Determining Default Probabilities for FSA Direct Loans

Abstract: A binomial logit model was used to analyze relationships between financial characteristics and loan performance for FSA direct borrowers receiving direct FO or OL loans in fiscal 2005. Not surprisingly, the results indicate a strong and direct relationship between many key financial variables and probability of default. Production specialization, however, was indicated to have just as important an impact on probability of default as many financial variables. Other strong indicators included farm size, membership in a targeted group, and the ability to obtain credit from commercial lenders.

Keywords: FSA credit programs, loan defaults, credit risk models, risk rating

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Identifying and rating credit risk is an essential aspect of portfolio management for both public and private sector lenders. Financial institutions typically evaluate credit risk based on a borrower's default probability and subsequent losses. An understanding of the relationship between loan default and borrower characteristics is essential in risk evaluation. Many lenders have not maintained databases which would enable such statistical analysis. USDA's Farm Service Agency (FSA), which administers both direct and guaranteed loan programs to farmers, has been no exception. Historically, FSA has only maintained electronic records of loan accounting and borrower demographic data. All other loan records have been maintained at the local office in hardcopy format. Thus, collecting this data would have been time consuming and costly.

In 2005, USDA's Farm Service Agency (FSA) implemented the Farm Business Plan, an accounting software package provided by the company ECI, which has allowed FSA to maintain detailed electronic records of borrower financial characteristics. The Farm Business Plan provides detailed borrower level data on key financial, structural, and demographic variables. In the research documented in this report, these data are used to analyze relationships between financial characteristics and loan performance for FSA direct borrowers receiving loans in fiscal 2005.

Virtually all financial institutions, public or private, utilize some type of risk-rating system. These systems serve a variety of purposes: facilitating loan origination; monitoring loan portfolio safety and soundness; determining capital requirements; and servicing loans. For public sector lenders such as FSA, risk rating can be an important determinant of budget outlays. The President's Office of Management and Budget (OMB) determines budget outlays for Federal credit programs based upon anticipated defaults, recoveries, and repayments. Federal credit programs are expected to utilize risk rating procedures to develop subdivisions of loans that are relatively homogeneous in cost, given the facts known at the time of obligation or commitment (OMB Circular A-11). These risk categories should group loans into cohorts that share characteristics predictive of defaults and other costs. Historically, these risk categories have utilized loan variables, such as loan type and size, and some descriptive variables, such as firm size and ownership type, but have excluded a firm's or individual's financial information.

The Statement of Federal Financial Accounting Standards states that each credit program should use an econometric default model to estimate probabilities of default for each risk cohort.[1] In this analysis a binomial logit model is developed to evaluate credit risk of FSA direct loans. Predicted default probabilities are then used to classify borrowers into groups considered more likely to default. This procedure is compared with FSA's current internal rating system to compare the ability of each to identify borrowers likely to default.

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[1] Federal Accounting Standards Advisory Board. "Amendments to Accounting Standards for Loans and Loan Guarantees", May 2000 Appendix C: The Accounting Standards in Statement of Federal Financial Accounting Standards No. 2. *35. Each credit program should use a systematic methodology, such as an econometric model, to project default costs of each risk category. If individual accounts with significant amounts carry a high weight in risk exposure, an analysis of the individual accounts is warranted in making the default cost estimate for that category.*

Past Studies

Agricultural credit assessment models have been used to evaluate, or screen, loan applications of potential borrowers and to assess, or review, the credit performance of existing borrowers. Miller and LaDue (1989) used farm size, liquidity, solvency, profitability, capital efficiency, and operating efficiency to develop credit-scoring models for indebted dairy farms. They estimated logit models to discriminate between successful and defaulting borrowers and observed that larger borrowers were classified correctly using financial ratios. Similiarly, Gallagher (2001) found credit assessment models predict that financial ratios such as leverage, liquidity, and profitability significantly influence loan performance. Turvey and Brown (1990) incorporated the cost of loan misclassification into a loan scoring model for a group of Canadian farm loans. Novak and LaDue (1994) found multi-period credit scoring measures provided more stable parameter estimates than single-period measures.

Most studies of loan default, especially among mortgage loans, rely on the option pricing theory of loan default (Quercia, McCarthy, and Stegman). This theory states that at the beginning of each period, a borrower has the option of (1) making a payment, (2) paying off a loan in full, or (3) defaulting on a loan and returning any secured property to the lender in return for debt cancellation. In determining whether to exercise the default option, these models presume that borrowers consider their equity in the secured property as a crude measure of when the option is ‘in the money”. In addition to equity, studies have shown that the default decision is influenced by transaction costs, moving costs, and potential damage to a borrower's credit rating, as well as borrower-related factors such as marital disruption and job loss (Epperson et al 1985, Quigley and Van Order 1991, Vandell and Thibodeau 1985).

Conceptual Framework

The fundamental issue of credit risk, regardless of whether the lender is a public or private lender, relates to expected loss (EL). The EL may be disaggregated into three elements which are typically analyzed separately (Barry). These elements are probability of default (PD), loss given default (LGD), and exposure at default (EAD). As explained by Barry, the probability of default indicates a loss may occur, while loss given default indicates the severity of default and how badly it affects the firm. Loss given default is net of any recovery attributable to liquidation of secured property and any deficiency judgments rendered through foreclosure and bankruptcy proceedings. Both PD and LGD are expressed in percentage terms which are then applied to the loan level (also called the exposure at default, EAD) to determine expected loss. The relationship between PD, LGD, EAD, and EL is expressed as follows:

$$EL = (PD * LGD) * EAD.$$

The PD can be predicted by the type of borrower, underwriting variables, loan size, maturity, payment frequency, borrower characteristics, or external economic factors (Featherstone, Roestler, and Barry). While the model is multiplicative, it is common in the finance literature to examine these aspects separately due to the inability to easily track loans through the default and recovery process. For FSA credit programs, such tracking is especially difficult because defaulted loans may be restructured or consolidated with other loans, thereby making it difficult to allocate losses or recoveries to the initial loan. Kachova and Barry as well as Featherstone, Roestler, and Barry modeled EL in this manner. Also, Featherstone and Boessen modeled loan loss severity using LGD * EAD separately from the PD.

Our analysis focuses only on the PD component of the equation. The PD was estimated for cohorts of farm ownership (FO), and farm operating (OL) loans made during fiscal 2005. Data limitations do not allow analysis of loans made under the emergency loan (EM) program or of loans obligated in years other than fiscal 2005.[2]

The particular conceptual framework used to analyze defaults depends somewhat on available data.[3] Binomial logit models represent a commonly used framework to analyze loan default. The binomial logit model utilizes a maximum likelihood estimation which is consistent and asymptotically efficient, and with large samples produces normally distributed coefficient estimates (Studenmund). The general form of the logistic model used in this analysis was:

[2] The Farm Business Plan included data on some, but not all, borrowers receiving loans prior to FY 2005. Borrowers receiving only a 1-year operating loan prior to FY 2005,or who paid-off their FSA loan prior to full implementation of the Farm Business Plan were not likely included in the database. The EM loan program made too few loans in FY 2005 to allow meaningful analysis, and was not considered.

[3] Within the residential housing literature, many recent studies have used a proportional hazards model. However, ideally these models require panel data of a borrower's financial condition over long periods of time along with the timing of defaults and payments

$$\text{PROB}\,(\text{Y\_DEF} = 1) = \frac{e^{B'X}}{(1+e^{B'X})}$$

Where Y_DEF represents borrower default in the FO or OL program, and X is the vector of factors hypothesized to influence default. Underwriting standards, many of which are established through regulation or statute, represent some of the key factors expected to influence default. Individual characteristics such as farm type specialization, marital status, organizational structure, and membership in a targeted group were also hypothesized to affect default probability. The empirical model used to estimate the probability of default was:

$$\begin{aligned}
&\text{LN(PD)/[1 - PD]} = \beta_0 + \beta_1(FARMTYPE) + \beta_2(LOANSIZE) + \beta_3(BEG) + \beta_4(SDA) \\
&+\beta_5(MARITAL_STATUS) + \beta_6(SOLE_PROP) + \beta_7(CASHFLOW) + \beta_8(DARATIO) + \\
&+\beta_9(LOW_EQUITY) + \beta_{10}(PERSONAL_EQUITY) + \beta_{11}(LIQUIDITY) + \beta_{12}(COVRATIO) \\
&+\beta_{13}(PROFITABILITY) + \beta_{14}(FSA_SHR) + \beta_{15}(HI_RISK_SHR) \\
&\beta_{16}(NUMBER_OF_LOANS) + \beta_{17}(LOAN_TYPE) + \beta_{18}(GTE) + \beta_{19}(FCS) + \varepsilon_I\,,
\end{aligned}$$

with variable descriptions provided in table 1.

Data

The analysis was undertaken using loan accounting data which was merged with borrower financial information from FSA's Farm Business Plan. The Farm Business Plan, which was fully implemented by FSA in mid-2005, is an on-line accounting system which documents cash flow, expenses, assets, debts, and other important financial information. Prior to this, FSA had utilized the Farm and Home Plan (FHP) since the 1940's. However, detailed records of the FHP were not filed electronically so FHP did not lend itself easily to analysis. The Farm Business Plan included data on all borrowers originating loans starting in fiscal 2005.

The borrower level data from the Farm Business Plan provided a unique customer number, farm balance sheet information, farm income statement, cash flow statement, personal (nonfarm) financial and income data, as well as data on race, gender, production specialty, years of farming experience, and marital status. Loan accounting data provided a unique customer identifier, loan number, obligation amount, outstanding balance, obligation date, loan term, and assistance code. The performance of borrowers receiving loans in FY 2005 was determined using borrower's end-of-month repayment status which was available through archived files. These data provided information on whether a borrower was current and, if in default, how many days the borrower had been in default. Data records are for individual cases (loans), but this analysis focused on borrower performance, whereby a default on one OL loan is considered as a default on all OL loans. Thus, this analysis examines the payment performance of borrowers receiving OL loans in FY 2005 on all outstanding OL loans. Data were merged using a unique customer identifier creating a unique dataset combining (a) financial and socioeconomic characteristics at time of loan obligation with (b) loan repayment patterns.

FSA loan applicants must meet general eligibility requirements with respect to participation in the farm enterprise and must meet certain financial criteria. At the time of loan application, loan officers evaluate a borrower's financial position (utilizing recent balance sheet and historical earnings trends as well as projections for the next year) and determine if they meet eligibility standards. Since eligibility requirements for FSA direct loans require that applicants demonstrate an inability to obtain credit from commercial lenders at reasonable rates and terms, underwriting criteria for direct FSA borrowers are less stringent that those of commercial lenders. For example commercial lenders typically expect borrowers to show a repayment capacity margin of at least 110 percent while FSA merely requires the borrower to show that a repayment capacity of 100 percent. Among new OL borrowers in fiscal 2005, 58.1 percent reported a coverage ratio of less than 110 percent compared to 64.1 percent of new FO borrowers who exhibited such a coverage ratio (table 2).

Past studies have shown the loan-to-value ratio to be one of the strongest indicators of default for all types of loans. Hence, FSA applicants are required to securitize all of their loans. But, the Farm Business Plan did not provide complete data on loan-to-value ratios for all borrowers. Loan-to-value ratios are less meaningful for OL borrowers while nearly all new FO borrowers had initial loan-to-values of 90 percent, except for down payment borrowers who had loan-to-value ratios between 80 and 85 percent. The debt-asset ratio and borrower net worth, which was available for all borrowers, should be highly correlated with the loan-to-value ratio and a strong indicator of default. Borrowers with greater indebtedness would be expected to be more likely to default. Likewise, borrowers with limited amounts of equity should be more likely to default. More solvent borrowers may be able to draw on their equity to meet any cash shortfalls. Borrowers with only limited capital invested in the farm business would be considered to be more likely to default, since there is less of a personal stake to protect. It was hypothesized that borrowers with less than $50,000 of net worth would be more likely to default.[4] This represented 40.1 percent of new OL borrowers and 28.5 percent of new FO borrowers (table 2).

Borrowers reporting a farming loss, as indicated by a negative return on assets reported on the Farm Business Plan, were considered more likely to default. Many farmers, however, rely heavily on non-farm sources of income to service outstanding farm debt. Net cash flow as was recorded in the Farm Business Plan, is the projected margin after debt servicing plus or minus capital sales/expenditures plus any beginning cash on hand and includes all owner withdrawals and non-farm income. Larger net cash flows would indicate a greater ability to withstand economic adversity and to continue to meet debt obligations. Likewise, borrowers with greater amounts of equity in liquid current assets should be more able to withstand financial adversity without defaulting. Personal equity was defined as personal current assets less personal current liabilities. While borrowers for both FO and OL loans reported close $0 of personal equity, the standard deviation of just over $20,000 indicated that at least some borrowers would have had some personal liquidity (table 2).

Farm type was disaggregated into five separate binary variables based on the NAICS code included in the Farm Business Plan. These farm types included some of the more common specializations and accounted for about 80 percent of borrowers. Beef, dairy, and grain farmers represented over two-thirds of all borrowers receiving OL loans in

[4] The threshold of $50,000 of net worth was approximately the median level on net worth for OL borrowers.

fiscal 2005 (table 2). In addition to differing economic conditions affecting different commodities, there are structural differences affecting the ability to repay. For example, the income received by dairy farmers is more regular basis and less uncertain than the income of beef or grain farmers. Compared to livestock or specialty crop producers, grain and cotton farmers receive a larger share of their income in Government payments which reduces some of the uncertainty.

The total amount of direct loans received by borrowers during a fiscal year was expected to have an impact on default rates. In most cases, borrowers only received one direct during a fiscal year. But, about one-fourth of all direct OL borrowers received 2 or more new OL loans in FY 2005 compared to less than 1 percent for FO borrowers. All OL loans received by a borrower during the same fiscal year were summed to create the independent variable LOANSIZE. A larger LOANSIZE indicates greater financial risk which would contribute to greater risk of default. Conversely, larger LOANSIZE may also indicate a larger farm size since larger farms are likely to borrow greater amounts. Since larger farms may achieve greater economies of size, a larger LOANSIZE may also indicate a reduced risk of default.

A share of FSA FO and OL loan funds are targeted for use by beginning and socially-disadvantaged (SDA) farmers. A beginning farmer is considered to be someone with 10 years or less of farming experience, regardless of age. An SDA farmer is one who is a member of a racial or ethnic minority or a woman. A majority of the direct borrowers in FY 2005 were beginning farmers; 69 percent of FO, 56 percent of OL (table 2). These percentages are greater than targeting levels since some beginning farmers received non-targeted funds. About 15 percent of both direct FO and OL borrowers were members of an SDA group, of which about 40 percent were women. A small share, 5 percent, of FO loans made to beginning farmers were down payment loans. Since beginning and SDA farmers typically have fewer financial resources, there borrowers were expected to be more likely to default.

Studies of consumer and residential finance have shown that individuals undergoing a change in their marital status tend to be more likely to default. A majority of direct borrowers were married couples. FO funds were highly targeted to beginning farmers, 32.8 percent of whom were still single (table 2). In comparison, about one-fifth of direct OL borrowers were single. Only 2 to 3 percent of direct borrowers were divorced. The expectation was that married couples should be the best credit risk because of the additional incomes which could be available to service any debt. Hence, both single and divorced borrowers were expected to have a greater probability of default.

Small farms have been defined as any operation with less than $250,000 in annual sales (USDA, 1998). A large majority of direct borrowers fell in this category. About 96 percent of FO and 83 percent of OL borrowers in FY 2005 would have been considered small farms (table 2). Since small farms lack the economies of size and financial resources available to larger farms, they were expected to be more likely to default.

Over 90 percent of direct borrowers were organized as a sole proprietorships as indicated by an individual being listed as the entity type (table 2). The remaining farms were partnerships, joint operations, limited liability corporations (LLC's) or family farming corporations. More complex organizations would have a greater number of individuals involved and, consequently, should have access to greater amounts of financial resources. Hence, borrowers organized as sole proprietorships were expected to be more likely to default than more complex entities.

Since commercial lenders have higher underwriting standards than FSA, borrowers who obtain a greater proportion of credit from commercial lenders should be more financially sound and, hence, less likely to default. Conversely, direct borrowers obtaining a larger share of their credit from FSA were expected to be more likely tor of default. Based on the lender name, which was available in the Farm Business Plan, FCS borrowers could be identified[5]. About 12 percent of OL borrowers and 21 percent of FO borrowers were indicated to also be an FCS borrower (table 2). FO borrowers may choose to borrow under the joint financing option, where FSA provides up to 50 percent of the credit while a private lender provides the rest. About one-third of direct FO's were made under this option in fiscal 2005. About 10 percent of OL and 17 percent of FO borrowers also had a FSA guaranteed loan outstanding. Since borrowers receiving funds through either the joint financing or guarantee program must be able to demonstrate creditworthiness sufficient to satisfy a private lender, they were considered less likely to default.

[5] There were only 95 FCS lending associations compared to 7,500 commercial banks and 1,300 savings banks. The large number of potential bank names made it impractical to identify institutions or to differentiate banks from other entities such as insurance companies, individuals, or input providers.

Highly fractionalized credit, as evidenced by a large number of loans, is another indicator of default probability. Using the loan schedule of the Farm Business Plan, the total number of loans to all lenders could be determined. Also, the loan schedule provided data on rates, terms, and payment status. Borrowers with larger shares of high-risk debt, which was defined as having higher interest rates, restructured terms, or was past-due, were hypothesized to be more likely to default. On average, OL borrowers held about $27,000 of this high-risk debt, or 7-percent of total, while FO borrowers held $46,000, or 10 percent of their total debt (table 3).

Results

Logistic Regression

Most of the factors hypothesized to impact on the probability of default for the OL program were found to be statistically significant with anticipated signs. Overall the model was highly significant with 18 of the 27 variables determined to be statistically significant in the OL model and 13 variables determined to statistically significant in the FO model (table 4; table 5).

Specialization in production of a certain commodities was indicated to one of the strongest default indicators. Farms specializing in dairy and grain production were shown to be less likely to default for both the FO and OL programs. The difference was especially pronounced among dairy farms, where log-odds ratios indicated the predicted default probability (PD) for dairy farms was half that of non-dairy farms for both FO and

OL loans (table 6).[6] For FO loans, the PD for grain farms was less than a third of that for non-grain farms. The PD was higher among cotton farmers as well as producers of specialty crops, which included producers of vegetables, fruit, nuts, greenhouse, and nursery products. Specialization in specialty crops increased the PD by over 75 percent for FO and 38 percent for OL programs compared to non-specialty crop farms. These results may reflect lower levels of government support typically provided to producers of specialty crops, or the greater regularity of payments to milk producers.[7] The lower PD's could also be a consequence of high grain and milk prices that may have benefited dairy and grain farmers more than producers of specialty crops over the last 3 years.

Beginning farmers were expected to be less likely to default for both the FO and OL programs. The parameter was statistically significant for both the OL and FO models, but had an unexpected sign (table 4; table 5) The log-odds ratios indicated beginning farmers were 18 percent less likely to default in the OL programs and 30 percent less likely to default in the FO program (table 6). This outcome was somewhat unexpected given that beginning farmers tend to have fewer financial resources. One explanation may be that the borrower training and financial training programs targeted to beginning farmers are having an impact in reducing defaults[8]. Or, this outcome may be a consequence of higher targeting goals whereby FSA may be extending credit to financially stronger beginning farmers in an effort to meet these increased targets.

[6] The log-odds ratio was defined as PD/(1-PD).

[7] FSA may receive an assignment whereby a portion of the farmer's milk receipts is paid to FSA in fulfillment of the debt (See 7 CFR 1404)

[8] Under 7CFR1924.74, a beginning farmer can be required to pursue financial training as a condition of obtaining a FSA direct loan.

The parameter for membership in an SDA group was statistically significant and had the expected sign for both programs (table 4; table 5). Log-odds ratios indicated that an SDA borrower was 50 percent more likely to default than non-SDA borrowers for the FO program and 63 percent more likely to default for the OL program. This result would be consistent with the fewer financial resources typically owned by SDA farmers.

The parameter for marital status was significant, but only in the OL model and only for the divorce indicator (table 4; table 5). Compared to married borrowers, divorced OL borrowers were 40 percent more likely to default (table 6). This would be consistent with results obtained from studies of consumer and residential mortgage default where changes in life situations have been found to increase default probabilities.

Loan size did not appear to be a very important factor influencing loan default. Borrowers with larger amounts borrowed through the OL program during FY 2005 were more likely to default, though the level of significance did not reach the 5 percent threshold (table 4). The effect was minor with a $100,000 increase in total the amount of OL funds borrowed during the year only increasing the PD by 0.01 percent.

Being a small farm borrower, defined as having less than $250,000 in annual sales, was found to have a statistically significant impact on default probability for the FO program.(table 4). While small farms were indicated to also be more likely to default for the OL program, the parameter was not statistically significant. Borrowers utilizing the

FO joint financing option, who tended to operate larger farms, were only 40 percent as likely to default as FO borrowers not utilizing the FO joint financing option. These results suggest that if may be the interrelationship between farm and loan size that influences default probability. Larger loan amounts do not necessarily increase default risk, as long as a large loan amount is consistent with a larger farm size.

In general, borrowers who were able to obtain a portion of their credit from a commercial lender were less likely to default. FO borrowers who were also FCS borrowers were only half as likely to default as non-FCS borrowers while OL borrowers with FCS loans were 25 percent less likely than non-FCS borrowers to default. OL borrowers who received a smaller share of their nonreal estate credit from FSA were also less likely to default. A 10-percentage point increase in FSA's share of nonreal estate debt increased default probability by 5 percent. The use of down payment loans by beginning farmers did not impact default probability. While down payment borrowers would generally be expected to have fewer financial resources, they were required to provide 10 percent of the purchase price using their own funds which could have alleviated much of the risk. Somewhat unexpectedly, the presence of an FSA guaranteed loan provided no indication of default probability. While having both a guaranteed and direct loan may indicate progress toward graduation for a direct borrower; it may also indicate a deteriorating financial position for a guaranteed borrower.

The organizational structure of the farm business was indicated to have an impact on default probability, but only for the OL program. OL borrowers organized as sole proprietorships were 35 percent less likely to default than borrowers organized as partnerships, family corporations, or LLC's (table 6). This was somewhat unexpected, given that more complex business structures should have access to more financial resources.

Among financial variables, solvency was indicated to be a strong default indicator, which was highly significant in both the FO and OL models (table 4; table 5). A 1 percent increase in the debt-asset ratio increased the PD by 0.7 percent for both programs (figure 1).[9] Other strong indicators of default included liquidity in personal assets, the total number of loans outstanding, and the share of outstanding debt considered to be high risk. Liquidity in personal assets was highly significant for both models. On average, every $5,000 increase in personal equity decreased the PD by 5 percent for FO and 2 percent for OL loans. The total number of loans outstanding to all lenders was also highly significant for both OL and FO programs (table 6). For every additional loan, the PD increased by 4.5 percent for FO and 3.5 percent for OL loans (figure 2). The share of total outstanding debt considered to be high risk was another strong indicator of default, though only for OL loans. Increasing the share of high risk debt by 1-percentage point increased the probability of default by 0.8 percent (table 6).

Borrowers with shortcomings in either debt coverage or liquidity were more likely to default in both the FO and OL programs. Borrowers who had coverage ratios of less than 110 percent were 63 percent more likely to default in the FO program and 20 percent

[9] This was determined by estimating the predicted probability of default across the entire data set at varying levels of the debt-asset ratio.

more likely to default in the OL program.   Illiquid FO borrowers, who were defined as current liabilities exceeding current assets, had a 67 percent greater chance of defaulting while illiquid OL borrowers had a 34 percent greater chance of defaulting compared to more liquid borrowers (table 6). Borrowers with a shortage of capital at the time of application, defined as net worth less than $50,000, were about 20 percent more likely to default in both programs. The parameter for net cash flow was significant for the OL program, though the PD did not appear very sensitive to changes in cash flow. A $10,000 increase in net cash flow was shown to only decrease the PD by 1.5 percent. Farmers experiencing a farming loss were actually shown to have a reduced PD on OL loans. This unexpected finding can probably be attributed to the greater importance of off-farm income relative to farm income in servicing debt, even among direct borrowers.

Comparisons to FSA Scoring Model

FSA uses a 4-category classification system to risk rate their direct loans. Federal statutes require FSA to annually classify all borrowers based on their ability to graduate to commercial credit. Also, borrowers receiving new loans must be classified upon loan closing.[10] FSA classification procedure awards points to each borrower based on measures of financial performance and operation stability in 5 categories: solvency; debt coverage; liquidity; profitability; and collateral. Borrowers with the best scores are classified as commercial and should have greatest potential to graduate to commercial credit.   Borrowers with modest credit shortcomings would be considered standard.

[10] See FLP-1 "FSA Handbook, General Program Administration" United States Department of Agriculture Farm Service Agency, Washington D.C. (Part VII, Section 4 'Borrower Account Classification). ftp://165.221.16.16/manuals/1-flp-r1.pdf

Typically, these borrowers have underwriting shortcomings standards in at least one of the aforementioned categories. Borrowers with multiple credit shortcomings, but are still meet minimum requirements with respect to debt coverage or collateral would be classified as acceptable.[11] The lowest category is considered marginal and would capture borrowers who are under-secured or with other significant credit shortcomings.

Estimating the PD by FSA's classification grouping reflects relative default risk, with the riskier classifications displaying greater PDs (figure 3). A majority of the OL borrowers classified as commercial or standard have PDs of less than 22.2 percent. And, a majority of those classified as marginal have PDs of over 28 percent. The predictive ability of the logistic regression model depends on the cut-off level chosen to identify borrowers considered likely to default. Borrowers with a PD greater than or equal to the cut-off level would be considered likely to default while borrowers with a PD less than the cut-off level would be considered not likely to default. Choosing a cut-off value equal to the mean PD of 0.23 would result in 65.1 percent of borrowers having been correctly classified in the OL model and 85.86 percent in the FO model (table 7). Meanwhile, 28.8 percent of borrowers would have been false positives in the OL model. A false positive means that a borrower was identified as likely to default by either the logit or FSA scoring model but did not. And, 9.1 percent of borrowers in the OL model were false negatives which mean they were not identified as likely to default but did not. As the cut-off value is increased, the false positives decrease while false negatives decline. Cut-

[11] Eligibility requirements stipulate that qualified FSA direct loan applicants be able to demonstrate cash flow and provide fully security for the loan.

off levels for PD of 0.28 would have resulted in a larger percent of borrowers being correctly classified but would have increased the false negatives.

The discreet classifications within FSA's internal borrower classification model provide little flexibility in establishing a cut-off to determine likely default. Choosing a marginal classification as a cut-off value to identify likely defaulters would correctly identify 70.5 percent of OL borrowers but would give 17.3 percent with false negatives. Using the 'Marginal' classification of the FSA internal scoring model to identify likely FO defaults would have correctly classified 81.9 percent with 8.7 percent false positives and 9.5 percent with false negatives.

One of the goals of a default classification system would be to identify borrowers in greatest need of special servicing options. Presumably, the special servicing options could be provided to help avoid default among those borrowers considered more likely to default. Thus, in addition to the percent correct, an important goal of a classification system would be to minimize false negatives. Using these criteria, the probabilistic default model would appear to represent an improvement over the FSA scoring model in risk rating. Also, the probabilistic default model provides greater flexibility in choosing a cut-off to predict default.

Summary

The results of the binomial logit model applied to FSA Farm Business Plan and loan performance data indicated a strong and direct relationship between many key financial variables, production specialization, membership in a targeted group, and the ability to obtain credit from commercial lenders. Borrowers who were more under-capitalized or illiquid were found to be more likely to default. Solvency, as measured using the debt-asset ratio, was indicated to be a strong default indicator for both the FO and OL models. Likewise, borrowers with a shortage of capital at the time of application were more likely to default in both programs. Borrowers with a larger proportion of their indebtedness at higher rates or with restructured terms were more likely to default. Liquidity in both personal and farm assets was highly significant for both models. Both OL and FO borrowers for whom current liabilities exceeded current assets had a greater chance of defaulting.

Borrowers with fractionalized credit or repayment issues were found to be more likely to default. The total number of loans outstanding to all lenders was also highly significant for both OL and FO programs. Borrowers who had coverage ratios of less than 110 percent were 63 percent more likely to default in the FO program and 20 percent more likely to default in the OL program.

Borrowers who are able to obtain a portion of their credit from a commercial lender were less likely to default. Borrowers who were FCS borrowers and those receiving a smaller share of their credit from FSA were found to be less likely to default. Also, borrowers utilizing the FO joint financing option were notably less likely to default.

Demographic factors were indicated to play an important role influencing loan defaults. Beginning farmers were unexpectedly shown to be less likely to default for both the FO and OL programs. A possible explanation may be the greater servicing attention given to beginning farmers as a result of targeted financial training programs. As was expected, SDA borrowers were over 50 percent more likely to default for the FO program and 63 percent more likely to default for the OL program. This result would be consistent with the fewer financial resources typically owned by SDA farmers. Compared to married borrowers, divorced borrowers were more likely to default, a result consistent with expectations.

Economic conditions unique to a commodity group may be one of the key factors affecting loan defaults. Farms specializing in dairy and grain production were shown to be less likely to default while cotton and specialty crop producers were more likely to default. These results may reflect structural differences or relative commodity prices for the time period analyzed.

Estimating the PD by FSA's internal classification verified that the riskier classes of borrowers were, in fact, more likely to default. Comparing FSA internal classification system with the results of the binomial logit suggested that the logit models greater flexibility better enabled an identification of borrowers in greatest need of special servicing options. Presumably, the special servicing options could be provided to help avoid default among those borrowers considered more likely to default.

Table 1. Variable Definitions.	
Variable	Definition
PD	Probability of default which is defined as =1 if borrower has ever been 90 or more days past due since September of 2005
FARMTYPE	
BEEF	1 if beef farm, 0 otherwise.
COTTON	1 if cotton farm, 0 otherwise
DAIRY	1 if dairy farm, 0 otherwise
SPECIALTY_CROP	1 if vegetable, fruit & nut, or nursery/greenhouse farm, 0 otherwise
GRAIN	1 if grain farm, 0 otherwise (corn or grain sorghum, soybean, wheat or other small grain)
LOANSIZE	Total dollar amount of direct OL or FO loans received by the borrower during the fiscal year
BEG	1 if borrower is considered a beginning farmer, 0 otherwise
SDA	1 if borrower is a member of a socially-disadvantaged group, 0 otherwise
MARRITAL_STATUS	
SINGLE	1 if borrower has never been married, 0 otherwise
DIVORCE	1 if borrower is divorced and not re-married, 0 otherwise
SMALL_FARM	1 if annual farm sales are less than $250,000, 0 otherwise
SOLE_PROP	1 if entity type is listed as 'Individual', 0 otherwise
CASHFLOW	Dollars of net cash flow after all obligations have been paid.
DARATIO	Ratio of farm debt to farm assets
LOW_EQUITY	1 if borrower has $50,000 or less of farm equity, 0 otherwise.
LOW_COVRATIO	1 if borrower has term debt coverage ratio of 1.10 or less, 0 otherwise
NOT_LIQUID	1 if borrower has a liquidity ratio of 1.0 or less, 0 otherwise
HI_RSK_SHR	Share of total principal outstanding on loans that have been restructured, refinanced, with rates greater than 9-percent, currently past-due or where the lender is identified as a credit card.
FARMING_LOSS	1 if borrower has a return on assets of 0% or less, 0 otherwise

Table 1. Variable Definitions. (continued)

Variable	Definition
PERSONAL_EQUITY	Dollars of personal current assets less personal current liabilities
FSA_SHR	
FSA_SHR_NR	Total share of total nonreal estate debt provided by FSA
FSA_SHR_RE	Total share of total nonreal estate debt provided by FSA
FCS	1 if borrower has an outstanding loan with the FCS, 0 otherwise
NUMBER_OF LOANS	Total number of loans from all lenders.
GTE	1 if borrower has an outstanding FSA guaranteed loan, 0 otherwise
LOAN_TYPE	
OP_LOAN	1 if 50% or more of direct OL debt is for a 1 year term, 0 otherwise.
REFI	1 if the primary purpose for new OL loan funds is to refinance existing indebtedness, 0 otherwise
DPAY	1 if the primary purpose for new FO loan funds is for down payment loan; 0 otherwise
JOINT	1 if the primary purpose for new FO loan funds is for joint finance loan; 0 otherwise

Table 2. Means of Variables Used in Logit Model Analyzing Direct Loan Default.

	OL	FO
	Percent of borrowers	
Borrowers defaulting	23.8	12.4
Farm type		
BEEF	31.3	32.3
COTTON	4.9	1.1
DAIRY	16.6	10.1
SPECIALTY_CROP	6.5	3.0
GRAIN	29.0	35.4
BEG	56.2	69.0
SDA	15.7	16.2
MARRIAL_STATUS		
SINGLE	27.8	33.8
DIVORCE	3.8	2.5
SMALL_FARM	82.1	94.5
SOLE_PROPRIETORSHIP	93.4	96.7
LOW_COVRATIO	58.1	64.1
LOW_EQUITY	40.1	28.5
	Dollars per borrower	
CASHFLOW	9,252	11,262
LOANSIZE	69,343	123,778
PERSONAL EQUITY	-2,704	376

Table 3. Means and Distribution of Key Financial Variables by Loan Type, for FSA Borrowers Receiving Direct OL or FO loans in Fiscal 2005.

	OL		FO	
	Mean	Standard Deviation	Mean	Standard Deviation
		Dollars per Borrower		
Loan size	69,858	54,891	123,703	56,929
7-yr loans	57,899	53,307		
1-yr loans	93,107	77,638		
Down payment			61,392	23,822
Joint financing			124,303	54,184
Annual farm sales	162,557	220,993	150,887	207,325
Net cash flow	7,440	42,568	7,804	41,880
Total farm assets	395,998	532,948	476,237	540,100
Current assets	60,046	138,409	76,188	134,360
Total farm liabilities	230,346	280,194	305,691	298,367
FCS Debt	14,956	79,307	33,635	172,574
Hi-risk debt	27,840	98,322	46,124	155,164
Real estate debt	81,396	156,486	194,048	160,991
Nonreal estate debt	148,950	151,963	111,643	162,677
Current liabilities	59,890	91,911	64,531	134,360
Intermediate liabilities	89,015	103,338	47,112	84,846
Total farm equity	165,651	345,488	170,547	304103
Current personal equity	-2,704	23,831	376	21,395
		Number per borrower		
Number of loans	6.7	5.0	6.6	4.6
Financial ratios		Percent		
Debt_assets ratio	58.2	27.4	64.1	31.1
Current ratio	1.64	1.91	2	2.33
ROA	3.66	3.55	1.78	6.78
Coverage ratio	1.07	1.72	1.09	4.02

Sources: FSA Farm Loan Programs Farm Business Plan;
FSA Farm Loan Data Base.

Table 4. Logistic Regression Results for Defaults on Direct OL Loans Made in FY 2005.

Variable	Estimate (Standard Error)	Wald Chi-Square	PR > Chi-Square	Level of signif-icance
INTERCEPT	-2.74064 (0.22719)	145.5256	<.0001	***
LOANSIZE	0.117857 (0.06214)	3.5974	0.0579	
BEEF	-0.0344 (0.09750)	0.1244	0.7243	
COTTON	0.274693 (0.15143)	3.2906	0.0697	
DAIRY	-0.731 (0.12242)	35.6582	<.0001	***
SPEC_CROP	0.317689 (0.13605)	5.4523	0.0195	**
GRAIN	-0.28078 (0.10055)	7.7979	0.0052	**
BEG	-0.16474 (0.07297)	5.0965	0.0240	**
SDA	0.491252 (0.08777)	31.3241	<.0001	***
SINGLE	0.073431 (0.08194)	0.8032	0.3701	
DIVORCE	0.323287 (0.16553)	3.8145	0.0500	*
SMFARM	0.149733 (0.09865)	2.3039	0.1290	
SOLE_PROP	-0.30636 (0.12669)	5.8482	0.0156	*
CASHFLOW	-0.19804 (0.08735)	5.14	0.0234	*
DARATIO	0.981452 (0.14836)	43.7635	<.0001	***
LOW_EQUITY	0.19922 (0.07685)	6.7208	0.0095	**
LOW_COVRATIO	0.157308 (0.06997)	5.0552	0.0246	*
NOT_LIQUID	0.292716 (0.07960)	13.5226	0.0002	**
HI_RSK_SHR	1.189458 (0.14653)	65.8957	<.0001	***
FARMING_LOSS	-0.22051 (0.07748)	8.1004	0.0044	**
PERSONAL_EQUITY	-0.56512 (0.12645)	19.9737	<.0001	***
FSA_SH_NR	0.742625	21.9506	<.0001	***

	(0.15851)			

Table 4. (continued)

Variable	Estimate (Standard Error)	Wald Chi-Square	PR > Chi-Square	Level of signif-icance
FCS	-0.2644	6.6765	0.0098	**
	(0.10233)			
NUMBER_OF_LOANS	0.048647	49.1056	<.0001	***
	(0.00694)			
OPLOAN	-0.07243	0.7203	0.3960	
	(0.08534)			
REF	-0.11087	1.1404	0.2856	
	(0.10382)			
GTE	-0.13431	1.5919	0.2070	
	(0.10645)			
Likelihood ratio ($H_{o\,:}\ \beta_i = 0$) -2 Log L		545.0687	<.0001	***
Number of observations	7,618			
Number Defaults	1,730			
Percent of loans defaulted	22.7			

* PR > Chi-Square ≥ 0.01 and < 0.05
** PR > Chi-Square ≥ 0.0001 and < 0.01
*** PR > Chi-Square < 0.0001

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Table 5. Logistic Regression Results for Defaults on Direct FO loans Made in FY 2005.

Variable	Estimate (Standard Error)	Wald Chi-Square	PR > Chi-Square	Level of signif-icance
INTERCEPT	-2.87573 (0.62578)	21.1184	<.0001	***
LOANSIZE	0.00482 (0.14877)	0.001	0.9742	
BEEF	-0.46226 (0.21139)	4.7817	0.0288	*
COTTON	-0.50174 (0.70996)	0.4995	0.4797	
DAIRY	-1.00639 (0.32399)	9.6486	0.0019	**
SPEC_CROP	0.48111 (0.37874)	1.6137	0.2040	
GRAIN	-1.32447 (0.25614)	26.7385	<.0001	***
BEG	-0.36973 (0.18894)	3.8293	0.0500	*
SDA	0.39062 (0.19627)	3.961	0.0466	*
SINGLE	0.05384 (0.18424)	0.0854	0.7701	
DIVORCE	0.36233 (0.49008)	0.5466	0.4597	
SMFARM	0.53377 (0.27084)	3.884	0.0487	*
DPAY	-0.56506 (0.52298)	1.1674	0.2799	
JOINT	-0.87097 (0.22640)	14.7991	0.0001	***
SOLE_PROP	-0.48632 (0.42098)	1.3345	0.2480	
DARATIO	0.84761 (0.28454)	8.8738	0.0029	**
CASHFLOW	-0.07594 (0.19699)	0.1486	0.6999	
LOW_EQUITY	0.16627 (0.20030)	0.689	0.4065	
LOW_COVRATIO	0.51990 (0.16674)	9.7226	0.0018	**
NOT_LIQUID	0.46395 (0.17144)	7.3236	0.0068	**
HI_RSK_SHR	0.07241 (0.43451)	0.0278	0.8677	

Table 5. (continued)

Variable	Estimate (Standard Error)	Wald Chi-Square	PR > Chi-Square	Level of signif-icance
FARMING_LOSS	0.23698	1.6101	0.2045	
	(0.18676)			
PERSONAL_EQUITY	-1.41565	14.187	0.0002	**
	(0.37585)			
FSA_SHR_RE	0.25170	0.4689	0.4935	
	(0.36758)			
FCS	-0.57159	5.1484	0.0233	**
	(0.25191)			
NUMBER_OF_LOANS	0.05918	10.7344	0.0011	***
	(0.01806)			
GTE	0.23711	1.0615	0.3029	
	(0.23014)			
Likelihood ratio				
($H_{o}: \beta_i = 0$) -2 Log L		196.625	<.0001	***
Number of observations	2,134			
Number Defaults	247			
Percent of loans defaulted	11.57			

* PR > Chi-Square ≥ 0.01 and < 0.05
** PR > Chi-Square ≥ 0.0001 and < 0.01
*** PR > Chi-Square < 0.0001

Table 6. Log-odds Ratios for Binary Independent Variables.

Variable	Program Model FO	OL
Farm type		
Beef	*0.630*	0.967
Cotton	0.605	1.315
Dairy	*0.366*	*0.481*
Specialty crop	1.618	*1.373*
Grain	*0.266*	*0.755*
Targeted Group		
Beginning farmer	0.691	*0.848*
SDA	*1.478*	*1.634*
Marital Status		
Single	1.055	1.076
Divorce	1.437	*1.382*
Financial Indicators		
Low equity	*1.181*	*1.221*
Low debt coverage	*1.682*	*1.170*
Illiquidity	1.590	*1.340*
Farming loss	1.267	*0.803*
Loan purpose		
Op. loan		0.930
Refinance		0.894
Down payment	0.568	
Joint financing	*0.419*	
FCS Borrower	*0.565*	*0.767*
FSA GTE borrower	1.268	0.874
Small Farm	*1.705*	1.163
Sole Proprietorship	0.615	*0.737*

Parameters which were statistically significant in the regression model are indicated in italics

Table 7. Predictive Ability of Default Model Compared with FSA Borrower Classification

OL Model	Probability of Predicted Default				Borrower classification	
Cut-off PD	0.10	0.14	0.23	0.28	Acceptable or marginal	Marginal
	--Percent of borrowers--					
Correct	31.0	42.2	65.1	72.3	53.2	70.5
False Positive	68.2	54.9	28.8	15.1	37.1	12.2
False Neg.	0.8	2.8	9.1	12.7	9.8	17.3
FO Model	Probability of Predicted Default				Borrower classification	
Cut-off PD	0.077	0.155	0.270	0.350	Acceptable or marginal	Marginal
	--Percent of borrowers--					
Correct	58.0	77.6	85.9	87.4	59.0	81.9
False Positive	40.2	17.9	6.3	3.0	34.8	8.7
False Neg.	1.8	4.5	7.8	9.6	6.2	9.5

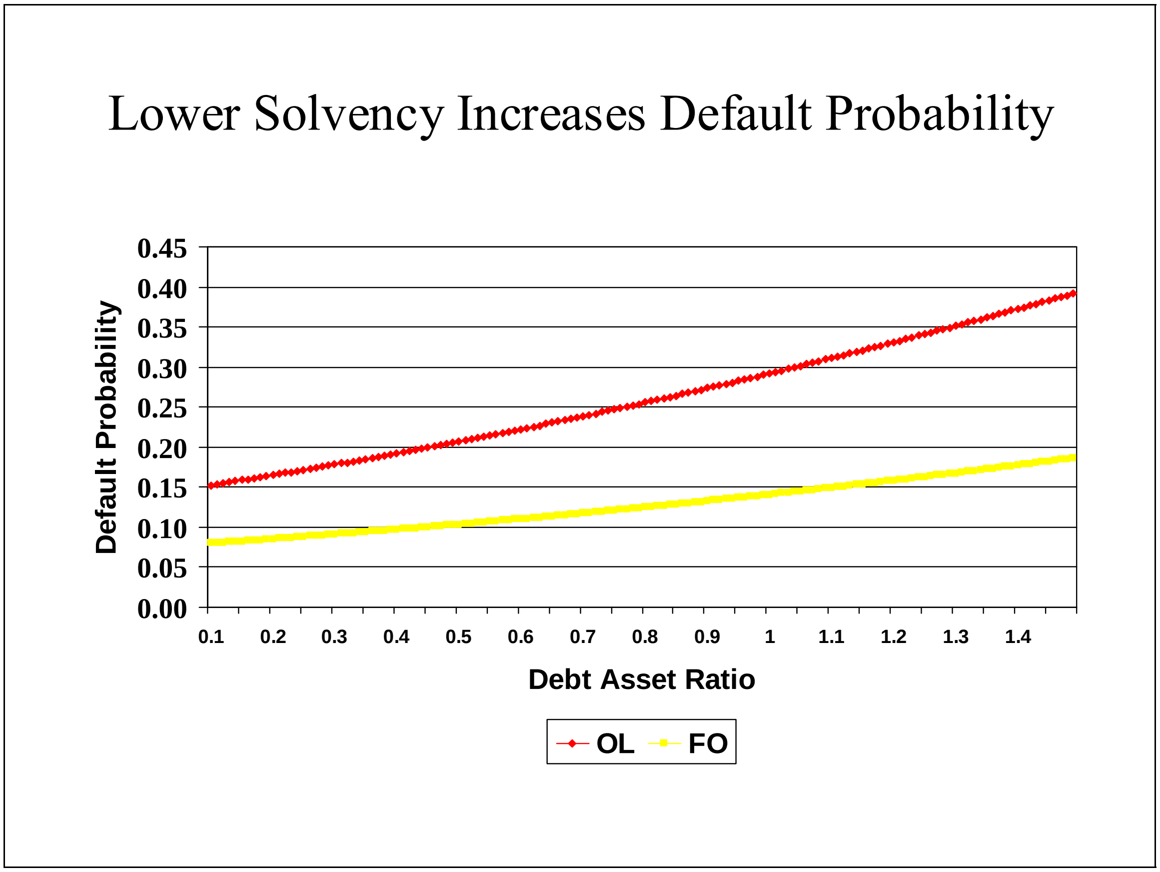

Figure 1. Probability of Default by Debt-Asset Ratio for Direct Loans Obligated in FY 2005.

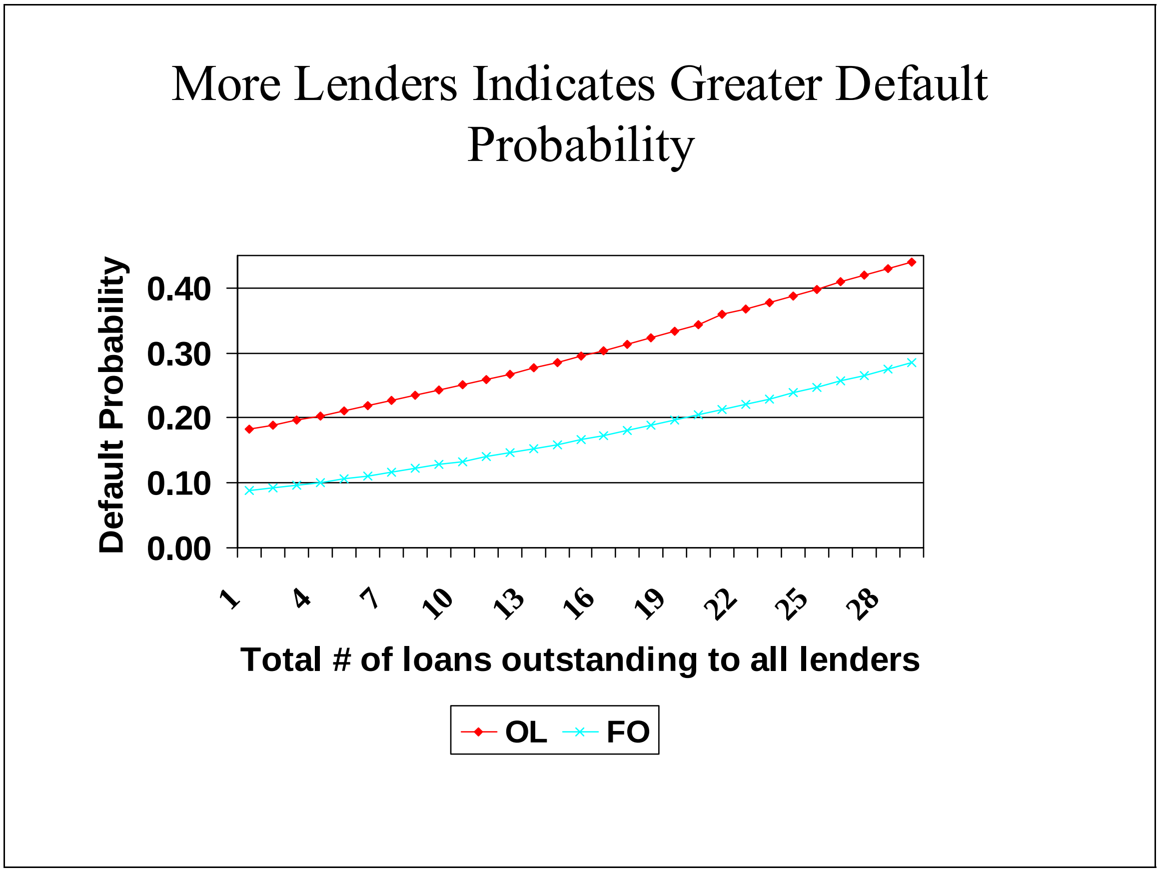

Figure 2. Default Probability by Number of Loans Outstanding to All Lenders.

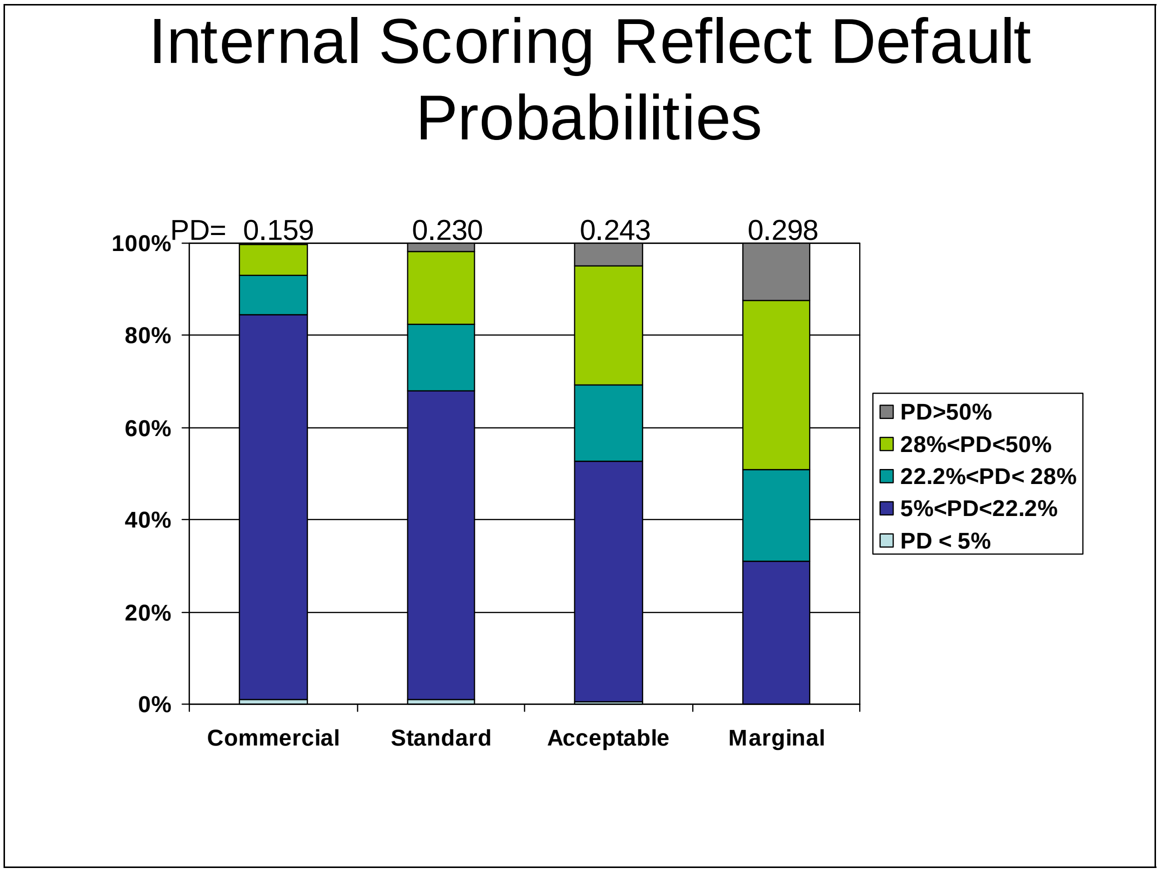

Figure 3. Distribution of Predicted Probability of Default (PD) by FSA Score.

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