NONMETROPOLITAN RESIDENTIAL MORTGAGE LENDING: LENDER'S SHARERS

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NonMetropolitan Residential Mortgage Lending: Lender Shares

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The urbanization of the population of the United States in the twentieth century has shifted the focus of the housing industry to the populations of cities and their problems. Anecdotal evidence indicates there may have been a reversal of the trend toward urbanization in the last decade or two, in part driven by the emergence of the Information Age and associated service industries. The ability to provide services via communications technology from remote or at least nonlocal geographic locations prompts a new look at the participants in nonmetropolitan housing markets; in this case the providers of housing finance.

One database which is emerging as a possible source for rural housing finance analysts is the data reported pursuant to the Home Mortgage Disclosure Act. This data, affectionately called the HMDA data, includes information on individual mortgage applicants and the properties they are interested in purchasing. The reporting requirements have changed several times recently and the data coverage is expanding although it still has important limitations.

The purpose of this paper is to explore the questions of which lenders are doing nonmetropolitan one-to four-family residential mortgage lending and what is the nature of their lending behavior. Related questions to be explored include whether Farmers Home Administration (FmHA) loans are an important market component, and what are the racial characteristics of nonmetropolitan borrowers.

The remainder of the paper will include a discussion of the HMDA data itself, analysis of nonmetropolitan lending as contained in the HMDA data in aggregate, and by lender group, and by state, and conclusions to be drawn about nonmetropolitan mortgage markets with suggestions for future research.

The Data

There are a variety of lenders which make mortgage loans in nonmetropolitan areas but there is not a universal repository for mortgage application data. Potential nonmetropolitan mortgage lenders include commercial banks, thrifts (including saving and loans and mutual savings banks), credit unions, mortgage banking companies, Farm Credit System (FCS) entities, individuals, builders, and possibly others. The depositories among these are subject to reporting requirements regarding their portfolio composition due to the presence of deposit insurance. However, this data does not give any information on number of loans, detailed information on loan terms, information on the borrower, or the location of the mortgaged property. Nondepositories are exempt from these reporting requirements on their lending activity.

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The Home Mortgage Disclosure Act was instituted to gather information on the distribution of mortgage credit on an individual application basis. It is a corollary to the Community Reinvestment Act (CRA). The CRA was designed to evaluate whether depositories which took deposits in specific geographic locations also made loans in those same geographic areas. In other words it was designed to address the inflow and outflow of credit in neighborhoods. HMDA on the other hand, reports on access to credit for individuals. HMDA focusses solely on mortgage credit while CRA applies to loans of all types.

Who Reports?

There are several criteria for determining who reports HMDA data in calendar year 1992 and they differ slightly for depository versus nondepository institutions. If a lender is a depository (commercial bank, thrift, or credit union) several conditions had to be met December 31, 1991. First, the lender had to have assets in excess of $10 million. Second, as of the same date the lender had to have a home or branch office in an MSA. Third, the lender had to have made at least one loan for the purchase or refinancing of a 1-4 family home. Finally, the lender was either (I) federally insured or regulated, (ii) the loan was insured, guaranteed, or supplemented by a federal agency, or (iii) the loan was intended for sale to Fannie Mae, Freddie Mac, or Ginnie Mae. If any of these are true the lender must report. Finally, if a lender is located in a state which has similar disclosure requirements, the lender may receive an exemption from HMDA reporting at the federal level.

Several reasons may exempt a nondepository lender from reporting. If it is not a "for profit" lender it need not report. If the lender's home purchase loan (including refinances) dollar volume did not exceed 10 percent of its total lending, it need not report. If the lender did not have a home or branch office in a Metropolitan Statistical Area (MSA) or received less than 5 mortgage loan applications of any type, it need not report. If the combined assets of the lender and any parent corporation were less than $10 million it need not report.

To Whom Do Lenders Report?

The depository institutions report to their primary federal regulator. These include the Federal Deposit Insurance Corporation (FDIC), the Office of Thrift Supervision (OTS), the Office of the Comptroller of the Currency (OCC), the Board of Governors of the Federal Reserve System (Fed), and the National Credit Union Administration (NCUA). The nondepository lenders report to the Department of Housing and Urban Development (HUD). These regulators consolidate the data under the auspices of the Federal Financial Institutions Examination Council (FFIEC) which serves as an umbrella organization for the financial regulators.

What Data Do Reporters Report?

Lenders report a set of variables taken from every loan application they receive whether they make the loan or not. These are incorporated into the Loan Application Register (LAR) which is eventually made available to the public. The variables are described below:

Loan type	conventional
	Federal Housing Administration (FHA) insured

Veteran's Administration (VA) guaranteed
Farmer's Home Administration (FmHA) insured

Loan purpose home purchase
refinancing of an existing mortgage
home improvement
multifamily

Occupancy owner-occupied principal dwelling
not owner-occupied
not applicable

Amount of the loan ($000)

Application Disposition originated
approved but not taken
denied
withdrawn
closed for incompleteness

Property location MSA code
State code
County code
Census tract number

Applicant race American Indian or Alaskan Native
Asian or Pacific Islander
Black
Hispanic
White
other
information not given by applicant in telephone or mail application
not applicable

Co-applicant race (same categories)

Applicant sex male
female
information not given by applicant in telephone or mail application
not applicable

Applicant income ($000)

Purchaser	loan not sold in calendar year covered by register Federal National Mortgage Association (FNMA or Fannie Mae) Federal Home Loan Mortgage Corporation (FHLMC or Freddie Mac) Government National Mortgage Association (GNMA or Ginnie Mae) FmHA commercial bank savings bank or savings association life insurance company affiliate institution other type of purchaser
Reasons for denial (up to three)	debt-to-income ratio employment history credit history collateral insufficient cash (down payment, closing costs) unverifiable information credit application incomplete mortgage insurance denied other

There are some additional data fields including the institutions identification number, some data quality and validity flags and other noneconomic information.

Data Quality

There are three major problems with this data which limit its usefulness in some analyses. They are lender reporting exemptions, item reporting exemptions, and errors. There are also some pitfalls to avoid when analyzing the data. These have to do with data not gathered and with the context within which the data are gathered.

Lender Reporting Exemptions.

The criteria for reporting are detailed above. These criteria leave a substantial portion of the mortgage applications unreported. Unfortunately the data are designed to capture information on the largest components of the population which means urban areas. Two lender groups under- or not represented in the nonmetropolitan areas are the Farm Credit System (FCS) and mortgage banking companies. Both are nondepositories.

The FCS escapes the reporting requirement through one of several avenues. Perhaps the most immediate exemption is the fact that FCS is a cooperative and can claim to be not for profit. Further, for many Associations in the FCS residential mortgages represent less than 10 percent of total loans. Other Associations have no offices in MSAs and receive less than 5 mortgage credit applications within MSAs annually. At any rate, FCS lenders would be a relatively small part of the total mortgage volume.

Mortgage banking companies are very important mortgage lenders in terms of market share nationally (about 50 percent) although their nonmetropolitan share has not been formally investigated until now. They are under-represented in the HMDA data due to their institutional structure and operational characteristics. They do not maintain a portfolio of loans but rather originate loans, hold them a very brief time (perhaps 60 days), and then sell them to investors. Consequently they are very highly leveraged firms with a small amount of assets even though they may originate an enormous volume of loans. Thus, many of them are not represented in the 1992 data because they fail the asset test.

Estimates of the share of total applications which are contained in the 1992 vary from 60 to 80 percent. Reporting requirements have already been altered to increase mortgage banking company participation in the 1993 data by adding a requirement that any nondepository lender making 100 or more home purchase loans (including refinancings) must report. Preliminary 1993 data show this will add about 750 mortgage banking companies to the data.

Item Reporting Exemptions.

The second area of difficulty in the HMDA data from the analysts perspective is the exclusion from reporting of certain applicant or property information. Of particular concern for this paper are the instances in which property location is not required. A lender may enter NA for each geographic variable on any application taken outside an MSA where the lender has an office or branch. Unfortunately this could be in either another MSA or a nonmetropolitan area. For a mortgage banking company having 5 applications in an MSA constitutes having a branch office there and requires providing all geographic codes.

Conversations with particular lenders reporting HMDA data indicate that most geographic codes of NA in the MSA category are nonmetropolitan applications. However, the analyst should be aware that assuming this will result in an upward bias in the estimates of nonmetropolitan activity.

Data Errors.

The HMDA data contain errors of both a quantitative and conceptual nature. Regulators screen the data for both quality and validity using broad parameters for each variable and requesting correction from lenders prior to making the data available to the public. Even after the error correction procedures were carried out by the regulators, some errors can be detected in the data.

<u>Quantitative errors</u>

Typical of these problems are census tract numbers which are not valid for the MSA in which they are purported to be located. These data can not be utilized in any analyses involving classification by neighborhood unless they can be corrected. However, even if the tract numbers cannot be corrected, if the loan records include valid data for all other variables, they can be used in other classifications.

The implications of quantitative errors vary according to the particular error. In many cases, the effect is to reduce the number of usable observations for the analysis. There are valid reasons, derived from the reporting requirements as laid out by the regulators, for some data to be missing. For example, applicant income may be missing because it was not used in the underwriting process and therefore need not be reported. Alternatively, it may not be reported because the data entry person for the reporting company failed to enter it. In the first instance its absence is valid and in the second instance it is an error. As a result, sorting the data by different variables results in different numbers of total observations for both valid and error-related reasons.

To illustrate the sorting problem, the following are the number of applications available when the 1992 data are sorted five different ways. Total one- to four-family applications are 9,997,874. This number falls to 9,272,555 when the data are sorted by the applicant race variable. When sorted by applicant income there are 7,671,455 applications. Sorting by applicant sex results in 6,955,447 valid applications. When applications are sorted by neighborhood using matching census data, the number of applications is 7,975,760.

Conceptual errors

Conceptual errors are beyond the analyst's control to correct. These arise when the reporting company misinterprets the nature of the data requested. One example would be a lender reporting the applicant's income taken from the application rather than the income verified during the underwriting process. The loan decision is based upon the income verified in the underwriting process. Thus, verified income should be employed when evaluating the lending decision.

A second conceptual error would be the recording of an incorrect census tract number on an application. While the property may not be located in the recorded tract, the recorded tract may in fact exist as a valid tract in that MSA. There would be no way, short of looking at the application, to know that the error had occurred. The same issue is existent for many of the variables in the data set, e.g., applicant income, sex, and race.

The implications of conceptual errors are that incorrect inferences may be drawn from statistical analysis. This error would be undetectable due to the conceptual and undetectable nature of the problem. For example, a particular software was determined to use a default character which, while intended to enter unknown as the race of the borrower, actually entered the applicant's race as American Indian. Were it not the case that the company analyst questioned the number of American Indian applicants the company had, the error would have gone undetected

Interpretation Pitfalls To Avoid

Market coverage: As noted above all mortgage applications for 1992 are not contained within this data. For example, the 1993 HMDA data will contain at least 750 more mortgage companies.

Common reporters: The number of reporters changes from year to year. Thus, when making inter-year comparisons of the data, analyses must account for the difference. One approach is to use a common reporter dataset.

The Economy: The performance of the economy will greatly affect the HMDA data. The mortgage industry was the beneficiary of a declining interest rate environment in 1992. This spawned a huge growth in refinance applications. Likewise, interest rates being the most important factor in housing affordability, there was a significant growth in lower income application activity. Year-over-year comparisons must account for the changing economic climate.

Policy changes: The FHA component of applications was likely affected by a 1991 change in the provisions covering the portion of closing costs which could be financed. The change was rescinded in mid-1992. Also, increased regulatory focus on minority and low income lending led lenders to increase outreach efforts to those groups of potential borrowers. Increasing credit risk is correlated with membership in these groups. This would tend to push down approval rates and push up denial rates as more applications are received.

Neighborhoods: Various analysts classify the data by neighborhood characteristics. Classifying applications by the minority concentration of the property's neighborhood omits important information. It is possible that the majority of a lender's applications received in a predominantly white neighborhood were from minority applicants. Further, this classification does not reveal the composition of the minorities populating that particular neighborhood.

Likewise, classification by the neighborhood's median income does not certify that the applications came from applicants whose individual incomes were near the median. Nor does it indicate whether the income is the household's total income. In some cases applicants used the income and credit record of one spouse as all installment credit in the household was carried in the other spouse's name and was an inferior credit history.

Applicant characteristics: Considering applicant race; if there are co-applicants both of the same race, the application is classified by that race but the reader cannot tell that there were co-applicants. The same is true of the sex, and income variables. For the joint race category, the reader cannot tell what the non-white applicant's race is nor which was the primary and which the co-applicant.

Loan types: The data are dominated by refinances in terms of loan dollar volume (61 percent) and number (52 percent). On the other hand, home improvement applications comprised 13 percent of total number of applications but only 3 percent of dollar volume. This is because the average home improvement loan is dramatically smaller than the average refinance of purchase loan. Also, some firms specialize in mobile home (manufactured home) lending. These types of loans tend to be riskier than other purchase mortgages and thus can be expected to have higher denial and lower approval rates.

Lender institutional differences: The four major lender groups feature institutional structures which dictate fundamentally different lending behavior. Only mortgage companies are not depositories. Being a depository affects the way mortgage lending is funded, priced, and the options regarding what to do with an originated loan. Deposit-taking lenders fund their mortgage operation internally and maintain a portfolio of assets including mortgages and other types of loans funded by those deposits. Thus, whereas mortgage companies who borrow funds on a line of credit (perhaps from a bank) in order to lend must sell their loans to investors to repay the line of credit, depositories can retain the loan in their portfolio or sell it depending on their objectives. This is a particular advantage when attempting to lend to riskier borrowers. Investors in mortgage securities are typically risk-averse. Thus, without a portfolio within which to hold riskier loans, mortgage companies simply can't make them. Furthermore, mortgage companies have only one product; mortgages. Depositories typically view mortgages as only one of a variety of products (earning assets) available to them and can utilize cross-product pricing strategies to competitive advantage in mortgage markets.

Results

These are 1992 data and include only nonmetropolitan one-to-four family mortgage applications. Jumbos are included in conventional applications. Jumbos are loans which exceed the limit on the size of loan the secondary market agencies (Freddie Mac and Fannie Mae) are allowed to purchase from lenders. Multifamily applications were excluded as they would distort the dollar volume measurements and there are some different dynamics in the approval process which we believe not to be comparable to the one-to-four market.

The data include reports from 9,073 lenders including 5,468 commercial banks, 1,395 saving associations, 1,706 credit unions, and 504 mortgage banking companies. These lenders reported a total of 9,997,874 applications for 1-4 family home purchase, home improvement, or refinancing loans. Of these applications, 1,968,329 or 19.7 percent were for nonmetropolitan properties. In general that means the properties were located in areas of population of less than 50,000 for cities and counties with populations of under 30,000.

All Lenders: Loan Purpose.

The nearly two million nonmetropolitan loan applications were for almost $140 billion in mortgage credit (Table 1). The average loan size was over $70,000. Purchase applications comprised about 45 percent of the total while refinances were slightly less than 42 percent. The remainder were home improvement applications. The nonmetropolitan shares were substantially different than the national totals. Nationally, home purchase applications were only 35 percent of the total with refinances taking a 52 percent share. Home improvement applications comprised nearly 14 percent of applications but less than 4 percent of dollar volume. Average application amount was about $19,000 versus $93,000 for refinances and $66,000 for purchases.

Not all applications actually resulted in loans of course. In fact overall only 63 percent of all applications resulted in a loan being originated (Table 2). This is substantially lower than the national rate of 72 percent. The purchase application origination rate for nonmetropolitan loans, 55 percent, lagged far behind the national figure of 70 percent. Home improvement and refinancing origination rates were close to national rates with home improvements slightly higher and refinancings slightly lower. The much lower approval rate of nonmetropolitan home purchase loans resulted in their comprising only 39 percent of all nonmetropolitan loans actually made.

By Lender Group: Loan Purpose.

Commercial banks dominate the nonmetropolitan market with a 50 percent share of total applications (Table 5). This is buttressed by their 72 percent share of the home improvement loan market. The absence of a large secondary market for its loan product restricts it to primarily portfolio lenders. These loans tend to be small balance and thus don't dominate the dollar volume of lending. Mortgage banking companies Have the largest share of home purchase applications nationally at 41 percent but in the nonmetropolitan market their share falls to 37 percent and commercial banks predominate at 45 percent market share. The bank share of refinance applications is even higher at 47 percent while thrifts hold second place at 28 percent share.

The share of applications which eventually become loans varies by lender (Table 6). The effects of portfolio versus nonportfolio institutional structure can be observed in the rate of origination. Mortgage banking companies originated 50 percent of their home purchase applications whereas banks originated 55 percent and other portfolio lenders originated about 68 percent. Not having a portfolio within which to hold loans means mortgage banking companies must sell all loans made into the secondary market. Investors have stringent criteria for controlling the riskiness of the mortgage product which are reflected in the underwriting standards. The nature of nonmetropolitan real estate markets is such that they are not as standardized as in metropolitan areas. Thus, the ability to make a loan with nonstandard characteristics is strongly related to having a portfolio.

All Lenders: Loan Type.

FmHA mortgages were not very important in the overall nonmetropolitan market in 1992. There were less than 1,500 total applications of which 56 percent were approved (Table 3).

Nearly 89 percent of applications which ultimately ended up as loans were for conventional loans (Table 4). they comprised over 90 percent of dollar volume. FHA applications comprised over 7 percent of nonmetropolitan loans while the reminder, slightly less than 4 percent, were VA.

The overall origination rate for the conventional applications was 64 percent which was exceeded only by the 67 percent for VA applications. Average loans size varied dramatically from over $80 thousand for VA loans to $55 thousand for FHA loans.

By Lender Group: Loan Type.

The nonmetropolitan market shares by lender group are quite different from market shares including urban applications. For example, mortgage banking companies hold over 70 percent share in FHA and VA products in the total market whereas in the nonmetropolitan markets these shares are 50 percent or less (Table 7). Nonetheless, the leading lender group for government backed mortgage product is mortgage banking companies. Commercial banks dominate the conventional market with over 50 percent of the total again in part due to their total domination of the home improvement market.

Ability to place a mortgage product in portfolio is again identifiable in looking at origination rates across lenders (Table 8). In the conventional loan market, mortgage banking companies have the lowest approval rates reflecting the importance of secondary market attitudes about risk.

All Lenders: Applicant Race and Loan Purpose.

There was a wide variation among applicants of different races regarding the purpose of the loans being applied for. African-American applicants were heavily focussed on home ownership with 62 percent of total black applications for this purpose (Table 9). The remainder of their applications were roughly evenly split between home improvement and refinancing applications. Only 33 percent of Asian applications were for purchase of a home. Over 62 percent were for the refinance of an existing mortgage.

African-Americans were the second largest applicant group after whites. The dominant=ant borrower group by race were whites with 89 percent of total applications.

All Lenders: Applicant Race and Loan Type.

All racial groups made the vast majority of their applications for conventional mortgage products. However, there was a significant difference among races over just how dominant the share was (Table 10). Asians made 94 percent of their applications for conventional loans while blacks made 79 percent. These were the highest and lowest shares. Blacks and Hispanics each made 14 percent of their applications for FHA-insured products, the highest rate among racial groups. Only 4 percent of Asians made application for an FHA product.

By Lender Group: Applicant Race and Loan Purpose.

Evaluating the relative market penetration of lenders among different racial groups points out the dominance of commercial banks among all groups except Asians and to a lesser degree, blacks (Table 11). However, the impact of loan purpose is fairly dramatic. Looking at home purchase loans only (Table 12) shows that the bulk of commercial bank lending is focussed among white borrowers. Mortgage banking companies have greater shares of home purchase loans applications from Hispanics, Asians and African-Americans. Saving associations also have significant penetrations of Hispanic and Asian communities.

Conclusions and Implications

The HMDA data are a useful tool for housing market analysts but suffer significant flaws. The analyst simply has to take care in pointing out what can and cannot be inferred from the data as applied. The most limiting aspect of the HMDA data for the nonmetropolitan housing market analyst is the issue of reporting exemptions and exclusions. The data are not designed to ensure 100 percent coverage of nonmetropolitan mortgage applications. Further, even where some application information is gathered, it is sometimes impossible to identify the geographic location of the application. Therefore, the tendency is to overestimate the amount of nonmetropolitan lending documented in the existing data. However, this may be offset by the unreported lending of exempted institutions.

Under these assumptions, the amount of nonmetropolitan application activity and resultant lending is nearly 20 percent of the national total. Approval and denial rates differ from metropolitan rates in that nonmetropolitan approval rates are lower and denial rates are higher in general and across loan purpose. This can probably be attributed to the less standardized nature of nonmetropolitan real estate, and the less liquid nature of the market for it. Evidence for this can be inferred from the dramatically lower approval rates for nonmetropolitan home purchase applications relative to the urban counterpart.

Secondary market agencies are talking about increasing mortgage credit flows to nonmetropolitan areas. Therefore, research into differences in mortgage product and market performance and property characteristics are warranted. Efficient access to capital for urban real estate has been fostered by the reduction of risk through standardized mortgage products and increased access to accurate risk assessment. Provision of this same information for nonmetropolitan markets will improve capital market accessibility.

Table 1. National Nonmetropolitan Mortgage **Applications** By Loan Purpose

	Number	Share (%)	Dollar Volume ($ mil.)	Share (%)	Average Size ($ thou.)
Purchase	875,644	44.5	57,567	41.3	65.7
Improvem't	269,070	13.7	5,014	3.6	18.6
Refinance	823,615	41.8	76,710	55.1	93.1
Total	1,968,329	100.0	139,291	100.0	70.8

Table 2. National Nonmetropolitan Mortgage **Originations** By Loan Purpose

	Number	Share (%)	Dollar Volume ($ mil.)	Share (%)	Average Size ($ thou.)
Purchase	482,863	38.7	36,450	39.5	75.5
Improvem't	167,649	13.4	3,224	3.5	19.2
Refinance	596,149	47.9	52,561	57.0	88.2
Total	1,246,661	100.0	92,236	100.0	74.0

Table 3. National Nonmetropolitan Mortgage **Applications** By Loan Type

	Number	Share (%)	Dollar Volume ($ mil.)	Share (%)	Average Size ($ thou.)
Conventional	1,730,188	87.9	125,359	90.0	72.4
FHA-insured	167,220	8.5	8,279	5.9	49.5
VA-guaranteed	69,443	3.5	5,570	4.0	80.2
FmHA-insured	1,478	0.1	82	0.1	55.3
Total	1,968,329	100.0	139,291	100.0	70.8

Table 4. National Nonmetropolitan Mortgage **Originations** By Loan Type

	Number	Share (%)	Dollar Volume ($ mil.)	Share (%)	Average Size ($ thou.)
Conventional	1,107,199	88.8	83,365	90.4	75.3
FHA-insured	92,015	7.4	5,034	5.5	54.7
VA-guaranteed	46,618	3.7	3,795	4.1	81.4
FmHA-insured	829	0.1	45	0.1	54.2
Total	1,246,661	100.0	92,240	100.0	74.0

Table 5. National Nonmetropolitan Market Share By Lender Group By Loan Purpose: Number of **Applications**

	Purchase	Improvement	Refinance	Total
Mortgage bankers	321,435	24,482	176,378	522,285
Comm'l bankers	394,940	192,429	386,150	973,519
Saving Assns.	147,674	29,023	231,592	408,289
Credit Unions	11,595	23,136	29,505	64,236
Total	875,644	269,070	823,615	1,968,329

Table 6. National Nonmetropolitan Market Share By Lender Group By Loan Purpose: Number of **Originations**

	Purchase	Improvement	Refinance	Total
Mortgage bankers	159,327	10,099	117,348	286,818
Comm'l bankers	215,293	120,603	289,302	625,198
Saving Assns.	100,246	17,875	166,917	285,038
Credit Unions	7,953	19,072	22,582	49,607
Total	482,863	167,649	596,149	1,246,661

Table 7. National Nonmetropolitan Market Share By Lender Group By Loan Type: Number of **Applications**

	Conventional	FHA-insured	VA-guaranteed	FmHA-insured
Mortgage bankers	409,865	83,800	28,249	371
Comm'l bankers	901,184	47,910	23,865	560
Saving Assns.	359,010	34,280	14,453	546
Credit Unions	60,129	1,230	2,876	1
Total	1,730,188	167,220	69,443	1,478

Table 8. National Nonmetropolitan Market Share By Lender Group By Loan Type: Number of **Originations**

	Conventional	FHA-insured	VA-Guaranteed	FmHA-insured
Mortgage bankers	225,642	42,250	18,693	233
Comm'l bankers	579,524	29,086	16,301	287
Saving Assns.	255,527	19,769	9,434	308
Credit Unions	46,506	910	2,190	1
Total	1,077,100	92,015	46,608	829

Table 9. National Nonmetropolitan Mortgage **Application** Shares By Loan Purpose And Applicant Race

	Native American	Asian	African-American	Hispanic	White
Purchase	5,481	14,372	51,520	27,389	712,272
Improvem't	1,651	1,961	16,330	14,069	186,366
Refinance	3,174	26,998	15,179	18,365	679,463
Total	10,306	43,331	83,029	59,823	1,578,101

Table 10. National Nonmetropolitan Mortgage **Application** Shares By Loan Type And Applicant Race

	Native American	Asian	African-American	Hispanic	White
Conventional	9,095	40,918	65,581	49,858	1,395,764
FHA-insured	869	1,785	11,745	8,137	128,863
VA-guaranteed	337	627	5,594	1,797	52,268
FmHA-insured	5	1	109	45	1,206

Table 11. National Nonmetropolitan Mortgage **Application** Lender Shares By Applicant Race, All Loan Purposes (percent)

	Native American	Asian	African-American	Hispanic	White
Mortgage bankers	25	35	36	27	25
Commercial banks	57	26	48	47	51
Saving Assns.	14	36	13	24	21
Credit unions	3	2	3	2	3

Table 12. National Nonmetropolitan Mortgage **Application** Lender Shares By Applicant Race, Home Purchase Loans (percent)

	Native American	Asian	African-American	Hispanic	White
Mortgage bankers	31	43	48	39	35
Commercial banks	57	26	42	38	46
Saving Assns.	11	21	10	22	17
Credit unions	1	1	1	1	1

Credit Risk Assessment and The Opportunity Costs of Loan Misclassification

Govindaray Nayak and Calum G. Turvey[1]

Credit portfolio management involves the identification and monitoring of loans across various risk classes. The performance of loan accounts determines the stability and profitability of financial institutions and it is for this reason that financial institutions screen loan applications before making credit decisions, and review existing loan accounts to decide the level of monitoring required. Despite the on-going development of statistical credit scoring models most models used by lenders or recommended by academics fail to explicitly consider lenders' profit maximizing objective, although profit maximization is usually assumed implicitly. The purpose of this paper is to present an alternative view of the credit assessment problem which explicitly includes the opportunity costs of misclassifying an acceptable or unacceptable loan. We review first traditional approach of credit assessment and then extend these models (i.e. Logit) to include the costs of misclassification. Assuming a profit maximizing objective we then establish the new selection criteria. This criteria is compared against a Logit model using Canadian Farm Credit Corporation loans data.

Credit Assessment and the Costs of Loan Misclassification

To combat asymmetric information many lenders in Canada and the United States have adopted formal credit evaluation models to screen loan applicants (Ellinger et al). Most credit assessment models can adequately predict the loan worthiness of a large portion of loans, but, none are perfect and are subject to error. In loan classification models there are two types of errors: Type I error refers to accepting a loan which is actually of high credit risk, and Type II error refers to rejecting a loan which is of low credit risk.

In both these cases the lender loses profits. For Type I error losses include not only lost principal, but also lost interest on principal during the period of litigation and foreclosure. In addition to loan losses there are incremental increases in administrative costs, legal fees, insurance costs, and property taxes. For Type II error, the lender foregoes the revenues associated with a good loan. Although it may be argued that rejecting a good loan is not too costly, it can be if the alternative loan is of high credit risk, so that full recovery of lost revenue may not be obtainable. The costs of Type I error are more visible since they are observed through loan losses, and loans which are temporarily in arrears. Type II error is not often observable because the ultimate disposition of the rejected loan is unknown.

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It is customary to define the expected profit from a loan advanced given the possible alternatives in repayment (i.e possibilities of regular repayment, temporary default and, foreclosure), considering only the cost of Type I error. The important thing to note is that the opportunity cost of lost interest income by rejecting a good loan (cost of Type II error) is not explicitly considered in the lenders profit functions. In order to increase the expected profit, the lending decision must include the opportunity cost of lost interest income by rejecting a good loan and in this context the inclusion of costs associated with Type II error in a credit scoring model is as important as including the cost of Type I error.

In formal (Logit, Probit credit scoring models etc.) and informal (ad hoc) credit scoring models the group assignment rule is based purely on the predicted probability of default (or other scoring criteria) in which a loan is accepted if it scores below a given cutoff and rejected otherwise. Such criteria implicitly assume that the costs of Type I and Type II errors are equal. In practice, these costs cannot be equal. If the costs of misclassification are not equal alternative criteria must be considered in which predicted default probabilities or likelihood values must be weighted by their respective costs of misclassification. In doing so there becomes an explicit trade off between the probability of default and cost of Type I error on the one hand and between the probability of repayment and cost of Type II error on the other hand. For example, if the predicted probability of default of a borrower is lower than the probability of repayment and the associated cost of Type I error is much larger than the cost of Type II error, then the lender will be better off by classifying that borrower as bad than as good. This study incorporates these opportunity costs into the credit assessment criteria to minimize the costs / maximize the profits to the lender.

Cost of Type I Error

The cost of Type I error is the cost of losing some portion of principal and interest on principal during the process/period of loan foreclosure. The incremental increase in administrative costs, legal costs, costs of taking possession, maintaining, and disposing the secured assets, and the concessions given by lowering the interest rate and/or waiving some portion of accumulated interest and/or principal increases the Type I error loss to the lender. Thus the cost of misclassifying an unacceptable loan (type=1) as an acceptable loan (type=0) can be defined as

$$(1)\qquad C(0/1)=([a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4+COST\text{-}AR]-[s*SL])*(PLL/\pi_1) +TCOST*(1-[PLL/\pi_1]).$$

Where,

- r is the interest rate
- a is the proportion of loans in default for less than 1 year
- b is the proportion of loans in default for more than 1 year but less than 2 year
- c is the proportion of loans in default for more than 2 year but less than 3 year

- d is the proportion of loans in default for more than 3 year
- $a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4$ is expected gross uncollected interest i.e the amount of income that could have been earned had the repayment been regular
- COST includes the costs of taking possession, maintaining (insurance premium, property tax etc.), disposing of the secured assets, legal costs, increased administrative costs and concessions given (waiver of a portion of accumulated interest and/or principal and reduction of the interest rate charged) in case of foreclosed loans
- TCOST is the costs of recovering the loan amount in temporary default which includes legal costs/lawyer notice fee, increased administrative costs and concessions given (waiver of a portion of accumulated interest and/or principal and reduction of the interest rate charged) in case of loans which are in default temporarily
- AR is the amount of income, including the rental income from the secured property, if any received during the process
- s is the security value trend adjustment factor
- SL is the security-to-loan ratio.
- PLL is the probability of loan loss

The expected cost of Type I error is the magnitude of loss for a $ loan when an unacceptable borrower is accepted as an acceptable borrower by the model. It can be seen that this cost consists of two components; one, the cost associated with loans that will be foreclosed and two, the cost associated with loans that will be in default temporarily. The assumption here, which is realistic also, is that foreclosed loans will be from the default group (i.e first a loan will become default and when there is no chance of recovery of arrears by usual follow-up/persuasion, lenders will go for foreclosure). So there is PLL/π_1 probability of a defaulted loan being foreclosed and $1-(PLL/\pi_1)$ probability of being in default temporarily.

Cost of Type II Error

The cost of Type II error is the opportunity cost of foregone revenue associated with a good loan. Though the cost of Type II error is not observable, and it can be argued that rejecting a good loan is not too costly, it can be costly if the alternative loan is of high credit risk. In this case, the lost revenue may not be obtainable and the cost of Type I error in the alternative loan adds to the cost. So Type II error is also equally important as far as the lender's profit is concerned. Thus the cost of misclassifying an acceptable loan (type=0) as an unacceptable loan (type=1) can be defined as

$$(2) \qquad C(1/0)=r-(\pi_0*r)+\pi_1\{([a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4+COST-AR]-[s*SLB])*(PLL/\pi_1)+TCOST*(1-[PLL/\pi_1]).$$

Where r, a, b, c, d, COST, TCOST, AR, s, PLL are defined as above and SLB is the average security to loan ratio.

The expected cost of Type II error is the magnitude of loss for a $ loan when an acceptable borrower is rejected as an unacceptable borrower by the model. This consists of three components. The first component is foregone interest income (r) by rejecting a good loan. The second and third components are based on the assumption that the lender will not keep the un-lent money idle and will lend that money to an alternative borrower. This alternative borrower, once again, may be good or bad. There is π_0 probability of this borrower being good and π_1 probability of being bad. So lender can get r interest income with π_0 probability and loose

$$[a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4+COST-AR]-[s*SLB])*(PLL/\pi_1)+TCOST *(1-[PLL/\pi_1]$$

with π_1 probability in the alternative loan.

These costs of misclassification cannot be negative. That is there may not be any cost to the lender, but there cannot be any gain by misclassification. So these costs can be either greater than, or equal to, zero.

Properties of Costs of Type I and Type II Errors Compared

In this section, the costs of Type I and Type II errors are compared and discussed with respect to variables of influence.

(i) The relation between the change in costs of Type I and Type II errors for a unit change in interest rate (r) depends on the probability of default (π_1) and the probability of loan loss (PLL). This relation can be summarised as follows:

(3) $\partial C(0/1)/\partial r = \partial C(1/0)/\partial r$ if $\pi_1 = \sqrt{PLL}$

(4) $\partial C(0/1)/\partial r > \partial C(1/0)/\partial r$ if $\pi_1 > \sqrt{PLL}$

(5) $\partial C(0/1)/\partial r < \partial C(1/0)/\partial r$ if $\pi_1 < \sqrt{PLL}$

The change in costs of Type I and Type II errors for a unit increase in interest rate (r) will be equal when $\pi_1 = \sqrt{PLL}$. If $\pi_1 > \sqrt{PLL}$, then a change in the cost of Type I error will be more than a change in the cost of Type II error. If $\pi_1 < \sqrt{PLL}$, then a change in the cost of Type II error will be more than a change in the cost of Type I error.

(ii) For a unit increase in COST and TCOST, the increase in the cost of Type I error is $1/\pi_1$ times more than the increase in the cost of Type II error.

(iii) Similarly, for a unit increase in AR and SL, the change in the cost of Type I error decreases $1/\pi_1$ times more than the change in the cost of Type II error.

(iv) For a unit increase in probability of loan loss, the cost of Type I error changes $1/\pi_1$ times more than the cost of Type II error changes; the direction of change depends on the values of LOSS[1] and TCOST.

(v) A unit increase in π_1 increases the cost of Type II error by interest rate (r), whereas the direction and size of change in the cost of Type I error depends on the values of TCOST and LOSS.

(vi) There is no relationship between probability of loan loss and probability of loan default as far as the cost of misclassifying a current loan as a non-current loan is concerned. There is a relationship between these two as far as the cost of misclassifying a non-current loan as current is concerned. But, the size and direction depends, once again, on the values of LOSS and TCOST.

Theory and Methodological Design

To examine loan acceptance criteria based on the opportunity costs of loan misclassification rather than probability cut-offs relative probability that a farm

[1]LOSS = $a(1+r)+b(1+r)^2+c(1+r)^3+d(1+r)^4$+COST-AR-[s*SL] i.e the amount of loss for a $ loan in case of foreclosure.

with observed characteristics x_i (such as debt to asset ratio, liquidity ratio etc.) is drawn from the delinquent or non-delinquent group can be estimated. In this case the existence of well-defined groups is presumed, so that the focus is only on the problem of deciding how to classify, as yet, unknown observations to obtain least expected loss to the lender.

Prediction

Classification probabilities and rules are constructed in an intuitively appealing fashion by comparing the two group likelihood functions. If the two groups are not of the same size, the likelihood must be weighted before they can be compared. Let π_0 be the a priori probability of an observation being drawn from group 0 (good loans), and π_1 be the priori probability of an observation being drawn from group 1 (bad loans). Let us choose regions R_0 and R_1 such that if the sample point falls in R_0, we classify the individual into group 0, and if it falls in R_1 we classify the individual into group 1. Suppose, the researcher perceives the cost of misclassification of C(0/1) and C(1/0), where C(i/j) is the cost of classifying an observation as group i when it truly belongs to group j. Following Anderson (1958) and Maddala (1983), the expected total cost of misclassification is

(6) $$Miscost = C(1/0)\pi_0\int_{R_1} f_0(x_n)\,dx + C(0/1)\pi_1\int_{R_0} f_1(x_n)\,dx.$$

Because

(7) $$\int_{R_1} f_0(x_n)\,dx + \int_{R_0} f_0(x_n)\,dx = 1$$

We have

(8)

$$Miscost = C(1/0)\pi_0[1-\int_{R_0} f_0(x_n)\,dx] + C(0/1)\pi_1\int_{R_0} f_1(x_n)\,dx$$

$$= C(1/0)\pi_0 + \int_{R_0}[C(0/1)\pi_1 f_1(x_n) - C(1/0)\pi_0 f_0(x_n)]\,dx$$

This *Miscost* is minimized if R_0 is chosen so that

(9) $C(0/1)\ \pi_1\ f_1(x_n) < C(1/0)\ \pi_0\ f_0(x_n)$.

Thus the classification rule for minimizing the expected costs of misclassification would be to assign an observation with characteristics index x_i to group 0 if

(10) $$\frac{f_0(x_n)}{f_1(x_n)} \geq \frac{C(0/1)\times\ \pi_1}{C(1/0)\times\ \pi_0},$$

and to group 1 otherwise.

It can be noticed that if costs of misclassification are equal i.e C(0/1)=C(1/0), then the classification rule is identical to assigning observations to the group with the highest probability. But in practice, these costs of misclassification are not equal.

Predictive Accuracy

The prediction accuracy involves a comparison of the predicted acceptable and unacceptable observations with the actual current and non-current observations. In Logit model the prior probabilities will be used as a cutoff to classify the borrowers as acceptable or not. Using the prior probability as a cutoff point is the latest advocation in the agricultural credit scoring techniques (Miller and LaDue,1989). This is done by determining the percentage of current and non-current loans in the sample. These percentages are used as the prior probabilities and on the basis of this a borrower will be classified into one of the categories. The prediction accuracy is assessed in the same way as in Cost minimization model.

Lender's Profit/dollar Loan

The performance of any credit scoring model should not be judged purely on the basis of its prediction accuracy or the proportion of errors. The opportunity costs associated with Type I and Type II errors in prediction are also important. To assess the performance of the Cost minimization model relative to the performance of the Logit model, we should have a common measure which can consider both the prediction accuracy and the opportunity costs of errors in prediction. Because the prediction accuracy of the Logit model may be more than the Cost minimization model, the opportunity costs associated with Type I and II errors may be less in the Cost minimization model. In this case it is not possible to compare the models' performances. The differences in the proportions of errors (Type I & II) and in the opportunity costs of these errors in prediction can be captured in the lender's profit / $ loan.

The model's expected lender's profit function for $1 loaned would be

$$(11)\qquad \frac{N_{00}}{N}\times\bar{r}+\frac{N_{10}}{N}\times -C(0/1)+\frac{N_{01}}{N}\times -C(1/0)+\frac{N_{11}}{N}\times$$

where

N = total number of borrowers

N_{00} = the number of borrowers classified as acceptable who are current

N_{01} = the number of borrowers classified as unacceptable who are current

N_{10} = the number of borrowers classified as acceptable who are non-current

N_{11} = the number of borrowers classified as unacceptable who are non-current
$\bar{r}$ = average interest income/dollar loaned

C(0/1) = cost of loaning a dollar by classifying a non-current loan as acceptable

C(1/0) = opportunity cost of not loaning a dollar by classifying a current loan as unacceptable

It may be noted that this profit of the lender is not the actual profit earned by lending. This profit function is credit scoring model's lender's profit function. From this we can only calculate the difference in the magnitude of expected profit between the Cost minimization and the Logit models given lending decisions are taken using these models.

Data and Model Variables

The data for this study were provided by the Farm Credit Corporation of Canada. The loans advanced during 1981 to 1988 and remaining outstanding as of January 31, 1992 were used. Data consist of 26 variables on 12668 loans.

Based on the relevance of the variables to loan default and their usage in past research (Lufburrow et al.; Barry and Ellinger; Miller and LaDue; Turvey and Brown; Turvey) the ratios of liquidity, profitability, leverage, efficiency, repayment ability and, security were used as the explanatory variables . The FCC also uses these variables in its Business Management Framework tools. Since the FCC loans are distributed across different regions and farm types, region and farm type dummy variables were used to capture the variations across region and farm type. These model variables are generated using existing variable definition. In addition to this, relevant data/information for computing the opportunity costs of misclassification are also collected i.e costs include maintaining the collateral during the loan foreclosure process (maintenance cost, insurance premium, property tax etc), the average length of time the loans will be in default once the foreclosure process is started, changes in collateral market value, legal costs, the amount of income received during the process, and the amount of interest and /or principal waived and interest rate lowered in case of negotiated settlements.

Validation of the Results of the Models

Using the same sample for estimation of the model and evaluation of the prediction accuracy may result in overly optimistic prediction accuracy. To overcome this problem the sample is first divided randomly into two sets - 75% of the data for estimation of the models and 25% as a hold-out sample for validating models results. The sample set was divided into two sets by random number choice. So the cases in the hold out sample are independent of the cases used in the estimation of the model and both the sets are drawn from the same distribution.

Results and Discussion

In this section we discuss the results of the analysis of the Cost minimization model and compare it with the results of the Logit model. The results of both these models are validated using hold out sample. We give empirical evidence to show the superiority of the Cost minimization model over the well recognised Logit model.

Estimation of the cost components

The information on interest rate (r), security to loan ratio (SL), probability of loan loss (PLL), and prior probabilities of current and non-current loans (π_0 and π_1) were readily available in the data provided by the FCC. Information on COST, AR, and TCOST are not readily available but estimates of these costs were collected by discussing the details with the officers of the FCC.

Classification Assignment Rules With The Opportunity Costs of Loan Misclassification

The group assignment rule in existing credit scoring models is purely based on the predicted probability of default with the costs of misclassification assumed to be equal. These costs, as defined earlier, are not equal. The inclusion of these costs results in a different assignment rule, than in the traditional models. It can be seen from the assignment rule in equation 10 that the likelihood functions (likelihood of being accepted and unaccepted) are weighted by their respective costs of loan misclassification. The difference in the costs of loan misclassification changes the weighted likelihood functions and their ratios. This results in change in assignment of observations to acceptable and unacceptable groups.

Of the 8718 observations of test sample, both the models predicted 4238 observations as acceptable and 1854 as unacceptable i.e 69.88% of observations are common in prediction (Table 1). The models differ in predicting the remaining 30.12% observations. 2611 observations predicted as unacceptable by the Logit model are predicted as acceptable by the Cost minimization model and 15 observations predicted as acceptable by the Logit model are predicted as unacceptable by the Cost minimization model. These results indicate how inclusion of costs of misclassification results in difference in predictions.

Table 1. Comparison of Group Assignment of Observations in Cost Minimization and Logit Models

Particulars of Prediction	Actual		
	Current	Non-current	Total
Predicted as acceptable by both the models	3488	750	4238
Predicted as unacceptable by both the models	833	1021	1854
Predicted as acceptable by Cost minimization model and unacceptable by Logit model	1426	1185	2611
Predicted as unacceptable by Cost minimization model and acceptable by Logit model	11	4	15
Total	5758	2960	8718

Evaluation of Predictive Accuracy of The Cost Minimization Model Relative to The Logit Model

The lender's profit not only depends on the prediction accuracy, but also on the opportunity costs of loan misclassification. Thus profits are maximized when the prediction accuracy is maximum and the costs of misclassification are minimum. The empirical results of the Cost minimization model indicates that the model meets this requirement. The extent of the superiority of this model is evaluated by comparison with the Logit model. The results of the prediction accuracy, the costs of Type I and II errors and, the expected lender's profit of the two models are compared in this section.

Comparison of Prediction Accuracies

The prediction accuracies of the Cost minimization and Logit models are

Table 2. Comparison of Prediction Accuracies of The Cost Minimization and The Logit Models

Particulars of Prediction	Cost Minimization Model		Logit Model	
	Test Sample	Hold-out Sample	Test Sample	Hold-out Sample
Prediction Accuracy (%)	68.12	66.93	65.44	60.23
Proportion of Current Loans Correctly Predicted (%)	85.34	84.81	60.77	49.06
Proportion of Non-current Loans Correctly Predicted (%)	34.63	32.12	74.53	81.97
Proportion of Type I Error (%)	65.37	67.88	24.47	18.03
Proportion of Type II Error (%)	14.66	15.19	39.23	50.94

presented in table 2. An overall prediction accuracy of the Cost minimization model of 68.12% is higher than the 65.44% obtained from the Logit model. Type I error (65.37%) is higher and Type II error (14.66%) is lower with the Cost minimization model in contrast to a Type II error (39.23%) and of Type I error (24.47%) obtained from the Logit model.

It can also be seen that the overall prediction accuracy of the Cost minimization model in the hold-out sample is 66.93% as against 60.23% of the Logit model. It can be observed that the prediction accuracy of the Cost minimization model in the hold-out sample has dropped by only 1.19% compared to the test sample, whereas this drop is 5.21% in the Logit model. This implies that the Cost minimization model is more consistent in prediction. As in the test sample, in the hold-out sample, there was more of Type I error (67.88%) and less Type II error (15.19%) with the Cost minimization model and more of Type II error (50.94%) and less of Type I error (18.03%) with the Logit model.

Comparison of Average Costs of Type I and Type II Errors and Expected Lender's Profit

Not only the proportion of errors but also the opportunity cost associated with each \$ of loan in error is important. The opportunity costs for both Type I and Type II error for a \$ loan is lower for the Cost minimization model compared to the Logit model (Table 3). The cost of Type I error per \$ loan is 0.1166 in the Cost minimization model and it is 0.1172 in the Logit model. Similarly, the cost of Type II error is 0.0692 in the Cost minimization model and it is 0.0757 in the Logit model.

The differences in the proportions of errors (Type I and II) and the economic consequences associated with the average costs of these errors are captured and compared in the expected lender's profit. The expected lender's profit takes both the proportions and average costs of these errors (equation 11) into consideration; it is used as a yard stick to compare these models. The expected lender's profit is 0.0328 in Cost minimization model as against 0.0158 of Logit model. It indicates that the expected lender's profit is 1.7% more in the Cost minimization model than in the Logit model. In the hold-out sample also, the opportunity costs for both Type I and II error for a \$ loan is less and the expected lender's profit is more in the cost minimization model compared to the Logit model.

Thus, the performance of the Cost minimization model outweighs the performance of the Logit model. The Cost minimization model performs better than the Logit model both in prediction accuracy and also in minimising the costs associated with the errors it makes.

Table 4.9 **Comparison of Costs of Misclassification and Expected Lender's Profit of Cost Minimization and Logit Models (per $ loan)**

Particulars of prediction	Sample	Number of Loans		Average Interest Income ($)		Average Cost ($)		Expected Lender's Profit ($)	
		CMM*	LM**	CMM	LM	CMM	LM	CMM	LM
Current loans correctly predicted	Test	4914	3499	0.1159	0.1135	-	-		
	Holdout	1630	943	0.1160	0.1134				
Current loans predicted as unacceptable	Test	844	2259	-	-	0.0692	0.0757		
	Holdout	292	979			0.0687	0.0757		
Non-current loans predicted as acceptable	Test	1935	754	-	-	0.1166	0.1172		
	Holdout	670	178			0.1167	0.1188		
Non-current loans correctly predicted	Test	1025	2206	-	-	-	-		
	Holdout	317	809						
Total Loans	Test	8718	8718					0.0328	0.0158
	Holdout	2909	2909					0.0312	0.0040

* cost minimization model
** logit model

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Application of Mathematical Programming Techniques in Credit Scoring of Agricultural Loans

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Introduction

Discriminant analysis (DA) or classification methods are used to classify an individual or object, based on a set of discriminatory variables or attributes, into one of a number of mutually exclusive groups. DA has emerged as an important decision making tool in many fields. DA is extensively used in business, biology, the social sciences and other areas that require classification processes. The methods has been widely applied in business fields such as: credit scoring (Srinivasan and Kim; and Turvey), bankruptcy assessment (Mahmood and Lawrence), for prediction of various events including credit card usage and tender offer outcomes, and personal evaluation or selecting employees (Eisenbeis).

Historically, statistical DA methods have been the standard to deal with classification problems. In recent years, many researchers have expressed concern about certain features of statistical DA models. In particular, statistical DA methods require restrictive assumptions of distributional form. For example, Fisher's Linear Discriminant Analysis model which perhaps is the most widely used DA method, requires assumption of multi-variate normal populations with the same variance/covariance structure. Unfortunately, violations of these assumptions occur regularly. Esinbeis argues that deviations from the normality assumptions, at least in economics and finance, more likely are the rule rather than the exception (p. 875). For example, the financial ratios normally used in credit scoring are rarely normally distributed. In addition, most empirical data include qualitative variables that cannot be multivariate normal (Goldstein and Dillon). The performance of statistical DA models, when underlying parametric assumptions are violated, are discussed by Baladrishnan and Subrahmanian; Lachenbruch, Sneeinger, and Revo; and Press and Wilson.

The statistical DA models also assume that misclassification costs are the same for all groups (Type I and Type II errors have equal significance). For example, the cost of turning down a good loan (Type I error) and the cost of accepting a bad loan (Type II error) are assumed to be the same. Furthermore, statistical DA models are not apt to adequately handle a complex discrimination problem. In certain situations, a side constraint might be necessary which would prohibit the use of statistical DA models. The aforementioned shortcomings of statistical DA models have prompted researchers to the development of several nonparametric DA techniques such as neural network, mathematical programming, and search methods. This paper focuses exclusively on the mathematical programming (MP) DA techniques.

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In recent years, considerable theoretical research has been devoted to the use of MP techniques to the classification problem. Hand; Freed and Glover (1981a, b) were the first to introduce the use of MP in DA. Glover, Keene and Duea argue that the MP approach to DA offers certain advantages over the statistical DA models. These include:

- MP methods are free from underlying parametric assumptions;
- Varied objectives and more complex problem formulation are easily accommodated;
- Varied misclassification costs can be easily incorporated into the model;
- Some MP methods, especially Linear Programming, lend themselves to sensitivity analysis; and
- MP are less sensitive to outliers since the model is based on the L1 metric rather than the L2 metric.

In several experiments utilizing Monte Carlo simulation data, researchers have found that some of MP techniques rival or outperform the statistical DA techniques in terms of the relative classification performance (Bajgier and Hill; Freed and Glover, 1986; Joachimthaler and Stam, 1988; and Rubin). This is specially true when the underlying assumptions of statistical DA models are not satisfied. In spite of these experimental results, there has not been an extensive study which compare the performance of alternative MP models using real-world data. Mahmood and Lawrence; and Srinivasan and Kim are the only researchers that have applied MP discriminant models to actual business data. But, the MP models they used was a rudimentary form of general MP models that have been found to perform poorly in practice (Bajgier and Hill; Markowski and Markowski, 1987). Moreover, neither author attempted to take advantage of inherent flexibility of MP models as stated above. The purpose of this paper is to compare alternative MP formulations in more detail and apply them to actual business data.

Specifically, the objective of the paper is to evaluate alternative MP techniques in credit scoring of agricultural loans using statistical DA models, namely Fisher's Linear Discriminant Analysis (FLDA) and Logit Discriminant Analysis (LDA), as a performance benchmark. The MP and statistical DA models are compared on the basis of classification ability on in-sample and hold-out sample data set. The paper is organized into four major sections. First, a two-group discrimination problem is discussed. This is followed by a brief discussion of statistical DA models. Next, we present MP discriminant models. Finally, we compare the classification performance of statistical and MP models.

Two-Group Discrimination Problem

The two-group discriminant problem deals with discrimination between two predefined groups and is the fundamental problem in DA. Two-group discriminant problem assumes that there are two well-defined populations, G_1 and G_2 (e.g., good loans vs bad loans), and it is possible to measure j discriminatory variables or attributes for each member of either population. The focus of DA is the determination of a numerical rule or discriminant function that allows the investigator to distinguish between two populations using the j attributes. A linear discriminant function can be expressed

$$Z_i = X_0 + B_{i1} X_1 + B_{i2} X_2 + \ldots.. B_{ij} X_j \qquad (1)$$

where, X_0 is a constant term; X_j is the weight assigned to variable j; B_{ij} is the value of the j^{th} variable for the i^{th} individual; and Z_i is the discriminate value for the i^{th} individual. For a cutoff or boundary value of b, the classification rule then becomes: if $Z_i \geq b$ then individual i is assigned to group G_1, otherwise individual i is assigned to group G_2. The cutoff value does not have to be the same for both groups. But, for simplicity, we assume the cutoff values for both groups are the same in this paper.

The goal of any DA model is to estimate parameters X and b so as to minimize the number of misclassifications for in-sample and/or hold-out sample data set. DA models are inherently different from each other according to their choice of criterion function and/or distribution assumption(s). In all DA models, X and b, are however determined from a set of observations for which their group membership is known.

Statistical Linear Discriminant Analysis

There exists an extensive body of literatures which discuses the statistical DA models. Interested readers are referred to Altman et al. and Maddala for a detailed discussion of statistical models in classification studies. For a discussion of credit scoring models and the theoretical consideration of credit scoring in agriculture, the interested reader is referred to Betubiza and Leatham; Miller and LaDue; Turvey; and Turvey and Brown. The statistical procedures of FLDA and LDA have been discussed extensively in the literature, and their detailed formulations are not repeated here.

Fisher Linear Discriminant Analysis

FLDA procedure computes the linear discriminant function (1) by maximizing the ratio of the between-group variance to the within-group variance. The derived linear discriminant function is known to be optimal in context of minimizing the total probability of misclassifications, provided the following conditions are held: (a) the distributions of the variable are multivariate normal, and (b) the variance-covariance of the variables are the same for both population groups (Johnson and Wichern). The coefficients for FLDA model are estimated by

$$\begin{aligned} X &= [((n_1-1)S_1+(n_2-1)S_2)/(n_1+n_2-2)]^{-1}(\mu_1-\mu_2) \\ X_0 &= -X'(\mu_1+\mu_2)/2 \end{aligned} \qquad (2)$$

where, S_g and μ_g are the variance-covariance matrix and mean vectors for group g ($g=1,2$), respectively, and n_g is the number of observations in group g. The cutoff value for FLDA is calculated by $b=ln(c_1p/c_2(1-p))$. Where c_1 and c_2 represent the misclassification costs for population 1 and 2, and p is the prior probability that the individual comes from population 1. The cutoff value for an FDLA model is equal zero, if the prior probability of group membership, and misclassification costs are the same.

Logit Discriminant Model

Some of the statistical DA models, such as LDA and PROBIT, define the discriminator value Z_i as a probability. The LDA model assumes a logistic distribution function to represent the probability that an individual i belongs to group g:

$$F(Z_i) = 1/[1 + \exp(-X_0 - B_{i1} X_1 - B_{i2} X_2 - \ldots - B_{ij} X_j)] \quad (3)$$

Where $F(Z_i)$ converts the value of Z_i to a probability value. The Maximum-likelihood technique is usually used to estimate the weights (Maddalla). The selection of the cutoff value for the LDA model is rather arbitrary. Typically, if the estimated probability is greater than 0.5, then the first alternative is selected (Amemiya).

Mathematical Programming Discriminant Analysis Models

MP approach to discriminant problems, like statistical DA models, try to construct a discriminant function or a separating hyperplane to classify an individual or an object into a prespecified group. For a two-group problem, the objective is to determine a weighting vector X and a scalar b so that it assigns as correctly as possible the individuals of Group 1 to one side of the separation hyperplane and the individuals of Group 2 to the other side. Stating it mathematically, the objective of a MP model is to find b and nonzero X, satisfying:

$$A_1 X \geq b \qquad i \in G_1 \qquad (4)$$

$$A_2 X < b \qquad i \in G_1 \qquad (5)$$

where, A_g is an $n_g \times j$ matrix of observations and $i=1,2....N$, where N is the total number of observations ($N=n_1+n_2$).

The separating hyperplane, $AX=b$, provides the boundary between two groups. When two-group are not linearly separable, then one needs a criterion to separate the group classifications. Then, the MP formulation of a discriminant problem can be cast as:

$$\underset{X,\, b}{Optimize} \; F(X, b) \qquad (6)$$

s.t:

$$A_1 X \geq b \qquad i \in G_1 \qquad (7)$$

$$A_2 X < b \qquad i \in G_2 \qquad (8)$$

$$X \neq 0 \qquad (9)$$

where $F(X,b)$ is the criterion function. The objective of this problem is to determine X and b that optimizes a certain criterion function. To develop the criterion function, one can incorporate deviation variables into (7) and (8).

$$\underset{X,\, b}{Optimize} \; F(E_1, I_1, E_2, I_2) \qquad (10)$$

$s.t:$

$$A_1 X + E_1 - I_1 = b \qquad i \in G_1 \qquad (11)$$

$$A_2 X - E_2 + I_1 = b \qquad i \in G_2 \qquad (12)$$

$X \neq 0$ (13)

where, E_g and I_g are deviation variables (what Glover, Keene, and Duea call external and internal deviations, respectively). A deviation is said to be external/internal if its associated observation is incorrectly/correctly classified (i.e., falls on the wrong/right side of the separating hyperplane). External/internal deviations represent the extent to which an observation is incorrectly/correctly classified. So, external deviations are undesirable while internal deviations are desirable. The above problem can be easily modified to handle multi-group classifications, as shown by Freed and Glover (1981b) and Gehrlein.

Depending on the choice of a criterion function, researchers have recently developed assorted MP models to deal with classification problems. Among the MP models are the minimize the sum of distances (MSD), the minimize the maximum distance (MMD), the mixed-integer (MIP), and the general l_p distance approaches. A variety of combinations of these basic methods have been proposed in the literature. Erenguc and Koehler (1990b) provide a comprehensive survey of various MP model formulations. As noted earlier, some of these models have proved to yield promising predictive power in studies using simulated data (Bajgier and Hill, Freed and Glover (1986); Joachimthaler and Stam 1988; and Rubin) and also using real data (Mahmood and Lawrence; and Srinivasan and Kim).

In last few years, there has been considerable research which has identified certain MP discriminant models, that, under certain data condition, exhibit some pathological problems which have not been experienced in applications of MP in other fields. Glover, Keene, and Duea classified these problems under the headings of degeneracy and stability. The solution to MP is said to be degenerate or unacceptable if $X=0$. The solution is unacceptable since all observations will be assigned to one group. The resultant discriminant functions lack any discriminatory power. The stability problem is referred to a situation where the solutions are not invariant to linear data translation and transformation. For a theoretical discussion of these problems see Koehler (pg. 19, 89b); Markowski and Markowski (1985); Freed and Glover (1986b); and Glover, Keene, and Duea.

Early MP models constrained b to be a constant to avoid the unacceptable solutions. It was tacitly assumed that choice of b would just scale the solutions but further research in this area found that it is not the case and still leads to $X=0$ for certain data configurations (Glover). Recently, several normalization alternatives have been suggested to overcome with these anomalies. Details regarding alternative normalizations can be found in Koehler (1990). Since it is possible that normalization eliminates a feasible region with potential optimal solutions, a user should be cautious when employing normalization. To this end, Rubin recommends that

> ... The precise impact of a particular normalization constraint is generally difficult to assess, and so the selection of normalization constraints tends to be arbitrary. Since trivial solutions generally do not occur when the training sample (estimation sample) are separable, perhaps users should initially omit such normalization constraints and incorporate them only after obtaining a trivial solution for a particular data set" [explanation in parentheses added] (Rubin, p16).

In this paper, normalization was incorporated into the MP models, if it was deemed to be necessary. In the remaining section, we will present four variants of MP discriminant models. These models are chosen among alternative MP models based on their competitive classification power and also their appropriateness dealing with credit scoring problem.

The first MP model, hereafter referred to as a MSD model, can be summarized as follows:

$$\underset{X,\, b}{Minimize} \quad e_1 E_1 + e_2 E_2 \tag{14}$$

s.t:

$$A_1 X + E_1 \geq b \qquad i \in G_1 \tag{15}$$

$$A_2 X - E_2 < b \qquad i \in G_2 \tag{16}$$

$$e_3 X + b = 1 \tag{17}$$

$$X, b \quad u.r.s. \tag{18}$$

$$E_1, E_2 \geq 0 \tag{19}$$

where e_1, e_2, e_3 are $1\times n_1$, $1\times n_2$, $1\times j$ matrices of ones, respectively, and E_g has dimension $n_g\times 1$. X and b are unrestricted in signs.The MSD model minimizes the sum of exterior deviations from the hyperplane. Equation (17), a normalization constraint suggested by Freed and Glover (1986a), is included to overcome the difficulties associated with unacceptable solutions. The normalization constraint requires the sum of all coefficients to be equal to some arbitrary (positive) constant (1 is used here). The constant term is only a scaling constant and does not affect the classification rates. The MSD model, without normalization constraint (17), was originally published by Freed and Glover (1981b).

The second MP model used in this study, called the optimize sum of distances (OSD) by Bajgier and Hill, has the following form:

$$\underset{X}{Minimize} \quad e_1 E_1 + e_2 E_2 \tag{20}$$

s.t:

$$A_1 X + E_1 \geq 1 \qquad i \in G_1 \tag{21}$$

$$A_2 X - E_2 < 1 \qquad i \in G_2 \tag{22}$$

$$X \quad u.r.s. \tag{23}$$

$$E_1, E_2 \geq 0 \tag{24}$$

MSD model is similar to OSD. Both model attempt to minimize the sum of external deviations from the hyperplane. But, in the OSD model, the cutoff value is preassigned to be equal to an arbitrary number (1 is used here) which precludes the need for normalization constraint.

The third MP model, hereafter referred to as the HB, seeks to:

$$\underset{X,\, b}{\mathit{Minimize}} \quad h_1 E_1 + h_2 E_2 - m_1 I_1 - m_2 I_2 \qquad (25)$$

$s.t:$

$$A_1 X + E_1 - I_1 = b \qquad i \in G_1 \qquad (26)$$

$$A_2 X - E_2 + I_2 = b \qquad i \in G_2 \qquad (27)$$

$$e_j X + b = 1 \qquad (28)$$

$$X,\ b \quad u.r.s \qquad (29)$$

$$E_1,\ E_2,\ I_1,\ I_2 \geq 0 \qquad (30)$$

$$h_1 \geq m_1,\ h_2 \geq m_2 \qquad (31)$$

where, h_g and m_g are $1 \times n_g$ matrix of nonnegative objective coefficients. The objective function of the HB model maximizes the weighted sum of interior deviations and minimizes the weighted sum of exterior deviations. Constraint (28) is included in the model formulation to prevent potential unbounded solutions. In practice, the h_g and m_g may reflect the relative importance of incorrect/correct classification to a particular group or individuals in the group. By modifying these weights and parameters, usually by LP post-optimization techniques as proposed by Glover, the solution might be tailored to meet a decision maker's specific goals. In other words, it might be possible to find a set of weights that achieves balancing of errors for a decision maker's particular set of data. (Markowski).

The HB model was first presented by Glover, Keene and Duea; they dubbed this model as a Hybrid model since it can encompass several variations of MP models by setting the corresponding weights equal to either $+\infty$ or $-\infty$. The HB model presented here is, however, different from the model presented by Glover, Keene and Duea. For simplicity, the maximum exterior deviation and the minimum interior deviation were deleted from the model formulation.

The final MP variant used in this study is a mixed integer programming model (MIP). The MIP model has the form:

$$\underset{X,\, b}{\mathit{Minimize}} \quad h_1 Y_1 + h_2 Y_2 \qquad (32)$$

$s.t:$

$$A_1 X + q Y_1 \geq b \qquad i \in G_2 \qquad (33)$$

$$A_2 X - q Y_2 \leq b \qquad i \in G_2 \qquad (34)$$

$$e_j X + b = 1 \qquad (35)$$

$X, b \quad u.r.s.$ (36)

$Y_1, Y_2 \quad \epsilon (0, 1)$ (37)

where h_g denotes the misclassification costs associated with group g; Y_i is binary variable that equal one if individual i is misclassified and zero otherwise; and q is a large positive number. The objective function of MIP model minimizes total misclassification costs. The interesting feature of the MIP model, as noted by Bajgier and Hill, is that it is the only model that directly attacks the goal of minimizing the number of misclassifications. Whereas, all other DA models (including parametric and nonparameteric models) use a surrogate criterion function to achieve the goal. If misclassification costs for both groups are the same, then, MIP directly minimizes the number of misclassification. Whereas, all other models minimize the amount or extent of misclassification from the hyperplane which might not be intuitively appealing to the users. Another interesting feature of MIP is that a constraint can be easily incorporated into the model to balance the number of misclassification for each group. In spite of its potential, the MIP model has not been widely utilized by researchers and practitioners because of a large computational cost and lack of efficient software. Koehler and Erenguc (1990a) recently developed a special purpose mixed integer algorithm which takes advantage of the problem's structure. Moreover, because of the recent decrease in computing cost and increase in computing power, some of general purpose mixed integer program packages can now be conveniently applied to solve larger MIP problems.

The discussion in the last two sections emphasized the estimation of a linear discriminant function for a two-group classification problem using alternative econometrics and MP credit scoring models. We have, however, omitted the theoretical aspects of credit scoring problem. As noted by Turvey "...the credit scoring models themselves will not be successful in assessing the success of a particular loan". There are several other factors that one has to consider in order to establish a successful credit scoring practice. The choice of discriminant variables, the level of subjectivity, the institutional constraints and several other factors are important consideration in any credit scoring study, but in this paper we only concentrate on providing a comparison between the classification performance of MP and statistical credit scoring models. Chhikara; Betubiza and Leatham; and Miller and LaDue provide a detailed discussion of credit scoring issues.

Data and Variable Selection

To perform a comparative analysis, the above models are applied to estimate the corresponding discriminant functions using a sample of credit application data. The classification power of these models are then tested based on their performance using in-sample and hold-out sample data. The credit application data used in this paper were collected by Canada's Farm Credit Corporation. The data are from actual 1981, 1982, and 1983 loan applications for which loans were made in the Saskatchewan Province. The applicants in Group 1 consist of individuals with recent histories of delinquent credit payments (noncurrent loans) and applicants in Group II consists of those individuals without recent delinquent credit payments (current loans) based on the status of the loan as of March 1990. The sample consisted of 754 current loan applications (38%) and 1,245 of noncurrent loan applications (62%). The sample data was divided into two subsamples- an in-sample and a hold-out samples. The in-sample data set was used for model developments and the resulting models were then validated using the in-sample and hold-out sample sets. In this study, 60% (1,199 loans) of total sample was used for model estimation.

The usual procedure in credit scoring studies is to select a large group of explanatory variables and reduce that to a smaller number of statistically significant variables. The above data set was recently used by Turvey in a study in which he compared alternative statistical credit scoring models. Our investigation only included the explanatory variables used in his study to avoid potential overfitting biases. Definition of the explanatory variables are presented in Table 1. Turvey and Brown; and Turvey provide a more formal definitions and explanations of the explanatory variables.

Table 1. Explanatory Variables for Credit Scoring Application

Variable	Variable Definition
Liquidity Ratio	Current asset / current liabilities
The Rate of Return on Assets	(Net farm income + interest expense) /total assets
Debt-to-Asset Ratio	Debt / assets
Loan-to-Security Ratio	(Loan + other prior changes + FCC prior mortgages + statutory charges) / total security
Contribution Margin	(Total Revenue - variable cost)/total revenue
Repayment Ratio	(Net farm income + depreciation + off-farm income-living costs + interest on term loans) /(principal + interest on term loans)
Refinancing Status	1 if loan is required for refinancing, 0 otherwise.

The HB and MIP models require the parameters h_g and m_g to be specified. As was discussed earlier, in practice, these parameters could be solicited from the user. Since the actual benefits and costs of external and internal deviations from the hyperplane for current and noncurrent loan applicants were not available for this study, a set of arbitrary values were selected for these parameters. Subsequently, four variants of HB model (denoted by HB-1, HB-2, HB-3, and HB-4) and three variants of MIP model (denoted by MIP-1, MIP-2, MIP-3) were tested. Table 2 presents the objective coefficients associated with variants of HB and MIP models.

The HB-1 model maximizes the total interior distances from the hyperplane and minimizes the total exterior distances from the hyperplanes. The HB-2, HB-3, and HB-4 maximize the weighted sum of interior distances and minimizes the weighted sum of exterior distances from the hyperplane. The objective is to provide a better balancing of errors between current and noncurrent loans by varying the objective coefficients assigned to interior and/or exterior deviations. As was discussed earlier, in contrast to other MP models, the objective function of MIP model has a direct and meaningful interpretation. For example, the MIP-1 model assumes that the misclassification costs for current and noncurrent loans are the same, hence, the MIP-1

Table 2. The Objective Coefficients for Varients of HB and MIP Models

	m_1	h_1	m_2	h_2
HB-1	1	1	1	1
HB-2	1	1	1	0.5
HB-3	1	1	1	0.25
HB-4	1.25	1	1	0.25
MIP-1	n.a.	1	n.a.	1
MIP-2	n.a.	0.645	n.a.	0.364
MIP-3	n.a.	2	n.a.	1

n.a.- Not Applicable

model directly minimizes the number of misclassifications for both groups. The MIP-2 model is similar to MIP-1 model, but the weights are proportionally weighted based on sample size in each group. The MIP-3 model, however, assumes that the misclassification cost for a noncurrent loan is twice as much as a current loan.

Overall, we tested eleven models, two parametric and nine nonparametrics models. The next section discusses the classification results of these models.

Classification Results

The classification performance on the calibration and hold-out samples of alternative models are presented in Tables 3 and 4. Table 3 presents the classification performance in terms of number of loans in calibration and hold-out samples, while Table 4 presents the same results in percentage. The results in Table 4 and 5 show that the classification performance for parametric models are not significantly different from each other. Both LDA and FLDA models, however, predict better than a pure naive model (i.e. predict better than the proportional prior probabilities for current loan, 36.4% and noncurrent loan, 63.6%). But, both MSD and OSD models perform significantly worse than LDA, FLDA and the naive model for both calibration and hold-out samples. Among four HB models tested, the classification performance of the HB-4 model in hold-out sample is worse than the other three HB models. The results in Table 3 and 4 show the HB-2, HB-3, and HB-4 models perform as well as statistical models in hold-out samples. However, all three MIP models perform marginally better than LDA and FLDA models for calibration and hold-out samples. The LDA classified correctly 601 of noncurrent loans in the calibration sample for a correct classification rate of 65%. While, the overall correct classification rate for LDA is 66% for the calibration sample (Table 4). The MIP-1, MIP-2 and MIP-3 models classified correctly 622, 609, and 609 of noncurrent loans in the calibration sample for a correct classification rate of 66%, 68%, and 68%, respectively. The overall correct classification rate for MIP-1, MIP-2, and MIP-3 are 67%, 67%, and 68% for the calibration sample, respectively, which marginally better than LDA and FLDA models. The results in Table 3 and 4 show that the LDA and FLDA models, however, provide a more balanced discriminant solutions than MP models. None of the MP models tested here show a higher correct classification for current loans.

Conclusions

The purpose of this study has been to compare the alternative statistical and MP credit scoring models in an empirical setting using the actual credit data. The results indicate that there are only a small differences in the classifying accuracy of statistical and MP approaches. The results of this study re-enforce the findings of the experimental studies which claim that the MP models are as competitive as statistical DA models. As was shown here, the MIP models even outperform the statistical models. We recommend the use of MP models in an applied environment when the incorporation of a side condition becomes necessary, or a small sample size is available, or a large number of explanatory variables is present, or the data set is heavily contaminated. In these situations, the MP models have the potential to perform better than the statistical DA models. Since there is no optimal DA model which fits all data sets in all situations, it may be a good practice to apply the data to alternative parametric and nonparametric DA models and choose the best model. In many credit scoring applications, even a moderate improvement in the ability to correctly classify may represent a significant increase in financial contributions.

Table 3. Classification Results Reported as a Percentage of Loans Classified Correctly and Incorrectly.

		Number of Loans Classified Correctly and Incorrectly					
		Current		Noncurrent		Classification[a]	
Data Sample	Models	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Calibration Sample							
	LDA	177	259	601	162	778	421
	FLDA	183	253	597	166	780	419
	MSD	143	293	493	270	636	563
	OSD	133	303	528	235	661	538
	HB1	123	313	622	141	745	454
	HB2	146	290	609	154	755	444
	HB3	159	277	594	169	753	446
	HB4	171	265	575	188	746	453
	MIP-1	107	329	687	76	794	405
	MIP-2	147	289	666	97	813	386
	MIP-3	132	304	680	83	812	387
Hold-out Sample							
	LDA	184	134	344	138	528	272
	FLDA	184	134	341	141	525	275
	MSD	109	209	316	166	425	375
	OSD	111	207	338	144	449	351
	HB1	130	188	379	103	509	291
	HB2	143	175	373	109	516	284
	HB3	148	170	365	117	513	287
	HB4	161	157	346	136	507	293
	MIP-1	116	202	420	62	536	264
	MIP-2	142	176	392	90	534	266
	MIP-3	134	184	407	75	541	259

[a] Current and noncurrent loans.

Table 4. Classification Results Reported as a Percentage of Loans Classified Correctly and Incorrectly

		Percent of Loans Classified Correctly and Incorrectly					
		Current		Noncurrent		Classification[a]	
Data Sample	Models	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Calibration Sample							
	LDA	41	59	79	21	65	35
	FLDA	42	58	78	22	65	35
	MSD	33	67	65	35	53	47
	OSD	31	69	69	31	55	45
	HB1	28	72	82	18	62	38
	HB2	33	67	80	20	63	37
	HB3	36	64	78	22	63	37
	HB4	39	61	75	25	62	38
	MIP-1	25	75	90	10	66	34
	MIP-2	34	66	87	13	68	32
	MIP-3	30	70	89	11	68	32
Hold-out Sample							
	LDA	58	42	71	29	66	34
	FLDA	58	42	71	29	66	34
	MSD	34	66	66	34	53	47
	OSD	35	65	70	30	56	44
	HB1	41	59	79	21	64	36
	HB2	45	55	77	23	65	36
	HB3	47	53	76	24	64	36
	HB4	51	49	72	28	63	37
	MIP-1	36	64	87	13	67	33
	MIP-2	45	55	81	19	67	33
	MIP-3	42	58	84	16	68	32

[a] Current and noncurrent loans

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AN ANALYSIS OF THE SCALE ECONOMIES AND COST EFFICIENCIES IN THE FARM CREDIT SYSTEM

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The Farm Credit System (FCS) in the United States is a nationwide network of borrower-owned lending institutions and affiliated service entities. The system's primary economic and political function is to provide reliable, competitively-priced credit to its owner-borrowers (Collender et al., 1991). The FCS has been undergoing substantial structural changes. Two important factors in these changes are the passage of the Agricultural Credit Act of 1987 (Act) and the increasing competition from the commercial banking industry.

The Act contains an extensive set of provisions including: (1) the mandatory merger of the Federal Land Bank (FLB) and the Federal Intermediate Credit Bank (FICB) of each district into a Farm Credit Bank (FCB), (2) the development of merger proposals among district FCBs, (3) the voluntary merger for the Bank for Cooperatives (BCs), and (4) the development of merger plans between Federal Land Bank Associations (FLBAs) and Production Credit Associations (PCAs).

As a result, FCBs have been formed in each district[1]. The nation is now served by eight FCBs, while twelve district BCs have merged into three. Furthermore, PCAs and FLBAs in several districts have merged to form Agricultural Credit Associations (ACAs). Direct lending authority has been granted to some FLBAs. These institutions are called Federal Land Credit Associations (FLCAs). Certain FLBAs or FLCAs and PCAs are also jointly managed. The organizational changes among FCS institutions from January 1, 1988 through January 1, 1993 are summarized in Table 1.

The competition among institutions lending to agriculture has increased over the past five years. Commercial banks have increased their emphasis on farm real estate lending and, thus, have increased their volume and market share of outstanding agricultural loans. The total loan volume excluding cooperatives loans for the FCS has decreased from about $61.6 billion (33.8% of total farm debt) in 1981 to about $35.6 billion (25.6% of total farm debt) in 1992. However, total outstanding agricultural loans for commercial banks have increased from about $38.8 billion (21.3% of total loans) to about $51.6 billion (37.0% of total loans) during the same period (U.S. Department of Agriculture, 1993). The future success of FCS institutions depends on their ability to adapt and operate more efficiently in the new environment.

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Some direct lending associations within the FCS have merged to become larger. Managements of other associations are considering whether merging with other associations would help them become more competitive. One motivation for merging is that an association may obtain scale economies by operating at a larger size. Another motivation for merging is that an association may use inputs more efficiently at a larger size. Thus, by reducing the overuse of all inputs, an association would reduce cost inefficiencies. It is not clear, however, if the associations can achieve scale economies or cost efficiencies by getting larger.

In the past few years, many studies have concentrated on analyzing scale economies and cost efficiency of commercial banks (e.g., Evanoff and Israilevich, 1990; Ferrier and Lovell, 1990; Bauer, Berger, and Humphrey, 1991; Berger and Humphrey, 1991; Berger, Hancock, and Humphrey, 1993) and agricultural banks (e.g., Featherstone and Moss, 1993; Neff, Dixon, and Zhu, 1993). However, comparatively few studies have focused on efficiency analysis of FCS institutions (e.g., Collender, 1991; Collender et al., 1991). Furthermore, most studies of bank efficiency used data for a single cross-section of firms, and the separation of inefficiency from random noise required strong assumptions about their distributions.

The objective of this study is to estimate and compare the scale economies and cost efficiencies for Farm Credit System direct lending institutions using a stochastic frontier approach with panel data. The maximum likelihood estimation technique (MLE) is used to obtain the scale elasticity estimates for institutions grouped by sized and cost efficiency measurements for each institution. In the next section, the estimation procedures in the cost frontier model are detailed. The data obtained from the Farm Credit Administration (FCA) Call Reports are also discussed in that section and are followed by results from empirical estimation of the scale elasticities and efficiency measurements. The concluding section summarizes the major findings and results of this study.

Estimation Procedures and Data

Estimation Procedures

Based on economic theory, both the cost function and the production function uniquely define the technology for a firm that is competitive in the input markets. Thus, either the cost function or the production function can be incorporated into the productive efficiency analysis and is normally called the cost frontier and production frontier approach, respectively. However, direct estimation of the production function poses two possible problems (Kumbhakar, 1987). First, estimation of the production function directly is appropriate only when input quantities can be treated as exogenous. Input demand functions are assumed to be independent of the firm's technical inefficiency. However, if outputs are exogenous and inputs are endogenous, direct estimation of the production function using output as the dependent variable is inappropriate. Second, direct estimation of the production function considers only technical inefficiency. Inferences about overall inefficiency cannot be made unless allocative inefficiency is also considered.

A major advantage of the cost function approach is that consistent estimates of the parameters can be obtained if output levels and input prices are exogenous. This is a basic behavioral assumptions behind cost minimization. Thus, in this study, the cost function approach will be used. The cost function considered in this study is the translog cost function. The translog cost function can be viewed as a local, second-order approximation to an arbitrary cost function and has been used extensively in the literature. The translog cost function is specified as follows[2]:

$$\ln TC = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln w_i + \sum_{k=1}^{m} \beta_k \ln y_k + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln w_i \ln w_j + \frac{1}{2}\sum_{k=1}^{m}\sum_{l=1}^{m} \delta_{kl} \ln y_k \ln y_l + \sum_{i=1}^{n}\sum_{k=1}^{m} \theta_{ik} \ln w_i \ln y_k + \epsilon, \tag{1}$$

where, α, β, γ, δ, and θ are parameters to be estimated, TC is total production costs, w is input price, and y is output quantity. The restrictions for linear homogeneity in factor prices of the cost function are also imposed as:

$$\sum_{i=1}^{n} \alpha_i = 1, \ \sum_{i=1}^{n} \gamma_{ij} = 0, \ \sum_{i=1}^{n} \theta_{ik} = 0, \text{ for all j, k.} \tag{2}$$

Following Aigner et al. (1977) and Meeusen and van den Broeck (1977), the error term, ϵ, is composed of two different types of disturbances:

$$\epsilon_{ft} = u_f + v_{ft} \tag{3}$$

where u_f is one-sided distributed, $u_f \geq 0$, which represents inefficiency and v_{ft} is a stochastic variable that represents uncontrolled random shocks in the production process with $f = 1, \ldots, F$ and $t = 1, \ldots, T$, where F and T are the total number of firms and time, respectively.

MLE will be used to estimate equation (1) to obtain the cost frontier and the associated inefficiency measurement for each institution. To estimate equation (1) by MLE, the probability density function (pdf) of the composed error term, $\epsilon_{ft} = y + _{ft}v$, needs to be derived. The distributional assumptions on the composed error are: u_f is i.i.d. one-sided distributed with half-normal density function, v_{ft} is i.i.d. with mean zero and variance σ_v^2, and u_f and v_{ft} are independent.

Following Pitt and Lee (1981) and Maddala (1983, p.195), the joint pdf $f(\epsilon_{ft})$ of ϵ_{ft} can be defined as follows:

$$f(\epsilon_{ft}) = \frac{2}{\sigma} \phi\left(\frac{\epsilon_{ft}}{\sigma}\right) \left[1 - \Phi\left(\frac{\epsilon_{ft}\lambda}{\sigma}\right) \right] \tag{4}$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u/\sigma_v$, and $\phi(\bullet)$ and $\Phi(\bullet)$ are the density function and distribution function of the standard normal, respectively. Then the log-likelihood function for the pooled data is

$$(5) \qquad \ln L = \frac{FT}{2} \ln \frac{2}{\pi} - FT \ln \sigma - \frac{1}{2\sigma^2} \sum_{f=1}^{F}\sum_{t=1}^{T} \epsilon_{ft}^2 + \sum_{f=1}^{F}\sum_{t=1}^{T} \ln [\ \Phi(\frac{\epsilon_{ft}\lambda}{\sigma})\ ].$$

After the model is estimated, the efficiency measurement for each institution can be obtained from the conditional mean of u_f given ϵ_{ft}. Jondrow et al. (1982) have shown that the distribution of u_f conditional on ϵ_{ft} is a normal distribution truncated at zero. The mean of u_f given ϵ_{ft} is expressed as follows:

$$(6) \qquad E\ (\ u_f | \epsilon_{ft}\ ) = (\frac{\sigma_u\sigma_v}{\sigma})[\ \frac{\phi(\frac{\epsilon\lambda}{\sigma})}{\Phi(\frac{\epsilon\lambda}{\sigma})} + \frac{\epsilon\lambda}{\sigma}\ ].$$

Given the availability of panel data, Kumbhakar (1986) has shown that the mean of u_f/ϵ_{ft}, a point estimator of u_f, is unbiased and consistent as $t \to \infty$.

Data

Data needed in estimating the cost function and, thus, the scale economies and cost efficiency include total costs (*TC*), output quantities, and input prices for each institution at each time period. Following Collender (1991), outputs considered in this study are accrual (*Y1*) and non-accrual (*Y2*) loans. Inputs include labor, physical capital, and other operating expenses. Because of data limitations, the price of labor (*W1*) is proxied by the average wage rate of the commercial banking industry in a county where each association located. The average wage rate was an average of the wage rate paid by all bank head offices in a county. This information was obtained from the FDIC Consolidated Report of Condition and Income (FDIC Call Reports). The price of physical capital (*W2*) is obtained by dividing occupancy and equipment expenses by the value of fixed assets. The price of other operating expenses (*W3*) is approximated by dividing total other operating expenses by the total assets. The FCS data are obtained from the FCA Call Reports that contain balance sheet and income statement information collected quarterly from all associations. Quarterly data with time series running from the first quarter of 1988 (1988Q1) through the fourth quarter of 1992 (1992Q4) are used in this study. The summary statistics for data used are presented in Table 2.

Empirical Results

The MLE parameter estimates for the translog cost function are presented in Table 3. Most parameter estimates are significant at the 1% or 5% level. The cost and scale elasticities and the cost inefficiency measure are derived from the parameter estimates (Table 4). The cost and scale elasticities, and cost inefficiency measures are calculated by different size groups for PCAs, ACAs, and FLCAs.

Economies of Scale and Cost Elasticity

The overall cost elasticity, the sum of product-specific cost elasticities, measures the percentage change in cost associated with one percent increase in all outputs. It is the measurement of the economies of scale. An overall cost elasticity less than one indicates that costs rise less than proportionately with an equiproportionate increase in all outputs.

All size groups of FLCAs and all but the largest size groups of PCAs and ACAs exhibit economies of scale (Table 4). For the most part, the smaller institutions had the lowest cost elasticities. The overall cost elasticities for PCAs range from 0.7806 of size less than $25 million in assets to 1.0631 of size more than $400 million in assets. The overall cost elasticities for ACAs range from 0.8777 of size $75-100 million in assets to 1.0343 of size more than $400 million. Overall cost elasticities for FLCAs range from 0.7749 of size $25-50 million to 0.9721 of size more than $400 million.

Comparisons of the overall cost elasticities among PCAs, ACAs, and FLCAs with the same size show that PCAs and FLCAs, in general, exhibit larger scale economies than ACAs. The result above suggests that PCAs and FLCAs will benefit more from restructuring to larger sizes than ACAs.

Scale Elasticity

The inverse of the product-specific cost elasticity is the product-specific scale elasticity that gives the percentage change in a specific output with one percent change in all inputs. The overall scale elasticity, on the other hand, shows the percentage change in all outputs for a one percent change in all inputs. The overall scale elasticity is the inverse of the overall cost elasticity. The returns to scale are often measured through the overall scale elasticity. A firm is considered to exhibit increasing, constant, and decreasing returns to scale as the scale elasticity is greater than, equal to, or less than one, respectively. All of the FLCAs and all but the larger PCAs, and ACAs have increasing returns to scale (Table 4). Only the PCAs with assets over $300 million and the ACAs with assets over $400 million have decreasing returns to scale.

Cost Inefficiency

Table 4 presents the inefficiency estimates for PCAs, ACAs, and FLCAs by size. As shown, PCAs with assets of $300-400 million are the least efficient (0.2578), while PCAs with assets less than $25 million are the most efficient (0.1295). Also, ACAs with assets less than $25 million are the most efficient (0.0892), while ACAs with assets more than $400 million are the least efficient (0.1527). FLCAs with $250-300 million in assets are found most efficient (0.0578), while FLCAs with assets of $50-75 million are the least efficient (0.1463).

There is not an obvious relationship between size and cost inefficiency (Table 4). Thus, these results provide evidence that a firm cannot use physical inputs more efficiently solely by increasing in size. A large association is just as likely to overuse physical inputs as a small association.

The overall inefficiency for individual PCA ranges widely from 0.047 of one PCA in the Wichita district to 0.528 of one PCA in the St. Spokane district[3]. The inefficiency measurement for each ACA also ranges widely, from 0.058 of one ACA in the Baltimore district to 0.533 of one ACA also in the Baltimore district. The range of inefficiency measurements for each FLCA is not as wide as that of PCAs and ACAs. The lowest inefficiency estimate is 0.032 for a FLCA in the Sacramento Western district, while the highest inefficiency estimate is only 0.273 for a FLCA in the St. Louis district.

Conclusions

The cooperative FCS has been undergoing substantial structural changes. The Agricultural Credit Act of 1987 and the increasing competition from the commercial banks are major driving forces of these changes. The success of FCS institutions depends on their ability to adapt and operate more efficiently in the new environment. Many direct lending associations have merged or are considering merging with other associations to gain scale economies and cost efficiencies. In this study, the scale economies and cost efficiency of the FCS direct lending institutions are estimated using the stochastic cost frontier approach.

Results indicate that FLCAs exhibit persistent economies of scale. PCAs exhibit scale economies until the size exceeds $300 million. Similarly, ACAs exhibit economies of scale until the size exceeds $400 million. PCAs and FLCAs, in general, exhibit larger scale economies than ACAs. Thus, there is evidence that the smaller associations can gain economies of size by merging into intermediate size associations.

Although some economies of scale were observed, there was no consistent evidence of cost efficiencies by size. Thus, it was just as likely that large or intermediate size association misused physical inputs as a smaller association. Moreover, the inefficiency estimates for PCAs and ACAs range widely. The least efficient PCA is 52.8% inefficient relative to the best practice PCA, while the least efficient ACA is 53.3% inefficient relative to the best practice ACA. Additional research could focus on other determinants of cost inefficiencies. Furthermore, changes in efficiency could be investigated.

Continued investigation of efficiencies within the Farm Credit System is warranted. Structural changes within the System are still occurring. Furthermore, it may take time before the structural and managerial changes translate into efficiency changes. The availability of detailed data prohibited direct comparisons among different types of associations or between districts. More complete data from institutions would allow direct comparisons among different types of institutions. This study only investigated the efficiency aspects of the structural changes within the System. Many factors besides cost efficiency are evaluated before mergers are initiated. The abilities of the firms to manage risk is an important factor in assessing a merger between institutions. Thus, motives besides changes in efficiency should be jointly considered when evaluating mergers.

Endnotes

1. The FICB of Jackson is in receivership.
2. For simplicity, the firm (f) and time (t) subscripts are suppressed.
3. Due to the lengthy report, the efficiency estimate for each individual PCA, ACA, and FLCA is not presented here. However, they are available from the authors.

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Table 1. Numbers of Farm Credit Institution, 1988Q1 - 1992Q4.

	FLB	FICB	BC	PCA	FLBA	FCB	ACA	FLCA	SC	Total
1988Q1	12	12	13	150	230	12	-	-	4	433
1988Q1	12	12	13	148	229	12	-	-	4	430
1988Q3	1	1	13	143	224	11	-	-	4	397
1988Q4	1	1	13	142	224	11	-	-	6	398
1989Q1	1	1	3	101	148	11	34	4	6	309
1989Q2	1	1	3	96	143	11	39	2	6	302
1989Q3	1	1	3	95	142	11	40	2	6	301
1989Q4	1	1	3	95	148	11	39	2	6	306
1990Q1	1	1	3	94	146	11	40	2	6	304
1990Q2	1	1	3	93	145	11	40	3	6	303
1990Q3	1	1	3	112	144	11	40	4	6	322
1990Q4	1	1	3	112	141	11	40	7	6	322
1991Q1	1	1	3	117	121	11	44	18	5	321
1991Q2	1	1	3	91	96	11	66	19	5	293
1991Q3	1	1	3	87	90	11	70	22	5	290
1991Q4	1	1	3	87	87	11	70	25	5	290
1992Q1	1	1	3	82	84	10	70	24	5	280
1992Q2	1	1	3	75	84	10	70	24	5	273
1992Q3	1	1	3	73	80	10	70	26	5	269
1992Q4	1	1	3	72	78	10	70	27	4	266

Source: FCS Call Reports, 1988Q1-1992Q4, Farm Credit Administration.
Note: FLB-Federal Land Bank, FICB-Federal Intermediate Credit Bank, BC-Bank for Cooperatives, PCA-Production Credit Association, FLBA-Federal Land Bank Association, FCB-Farm Credit Banks, ACA-Agricultural Credit Association, FLCA-Federal Land Credit Association, and SC-Service Corporation.

Table 2. Summary Statistics of Sample Farm Credit Associations.

	PCA (N=1756)				ACA (N=798)				FLCA (N=97)			
Variable	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Accrual Loans ($million)	68.5	99.5	7.0	932.3	216.9	397.3	17.3	3,276.8	168.2	209.6	23.4	2,037.5
Nonaccrual Loans ($ million)	3.5	6.7	0.001	72.5	6.7	20.8	0.001	225.7	6.5	21.8	0.029	214.1
Price of Labor ($1,000)	27.3	4.4	17.1	61.2	28.6	6.4	18.5	108.2	30.9	5.4	18.5	40.1
Price of Physical Capital ($)	0.072	0.099	0.004	0.923	0.047	0.019	0.008	0.152	0.094	0.123	0.024	0.809
Price of Other Operating Expenses ($)	0.0017	0.0011	0.0002	0.0243	0.0014	0.0007	0.0001	0.0063	0.0013	0.0005	0.0004	0.0031
Total Cost [a] ($1,000)	469.4	807.4	9.0	8,285.0	975.4	1,751.8	118.9	13,146.9	545.1	581.4	100.	5,734.9
Total Assets ($ million)	87.3	135.2	2.1	1,266.6	244.3	459.0	21.6	3,715.5	185.9	239.7	27.6	2,325.8

[a] Non interest operating cost that includes labor, physical capital and other operating expenses.

Table 3. Parameter Estimates for the Translog Cost Function.

Variable	Parameter Estimate	Standard Error
Log(Y1)	0.7515	0.0630*
Log(Y2)	0.1311	0.0457*
Log(W1)	1.0939	0.1871*
Log(W2)	0.0450	0.1154
Log(Y1)log(W1)	-0.0819	0.0086*
Log(Y1)log(W2)	-0.0094	0.0080
Log(Y2)log(W1)	-0.0026	0.0060
Log(Y2)log(W2)	-0.0101	0.0043**
Log(Y1)log(Y1)	0.0897	0.0042*
Log(Y1)log(Y2)	-0.0132	0.0026*
Log(Y2)log(Y2)	0.0205	0.0023*
Log(W1)log(W1)	-0.0434	0.0277
Log(W1)log(W2)	0.0414	0.0160*
Log(W2)log(W2)	-0.0776	0.0102*
$1/\sigma$	3.9562	0.1277*
λ	1.0088	0.1203*
Constant	-3.5929	0.7580*
σ_u^2	0.0322	
σ_v^2	0.0317	
Log of Likelihood Function	401.94	

Note: Y1 - accrual Loans, Y2 - Nonaccrual Loans, W1 - Price of Labor, W2 - Price of Physical Capital.
*Statistically significant at the 99% level
**Statistically significant at the 95% level

Table 4. Cost and Scale Elasticities and Inefficiency Estimates by Asset Size.

Institution	Asset Size ($1,000,000)	Overall Cost Elasticity	Overall Scale Elasticity	Inefficiency Estimate
PCA	0 - 25 (N=316)	0.7806	1.2810	0.1295
	25 - 50 (N=424)	0.8186	1.2216	0.1432
	50 - 75 (N=461)	0.8653	1.1557	0.1476
	75 - 100 (N=217)	0.8804	1.1358	0.1585
	100 - 150 (N=193)	0.9108	1.0980	0.1564
	150 - 200 (N=60)	0.9131	1.0951	0.1476
	200 - 250 (N=5)	0.905	1.1050	0.1409
	300 - 400 (N=11)	1.0225	0.9780	0.2578
	More Than 400 (N=69)	1.0631	0.9406	0.2124
	All Sample (N=1756)	0.8548	1.1698	0.1489
ACA	0 - 25 (N=8)	0.8787	1.1381	0.0892
	25 - 50 (N=47)	0.8843	1.1309	0.1239
	50 - 75 (N=106)	0.8884	1.1257	0.1448
	75 - 100 (N=79)	0.8777	1.1394	0.1206
	100 - 150 (N=125)	0.9046	1.1054	0.1432
	150 - 200 (N=145)	0.9306	1.0745	0.1328
	200 - 250 (N=72)	0.9153	1.0925	0.1322
	250 - 300 (N=70)	0.9203	1.0865	0.1406
	300 - 400 (N=89)	0.9658	1.0354	0.1389
	More Than 400 (N=57)	1.0343	0.9669	0.1527
	All Sample (N=798)	0.9215	1.0852	0.1367
FLCA	25 - 50 (N=6)	0.7749	1.2905	0.074
	50 - 75 (N=5)	0.8693	1.1503	0.1463
	75 - 100 (N=18)	0.8833	1.1321	0.1246
	100 - 150 (N=12)	0.9147	1.0932	0.1146
	150 - 200 (N=39)	0.9202	1.0868	0.0622
	200 - 250 (N=1)	0.8643	1.1570	0.0683
	250 - 300 (N=6)	0.9353	1.0691	0.0578
	More Than 400 (N=10)	0.9721	1.0287	0.0840
	All Sample (N=97)	0.9068	1.1028	0.0874

Note: N represents number of observations.