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# Pricing farm loans for credit risk<sup>†</sup>

Keith Bramma\*

This article analyses the risk-return efficiency of limits to which loan pricing accounts for credit risk in the Australian-farm sector. A key issue faced by banks is the trade-off between raising returns through higher risk premiums and the possibility of impairing credit quality. The simulation results suggest that the stochastic efficiency of the size of risk-pricing limits is positively related to volatility of farm income when dynamic relationships are considered. This finding implies that Australian banks should price further across the credit-risk spectrum to farm businesses with relatively volatile incomes compared to those with stable incomes.

## 1. Introduction

Credit risk involves the possibility of default on promised loan payments by borrowers. Pricing for credit risk by banks is an imperative in a deregulated and competitive lending environment (Gray and Cassidy 1997). Without risk pricing, low-risk borrowers view loans priced according to a simple-average-interest rate on offer as expensive and seek finance from competing banks. When low-risk borrowers exit a loan portfolio, high-risk borrowers remaining in the bank's portfolio are inadequately priced for credit risk (Miller, Ellinger, Barry and Lagili 1993). To guide loan-pricing behaviour, banks are focusing on applying the concepts of risk measurement, diversification and pricing for risk on tradeable securities as developed in portfolio theory by Markowitz (1959) and Sharpe (1964). However, in pricing borrowers across the credit-risk spectrum, banks are faced with trade-offs between raising their returns and the possibility of exacerbating their level of credit risk exposure.

The limited trading of loan securities result in insufficient market-based information to identify the nature of the trade-off between risk and returns on many types of risk-classified portfolios (Whitelaw 1997). The empirical evaluation of loan-pricing rules therefore involves the use of experiments. Direct experiments in the retail market place could be performed but such experiments can lead to disruptions in the normal course of banking business. Simulation

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models are an alternative means for assessing the risk-return efficiency of different credit-policy settings (Carmichael and Davis 1991). Most simulation applications of portfolio theory to banking has been on portfolio management issues relating to either balance-sheet or bond-portfolio structures (see Whitelaw (1997) for a review). In contrast, Gollinger and Morgan (1993) sought to specifically model the problem of risky loan selection for a commercial-bank-loan portfolio. While they recognised the difficulties in applying the standard Markowitz-Sharpe framework to loan-portfolio-management issues, little emphasis was placed on linking feed-back mechanisms between risk pricing and borrower performance, and the impact these feed-backs may have on returns earned on a bank's loan portfolio.

The aim of this article is to evaluate the risk-return efficiency of limits to which farm loans in Australia may be priced for credit risk by banking institutions. The empirical analysis considers what factors determine efficient limits on risk pricing using a stochastic-simulation model. The research finds that bank profits may be increased without compromising risk by pricing further across the credit risk spectrum to farm businesses in regions and industries within Australia with volatile incomes compared to those with relatively stable incomes. The structure of the article is as follows. Section 2 presents the key principles of portfolio theory and then integrates key concepts of insurance theory on which credit-risk-classification systems are based into the portfolio theory framework. Section 3 provides an overview of the method of analysis. Section 4 gives an outline of the key features of the loan-portfolio model that is representative of an operating environment of lenders with significant distribution networks servicing the Australian-farm sector. Section 5 describes the data used to underpin the simulation model. Section 6 presents the results of the credit-policy simulations. Section 7 discusses some of the key factors influencing the results. A conclusion is presented in Section 8.

## 2. Theory

### 2.1 Key principles of portfolio theory

In portfolio theory, investors are assumed to make choices between risky securities on the basis of their risk and return (Markowitz 1952, 1959). The expected (mean) return of a security is used as an indicator of its anticipated profitability. In general terms, the expected value of an investment is simply the possible return outcomes weighted by their probability of occurrence. The security's forecast uncertainty is measured by the variance

(or standard deviation) and is used as an indicator of risk. A decision rule for evaluating risky alternatives can be based solely on their expected returns and variance (Markowitz 1952). The ‘expected return-variance’ or ‘mean-variance’ rule (the E-V rule) can be defined as follows. Security  $i$  will be preferred to security  $j$  if one of the following two conditions hold.

- Expected return of security  $i$  exceeds (or is equal to) the expected return of security  $j$  and the variance of  $i$  is less than the variance of  $j$  or
- The expected return of security  $i$  exceeds that of security  $j$  and the variance of  $i$  is less than (or equal to) that of  $j$ .

The E-V rule may also be applied to portfolios of securities to define an efficient portfolio in terms of an optimal set of portfolio weights for different securities (Markowitz 1959). An investor can fully nullify portfolio risk associated with security returns behaving independently of each other (unsystematic risk) by diversifying across a large number of different types of securities. If a large number of securities are included in a portfolio, the remaining portfolio risk, termed systematic risk, converges to the average covariance of the rates of returns of all securities included in the portfolio. An efficient frontier may be defined that consist of optimal combinations of different securities in terms of their weightings into portfolios that minimise portfolio risk for each level of expected-portfolio returns.

The Capital Asset Pricing Model (CAPM) takes Markowitz’s framework a step further by examining its implications for pricing risky-capital assets (Sharpe 1964, Linter, 1965, Mossin, 1966). The CAPM simplifies the Markowitz framework by establishing a benchmark index of the market-value-weighted portfolio of all possible risk investments. When risk-free securities are introduced, the CAPM indicates that there is one unique portfolio on the efficient frontier that investors may hold called the market portfolio. Investors may hold proportions of the market portfolio and risk-free securities depending on their preference for risk. The process of arbitrage ensures that capital-asset prices reflect full diversification by market participants. The CAPM shows that returns for risky securities are compensated for market risk only. The CAPM indicates that there exists a capital-market line on which all efficient portfolios lie. Further, a security market line may be derived which sets out a linear relationship between expected returns and risk of individual securities. From this relationship, the CAPM measures the size of the risk premium required to be incorporated into the returns of a risky security through a measure of systematic risk called beta.

## 2.2 Portfolio theory and credit risk

### 2.2.1 Expected returns and insurance theory

Credit risk gives rise to deviations from the promised rate of bank returns from a portfolio of borrowers. The upside of bank returns from the average borrower in a portfolio segment is limited to promised-interest payments and changes in bank assets due to repayments or drawings on loan facilities. A financial institution usually does not benefit if borrowers improve their performance. On the downside, bank's returns are limited in simple terms by the extent to which collateral is pledged as security by borrowers. Collateral is used by lenders to limit borrower incentives to default on their loans and to cover the possibility of capital losses on loan securities in the event of borrower default (Plaut 1985).

A portfolio of business borrowers may be segmented by region, industry and loan maturity. Regional and industry segmentations give relatively homogeneous business asset structures and borrower income distributions. Banks also employ risk-classification systems with several risk classes to measure different rates of expected losses across a number of borrowers (Brice 1992, Boffey and Robson, 1995).<sup>1</sup> Abstracting from transaction costs and stage of loan maturity, the expected rate of returns from the average borrower in a portfolio segment is the sum of the promised rate of return and the expected rate of capital loss weighted by their probability of occurrence:

$$(1) \quad (1 + r_{jgt}^e) = (1 - d_{jgt}) \cdot (1 + r'_{jgt}) + d_{jgt} \cdot cl_{jgt}^e$$

and

$$(2) \quad cl_{jgt}^e = \begin{cases} 0 & \text{if } scr_{jgt} \geq 1 \\ 1 - scr_{jgt} & \text{if } scr_{jgt} < 1 \end{cases}$$

where  $r^e$  = expected rate of interest (or equivalently, expected bank returns per unit of loan);

$d$  = probability of default;

$r'$  = promised rate of interest;

$cl^e$  = expected-rate of loan loss; and

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<sup>1</sup> Each risk class is used to establish average expected-loss rates for a portfolio of borrowers. Each risk class defines ranges of the probability of default and the security-cover ratio for classification of individual borrowers.

$scr$  = expected-security-cover ratio (expected collateral value per unit of loan).

and subscripts

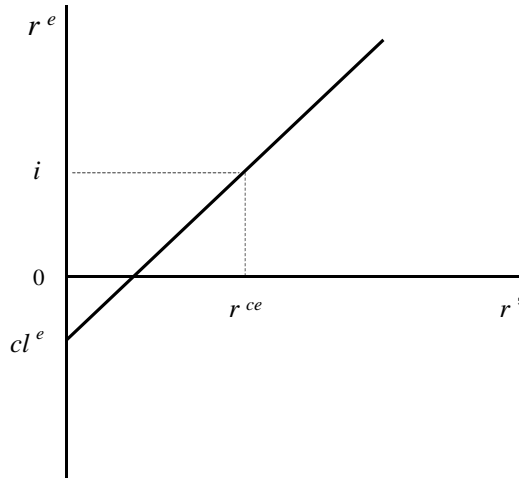
$j$  = region-industry segment;

$g$  = risk class; and

$t$  = time period.

Equations (1) and (2) define a relationship between the expected rate of return and the promised-interest rate for a particular region-industry segment and risk class. A risk class defines a certain rate of expected loss. The expected-loss rate is given by the second term in equation (1). In Figure 1, a portfolio of prospects for the expected rate of return is illustrated for different levels of the promised-interest rate. In this Figure, the relationship assumes that the probability of default of the borrower remains independent of the promised-interest rate. The loan-loss in event of default in Figure 1 is given by the symbol,  $cl^e$

**Figure 1 The promised-interest rate and bank-expected rate of return**



The issue of compensation for expected losses on loan securities is not found in the Markowitz-Sharpe framework, though it has parallels to the insurance problem. The insurance problem involves how to manage the possibility of losses on insurance contracts through risk spreading. In standard insurance models, risk spreading involves investors with possibly different risk attitudes sharing the same risk. In the case of credit markets, holders of loan contracts or securities (borrowers) are assumed to be risk averse. Each borrower faces a particular income distribution that presents the possibility of default on their loan in some future time period. The lender shares the risk of default on loan securities that are issued to borrowers. To limit the impact of this risk, the lender seeks to

spread this risk across many different types of borrowers (Nelson and Loehman 1987). In contrast, risk on a security in the CAPM framework is only measured by beta.

Insurance theory suggests that a firm confronted with a portfolio of prospects on an asset is willing to pay an insurance premium to an insurance firm to avoid adverse outcomes (Hey 1984, p 447). The insurance firm undertakes to pay the firm the losses accruing to the insured in the event of an adverse outcome. Bierman and Hass (1975) argue that lenders will pursue an expected-loss compensation policy to give an actuarially fair price for self-insurance. This policy rule assumes that the risk premium is set equal to the expected loss on a loan security. In this event, the contractual interest rate that is charged to a loan security in risk class  $g$  is equal to the certainty-equivalent-promised rate of interest rate defined as  $r^{ce}$  in Figure 1. This interest rate is equivalent to the risk-free-interest rate,  $i$ , plus a certainty-equivalent-risk premium,  $rp^{ce}$ . This risk premium is commonly referred to as the default-risk premium in the literature, and is a function of the probability of default and the loss rate expected for risk class  $g$ .<sup>2</sup>

$$(3) \quad r_{jgt}^{ce} = i + rp_{jgt}^{ce}$$

### 2.2.2 Portfolio theory implications of insurance

An insurance firm acts to spread its risks by combining numerous insurance contracts into a portfolio (Nelson and Loehman 1987). So long as the loss rates between different contracts are independent, the insurance firm is compensated for any expected losses via payment of premiums by firms not experiencing adverse outcomes. Similarly, when loan securities of similar expected-loss rates are segmented using a risk-classification system by a bank, the expected returns for each risk class will equal promised returns less the expected-loss rate. Since the income earned from the certainty-equivalent risk premium equals the expected-loss rate under risk spreading, the return earned on the portfolio of loan securities in risk class  $g$  is equal to the risk-free-rate of return.

The variance of returns on a portfolio of loan securities in a risk class occurs in the form of unexpected deviations in losses from loan securities around their expected levels (Davis 1990, Wyman 1991, Foss 1992). Unsystematic risk for the risk class occurs as a consequence of

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<sup>2</sup> The certainty-equivalent-risk premium is calculated by substituting the risk-free rate of return  $i$  for  $r^e$  in equation (1), and then rearranging equation (1) to give the difference between  $r^{ce}$  and  $i$ .



losses on individual loan securities behaving independently of each other. Unsystematic risk is forced to zero in a competitive credit market if the number of loan securities in a risk class is very large (Bramma and Batterham 1994). Since unsystematic risk is effectively forced to zero under risk spreading, the appropriate rate of return according to the CAPM is the risk-free-rate of interest.

Systematic risk in each risk class depends on the extent to which losses on each individual loan security is correlated with losses on the whole portfolio. If the same mix of securities (in terms of types of borrowers that hold loan securities) exist across each risk class, systematic risk in each risk class will be equivalent to systematic risk associated with the total-loan portfolio. Since investors are averse to portfolio risk, they require compensation for bearing unexpected losses that occur on systematic basis. Accordingly, the CAPM suggests that the required compensation for this risk is equal to the market-risk premium. Systematic risk on loan securities occurs as a result of correlation among the loss distributions between different types of borrowers (Kao and Kallberg 1994). Since the probability of default is directly related to the income distributions of borrowers, correlation of loss distributions might be expected to occur as a result of a common set of exogenous factors affecting income distributions of borrowers in different regions and industries. Hence, the diversification principle of portfolio theory applies not to individual loan securities but to portfolios of loan securities categorised along regional and industry lines.

If a lender is fully diversified across a large number of similar sized region-industry segments, unsystematic risk is forced to zero. In this circumstance, the size of beta is determined by the extent to which the returns from borrowers from a portfolio segment covary with returns to the total portfolio standardised for the variance of portfolio returns.<sup>3</sup> The portfolio-risk premium (*prp*) for bearing beta risk is measured by  $\beta_j \cdot (E(r_p) - i)$  where the market-risk premium is given by  $E(r_p) - i$ .<sup>4</sup> The expected return on a loan security may be given by

$$(4) \quad r_{ij}^e = i + prp_j.$$

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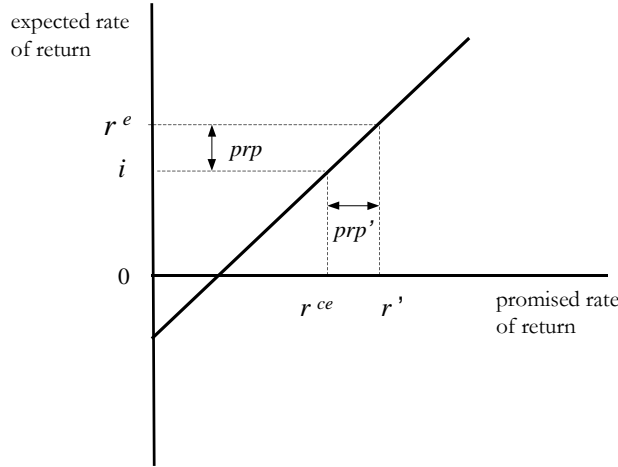
<sup>3</sup> If the portfolio variance is substituted for the market portfolio variance, beta for portfolio segment  $j$  may be calculated using the standard formula for measuring beta  $\beta_j = Cov(r_j, r_p) / Var(r_p)$ . The loan-security-market line is given by  $r_j^e = i + \beta_j(E(r_p) - i)$  to give the expected return for all loan securities in a region-industry segment.

<sup>4</sup> If  $\beta_j = 1$ , the portfolio-risk premium for segment  $j$  is equal to the market risk premium. Bank returns from borrowers in segment  $j$  vary coincidentally with portfolio returns. If  $\beta_j > 1$ , the portfolio-risk premium for segment  $j$  is greater than the market risk premium. Bank returns from borrowers in segment  $j$  vary more than coincidentally with portfolio returns. If  $\beta_j < 1$ , the portfolio-risk premium for segment  $j$  is less than the market risk premium. Bank returns from borrowers in segment  $j$  vary less than coincidentally with portfolio returns.

The incorporation of the portfolio-risk premium for loan securities in risk class  $g$  into the promised-interest-rate structure is achieved by adding a promised-portfolio-risk premium to the risk-free rate,  $i$ , and the certainty-equivalent risk premium,  $rp^{ce}$  as shown in equation (5). Figure 2 shows the relationship between the promised-interest rate and expected-bank returns with and without a portfolio-risk premium.

$$(5) \quad r'_{jgt} = i + rp^{ce}_{jgt} + prp'_j$$

**Figure 2 The promised-interest rate, bank expected rate of return and the portfolio-risk premium**



Each lender in a perfect capital market is responsible for extracting all potential gains from diversification through pricing for beta risk. There are, however, several physical limits to which lenders may be able to diversify and to spread risk. These physical limits may lead to risk concentrations within a loan portfolio held by a lender (Kao and Kallberg 1994). First, some regional and industry categorisations may be sufficiently large so as to outweigh the variances of returns for smaller industries and regions. Second, differences in the nature of firm concentration in regions and in industries may lead to unequal weightings of loan securities within a region-industry segment. Finally, if individual borrowers of similar size hold loan securities of dissimilar size, then the portfolio weights on the loss-probability functions will also influence actual-loss rates on these loan securities both within risk classes and within region-industry segments. These weighting variations may limit a lender's capacity to utilise the 'law of large numbers' on which risk spreading and diversification principles are based (Wyman 1991).<sup>5</sup>

<sup>5</sup> Beta pricing of loan securities will not be as efficient as implied in the Sharpe CAPM framework if risk concentrations occur. In this case, banks may apply portfolio-risk premiums to higher orders of portfolio categories,

### 2.3 Pricing limits

There are limits to which banks may price for credit risk. The pricing rules described in the previous section assume independence between the probability of default and the promised rate of interest. Expected returns earned from borrowers in certain portfolio segmentations will be at variance to the expected return on which the promised-interest rate was based if the independence condition is violated. Efficient pricing for credit risk may only occur over a range of the promised-interest rate. In this range, higher promised-interest rates result in negligible impacts on borrowers' expected probability of default. Beyond a particular point, *rpl*, higher risk premiums may lead to sufficiently high promised-interest rates such that they lower expected returns to the bank (see Figure 3). In this event, banks may use a risk-pricing limit on borrowers to circumvent pricing impacting on expected returns.<sup>6</sup>

Higher promised-interest rates may eventually impact on expected-bank returns for two reasons: first, borrowers already burdened by debt undertake riskier investments; and second, borrowers experience adjustment difficulties in response to unanticipated short-term changes in economic conditions. When borrowers are burdened with debt, agency-theory models suggest that adverse incentives and moral hazards can lead to higher-risk borrowers responding to higher interest rates by undertaking riskier investments (Saunders 1994, p 164). As promised-interest rates are increased, a point exists at which significant changes in a borrower's mode of operation are required. As financing costs increase relative to operating expenses, higher financing costs provide incentives to borrowers to invest in activities with higher expected-net returns (Saunders 1994, p 164). Given the expected return-risk trade-off, higher expected returns can only be achieved through riskier investments and thus increasing the probability of default more than proportionately to an incremental increase in the promised-interest rate. When borrowers are subject to large and unanticipated changes in income, both their credit reserves and their probability of default will vary widely through time.<sup>7</sup> For a given amount of credit reserves, borrowers with high-income variability will incur

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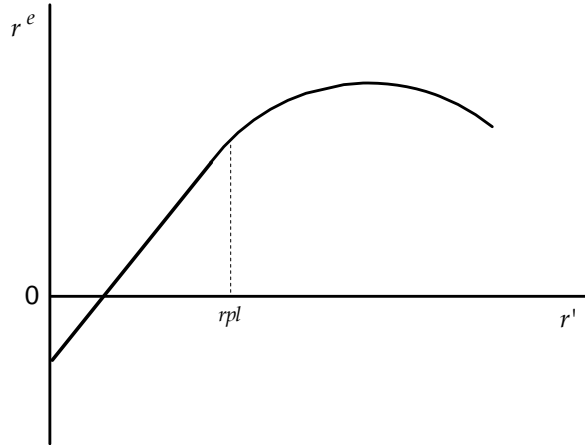
for example, by country and by sector, rather than by region and by industry, to assure diversification and risk spreading. Lenders may fine-tune their credit-risk-management strategies through reliance on non-pricing methods on lower orders of regional-industry categories.

<sup>6</sup> The risk-pricing limit ultimately defines a spectrum for acceptable credit quality. The credit quality of loan applicants is impaired if loan pricing impacts on their probability of default.

<sup>7</sup> Credit reserves are defined as the difference between the maximum liabilities permitted by a lender defined in loan contracts and the actual liabilities of a borrower

large changes in risk premiums being factored into their promised interest rates compared to borrowers with relatively stable incomes.

**Figure 3 The promised-interest rate and the expected-interest rate with dependency between the expected-default probability and the promised-interest rate**



The risk-pricing limit for borrowers with volatile incomes could feasibly be set at higher levels than for borrowers with relatively stable incomes.<sup>8</sup> While high-income volatility means less certain outcomes in the forecast period, high-income volatility under certain assumptions also means that borrowers have greater capacity to trade their way out of financial difficulties. Once borrowers' credit reserves are depleted, the capacity of lenders to price for credit risk in a dynamic context depends on the probability that borrowers will earn a high income in the forecast period. Borrowers with high-income volatility face the prospect of a large income in the forecast period to replenish their credit reserves. In contrast, borrowers with low-income volatility face little prospect of a large income in the forecast period to replenish their credit reserves.

## 2.4 Impact of loan-product-construction options

Banks have various options in controlling their credit risk through the initial construction of loan products and through reconstruction of loan products when borrowers fall into default. For example, fixed-interest-rate loans generally reduce credit risk relative to variable-interest-rate products, though inflation trends can strongly influence credit risk associated with variable-interest and fixed-interest loan products (Pederson 1992). More flexible principal-

<sup>8</sup> The nexus between the efficient size of the risk-pricing limit and income volatility depends on the nature of serial correlation of borrower incomes. Negative and zero serial correlation in borrower incomes leads to a positive relationship between the efficient size of the risk-pricing limit and variability of borrower income. The relationship becomes negative at

repayment conditions may also provide a means for minimising the influence of loan product on credit risk (Lee 1979; Boehlje and Eidman 1988; Pederson, Duffy, Boehlje and Craven 1991).

In the event of default, there is a range of options open to a bank to restructure loan products by extending the size of a borrower's credit reserve in the short term. These restructuring options include extension of maximum-credit limits, forgiveness of term-loan principal and interest, or an extension of the term over which a loan is repaid (Pederson, Boehlje, Doye and Jolly 1987, Lawrence and Arshadi 1995).<sup>9</sup>

### 3. Method of analysis

#### 3.1 Capital-budgeting approach

The present-value method for measuring bank returns must be used to value a loan security portfolio when loan securities are illiquid (Kao 1993). The single-period framework as suggested by the Markowitz-Sharpe paradigm does not provide for easy valuation of illiquid portfolios. Illiquidity of loan securities means that purchases and liquidations of loan securities can only be achieved gradually over time (Gollinger and Morgan 1993). Banks face difficulties in cancelling existing loan contracts held by their borrowers. Under the capital-budgeting approach, returns from loan securities are analysed within a multi-period framework. Projected returns on each security through time are discounted by the expected rate of return required and are weighted by their absolute-dollar values to measure portfolio performance.<sup>10</sup> The capital-budgeting approach also enables evaluation of the impact of disproportionate-sized loan securities on portfolio returns because absolute dollar values are used to determine their weightings.

#### 3.2 Decision problem

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some critical point for positive-serial correlation in borrower incomes. The more positive serial correlation in borrower incomes becomes, the more negative the relationship between the risk-pricing limit and income volatility also becomes.

<sup>9</sup> The degree of impact of loan-product structure and loan restructuring options on credit risk depends on their influence on the time path of the credit reserves available to the borrower, and therefore the dynamic profile of default risk through the maturity term.

<sup>10</sup> The expected return required on loan-portfolio assets used as the discount rate also gives a price-setting rule when the capital-budgeting approach is used to undertake loan-security valuation. Borrowers are assumed to pay the promised-interest rate derived by reference to the required rate of return that will provide an expected stream of cash flows to the bank with at least a positive expected net present value (Davis 1990).

The decision problem under analysis is to choose between different credit-policy regimes that bank-decision makers may wish to apply. A credit-policy regime, denoted as  $i$ , may be defined as a composition of policies encompassing rules for:

- pricing
- credit-quality limits
- collateral requirements
- credit limits
- loan-product types
- problem-loan-resolution options.

Each individual credit-policy regime gives rise to pay-offs in terms of loan security returns to the bank. These pay-offs are subject to a range of constraints that decision-makers cannot control. The pay-off from the  $i$ -th credit-policy regime may be given by the probability-density function of the net-present value of bank portfolio returns,  $NPV(BR_{ip})$ , over the investment horizon,  $n$ , shown by equation (6)

$$(6) \quad f(NPV(BR_{ip}))$$

where the measure of the net-present value of bank returns is measured by

$$(7) \quad NPV(BR_{ip}) = \sum_{t=1}^n \frac{BR_{ipt}}{(1 + E(r_p))^t} + \frac{L_{ipn}}{(1 + E(r_p))^n} - L_{ip0}$$

where  $BR$  = bank returns;

$L$  = outstanding loan balances;

$E(r)$  = expected rate of return;

with subscripts denoted by

$p$  = portfolio;

$t = 1, \dots, n$  time periods; and

$i = 1, \dots, k$  credit-policy regimes.

In the  $NPV$  simulations undertaken in this article,  $n$  is set to 50 years. The number of samples of  $NPV$  of bank returns taken to estimate equation (6) for each credit-policy regime is 200

observations. The discount rate is calculated using the weighted-average-cost-of-capital approach (Modigliani and Miller 1958, 1963).<sup>11</sup>

### 3.3 Credit-policy regimes

Six credit-policy regimes are examined in this article. The credit-policy regimes include three different settings for the risk-pricing limit applied, and two problem-loan-resolution-policy options (see Table 1). A loan-restructuring rule is contrasted to an option where borrowers are offered no extension to their credit reserves when they default. The loan-restructuring rule examined is defined in terms of ‘interest only with credit extension’. The term-loan facility of the defaulting borrower is first placed on an interest-only basis. When forgiveness of term-loan-principal payment is not sufficient to stave off default, then the maximum-credit limit of the borrower is extended to meet the required amount of liquidity. Maximum-permissible borrowings of farmers are also required be fully secured if restructuring is to occur. If a borrower performs in the year following loan reconstruction, term-loan repayments are recalculated on the basis of no change in the original maturity date. The calculation also ensures that full repayment of the new term-loan balance occurs at the conclusion of the loan. Borrowers are not offered restructuring in their first year or during the final three years of the maturity term.

**Table 1 Credit-policy regimes under analysis**

Credit-policy identifier	Risk-pricing limit	Problem-loan-resolution policy
1	5.0%	No
2	5.0%	Yes
3	2.5%	No
4	2.5%	Yes
5	7.5%	No
6	7.5%	Yes

Each credit-policy regime includes the following set of assumptions.

- (a) Pricing for credit risk in the acceptable credit-risk spectrum is assumed to account for default risk only because only fully-secured loans is considered. The portfolio-risk

<sup>11</sup> The weighted-average-cost of capital is estimated using data on the long-run structure of a bank using known average bank statistics with consideration given to minimum capital adequacy requirements required in the year 1996 (Bramma 1999, p 196).

premium is assumed to be embodied in the bank rate of return required on equity capital for the Australian farm sector as a whole.

- (b) Credit reserves of acceptable-loan applicants are calculated using a predetermined proportion of the maximum permissible liabilities. This minimum-credit reserve limit is set at 14.2% of fixed assets in the projections.
- (c) Collateral pledged by loan applicants is set equal to the estimated-market value of fixed assets.
- (d) Configuration of the credit-risk-classification system is assumed to be a 3x3 matrix. In the default risk dimension, ranges for the probability of default are assumed to be 0%-2%, 2%-4% and 4%-6%. In security risk dimension, expected-security-cover ratios are assumed to be 7.72 times, 2.57 times and 1.54 times maximum-permissible liabilities.
- (e) Maximum-credit limits for acceptable-loan applicants are equal to the inverse of the expected-security-cover ratio specified above in point (d). Under this rule, maximum-credit limits are set at 1.84 times, 5.51 times and 9.2 times the value of fixed assets. These three limits equated to maximum possible farm equity-asset ratios equal to 90%, 80% and 70% respectively on a portfolio basis.
- (f) Maximum-credit limits are fixed for the duration of the maturity term. In the final year of the loan, the limit is forced to zero to ensure full loan repayment.
- (g) Fixed-debt-servicing requirements of borrowers are assumed to include term-loan principal and interest payments, interest payments on the overdraft and loan fees and charges. Fixed-debt-servicing requirements are made regardless of the liquidity position of the borrower except in the case where a problem loan restructuring rule is applied.

### 3.4 Choice criteria

The choice between uncertain prospects from  $k$  number of credit-policy regimes is achieved using an efficiency criterion. Hadar and Russell (1969), Hanoch and Levy (1969), Rothschild and Stiglitz (1970) and Whitmore (1970) suggest ordering uncertain prospects using stochastic dominance (SD) criteria.<sup>12</sup> The SD approach can be used to define efficient sets of credit-policy regimes under alternative (progressively more stringent) conditions regarding the risk-return preferences of decision-makers. In this approach, the general characteristics of the

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<sup>12</sup> The key advantage of the SD approach over other selection criteria is that the precise form of the decision-maker's utility function does not need to be specified.



credit-policy maker's utility function are defined in terms of first-order, second-order and third-order stochastic dominance.

- First-order stochastic dominance (FSD) assumes that credit policy makers prefer more wealth to less.
- Second-order stochastic dominance (SSD) assumes that credit policy makers are averse to risk in addition to FSD.
- Third-order stochastic dominance (TSD) assumes that credit policy makers become decreasingly averse to risk when they become wealthier in addition to FSD and SSD.

Anderson, Dillon and Hardakker (1977, p 313-318) outline in detail the application of SD selection criteria for uncertain prospects using discrete-probability functions. In the SD approach, repeated pair-wise comparisons of return distributions for different credit-policy regimes are made to determine whether particular credit-policy regimes are not dominated.

### 3.5 Computer program

The number of portfolio segmentations dictated the design of the computer program. There are 3,780 portfolio segmentations potentially developed for analysis. A model of a farm borrower is built for each portfolio segment.<sup>13</sup> Each farm model is subjected to the six credit-policy regimes shown in Table 1 in a given simulation year. The large size of the credit-policy experiments required the simulations to be performed using computer programs that extracted farm-surveys data on an individual region-industry segment basis. The prior financial history of borrowers across the maturity profile must be known in order to project future performance. Consequently, the computer program was split into two separate components: a historical program called INIT and a projection program called EVAL. The program INIT generates starting conditions for the average farm borrower in each portfolio segment for input into the projection program EVAL. The program INIT is subjected to the economic environment for the period 1978-79 to 1995-96. Each farm model is given a history regarding its cash flow, taxation and balance-sheet statements that are consistent with the recent history for the economic environment and a particular regime for

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<sup>13</sup> The 3,780 farm models may be compared to 70,658 broadacre and dairy establishments in Australia as at 31 March 1996 (ABARE 1997a). Data on average farm statistics resulted in 42 region-industry classifications within Australia. Each farm model is assumed to utilise a variable-interest-term loan with a loan maturity of 10 years. The configuration of the credit-risk-classification system is assumed to be a 3x3 matrix giving a total of 9 credit-risk classes. The calculation for the number of portfolio segments is given by  $42 \times 10 \times 9$ .

credit-risk management. The program EVAL relies on scenario forecasts extracted from probability-distribution functions defined for stochastic variables comprising the uncertain-economic environment. The input of scenarios for the economic environment gives annual estimates of values of loan returns and bank assets for a given credit-policy regime over the investment horizon of 50 years. The *NPV* of bank returns for a particular scenario of the economic environment is calculated using equation (7). Different sample values of the *NPV* of bank returns are estimated by repeating the above process several times. A program called ADDBR is then used to aggregate region-industry estimates of *NPV* of bank-returns to an Australia-wide basis.

A program called STOCHASTIC is used to identify discrete-probability-distribution functions of *NPV* of bank returns from sample values of *NPV* generated by EVAL and ADDBR. The program STOCHASTIC is also used to evaluate pairs of probability distribution functions of *NPV* for their stochastic efficiency.<sup>14</sup>

## 4. Loan-portfolio-simulation model

### 4.1 Bank model

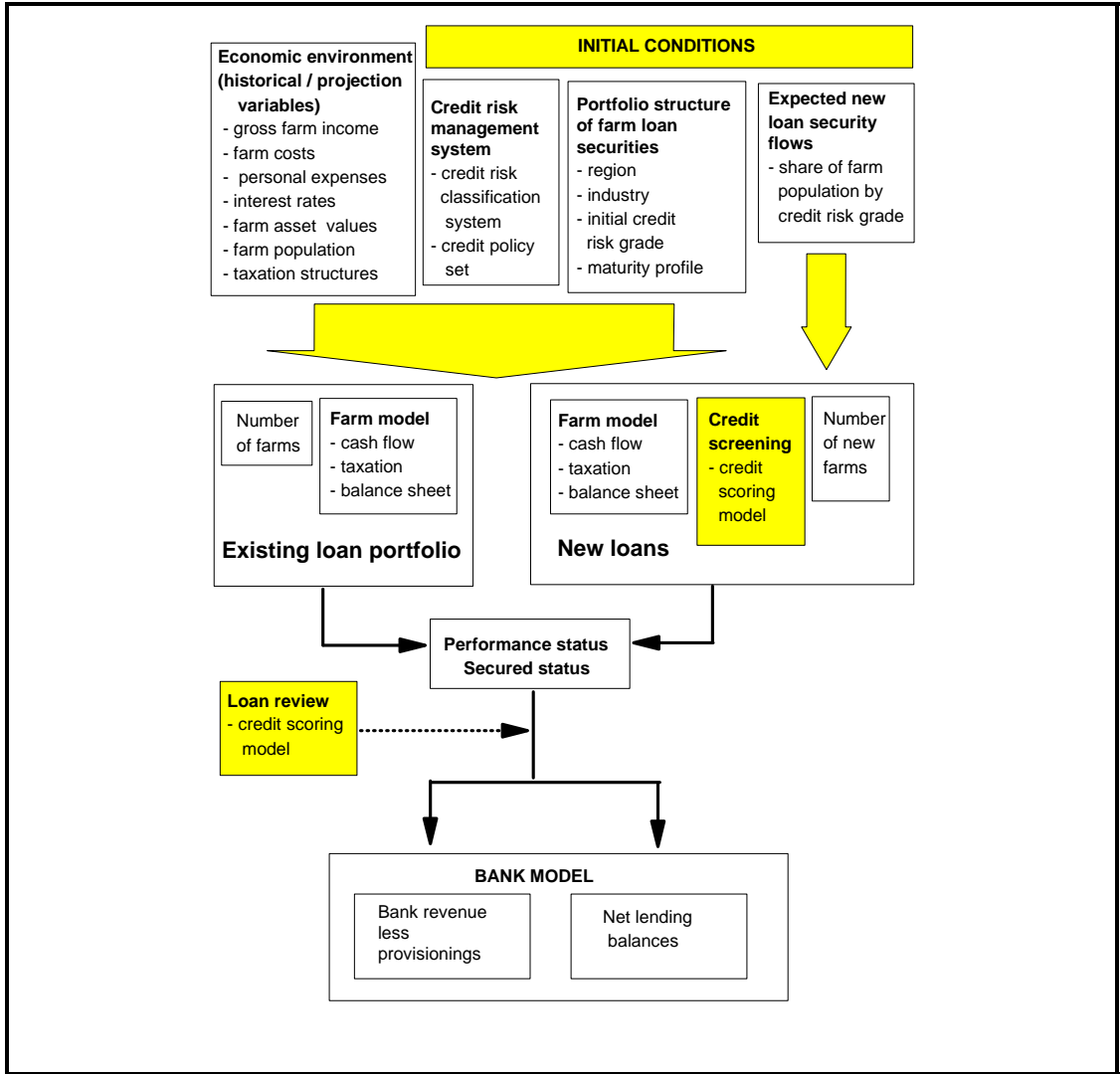
A full specification of the simulation model is available in Bramma (1999). The simulation model is illustrated in Figure 3. In brief, key inputs of the model at the start of each period include the credit-risk-management system, the uncertain economic environment, a portfolio structure of farm-loan securities and expected-new-loan-security flows. The final output of the simulation model at the end of each time period is a measure of bank returns for input into equation (7) to calculate *NPV*. The returns on the total-loan portfolio in time period  $t$ ,  $BR_{pt}$ , is found by summing the bank returns from each portfolio segment across  $m$  region-industry segments,  $h$  credit risk classes and  $nt$  years of maturity.

$$(8) \quad BR_{pt} = \sum_{j=1}^m \sum_{g=1}^h \sum_{a=1}^{nt} BR_{jgat}$$

Bank returns for a portfolio segment of a particular stage of maturity is found by multiplying the average returns from borrowers holding securities of a particular

### Figure 4 Schematic diagram of simulation model

<sup>14</sup> Program STOCHASTIC was sourced from Anderson, Dillon and Hardakker (1977) p 313-318. Programs INIT, EVAL and ADDBR were written by the author. Each program is written using FORTRAN computer language.



stage of maturity,  $\overline{BR}_{jgat}$ , times the number of borrowers held in the segment at the beginning of time period  $t$ ,  $X_{jga-1t-1}$ .

$$(9) \quad BR_{jgat} = \overline{BR}_{jgat} \cdot X_{jga-1t-1}$$

Average bank returns from a portfolio segment is estimated by measuring loan revenues ( $\overline{RL}$ ) and actual loan losses. Actual loan losses are measured using standard-bank-accounting conventions for taking provisions for bad and doubtful debts ( $\overline{PB}$ ).

$$(10) \quad \overline{BR}_{jgat} = \overline{RL}_{jgat} - \overline{PB}_{jgat}$$

Loan revenues include interest payments and loan fees and charges made by performing borrowers. Provisions for bad and doubtful debts are made when borrowers enter default. In

the event of default, provisions are calculated as the difference between the salvage value of collateral and loans outstanding held by the average borrower in the portfolio segment. The salvage value of collateral in a region-industry segment is assumed to be stochastic. The distribution of the salvage value includes a constant mean with a variance that is directly related to gross-farm income in a region-industry segment.

## 4.2 Farm model

Each farm model contains a cash-flow statement, a taxation statement and a balance-sheet statement. These statements assess a farm model's default status and the amount of funds repaid to the bank under different scenarios. In simulating farm performance, stochastic variables include gross income and interest rates for the overdraft and term-loan facilities. All stochastic variables are assumed to be log-normally distributed with fixed means and constant covariances.

A key equation of the farm model is the cash-flow statement. Once scenario values describing the economic environment for a particular year are drawn from their distributions, the farm model is used to assess whether the scenario for the economic environment results in a positive cash surplus including credit reserves for a portfolio segment. Cash surplus including credit reserves,  $CSR$ , in each time period is equal to the following:

$$(11) \quad CSR_{jgat} = GOS_{jgat} + CR_{jgat} - FDR_{jgat} - PE_j$$

and

$$(12) \quad GOS_{jgat} = GI_{jgat} - FC_{jt} - TAX_{jgat}$$

where  $GOS$  = gross operating surplus;  
 $CR$  = credit reserves;  
 $FDR$  = fixed-debt-servicing requirements;  
 $PE$  = minimum-personal expenses;  
 $GI$  = gross income;  
 $FC$  = farm costs; and  
 $TAX$  = taxation payments.

If  $CSR$  is greater than or equal to zero, then the farm model makes loan repayments to the bank. If  $CSR$  is negative, then the farm model is in default and a loan-restructuring option is applied. In simulating  $CSR$ , several modelling assumptions are made.

- Scenario values of gross income are drawn from a gross-income distribution for a particular region-industry segment. Gross income for each farm model in a credit-risk class within a region-industry segment is adjusted by a well-defined productivity parameter using a credit-screening model. The credit-screening model places data available for the average farm in region-industry  $j$  into each  $g$  risk class (see Bramma 1999, p 148-157 for more detail).
- Expected values of farm costs are fixed. Scenario values of farm costs are assumed to be positively related to gross income.
- Taxation payments are calculated using a taxation statement that is based on income taxation only. Interest and loan fee payments are 100% deductible if income tax is payable. Income splitting between two partners and seven-year-tax-averaging provisions are also assumed to be used by all borrowers.
- Minimum-personal expenses are assumed to be constant through time. However, cumulative-cash surpluses over two consecutive years are consumed and the overdraft balance is drawn down to zero in the second year.
- Changes in farm liabilities depend on cash-balance outcomes, term-loan repayments and restructuring implications if default occurs.

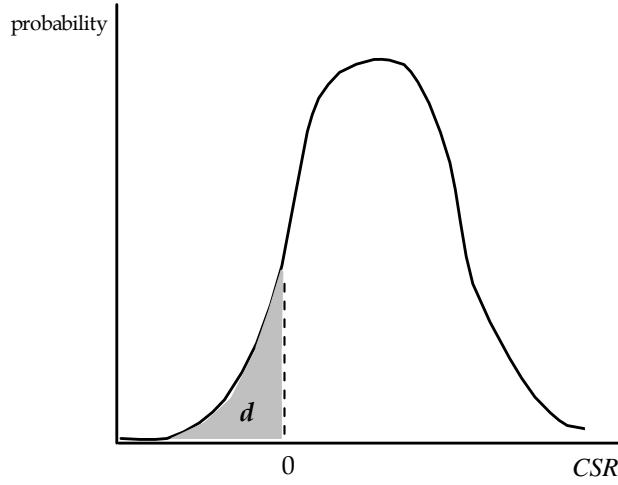
A loan-review-farm model is used to make annual estimates of the probability of default at the end of each year for loan pricing purposes in the next year. The probability of default,  $d$ , may be defined as the probability that the business is unable to generate a minimum level of gross operating surplus to meet the outgoing funding requirements of the business including debt servicing and funds required for personal expenditure (Gabriel and Baker 1980). This relationship is illustrated in Figure 5 and is defined algebraically as follows:

$$(13) \quad P(CSR_{jgat} \leq 0) \leq d_{jgat}$$

### 4.3 Farm numbers model

The number of borrowers held by a bank in a portfolio segment for loans at the start of the first year of a loan maturity (ie,  $a = 0$ ) depends on farm population levels and bank capture

**Figure 5** *CSR* distribution and the expected probability of default



rates. Projected farm population levels are modelled as a function of time. At the end of the maturity term (ie,  $a = nt$ ), all borrowers are assumed to exit the portfolio segment. During the maturity term (ie,  $1 \leq a < nt$ ), the number of borrowers continuing in portfolio segment depends on whether the farm model predicts default. If  $CSR$  is at least zero, all borrowers are assumed to continue into the next time period. If  $CSR$  is less than zero, all borrowers are assumed to default. These conditions may be algebraically expressed as follows:

$$(14) \quad X_{jgat} = \begin{cases} k_{jg}(t) & \text{if } a = 0 \\ X_{jga-lt-1} & \text{if } CSR_{jgat} \geq 0 \text{ and if } 1 \leq a < nt \\ 0 & \text{if } CSR_{jgat} < 0 \text{ and if } 1 \leq a < nt \\ 0 & \text{if } a = nt \end{cases}$$

## 5. Data

Region-industry groupings are defined in farm surveys compiled by the Australian Bureau of Agricultural and Resources Economics (ABARE) in their Australian agricultural and grazing industries surveys (AAGIS) and Australian dairy industry survey (ADIS) (ABARE 1997a). The coverage of ABARE farm surveys includes five broadacre industry segments and a dairy industry across Australia. The broadacre industries include Wheat and other crops, Mixed livestock-crops, Sheep-beef, Sheep and Beef. Regional coverage assumed 27 regions and included all States plus the Northern Territory (see Table 3 and Figure 6).

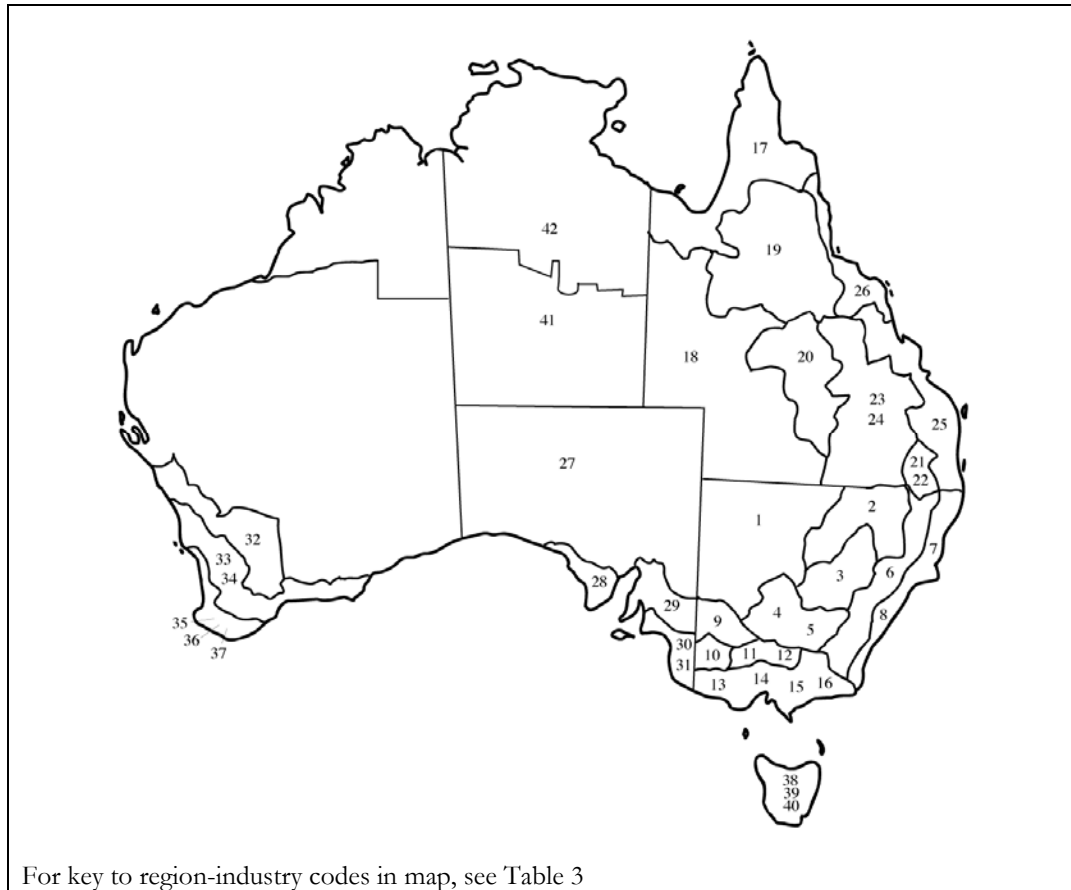
**Table 3 Region-industry specifications and codes**

Region industry code	ABARE description code	Region description	Industry description
1	1113	NSW - pastoral zone	Sheep-beef
2	1212	New South Wales - wheat-sheep zone 1	Mixed livestock-crops
3	1222	New South Wales - wheat-sheep zone 2	Mixed livestock-crops
4	1232	New South Wales - wheat-sheep zone 3	Mixed livestock-crops
5	1236	New South Wales - wheat-sheep zone 3	Dairy
6	1315	New South Wales - high rainfall zone 1	Sheep
7	1324	New South Wales - high rainfall zone 2	Beef
8	1326	New South Wales - high rainfall zone 2	Dairy
9	2211	Victoria - wheat-sheep zone 1	Wheat and other crops
10	2221	Victoria - wheat-sheep zone 2	Wheat and other crops
11	2232	Victoria - wheat-sheep zone 3	Mixed livestock-crops
12	2236	Victoria - wheat-sheep zone 3	Dairy
13	2313	Victoria - high rainfall zone	Sheep-beef
14	2314	Victoria - high rainfall zone	Beef
15	2315	Victoria - high rainfall zone	Sheep
16	2316	Victoria - high rainfall zone	Dairy
17	3114	Queensland - pastoral zone 1	Beef
18	3124	Queensland - pastoral zone 2	Beef
19	3134	Queensland - pastoral zone 3	Beef
20	3145	Queensland - pastoral zone 4	Sheep
21	3211	Queensland - wheat-sheep zone 1	Wheat and other crops
22	3216	Queensland - wheat-sheep zone 1	Dairy
23	3222	Queensland - wheat-sheep zone 2	Mixed livestock-crops
24	3224	Queensland - wheat-sheep zone 2	Beef
25	3314	Queensland - high rainfall zone 1	Beef
26	3324	Queensland - high rainfall zone 2	Beef
27	4115	South Australia - pastoral zone	Sheep
28	4211	South Australia - wheat-sheep zone 1	Wheat and other crops
29	4222	South Australia - wheat-sheep zone 2	Mixed livestock-crops
30	4315	South Australia - high rainfall zone	Sheep
31	4316	South Australia - high rainfall zone	Dairy
32	5125	Western Australia - pastoral zone	Sheep
33	5212	Western Australia - wheat-sheep zone	Mixed livestock-crops
34	5221	Western Australia - wheat-sheep zone	Wheat and other crops
35	5314	Western Australia - high rainfall zone	Beef
36	5315	Western Australia - high rainfall zone	Sheep
37	5316	Western Australia - high rainfall zone	Dairy
38	6313	Tasmania - high rainfall zone	Sheep-beef
39	6315	Tasmania - high rainfall zone	Sheep
40	6316	Tasmania - high rainfall zone	Dairy
41	7114	Northern Territory - pastoral zone South	Beef
42	7154	Northern Territory - pastoral zone Nth	Beef

Specifications for farm-level data on a variable-by-variable basis are discussed below. All variables measured in monetary terms are deflated by the Australian consumer price index to express time series in 1995-96 dollars.

- (a) Gross-farm income includes total-enterprise receipts plus other receipts earned from non-enterprise activities. Log-normal probability distributions for gross incomes are estimated using sample-value formulas on deflated-income data for the 18-year period to 1995-96.
- (b) Farm-surveys data on farm costs are split into their fixed and variable components. Expected values of farm cost components are proxied by the means of the farm costs time series. The sensitivity of variable costs and fixed costs to gross income are estimated

**Figure 6 Map of Australia with region-industry codes**



for the 42 region-industry segments using regression analysis on data comprising the 18-year period to 1995-96.

- (c) Personal expenses are proxied by ABARE's operator estimates of the labour input of operators, partners and their families imputed at the relevant Federal Pastoral Award rates.
- (d) The value of fixed assets comprised land and fixed improvements used by the farm business estimated by ABARE farm surveys.
- (e) The expected value of the salvage ratio (defined as the percentage of the market value of farm assets) is assumed to be 70%. The sensitivity of landed-asset values to gross-farm income by region-industry segment is estimated using regression analysis. These sensitivity measures are used to generate the scenario-salvage value of farm assets around their mean values resulting from fluctuations in farm income.



- (f) Time-series data on farm population by region-industry segment were supplied by ABARE. The bank's share of farm population to enter each region-industry segment is assumed to be 2%. The share of farm population by default-risk class of acceptable-credit quality is proxied using distributional data on farm productivity.
- (g) The number of deposits and cheques drawn by the average farm by region-industry segment for calculating loan fees and charges is assumed to be a function of enterprise mix and type.
- (h) Overdraft and term-loan interest rates data is sourced from ABARE (1997b). Sample variances of the overdraft and term-loan-interest rate time series are calculated over the 18-year period to 1995-96. These sample variances are used to proxy interest-rate volatility.
- (i) Loan fees and charges include bank fees, bank charges and non-bank fees and charges (Bramma 1999, p 168).

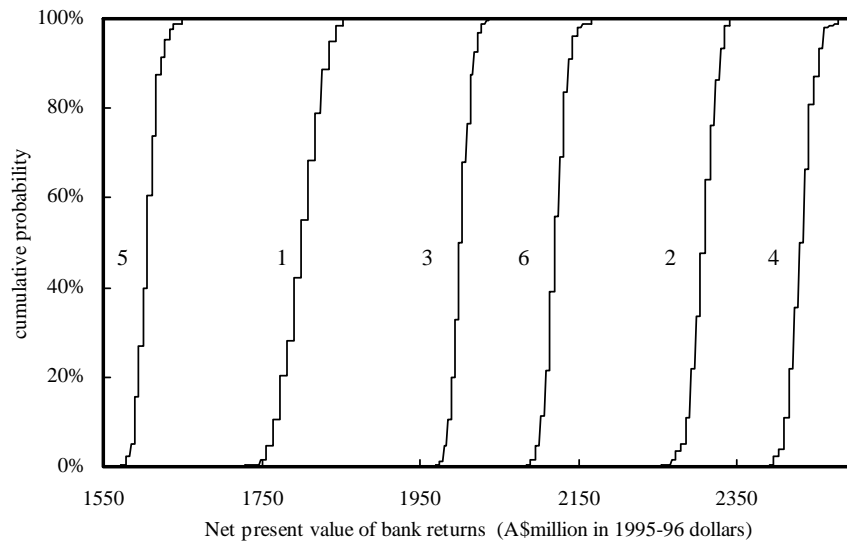
## 6. Results

The results of the credit-policy simulations are displayed as cumulative-probability-distribution functions in Figure 7 for a bank portfolio that includes all region-industry segments under analysis. One simple form of dominance is immediately apparent in Figure 7.<sup>15</sup> Each of the six credit policies may be ranked solely in terms of first degree stochastic dominance (FSD). In particular, credit-policy set 4 ( $r_p=2.5\%$  with 'restructuring' option) is stochastically dominant in the first degree over the five alternative credit-policy sets considered in the investigation.<sup>16</sup> A risk-pricing limit of 2.5% dominates a risk-pricing limit of 5% which in turn dominates a risk-pricing limit of 7.5%. The pattern of dominance for the risk-pricing limit in loan reviews is the same regardless of the restructuring option. The 'restructuring' option is also dominant for all levels of the risk-pricing limit under examination over the 'no restructuring' option.

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<sup>15</sup> The values of *NPV* of bank returns estimated for each credit-policy regime are large and positive. Bank profits in the bank returns measure does not account for resource costs associated with the banking business, and *NPV* of loan balances at the end of the simulation period are both large and positive.

<sup>16</sup> *T*-statistics associated with Australia-wide portfolio estimates of the mean of *NPV* of bank returns are significant at the 1% level. At the region-industry level, *t*-statistics on all but one credit-policy regime for one region-industry segment were also significant at the 1% level. The large *t*-statistics indicate that credit-policy evaluations involving the first-order stochastic-dominance criterion are robust.

**Figure 7 Cumulative frequency functions for credit-policy regimes**

Credit-policy set 4 is not the most efficient regime for all region-industry segments. In fact, 21 of the 42 region-industry segments do not show credit-policy set 4 as the most efficient credit-policy regime. However, region-industry segments that exhibit FSD for credit-policy set 4 as a group accounted for 47% of the total farm population in 1995-96 and 43% of the expected *NPV* of bank returns estimated for the total-bank-loan portfolio. The second most common credit-policy option assessed to be most efficient is credit-policy set 6 (*rpl*=7.5% with ‘restructuring’ option). Credit-policy set 6 is FSD for 11 region-industry segments. As a group, these region-industry segments accounted for 19% of the total farm population in 1995-96. The third most common credit-policy option found to be most efficient is credit-policy set 2 (*rpl*=5% with ‘restructuring’ option). Credit-policy set 6 is FSD for 4 region-industry segments. These region-industry segments accounted for 17% of the total farm population in 1995-96.

Some region-industry segments exhibit a range over which the risk-pricing limit may be efficient in terms of stochastic dominance with a unique choice between the 6 credit-policy sets not obtained using either first-order, second-order or third-order stochastic dominance criteria. As a group, these region-industry segments accounted for 8% of the total farm population in 1995-96. Two region-industry segments exhibit third-order stochastic dominance (TSD) between risk-pricing limits of 2.5% and 5%. Under both pricing strategies, the ‘restructuring’ option was dominant. Similarly, two other region-industry segments exhibit

TSD between risk-pricing limits of 5% and 7.5%. Again the restructuring option was the favoured option.

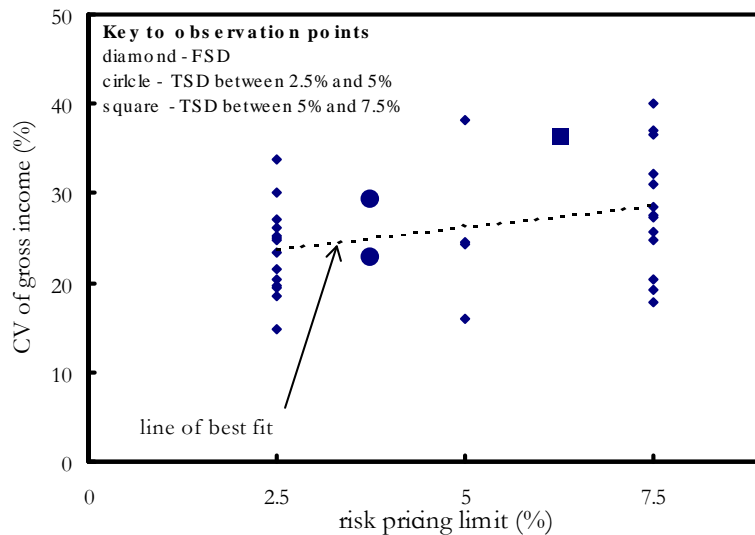
Finally, two region-industry segments exhibit TSD between credit-policy sets 5 and 6 ('no restructuring' option and  $rpl=7.5\%$  versus 'restructuring' option and  $rpl=7.5\%$ ). However, these two region-industry segments as a group only account for 0.6% of the total farm population.

## 7. Discussion

The major contributing factor determining the stochastic efficiency of the risk-pricing limit in loan reviews by region-industry segment appears to be variability of gross income.<sup>17</sup>

Variability of gross income is measured by the coefficient of variation (CV) of gross income in each region-industry segment for the 18-year period to 1995-96. For region-industry segments where FSD was indicated, averages of CV of gross income associated with risk-pricing limits of 2.5%, 5% and 7.5% were 21.2%, 25.7% and 28.2% respectively (see Figure 8). However, the range of CV of gross income in each of the three groups is wide.

**Figure 8 Scatter plot of credit-evaluation results against CV of gross income for the broadacre sector**



<sup>17</sup> Profitability, the relative importance of fixed assets in farm-business-asset structures, farm population trends and the sensitivity of salvage values of farm assets to current-gross income appeared to have negligible effects on the results. Other factors that may affect stochastic-efficiency outcomes relate more generally to the design of the simulation experiments. Design attributes include; first, the productivity parameters estimated to align region-industry data on new farm business borrowers to the credit-risk-classification system, and second, the experimental and statistical design used in the credit-screening, loan-review and policy-simulation experiments (Bramma 1999, p 247).

At the disaggregated level, sample sizes on which to make robust observations on relationships are small. However, a positive relationship between the level of risk-pricing limit found to be stochastically efficient and CV of gross income is broadly observed across four broadacre-industry classifications. The exception is the sheep industry. A slightly different pattern emerges for the dairy industry in which a low CV of gross income is estimated compared to the broadacre sector. A risk-pricing limit of 2.5% was assessed to be FSD across all regions in which the dairy industry occurs. Regional impacts within the broadacre sector on the relationship between risk-pricing limits and volatility of gross income were mixed. A strong positive relationship was found for the wheat-sheep zone. However, the relationship for the broadacre sector in either the pastoral zone or the high rainfall zone was not found to be as strong as the relationship found for the wheat-sheep zone.

The underlying reason for the positive relationship between volatility of gross income and efficient level of the risk-pricing limits in loan reviews appears to be linked to the range over which credit reserves of borrowers may potentially vary over time as discussed in Section 2.3. The results in this article may therefore be sensitive to a range of modelling and statistical assumptions. Importantly, the simulations assumed zero serial correlation in gross incomes. Validation testing found that zero serial correlation is generally applicable in the broadacre sector using data for gross income in the 18-year period to 1995-96 (Bramma 1999, p 226). In contrast, the dairy industry exhibited positive first-order serial correlation in all regions with the exception of regions in Victoria. Since serial correlation for gross income was indicated for the dairy industry, a negative relationship between volatility of gross income and efficient levels of risk-pricing limits may be found with further research.

These findings are contingent on well-defined credit-underwriting standards to be applied in loan originations.<sup>18</sup> Credit-underwriting standards in the simulation experiments are formulated to procure farm-business borrowers with loans that are fully secured using fixed assets and with default probabilities of no more than 6%. The credit-scoring results indicate that for farm business borrowers in Australia to achieve acceptable-credit quality, they must have high levels of productivity compared to the region-industry average (Bramma 1999, p 249).<sup>19</sup>

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<sup>18</sup> Credit-underwriting standards define acceptable entry conditions for all loan applications.

<sup>19</sup> Credit scoring is the systematic assessment of a borrower's financial data and other attributes to reach an assessment of a borrower's credit quality for placement into a credit-risk class (Barry and Ellinger 1989).

The reasons for the dominance of the ‘restructuring’ option over the ‘no restructuring’ option are straightforward. In brief, loan restructuring to an ‘interest only’ basis with possible credit limit extension - when default occurs - provides farm businesses greater capacity to better manage cash-flow fluctuations arising from volatile farm incomes. However, the finding that restructuring is stochastically efficient has one caveat; bank costs are assumed to be exogenous to credit risk. Loan restructuring can incur significant legal and administrative costs compared to the ‘no restructuring’ option.

## 8. Conclusions

This article analyses the risk-return efficiency of limits to which loan pricing accounts for credit risk in the Australian-farm sector. A key issue faced by banks is the trade-off between raising returns through higher risk premiums and the possibility of impairing credit quality. Banks may specify limits to which credit risk is priced into loans to ensure that credit quality is not impaired. The simulation results in this article suggest that there is a positive relationship between volatility of farm income and stochastic efficiency of the size of risk-pricing limits when dynamic relationships are considered. This positive relationship occurs despite the general notion that more volatility in gross incomes indicates more uncertainty surrounding their future values.

A key implication for credit policy is that Australian banks should price further across the credit risk spectrum to farm businesses with relatively volatile incomes compared to those with stable incomes. The simulations also found that this conclusion is not affected by different loan-restructuring strategies employed in the analysis. The placement of farms in default on an ‘interest-only basis with the possibility of credit extension’ also provides for large net benefits compared to providing borrowers with no option for loan restructuring.

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