.3	3.0	7.5
1993	4.0	7.5	5.4	5.0	2.7	6.9
1994	3.7	5.7	4.9	5.3	2.9	6.1
1995	3.5	5.2	4.7	4.4	2.6	5.6
1996	3.8	5.3	4.1	4.5	2.9	5.4
1997	3.3	4.7	3.5	3.8	2.6	4.9
1998	2.8	4.5	3.1	3.8	2.7	4.5
1999	2.5	4.3	3.0	3.0	2.9	4.2
2000	2.6	4.3	3.2	3.7	3.0	4.0
2001	3.3	5.4	4.4	4.3	3.1	4.7
2002	4.0	6.5	5.1	5.1	3.6	5.8
2003	4.5	6.7	5.1	5.4	4.0	6.0

Appendix 10 Continued

Real Weighted Exchange Rates

Year	Corn	Soybeans	Wheat	Meat
1982	119.90	127.50	111.80	115.55
1983	122.90	134.20	118.60	118.88
1984	127.60	142.40	124.40	120.82
1985	131.30	146.60	130.00	125.19
1986	110.20	119.40	121.70	109.91
1987	99.80	106.10	121.20	103.09
1988	88.10	95.70	112.90	93.53
1989	94.66	105.04	122.13	97.57
1990	99.70	99.40	121.12	101.54
1991	100.80	99.40	121.12	93.56
1992	100.80	92.48	124.97	87.61
1993	100.80	92.48	124.97	80.21
1994	90.80	92.48	124.97	74.47
1995	89.10	92.48	124.97	73.77
1996	96.40	96.00	100.70	78.12
1997	115.70	115.20	103.90	83.21
1998	121.67	131.07	108.36	91.47
1999	131.72	142.63	115.02	87.02
2000	125.85	140.97	121.59	85.76
2001	126.17	156.78	127.33	93.74
2002	138.42	167.93	136.81	95.84
2003	142.99	161.85	139.79	102.16

Appendix 10 Continued

Other Macroeconomic Variables

Year	Rate of Inflation	Short Term Interest Rate	Short Term Interest Rate	Disposable Income
1982	5.16	10.72	15.61	2341.40
1983	3.37	8.62	13.07	2513.70
1984	3.60	9.57	13.84	2805.10
1985	2.78	7.49	12.43	2994.90
1986	2.37	5.97	10.04	3163.10
1987	2.79	5.83	10.04	3358.10
1988	3.72	6.67	10.48	3648.40
1989	3.54	8.11	10.33	3898.40
1990	4.06	7.51	10.17	4139.38
1991	3.10	5.41	9.38	4310.28
1992	2.14	3.46	8.46	4601.33
1993	2.31	3.02	7.51	4761.92
1994	2.15	4.29	8.52	4992.73
1995	1.95	5.51	8.18	5226.78
1996	1.85	5.02	8.19	5485.23
1997	1.48	5.07	7.90	5765.63
1998	1.13	4.78	7.04	6156.30
1999	1.54	4.64	7.61	6441.05
2000	2.27	5.82	8.26	6907.73
2001	2.51	3.39	7.03	7187.43
2002	1.51	1.63	6.54	7535.20
2003	1.74	1.01	5.19	7871.60

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