Explaining Regional Demand for Federal Farm Credit Programs: An Ordinal Probit Approach

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Selected Paper
Annual Meetings of the American Agricultural Economics Association
Chicago, IL
August 5-8, 2001

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Abstract

Demand for federally subsidized farm credit varies regionally, with farm borrowers in some regions very dependent on USDA credit programs. Counties are grouped based on their level of demand for Farm Service Agency (FSA) direct farm ownership (FO) and farm operating loans (OL). Ordinal probit techniques are applied to analyze factors influencing county-level variation in the use of the loan programs. Results suggest that counties with the highest level of demand are more likely to have a Farm Credit System branch office, are more likely to be dependent on farming, have a greater share of farms owing debt, and have fewer guaranteed FSA borrowers and racial and ethnic minorities.

Introduction

USDA's Farm Service Agency (FSA) provides subsidized farm loans to family-sized farmers unable to obtain credit from conventional sources at reasonable rates and terms. FSA operates direct lending programs and offers loan guarantees on farm loans made by private sector lenders. In fiscal 2000, FSA lent over $1 billion in direct loans and guaranteed another $2.7 billion in farm loans (USDA 2001). The direct and guaranteed farm loan programs each account for about 4 percent of the total outstanding farm debt. Starting in the 1990s FSA loans have been targeted to certain under-served groups, such as racial minorities and beginning farmers.

While FSA's national share of farm debt is relatively modest, there is considerable variation in farmer use of FSA's farm loan programs across regions, within states, and between counties (USDA 2000). In about a third of all U.S. counties, at least one-fifth of indebted farmers in 1997 with at least $10,000 in gross farm sales had a direct farm ownership (FO) or operating loan (OL) loan. In some counties, in the Northeast and the Great Plains, as much as half of all of these farm borrowers have at least one FSA loan, while in the Corn Belt and along the Pacific relatively few indebted farm borrowers had a direct loan.

Little analysis has been completed thus far that might explain observed regional differences in FSA lending patterns. This is especially true for the direct lending programs. A 1990 National level study by Sullivan and Herr developed 3 regression models to examine bank usage of FSA's guaranteed farm loan program. Dixon et al. used county level data to model bank willingness to use FSA guarantees and guarantee loan volume, but limited their study to the state of Arkansas. Settlage et al. modeled loan losses on FSA guaranteed loans for fiscal 1990-97 using USDA regions. Turvey and Weesink made empirical estimations of farm loan demand for Canada using cross-sectional and time-series data from the government owned Farm Credit Corporation. Neither of these studies specifically attempted to explain regional differences in program use.

This research attempts to explain variation in county-level usage of FSA loan programs using an ordinal probit modeling technique. The level of demand for FSA programs within a county is defined by loan program market penetration within a county. The model examines explanatory factors that affect program usage across counties, such as the availability of commercial credit, program targeting requirements, credit risk, and borrower creditworthiness for 1997.

Mapping FSA's market share shows that counties tend to be regionally clustered according to the level of demand (figure 1). High demand is evident in the Mississippi Delta, Northern Plains, and Texas High Plains, while low-demand characterizes California, Corn Belt, and Central Texas. Partitioning of FSA borrowers into different sub-groups enables researchers to study the borrowing behavior and characteristics of these groups. Do groups of counties with high-use of FSA programs have fewer lending alternatives from private lenders? Or do groups of counties with higher demand for FSA credit programs merely exhibit greater lending risk? An improved understanding of variation in regional demand for FSA loan services can also help in improving program delivery. During the 1990s, some USDA county offices were consolidated into service centers and further consolidation is possible. Understanding factors that influence local program usage can be important to future office location policies.

Theoretical Methodology

The dependent variable was defined as the county's classification as to its reliance on FSA direct FO and OL loan programs where:

> *Low-use*, ($y = 0$) = less than 10.5 percent of indebted farmers with sales > $10,000 had an FSA loan,
> *Medium-use*, ($y = 1$) = between 10.5 and 21.5 percent of indebted farmers with sales > $10,000 had an FSA loan,
> *High-use*, ($y = 2$) = greater than 21.5 percent of indebted farmers with sales > $10,000 had an FSA loan.

Low-use represents the lower one-third of the distribution while medium-use represents the upper one-third of the distribution. Since the dependent variable represents a ranking, an ordinal probit model is considered the most appropriate framework. The model is built around a latent regression model:

$$y^* = \beta' x + \varepsilon,$$

where y^* is an unobserved index. Though unobserved, the value of y^* determines the ranking.

$$\begin{aligned} y &= 0 \quad \text{if } y^* \leq 0, \\ &= 1 \quad \text{if } 0 < y^* \leq \mu_1, \\ &= 2 \quad \text{if } \mu_1 < y^* \leq \mu_2, \end{aligned}$$

The μ's are unknown parameters, which are estimated along with the β coefficients. The variable x represents a vector of measurable factors while ϵ represents normally distributed unmeasurable factors. With the normal distribution we have the following probabilities:

Prob(y = 0) $\phi(- \beta' x)$,
Prob(y = 1) $\phi(\mu_1 - \beta' x) - \phi(- \beta' x)$,
Prob(y = 2) $\phi(\mu_2 - \beta' x) - \phi(\mu_1 - \beta' x)$,
where ϕ represents the standard normal function.

The ordinal probit model is estimated using maximum likelihood techniques. Using the above techniques, the marginal effects of the regressors, x, on the probabilities that a county is low-, medium-, or high-use can be determined.

Data Sources

The model is estimated with data compiled from a number of sources, but drew heavily on Census of Agriculture data. Data selected are for time periods consistent with the 1997 Census of Agriculture. The number FSA loan program borrowers within each county were obtained from Farm Service Agency loan files. A number of explanatory variables were obtained or constructed from the Census of Agriculture or other data sources. Personal and farm income and certain demographic data were obtained from the U.S. Department of Commerce. Data on crop insurance were obtained from USDA's Risk Management Agency. Data on commercial bank and the Farm Credit System location were constructed from data from the Federal Deposit Insurance Corporation and Farm Credit Administration, respectively.

County-level market penetration varied from 0 to over 100 percent. Estimates greater than 100 percent reflect the possibilities of multiple entities associated with each farm. For example, a son or daughter may take out an OL loan to purchase equipment while the father has an outstanding FO loan. Yet, if the farm were organized as a sole proprietorship, Census would only count the father as a farmer. Also, there may be cases where a borrower is no longer actively farming, but still has outstanding FSA indebtedness.

Model Specification

Dependent Variable

We examine demand for FSA credit in local credit markets (MKTSHR) by calculating the ratio of FSA direct borrowers within a county to the number of indebted farms with at least $10,000 in farm sales (See table 1 for definitions of model variables). Only those FSA borrowers with direct operating loans (OL) or farm ownership (FO) loans are included, as the eligibility and targeting criteria for emergency loans, EM, are different.[1] All indebted farms within a county are those operators that reported having interest expenses in 1997. Eliminating very small farms from the market reduces estimation distortions that arise from including retirement, lifestyle, hobby and other similar typology groups. Farms with under $10,000 in sales account for about half of all farms, but produce less than 2 percent of the value of food and fiber. Furthermore, as discussed later, the mission of FSA requires them to serve family-sized farms and as such relatively little lending goes to very small farms (USDA 2000). Counties are classified as low-, medium-, or high-use based on their use of FSA farm loan programs.

Explanatory variables

A number of variables are hypothesized to influence FSA market penetration at the county level. Explanatory variables can be organized along the mission of the programs. These include measures relating to loan targeting and credit rationing, the competitiveness of local credit markets, and creditworthiness of farms within the county.

Targeting

FSA loans are intended to serve family-sized farms and under-served groups of family farms (Dodson and Koenig). Congress provided no definition of a family farm, but FSA guidelines for determining a family farm stipulate that the farming operation compares to similar farming operations in the community and that the family provides most day-to-day labor and management decisions. The programs are not intended to serve lifestyle or hobby farmers and research indicates that this appears to be the case (USDA 2000). Caps on total loan program indebtedness ($200,000 for the direct OL and FO programs) are the primary means to ensure family-farms have primary access to FSA credit. USDA research showed that in 1997, 89 percent of direct loan borrowers and 82 percent of guaranteed loan borrowers met the National Small Farm Commission definition of a small farm (less than $250,000 in sales).

To measure the influence of family farm targeting on county level market penetration we include variables for farm size (SIZE) and family farm presence (SHREFAR). SIZE is hypothesized to have a positive coefficient since the greater the number of middle-sized farms in the county the greater the likelihood that the county will be classified as a high-use county. Likewise, counties with greater shares of their farmers listing their primary occupation as farming (SHREFAR) is hypothesized to have a positive coefficient, since the greater percentage of full time farmers in the county would increase the likelihood that a county be classified as a high-use county.

FSA loan programs are targeted to specific groups of individuals considered to be socially disadvantaged (SDA).[2] This definition includes racial and ethnic minorities and women. Targeting of loans is accomplished by setting aside a share of the annual loan funding for use by SDA applicants based on the proportion of SDA farmers or residents in the state. Koenig and Dodson show that FSA lending to racial and ethnic borrowers tends to be correlated with geographic concentration of these individuals and that a relatively high share of new lending now goes to these groups.

To measure SDA targeting requirements we include variables for the share of farms with a least $10,000 in sale that are operated by women (WOMEN) and the total share of all farms with $10,000 in sales that were operated by racial and ethnic minorities (RACE). We hypothesize that counties with higher shares of these target groups will more likely be classified as high-use counties, and, therefore a positive coefficient is expected on these variables.

FSA farm loans are also targeted to beginning farmers, with priority given in annual program funding over general applicants.[3] To measure the impact of this targeting goal on county market penetration, the share of farmers meeting the beginning farmer eligibility criteria is compared with the total number of farms within a county that is most likely to be eligible (TARBEG). This includes those under 45 years of age with less than 10 years experience operating a farms and who reported sales of between $10,000 and $500,000 in sales. Counties with a larger than average presence of this targeted group would be expected to be high-use counties.

Competitive Markets and Credit Access

The competitiveness of local farm credit markets could also be a factor that explains FSA lending patterns. Counties with less competitive agricultural credit markets could be more reliant on FSA loan programs. Typically, rural credit markets are less competitive than their urban counterparts. But, while there are fewer lenders in rural areas those that are there tend to be much more focused on farm lending. In contrast, lenders located in counties near metro regions may choose alternative investment options, which may be more lucrative and less risky than agricultural lending.

Two variables used to measure credit market access are FCS5MI and AGBANK. FCS5MI is one if a Farm Credit System branch office is within the county or an office is located within 5 miles of the county's border. AGBANK is one if at least one branch of a commercial bank with a significant farm loan portfolio is located within the county.[4] Both are hypothesized to negatively impact whether a county is classified as a high-use county.

The share of total land in farming (LANDFARM) within the county was included as a proxy for the importance of farming in a county. Rural counties with a small amount land devoted to agriculture or more urban counties are expected to be more likely to be classified as high-use counties because fewer lenders might be active in farm lending in these areas.

Credit Risk and Creditworthiness

Because FSA loans serve high-risk borrowers, those unable to obtain credit elsewhere, counties with greater farming risk or more subject to natural disasters should be more likely to be classified as high-use counties. The loss pay out ratio on Federal Crop Insurance Corporation loans was selected as a proxy for the level of production risk within a county (LOSSRATE).[5] The higher the loss rate in the county the greater the likelihood the county would be a FSA high-use county.

We also hypothesize that counties dependent on a single commodity are more likely to be FSA high-use counties. This occurs because their dependence on a single commodity implies greater credit risk to lenders. If a county had greater than 33 percent of its total value of production devoted to a particular commodity, it was identified as commodity dependent. Counties dependent on poultry, dairy, beef, cotton, and wheat production were identified and included in the model.

High per capita incomes generally imply greater non-agricultural investment alternatives for lenders. Likewise, non-agricultural investment alternatives may inflate land values above the land's agricultural earning potential. Given these alternatives, commercial lenders are more likely to forego farm loans resulting in greater use of FSA loan programs. To test this hypothesis variables for per capita county income (PCAPITA) and the ratio of average price of farmland to net earnings per acre (AVGPE) were included in the model. County AVGPE tends to be higher in metro areas and in regions characterized by enterprises that generate lower income, such as cow-calf farms.

The degree of financial leverage or the indebtedness of farm borrowers would be expected to positively influence whether a county is high user of FSA farm loan programs. To test for the influence of leverage the ratio of interest expenses to total expenses (INTOT) and the percentage of total farms reporting paying interest on farm debt (INDEBT) were included in the estimations. Finally, to account for substitutability with credit offered through FSA's guaranteed farm ownership and farm operating loan programs, a variable for the share of total farms in the county with a guaranteed FSA loan (GTEUSE) was included in the model. This variable is hypothesized to have a negative coefficient.

Model Estimation Results

Of the targeting variables, only the presence of high levels of racial and ethnic minorities in farming (RACE) was found to have a significant effect on being classified. But, the sign was not as expected. Counties with higher concentrations of minority farmers were less likely to be high-use counties. Many of the counties with higher concentrations of racial and ethnic minorities in farming were located in California and the Southwest, reflecting the higher Hispanic populations in these areas. But, FSA farm loan programs tend to be less important in these regions. Segregation of Hispanic farmers from black farmers and American Indians within the model may indicate more targeting of these groups. Also, many of the FSA direct loans to minorities were EM loans, which were not considered in this study.

There was no indication that counties with a greater presence of beginning farmers (TARBEG) or women farmers (WOMEN) were more likely to be high-use counties or less likely to be low-use counties. But, this result should not be entirely unexpected given that targeting provisions for these groups were not implemented until 1994 and there may not yet have been sufficient loans made to these groups to notably change the composition of the portfolio. Examination of only loans made since implementation of targeting to socially disadvantaged groups and to beginning farmers would be more indicative of the effectiveness of targeting.

Counties where a larger share of the farmers considered farming to be their primary occupation (SHREFAR) were not indicated to be any more likely to be high-use or less likely to be low-use counties. Farming as a primary occupation is much more common among farms located in the Great Plains, Mississippi Delta, and rural New England, which are areas where FSA loan programs are more important. But, FSA loan programs are also important among counties where farm operators are less likely to consider farming to be their primary occupation such as the Southeast, Arkansas, West Virginia, and Utah. Counties with a larger share of farms with sales between $50,000 and $250,000 (SIZE) were no more likely to be in the high-use group. While program usage is high in regions where these size farms dominate, such as the Great Plains, program demand is also high in the South where farms tend to be larger.

Results presented here do not indicate that counties more dependent on FSA credit programs have less credit access. In fact, closer proximity to FCS branch offices (FCS5MI) increased the probability of being a high-use county. Counties with FCS branches located within 5 miles of the county line had a higher demand for FSA credit programs. This is contrary to the expectation that more private credit sources imply greater credit availability. This result may be more reflective of the structure of credit markets rather than proximity to credit sources. FCS branch offices tend to be more common in regions where FCS is the predominant lender, such as the Southeast and Mid-Atlantic. Thus, this may simply reflect that FCS has more borrowers to serve in these high-use counties.

The variable reflecting the presence of agricultural bank branches (AGBANK) was not significant. However, over 1,900 counties nationwide have at least one branch of an agricultural bank. Thus, the independent variable used in the analysis may be too broad to measure credit accessibility. Subsequent analysis should examine the number of agricultural bank branches within a county or their importance within the county bank market.

There was no indication that the greater importance of farming within the county (LANDFARM) increased the availability of credit from private lenders. In fact, those counties with a larger share of land devoted to farming were more likely to be high-use counties. This reflects the importance of the FSA loan programs in the Great Plains, Mississippi Delta, and Piedmont regions where farming is the primary use of land. The reliance of these local economies on agriculture may expose commercial lenders to additional risk, resulting in more conservative lending practices which, in turn, would result in more farmers turning to FSA for their credit needs. Conversely, if may merely reflect the fact that as farming activity rises in a county demand for all types of credit, including that supplied by FSA, rises.

Counties with a greater presence of financial risk were more likely to be in the high-use group. Those counties where larger shares of farms had debt (INDDEBT) were more likely to be in the high-use group. This may reflect greater financial risk among farms within a county discouraging private lenders and resulting in a greater share of farmers in the county being unable to obtain private credit. The other variable for measuring leverage (INTOT) proved to be insignificant.

Counties with higher personal income over the past 10 years (PCAPITA) were more likely to be high-use counties. Higher per capita personal incomes tend to be located in or near metro regions while counties with low per capita personal incomes tend to be more rural. This suggests that lenders may be shying away from farm lending in regions and focusing on other lending where county incomes are stronger.

Counties with fewer guaranteed borrowers relative to all indebted farmers (GTEUSE) were more likely to be high-use. Conversely, those counties with higher levels of demand for direct programs are also those counties with fewer guaranteed borrowers. There are two apparent explanations for this result. One is that the direct and guaranteed programs are substitutes. The presence of an active guarantee program within a county enables more farmers to obtain private credit than otherwise would have been able to. Or this relationship may simply reflect a greater financial risk among farmers in high-use counties. This greater financial risk results in higher usage of the direct program as lenders shy away from making guarantees to such borrowers.

It was expected that commercial lenders would restrict lending in counties where there were few opportunities to diversify their loan portfolios. But, county level commodity concentration did not appear to be an important factor influencing the level of demand for FSA credit programs. Only counties with high levels of beef and cotton production were found to have a significant relationship with the level of program demand. But, in both of these cases the signs were not as expected. Counties which were specialized in cotton or beef were less likely to be high-use counties and less likely to be low-use counties. For cotton, however, many of the credit need could have been met through the EM program rather than the regular OL. Beef counties tend to be located in the Mountain States, east Texas, and Ozarks, regions where FSA credit programs are less important.

There was no significant relationship with FCIC loss rates (LOSSRATE). Higher loss rates are likely to reflect weather-related production losses. But, counties experiencing weather related production losses are likely to be eligible for EM loans. Thus, farmers in these counties may have utilized the EM program, which was not considered in this analysis. Also, there is considerable variation in loss rates overtime and the two year time period may have been insufficient to capture its effect.

Conclusions

While FSA credit programs represent a relatively minor supplier of total farm credit in the US, many regions, states, and counties are more highly dependent on FSA as a credit source. In about a third of all U.S. counties, one out of every five indebted farmers had either a direct OL or FO loan. The level of dependence on FSA loan programs appears to follow regional patterns with high-use counties clustered in Northeast, Great Plains, and Mississippi Delta. Low-use counties were clustered in the Corn Belt and Western States.

Results from an ordinal probit analysis indicate some relationship between regional and demographic factors and FSA program usage. Demand for FSA direct OL and FO loans was defined by the share of all indebted farms with at least $10,000 in sales that borrowed from these loan programs. Explanatory variables included those measures relating to loan targeting and credit rationing, the competitiveness of local credit markets, and creditworthiness of farms within the county.

Counties more dependent on FSA credit were more likely to have a FCS branch office. This seems to suggest that increased accessibility to FCS credit increases demand for FSA loan programs. But, it could also reflect the fact that FCS branches are located in counties with more borrowers. High-use counties were also more likely to have fewer FSA guaranteed borrowers relative to all indebted farmers. This suggests that the direct and guaranteed programs may be substitutes. Or this relationship may simply reflect a greater financial risk among farmers in high-use counties.

Counties where farming represented a larger share of land use were more likely to be highly dependent on FSA direct loan programs. While contrary to expectations, this may reflect the fact that there are fewer commercial lenders in rural regions. Leverage also had an impact on whether a county was classified as a FSA high-use county. Counties where a greater share of the farmers reported debt were more likely to be in the high-use group.

Of the targeting variables, only the presence of high levels of racial and ethnic minorities in farming (RACE) was found to have a significant effect on being classified. But, the sign was not as expected. Counties with higher concentrations of minority farmers were less likely to be high-use counties. Many of the counties with higher concentrations of racial and ethnic minorities in farming were located in California and the Southwest, reflecting the higher Hispanic populations in these areas. But, FSA farm loan programs tend to be less important in these regions. Segregation of Hispanic farmers from black farmers and American Indians within the model may indicate more targeting of these groups. Also, many of the FSA direct loans to minorities were EM loans, which were not considered in this study.

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Figure 1. Share of County Indebted Farms with an FSA Direct Loan

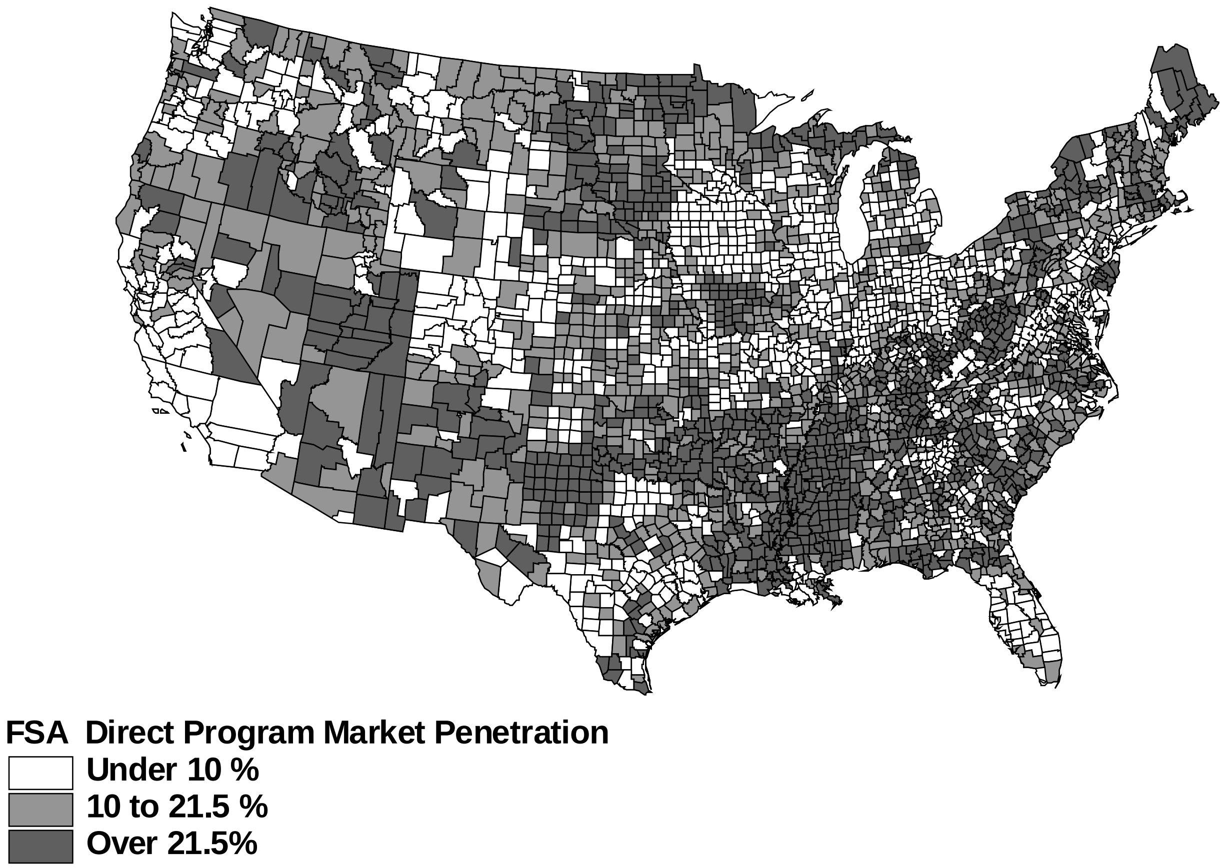

Table 1. Model Variables and Expected Relationship with Market Penetration.

Variable	Description	Expected Sign
MKTSHR	Share of FSA direct OL and FO borrowers to total farm borrowers with at least $10,000 in sales	
	Targeting	
SHREFAR	Percentage of total indebted farms with > $10,000 sales where farming is the primary occupation	+
SIZE	Percentage of total indebted farms with $50,000 to $250,000 in sales	+
RACE	1 if 7.5 percent or more of the farms with at least $10,000 in sales are operated by a racial or ethnic minority, 0 otherwise	+
WOMEN	Ratio of farms operated by women to total farm with at least $10,000 in sales,	+
TARBEG	1 if 4.5 percent or more of farms in the county are operated by persons having less than 10 or fewer years operating a farm, under 45 years of age, and having between $50,000 and $500,000 in sales, 0 otherwise	+
	Competitiveness of Market and Credit Access	
FCS5MI	One if a FCS branch office is within the county or within 5 miles of the border	-
LANDFARM	Share of total county land that is devoted to agricultural uses	+
AGBANK	One, if at least one branch office of a bank with a farm loan to total loan ratio of at least 0.10 is present	-
	Credit Risk and Creditworthiness	
INTTOT	Ratio of interest expenses to total farm expenses, farms with > $10,000 sales	+
INDEBT	Share of farms with at least $10,000 in sales reporting interest payments	+
LOSSRATE	Ratio of FCIC indemnity payments made to premiums collected for 1995-96	+
AVGPE	Ratio of average per acre farmland value to net farm earnings per acre	+
WHTCTY	1, if more than a third of county gross farm incomes from wheat production	+
COTTCTY	1, if more than a 20 percent of county gross farm income from cotton production	+
BEEFCTY	1, if more than a third of county gross farm income is from beef production	+
DAIRYCTY	1, if more than a third of county gross farm income is from dairy production	+
CORNCTY	1, if more than a third of county gross farm income is from corn production	+
POULTCTY	1, if more than a third of county gross farm income is from poultry production	+
GTEUSE	Ratio of guaranteed borrowers to total borrowers with at least $10,000 in sales	-
PCAPITA	Average per capita income over the last 10 years	+

Table 2. Ordinal Probit Model Results.

VARIABLE	PARAMETER ESTIMATES	
	Coefficient	Std. Error
CONSTANT	-0.91567***	(0.2243)
SIZE – Share of total farms with$50,000 < Annual Sales < $250,000	0.23200	(0.0029)
SHREFAR- Share of Farms with Farming as Primary Occupation	0.00366	(0.0031)
WOMEN - Share of Farms Operated by Women	0.00754	(0.0069)
RACE – Higher Racial Minority Population	-0.16555*	(0.0733)
TARBEG - Higher Concentrations of Beginning Farmers	0.00962	(0.0613)
FCS5MI- FCS Branch Office Located in County Or Within 5 Miles of County	0.19570***	(0.0440)
AGBANK- Agri. Bank Branch Located in County Or Within 5 Miles	0.04625	(0.0543)
LANDFARM - Land in Farms/Total Land	0.00401***	(0.0010)
GTEUSE - Guaranteed Borrowers/Total Borrowers	-0.01687***	(0.0018)
INTTOT – Interest Expense/Total Expenses	0.00194	(0.0090)
INDEBT – Share of Farms With Interest Expense	0.00603**	(0.0021)
LOSSRATE - County-level FCIC Loss Rate	0.03220	(0.0226)
AVGPE – Farmland Value/Net income	0.00004	(0.0002)
PCCAPITA – Personal Income as percent of U.S. Average	0.00779***	(0.0016)
WHTCTY – Wheat County	-0.11706	(0.1201)
COTTCTY - Cotton County	-0.41286***	(0.1176)
BEEFCTY – Beef County	-0.17737***	(0.0454)
DAIRCTY – Dairy County	-0.07222	(0.0998)
POULTCTY - Poultry County	0.01358	(0.0492)
CORNCTY – Corn County	-0.04816	(0.0670)
MU (μ)	0.94563***	(0.0264)

* Significant at .05; ** Significant at .01; *** Significant at .005.

Table 3. Sensitivity to Changes in Significant Independent Variables.			
	Probabilities		
	P(Low)	P(medium)	P (high)
RACE			
Yes	0.48	0.33	0.19
No	0.42	0.35	0.23
FCS5MI			
Yes	0.29	0.36	0.35
No	0.40	0.36	0.24
LANDFARM			
25%	0.37	0.36	0.27
50%	0.33	0.36	0.31
75%	0.30	0.36	0.34
95%	0.27	0.36	0.37
INDEBT			
35%	0.38	0.35	0.27
50%	0.34	0.46	0.46
65%	0.31	0.46	0.46
80%	0.28	0.46	0.46
PCAPITA			
50%	0.41	0.35	0.24
75%	0.34	0.36	0.30
100%	0.27	0.36	0.37
125%	0.21	0.35	0.45
GTEUSE			
0%	0.25	0.36	0.40
5%	0.27	0.36	0.37
15%	0.33	0.36	0.31
20%	0.36	0.36	0.28
COTTCTY			
Yes	0.48	0.33	0.18
No	0.32	0.36	0.31
BEEFCTY			
Yes	0.37	0.36	0.27
No	0.31	0.36	0.33

Table 4. Sensitivity to Changes in Significant Independent Variables.			
	Marginal Elasticties		
VARIABLE	P(Low)	P(medium)	P (high)
RACE	0.0596	-0.0111	-0.0585
FCS5MI	-0.0704	0.0013	0.0692
LANDFARM	-0.0014	0.0000	0.0014
INDEBT	-0.0022	0.0000	0.0021
PCCAPITA	-0.0028	0.0001	0.0028
GTEUSE	0.0061	0.0001	-0.0060
COTTCTY	0.1486	-0.0027	-0.1459
BEEFCTY	0.0064	-0.0012	-0.0627

Endnotes

[1] FO loans can be used to acquire, enlarge, or improve a farm or ranch; OL loans provide short- to intermediate term production or chattel financing; EM loans cover production and physical losses or both in counties declared as disaster areas. EM loans do not have beginning farmer and Socially Disadvantaged targeting requirements and until 1996 did not have family farm targeting requirements.
[2] The Agricultural Credit Act of 1987 defined SDA individuals as those who may have been subject to discrimination because of their identity as members of a group, without regard to their individual qualities.
[3] A beginning farmer has no more than 10 years owning or operating a farm or ranch and must have at least 3 years to qualify for a direct FO loan. Seventy percent of direct FO annual funding and 35 percent of direct OL funding is reserved for use by beginning farmers until the last month of the fiscal year. Unused guaranteed OL authority can be transferred at year end to satisfy unmet direct FO demand by beginning farmers. Funding is allocated to states based on Census of Agriculture share of beginning farmers in the state.
[4] A bank and its branches are considered to be agricultural banks if a least 10 percent of the banks total loans were classified as agricultural loans on July 1, 1997. Two common measure for measuring agricultural banks are the Federal Reserve's definition which defines an agricultural bank as having a greater than average share of farm loans to total loans and the FDIC's definition which states the bank must have at least 25 percent of its total loans to agriculture. These two definitions were thought to be too restrictive for many regions.
[5] The data used is the ratio of indemnity to premiums collect for the 1995 and 1996. Data for earlier years was unavailable and using a longer time frame could significantly affect this variable.