Factors Determining the Use of Guaranteed Loans by U.S. Commercial Banks

Latisha A. Settlage, Bruce L. Dixon,
Bruce L. Ahrendsen, and Steve R. Koenig*

Selected paper prepared for presentation at the American Agricultural Economics Association annual meeting, Long Beach, California, July 23-26, 2006

* Latisha Settlage is Assistant Professor of Economics at the University of Arkansas, Fort Smith; Bruce Dixon and Bruce Ahrendsen are Professor and Associate Professor of Agricultural Economics, University of Arkansas, Fayetteville and the Division of Agriculture; and Steve Koenig is Agricultural Economist, USDA Farm Service Agency. Financial support from IFAFS grant USDA-CSREES 00-52101-9630 is gratefully acknowledged. The assistance of Sheila Oellrich and Diana Danforth is appreciated.

Factors Determining the Use of Guaranteed Loans by U.S. Commercial Banks

The use of Farm Service Agency (FSA) loan guarantees has grown in importance over the past decade. In fiscal 1999, the level of new guaranteed obligations rose to over $2 billion–clearly more than the obligations for direct loans. Total guaranteed obligations remained above $2 billion for the next five years. In fiscal 2003, total guaranteed obligations reached an all-time high of $2.6 billion. The FSA guaranteed loan program is the major form of government supported credit assistance for production agriculture. It is clear Congress intends the FSA guaranteed loan program to continue to serve family-sized farm operations by providing government assisted credit when private sources decline to do so without government backing. In addition, a considerable proportion of the program's annual allocation is directed toward beginning and socially disadvantaged[1] (SDA) borrowers. Given the significant support that this program provides to production agriculture, it is critical that key aspects be examined in order to determine whether efficient delivery of federal funds is being achieved. This study provides information on how to encourage more lender use and increase overall program efficiency.

Purpose and Overview of Study

This study examines factors impacting the use of FSA guaranteed loans by commercial banks in the U.S. during fiscal years 1995-2003. Annual funding for the FSA guaranteed loan program is obligated by the federal government, but banks and other creditor providers are the actual sources of loan principal. To be eligible for program support, agricultural borrowers must be creditworthy, family-sized operations unable to receive credit at reasonable rates and terms in

[1] The Agricultural Credit Act of 1987 (P.L. 100-233) defines an SDA farmer as one who may have been subject to racial, ethnic, or gender prejudice because of their identity as members of a group without regard to their individual qualities. Generally, beginning farmers have less than 10 years experience owning or operating a farm.

the absence of a guarantee. If the borrower defaults, the federal government reimburses the lender for a portion (up to 95 percent) of lost principal and interest. While banks are not the only credit providers using FSA loan guarantees, they are the major recipients.

Although a number of studies have analyzed various dimensions of the guaranteed program in the past, this study is the first to use a multi-state, multi-year approach at the bank (firm) level. Past analyses of the program have shown that there is significant geographic disparity in the use of guaranteed loans. The results of this study provide a better understanding of the past performance of the guaranteed program and how well program policy and structure have ensured serving the intended farmer-operator clientele.

The study identifies lender and farm financial characteristics that influence the propensity of a bank to use guaranteed loans as well as variables that affect the level of program usage. A previously-developed bank portfolio selection model with investment choices for agricultural loans, non-agricultural loans, and government securities is modified to include an asset choice for guaranteed agricultural loans (which offer lenders reduced exposure to loss but carry higher transactions costs). The model implied by the solution to this expected profit maximization problem is then estimated using a double-hurdle, econometric model. Choice of independent variables for the econometric model is guided by the theoretical model. Bank asset size, loan-to-asset ratio, agricultural loan-to-total loan ratio, and multi-bank holding affiliation are among the lender variables considered. State-level farm financial variables include debt servicing ratio, debt-to-asset ratio, variability in net farm income, variability in the value of farm assets, and other variables.

Bank use of the program is considered for three categories of farm borrowers: all guaranteed, beginning only, and SDA only. For each borrower category, separate regression models are estimated for farm ownership (longer term, primarily real estate) and operating loans (short to medium term, primarily non-real estate). A double-hurdle specification is employed to account for incidental truncation in the loan volume dependent variable. Incidental truncation occurs because loan volume is only observed if a bank makes a guaranteed loan. The first equation is a "selection" equation and is estimated as a probit model with the binary dependent variable indicating whether a bank made a guaranteed loan to a borrower(s) in a given year. It predicts the likelihood of a bank using guaranteed loans to serve its farm borrowers. The second equation is a "volume" regression equation and is estimated using the dollar amount of guaranteed loans made by a bank in a given year as the dependent variable. The second equation explains variations in loan volumes for banks originating guaranteed loans.

Review of Prior Studies

Five prior studies focused on the use of FSA guaranteed loans (Koenig and Sullivan (1991), Sullivan and Herr (1990), Dixon, Ahrendsen, and McCollum (1999), Settlage et al. (2001b), and Dodson and Koenig (2003)). The Koenig and Sullivan study was a descriptive analysis of commercial banks making at least one guaranteed loan in fiscal 1988. Sullivan and Herr again used fiscal 1988 data to examine the characteristics of participating lenders and how lender behavior affected the guaranteed loan program. Dixon, Ahrendsen, and McCollum identified characteristics of banks and economic forces that influenced commercial bank utilization of FSA guarantee programs in Arkansas during fiscal years 1990-1995. Settlage et al. (2001b) identified which farm operator, farm economy, and commercial bank characteristics were most important in determining guaranteed loan principal outstanding in the U.S. for 1990-1998. Dodson and Koenig (2003) used county-level data to model the use of FSA farm loan programs between 1995 and 1999.

All but one of the previously discussed studies faced sample constraints. While national in scope, both Koenig and Sullivan and Sullivan and Herr examined only one year of data, fiscal 1988. Guaranteed loans were just beginning to overtake direct loans as the favored credit delivery instrument to FSA borrowers in 1988. Since 1988, the dollar volume of guaranteed loans has increased substantially. In addition, 1988 was a recovery period for the agricultural sector after the bust of the early 1980s, so it is quite likely that the results of those studies were influenced by uncommon economic conditions.

Dixon, Ahrendsen and McCollum tried to capture the time dimension by using six years of data. Changes in farm income and value of land were weak proxy variables for completely measuring farm financial conditions. Furthermore, they sampled in a relatively small geographic area, one state, so their results need to be tested on a national basis to have greater validity for policymaking and program evaluation. The Settlage et al. (2001b) principal outstanding models were national in scope, but the level of aggregation at the state level complicated the interpretation of results from a policymaking perspective. This study overcomes the sampling issues faced by these previous studies by choosing a national sample over a span of nine years, fiscal 1995 through 2003, and obtaining data at the bank (firm) level.

There are major differences between the present study and that conducted by Dodson and Koenig (2003). The first is the difference in observational unit. Dodson and Koenig (2003) followed a county-level approach, while the current study employs a firm-level approach to guaranteed loan use. The second difference lies in the explanatory variables chosen for the models, particularly those relating to lenders. The county-level models of the previous authors failed to incorporate lender characteristics (other than simple presence within a county which was positive and significant) as indicators of guaranteed loan use. This study seeks to identify bank-level variables that determine use of guaranteed loans by banks.

The previous studies did not specifically model guaranteed loan origination to SDA and beginning farmers. Targeted lending to SDA and beginning farmers is a critical aspect for the future of the guaranteed loan program. The guaranteed loan volume originated to these groups has increased significantly in past years. Given the mandate of FSA to target these two borrower groups, there is no indication that their importance to the guaranteed loan program will lessen. The present study examines commercial bank lending to these farmer borrower groups by estimating sub-models that explain the propensity of banks to make loans to SDA and beginning farmers as well as the volume of loans made to these groups.

Research Methodology

The propensity and intensity of guaranteed loan usage by lenders can be modeled by a variation of Pederson's approach to determining bank lending decisions. Pederson (1992) analyzed portfolio adjustments of commercial agricultural banks in Minnesota during the period 1976-87. He developed an asset allocation model in which the bank's problem was to select the mix of loan assets and securities that would generate desired levels of portfolio return and risk.[2] The framework was used to identify portfolio adjustments to changes in expected rates of return and alternative sources of risk. Following this approach, optimal portfolio mix is determined by maximizing the firm's objective function subject to a constraint. The firm is assumed to be risk averse in a risky environment. The ultimate goal of the modeling is to derive a behavioral equation that explains the quantity of guaranteed agricultural loans originated by banks in a given year.

[2] The return and loss equations for fixed and variable rate loans in his models were specified in Santomero (1983).

As in Pederson, the portfolio allocation decision for a bank can be stated as:

$$\begin{aligned} &\underset{q_i}{\text{Maximize}} \qquad E(\pi) - \frac{\lambda}{2} Var(\pi) \\ &\text{subject to} \qquad \sum_{i=1}^{4} \rho_i q_i = W. \end{aligned} \tag{1}$$

Here, λ is the coefficient of absolute risk aversion, and *W* is the amount of bank funds available for investment. $E(\pi)$ and $var(\pi)$ are expected profit and variance of profit, respectively. The quantity of funds invested in the i[th] asset category is represented by q_i. The ρ_i indicate the portion of q_i that counts against the bank's lending limit. A bank may invest in variable and fixed rate contracts in three loan markets: (1) non-agricultural, (2) agricultural non-guaranteed and (3) agricultural guaranteed. In addition, banks may invest in short-term government securities. The subscript *i* indexes the asset market (1=non-agricultural loans, 2=agricultural non-guaranteed loans, 3=agricultural guaranteed loans, and 4=government securities). The constraint in the above maximization problem is modified from Pederson to accommodate the fact that only the non-guaranteed portion of a guaranteed loan (ρ_3) counts toward a bank's legal lending limit (for non-guaranteed loans and government securities, ρ_i equals one).[3]

The profit identity is written as:

$$\pi = \sum_{i=1}^{3} [q_i(R_{iV} - R)\varphi_i + q_i(R_{iF} - R)(1 - \varphi_i)] + q_4(r - R) \tag{2}$$

where R_{iV} and R_{iF} are the *ex post* random returns from variable and fixed rate contracts in each loan category and φ_i is the proportion of variable rate loans held in each loan category. The rate of return earned on government securities held by the bank is *r*, and R is the market interest rate

[3] In practice, banks may choose ρ_3. While in reality ρ_3 is variable, it is standard practice for it to be fixed at 0.1 or 0.05 depending on the type of loan. In this model, it is not considered as a decision variable.

(cost of funds). As in Pederson, the bank is assumed to formulate an estimate of market rate variability and then set the spread between the fixed and variable rate to compensate for rate uncertainty. Borrowers then choose between fixed and variable rate loans, so the proportion of variable-rate lending is exogenous to the bank. In the model, R_{iV} (R_{iF}) are functions of several factors including the variable (fixed) contract rate, the underlying expected profitability of the project for which the loan proceeds fund, the overall variance of the returns of the funded project, the overall variance of the market interest rate (R_{iV} only), and the transaction cost associated with making a particular type of loan.[4]

The general solution to the maximization problem implies that the optimal allocation of assets is a function of the proportions of variable-rate loans in each of the three loan asset categories, loan demand (which when observed reflects not only borrower but also lender behavior), expected returns and variance of returns on projects funded by each loan type, variance of the market interest rate, covariance between the market interest rate and expected returns on projects for each loan type, covariance between expected returns of projects across loan types, the transaction cost associated with making a particular type of loan, the expected rate of return on securities, and the level of funds available to the bank to make additional loans.

Econometric Considerations

A complete bank model would contain multiple equations each expressed as a function of the several variables listed above. Each equation would correspond separately to each of the loan categories in the bank's portfolio. As pointed out by Pederson, portfolio equilibrium adjustments imply that the allocations to each asset category are determined simultaneously. From an econometric standpoint, the most efficient approach to estimating a system of

[4] Derivation of both expected return equations may be found in Settlage (2005).

simultaneously determined asset equations is Zellner's seemingly unrelated regression (SUR) (Greene). However, in the case of this particular model, it is not possible to use a conventional SUR approach. One reason is the large number of zero observations on the dependent variable corresponding to guaranteed agricultural loan volume. Most banks do not make FSA guaranteed loans and even those who make FSA guaranteed loans do not necessarily do so every year. The information contained in the dependent variable corresponding to volume of guaranteed loans is part qualitative (to make a guaranteed loan or not make a guaranteed loan) and part quantitative (the volume of guaranteed loans made).

One procedure used to analyze such limited dependent variables in a single equation framework is tobit (Tobin). An alternative approach that allows greater flexibility in modeling the effects of the independent variables on both the decision to participate in the guaranteed loan program and the level of guaranteed loan participation is to use a two-equation, double-hurdle model. The double-hurdle model as developed in Greene is as follows. First, a "selection" equation is specified as:

$$\begin{aligned} &\text{Prob}[q_{it} > 0] = \Phi(\boldsymbol{\gamma}'\mathbf{w}_{it}), \qquad && z_{it} = 1 \quad \text{if } q_{it} > 0, \\ &\text{Prob}[q_{it} \leq 0] = 1 - \Phi(\boldsymbol{\gamma}'\mathbf{w}_{it}), \qquad && z_{it} = 0 \quad \text{if } q_{it} \leq 0. \end{aligned} \tag{3}$$

where q_{it} is equal to the amount of guaranteed loans made, z_{it} is a binary variable that equals 1 if a bank is observed to make a guaranteed loan in a given year (q_{it} is positive) and 0 if a bank does not make a guaranteed loan (q_{it} is zero) and $\Phi(.)$ is the standard normal cumulative density function. The "selection" equation ($\boldsymbol{\gamma}'\mathbf{w}_{it}$) determines whether or not a bank will participate in the guaranteed loan program in a given year.

The second step is to specify a "regression" equation for nonlimit observations:

$$E[q_{it} | z_{it} = 1] = \boldsymbol{\beta}'\mathbf{x}_{it} + \beta_\lambda \lambda_{it} \tag{4}$$

where β_λ is the product of the error term for (4) and the correlation coefficient between the error terms in (3) and (4) and λ_{it} is the inverse Mills ratio (IMR) which is a function of the "selection" equation parameters. The "regression" equation models the level of participation by a bank making at least one guaranteed loan in a given year. The IMR accounts for the incidental truncation of the dependent variable in the "regression" equation.

In order to use the double-hurdle approach, the "selection" equation for the guaranteed loan model is estimated as a probit model on the full set of data (all banks in the U.S. in every sample year). The resulting parameters are used to estimate the IMR for each observation which is then included as a regressor in (4). The "regression" equation is estimated using ordinary least squares (OLS) on the sub-sample composed of all banks making at least one guaranteed loan in a given year. The resulting t-ratios of the individual parameter estimates have an asymptotic, standard normal distribution. This is the Heckman (1979) approach.

The above discussion relates only to one equation in the portfolio, the guaranteed agricultural loan equation. As every previous study on FSA guaranteed loan has recognized, there are two very different types of guaranteed loans. There are farm ownership (FO) loans that are used for purchasing real estate and operating (OL) loans that are used for annual expenses as well as purchase of intermediate assets.

As shown in the one-state sample of Dixon, Ahrendsen, and McCollum, coefficients associated with explanatory variables in the FO and OL models differ in magnitude and significance level. This is likely due to differences in the term structures, purposes and volume usage of the two loan types. In the current study where the sample includes the entire U.S., pooling the observations into one model would likely result in a specification error. It is unlikely that the two dependent variables respond identically to a given variable so that coefficients would not be homogeneous across the two samples. Therefore, separate double-hurdle models are needed, and a sampling problem arises with the SUR framework.

Recall, the first equation in the double-hurdle process is estimated using the entire sample of banks. However, the second equation is estimated using only the data contained in the sample of banks that used the guaranteed program by originating at least one loan. This avoids the problem of numerous zero observations on the dependent variable. In order to estimate separate double-hurdle models for FO and OL loans, two samples are needed. One censored sample would contain lenders who made at least one FO loan in a given year and the other would be comprised of banks who made at least one OL loan in a given year. The samples for the "regression" equations are not identical across the two equations. Four cases arise: (1) a bank made at least one FO loan but did not make an OL loan, (2) a bank made at least one OL loan but did not make a FO loan, (3) a bank made at least one FO loan and at least one OL loan, and (4) a bank made no FSA guaranteed loans of either type. Using a SUR approach in such a situation would be exceedingly difficult. The joint distribution of the error terms of the implied bivariate probit model, the regression terms with the IMR terms and those regression models without IMR would be very complex as well as the problem of unequal sample sizes for the various equations in the complete model. But given the very large sample sizes in this study, a more practical alternative is utilized.

In order to get around this difficulty, only the equation corresponding to the loan asset of particular interest to the study—guaranteed loans—is estimated using separate samples for FO and OL loans. By choosing to ignore the other assets in the bank portfolio, some estimation efficiency is lost because information contained in the cross-equation restrictions is excluded as well as the joint distribution of the error terms. This loss of information can be of particular significance in small-sample applications. Given the sample size in this study (the sample size approaches the size of the population of banks times the number of years), the efficiency loss is likely minimal and the estimated parameters are consistent.

Empirical Loan Usage Model

Three four-equation models are estimated. In any given model one selection equation (3) and one regression equation (4) are estimated for FO loans and a corresponding pair for OL loans. Each of the four equations contains the same explanatory variables, though the estimated coefficients corresponding to those variables may differ in sign and magnitude.[5] The models vary by sample. The first model has all guaranteed loans, the second sample contains only beginning farmer guaranteed loans and the third model has SDA guaranteed loans.

Limitations on the availability of data challenge the empirical specification of the models. For many of the desired variables, it is impossible to obtain an actual data series because the exact variable is either unobservable or data have not been recorded in any readily accessible format. In those situations, an alternative (proxy) variable that likely reflects the preferred variable is substituted. This section addresses the choice of variables used in the econometric estimation of the loan usage models. More specific information regarding the construction and sources of all explanatory variables may be found in Settlage (2005).

The first set of explanatory variables contained in (3) and (4) are the proportions of variable rate loans made in each of the three loan asset categories: non-agricultural, non-guaranteed agricultural, and guaranteed agricultural. While it is possible to obtain the proportion of variable rate guaranteed agricultural loans (*VRG*) at the lender level from FSA, comparable data do not exist for the proportions of variable rate non-guaranteed agricultural (*VRA*) and non-agricultural loans (*VRN*). Pederson also encountered this problem. As a proxy, he used the

[5] A priori, the sign expectations for a given explanatory variable are identical across the four equations.

percentages of farm and commercial-industrial loan volumes written with floating rates which are available from national quarterly bank surveys performed by the Federal Reserve System.[6]

Two prior studies suggest suitable proxies for the agricultural and non-agricultural loan demand parameters. Turvey and Weersink's loan contract (demand) model for agricultural loans was composed of variables reflecting loan risk probability (liquidity, solvency, profitability, repayment capacity, security, farm enterprise type, and region) and interest rates. Humphrey and Pulley's composite model of bank profit included not only financial inputs (labor, deposits, and physical capital) and outputs (deposits and loans) but also a vector of influences recognized within the banking industry to affect profitability. Growth in population and per capita income as well as the funding-loan rate spread were characterized in their study as indicators of loan demand intensity. They included loan-to-asset ratio to reflect bank risk.

In this study, debt servicing ratio (*DSR*), debt-to-asset ratio (*DAR*), coefficient of variation in net farm income (*CVFI*), and coefficient of variation in the value of farmland and building (*CVLB*).are included in the loan usage model to proxy the borrower component of the loan demand functions for agricultural loans. Annual data for these farm financial variables are available at the state level from the Economic Research Service (ERS). In addition to these farm financial variables, regional binary variables are included in the model to account for geographic differences in loan demand and geographic concentrations of beginning and SDA farmer populations. The coefficient of variation in annual per capita (state) personal income (*PCI*) is included to proxy the demand intensity for non-agricultural loans, while lender loan-to-asset ratio (*LAR*) is included to proxy the lender component present in the loan demand functions.

As noted in Pederson, comparable data on agricultural and non-agricultural sector returns are difficult to find. Pederson assumes banks qualify or approve their borrowers at the existing

[6] This variable is constant across banks for a given year.

or expected loan rate and that the underlying project generates returns with expected value equaling or exceeding the outlays required to service and repay the debt (though some actual outcomes may deviate from the expected level of returns). A series of regional interest rates are obtained from the Federal Reserve's Survey of Terms of Bank Lending to Farmers and used to proxy the expected rate of return on agricultural loan projects (*ARET*). Expected rates of return for guaranteed agricultural loans (*GRET*) are computed from guaranteed loan data provided by FSA, and non-guaranteed agricultural loan rates of return (*NRET*) are calculated from FDIC Call Report data as described in more detail in Settlage (2005).

Following Pederson, it is assumed the effects of the credit risk variables are mapped into the expected default rates for each loan type. Thus, the expected default rate on guaranteed loans (*GDEF*) is assumed to reflect the variability of guaranteed loan returns, the covariation of guaranteed loan returns with non-guaranteed loan returns, and the covariation between guaranteed loan returns and the market interest rate. The expected default rates for non-guaranteed agricultural loans (*ADEF*) and non-agricultural loans (*NDEF*) follow the same convention. The seasonally adjusted charge-off rates reported quarterly by the Federal Reserve for agricultural loans were used to model the variable *ADEF*, while the variable *NRET* was calculated for each bank using quarterly Call Report data.

The bank's actual monetary cost of making a loan is nearly impossible to estimate. The actual cost encompasses the potential resources expended in originating and servicing the loan as well as collecting on the loan in the event of a default. Most of these costs are not measurable in terms of dollar amounts from the data available. To proxy the costs associated with making the types of loans considered in this study, the following variables are used: bank affiliation with a multi-bank holding company (*MBHC*), agricultural loan-to-total loan ratio (*AGTL*), and guaranteed major lender status (*MAJLDR*).

The expected rate of return or yield on securities (*SRET*) is computed using Call Report data for each lender, and the variance of the market interest rate (*MKTVAR*) is derived from the monthly federal funds rate series. Total bank funds are measured by total bank assets (*ASSET*).

The exact empirical specification of the loan usage model can be written as below

$$\begin{aligned} Y_{kit} = {} & \beta_{k0} + \beta_{k1} VRG_{it} + \beta_{k2} VRA_{it} + \beta_{k3} VRN_{it} + \beta_{k4} DSR_{it} + \beta_{k5} DAR_{it} \\ & + \beta_{k6} CVFI_{it} + \beta_{k7} CVLB_{it} + \beta_{k8} PCI_{it} + \beta_{k9} LAR_{it} + \beta_{k10} GRET_{it} \\ & + \beta_{k11} ARET_{it} + \beta_{k12} NRET_{it} + \beta_{k13} GDEF_{it} + \beta_{k14} ADEF_{it} \\ & + \beta_{k15} NDEF_{it} + \beta_{k16} MBHC_{it} + \beta_{k17} AGTL_{it} + \beta_{k18} MAJLDR_{it} \\ & + \beta_{k19} SRET_{it} + \beta_{k20} MKTVAR_{it} + \beta_{k21} ASSET_{it} + \beta_{k22} REGION_{it} + e_{kit} \end{aligned} \tag{5}$$

where *k* indicates equation number. The first equation corresponds to the FO selection equation, the second equation corresponds to the FO regression equation, and the third and fourth equations correspond to OL selection and regression equations, respectively. Equation (5) is modified to include the IMR for the regression equations.

The selection equations are estimated using the entire population of banks in the U.S. as the sample for all three models. The FO (OL) selection equation dependent variable is defined as 1 if a bank is observed to make a FO (OL) guaranteed loan in a given year, 0 otherwise. The IMRs are estimated and the sample is reduced to having only observations for banks with a positive FO (OL) guaranteed loan volume in a given year.[7] This reduced sample is used to estimate the regression equations that include the estimated IMRs. The dependent variables in the regression equations are the annual volumes of FO and OL guaranteed loans observed for a given bank, respectively.

[7] For the second and third models, only observations for beginning farmer and SDA loans are in the reduced samples.

Results and Discussion

The results of the estimated selection and regression equations for guaranteed FO and OL loan usage for all borrowers are listed in table 1. In order to assess the validity of the equations, the hypothesis that all coefficients equal zero was tested. In all four equations (selection and regression models for both FO and OL loans), this hypothesis was clearly rejected. Measures of explanatory power were also considered. The probit model predicted 91% of the observations correctly. This result was only slightly better than if all observations were predicted as not making a loan. In that case, the prediction success rate would have been 90% (90% of the observations in the primary sample had a value of zero for the FO guaranteed lender indicator). The probit model correctly predicted 83% of the observations (1% better than the naïve approach of predicting no guaranteed loans made).

The R-squared for the FO regression equation indicated that the independent variables explained 11% of the variation in the amount of FO loan volume originated by banks in a given state. This means most of the variation in the level of FO guaranteed volume was left unexplained—not unusual for firm level data since much of the variability is firm specific. Also, there was difficulty in finding suitable lender-level proxies for the variables indicated by the theoretical model to be included in the models. The level of aggregation was likely too high. Dixon, Ahrendsen, and McCollum as well as Dodson and Koenig (2003) examined a number of variables, particularly those that represent borrower demand, at the county level.[8] However, given the national scope of this study, it would have been enormously difficult to follow such precedents resulting in considerable measurement error. Model fit for the OL regression

[8] Dodson and Koenig (2003) measured the loans by the borrower county of origination, and the unit of observation in this study is bank by state of origination. With branching it is difficult to know exactly what county a bank is "in" and what competition is in that market.

equation was better with an R^2 of .21. This may be due to the fact that many more OL loans are made than FO loans.

FO Loan Usage Model

In the FO selection model, thirteen of the 21 variables (including the constant but not accounting for the regional binary variables) were significant at the 5% level. All significant variables had expected signs except *PCI*, *FOGRET*, and *SRET*. The estimated coefficients for *DSR*, *DAR*, and *CVLB* indicated that rising debt servicing ratios, debt-to-asset ratios and increasing variation in the value of real farm assets at the state level were associated with a higher likelihood that banks would originate guaranteed FO loans. Increases in these three farm financial demand variables would be associated with an overall reduction in repayment capacity and increasing risk in the agricultural sector. Such factors would likely persuade a lender considering an agricultural loan to use a loan guarantee.

Significant and positive coefficients were found for the variables *LAR*, *MBHC*, *AGTL*, *MAJLDR*, and *ASSET*.   The estimated models signified that banks with higher loan-to-asset ratios, affiliated with multi-bank holding companies, lending larger proportions of their total loan portfolio to agriculture, having significant past history of using guaranteed loans, and larger asset size were more likely to originate guaranteed loans. Dixon, Ahrendsen, and McCollum also found significant coefficients for *LAR*, *AGTL*, and *ASSET* in their modeling of the propensity of Arkansas banks to use guaranteed FO loans during fiscal 1990-95. The significant marginal effects[9] for *LAR* and *AGTL* in the model were .209 and .290, respectively. These indicated that a .01 unit change in a bank's loan-to-asset ratio led to a .002 increase in the probability of the bank

[9] The marginal effects contained in tables 1, 2, and 3 represent the change in the dependent variables for a 1 unit change in the independent variables. Since a number of the independent variables are ratios, a change of .01 is more likely. The marginal effects for those variables are divided by 100 for more logical interpretation.

making a guaranteed FO loan, while .01 unit change in a bank's agricultural loan-to-total loan ratio resulted in a .003 greater chance.

The unexpected negative signs for *PCI* and *FOGRET* are puzzling. With respect to *PCI*, it could be that more variation in incomes signals unfavorable economic conditions, and banks cut back on all types of loans including guaranteed loans. As for *FOGRET*, the theory of the risk structure of interest rates would indicate that rates of return across the various asset types are related. It is possible that *FOGRET* is accounting for more than just the return on guaranteed agricultural loans. Perhaps it also reflects some of the variation in the rate of return on agricultural loans. *ARET* is insignificant and expected to be negative. If *FOGRET* is explaining some of the variation in the dependent variable attributed to both itself and *ARET* and the negative impact on *ARET* is outweighing the positive expected impact of *FOGRET*, then this would account for the sign contrary to expectations.

It was expected that higher rates of return on alternative asset choices (like securities and non-agricultural loans) would lead to a lower probability of guaranteed loan use. The negative sign for *NRET* is consistent with this expectation, but the positive sign on *SRET* is not. Perhaps banks associate higher rates of return on securities with more stable and favorable economic outlooks, and thus expand lending to all sectors. Pederson found similar results. In his models, higher rates of return on non-agricultural loans led to proportionate lending increases to both agricultural and non-agricultural loans. In addition, an increase in the rate of default on agricultural loans was significantly associated with decreases in lending to both types of loans.

Sixteen of 22 variables in the FO regression equation (including the constant and IMR) had coefficients significant at the 5% level. However, only four of the variables with significant estimated coefficients had marginal effect calculations that were significant (*DSR*, *CVLB*, *ARET*, and *NDEF*). The marginal effects indicated that banks holding deposits in states in which the debt servicing ratio increases by .01 was expected to originate $18,410 less in guaranteed FO loan principal per year. Similarly, banks holding deposits in states in which the coefficient of variation in the value of real farm assets increased by .01 unit were anticipated to make $34,080 more guaranteed FO loan volume. If there was a .01 increase in the rate of return on agricultural loans, then banks would have increased the amount of guaranteed FO loan volume by approximately $74,940. Finally, a .01 increase in the expected rate of default on non-agricultural loans was likely accompanied by a $55,300 increase in guaranteed FO loan principal.

Ten of the variables with significant coefficients in the FO regression model were also significant in the FO selection model. All retained the same signs as they had in the selection equation. The bank variables significantly impact not only the propensity of guaranteed FO loan usage by banks, but also the level of usage. The positive *NDEF* coefficient supports the portfolio switching argument made previously in which banks shift the assets in their portfolio to take advantage of higher rates of return and lower expected risk. If presented with higher expected default rates on non-guaranteed agricultural loans, banks would likely choose holding more FO guaranteed loans and fewer non-guaranteed assets. Higher expected rates of return on agricultural loans lead banks to hold more of all types of agricultural loans including guaranteed FO loans.

OL Loan Usage Model

For the OL selection probit model, there were a number of significant coefficients. As in the FO selection equation, the significant coefficients for *DSR*, *CVLB*, *PCI*, *LAR*, *MBHC*, *AGTL*, *MAJLDR*, *SRET*, *MKTVAR*, and *ASSET* had positive signs. Like in Dixon, Ahrendsen, and McCollum, higher values for the variables *LAR* and *AGTL* were associated with an increase in the propensity of a bank to originate a guaranteed OL loan. The positive signs for *DSR* and *CVLB* are consistent with expectations. As higher proportions of cash farm income are needed to service debt and as variation in the value of farmland and buildings (real farm assets) in the state for which a bank holds deposits increases, the likelihood of banks in those states using OL guarantees increases.

The model indicated that an increase in *PCI* was associated with a higher probability of guaranteed OL loan usage. The positive sign for *PCI* was consistent with expectations. More variability in the source of repayment for loans likely made banks cautious and prompted them to take advantage of the safety in repayment that guarantees offer. The marginal effect on the coefficient for this variable indicated that a .01 increase in *PCI* led to a .0015 increase in the probability of a bank originating an OL guaranteed loan. The negative sign for *ADEF* reflected cautiousness on the part of banks. Although it was anticipated that increases in the expected rate of default on non-guaranteed agricultural loans would cause banks to choose other types of assets available to them, namely guaranteed agricultural loans, it appeared that banks in the sample did not make the switch. Perhaps when agricultural default rates go up, banks shy away from lending to this sector in general.

Many of the same variables statistically significant in the OL selection equation are also significant in the OL regression equation. A number of them had signs as expected and were consistent with those signs discussed in the previous models. Once again, the bank-specific variables—*ASSET*, *LAR*, and *AGTL*—were significant and positive indicating heavier use of OL loan guarantees by banks with larger asset size and relatively more aggressive lending policies, both in general and toward agriculture. Consistent with the other three equations in table 1, the variable representing heavy past usage of the guaranteed loan program, *MAJLDR*, was highly significant.

As in the OL selection equation, the coefficients for *PCI* and *CVLB* were significant as were their marginal effects. Banks holding deposits in states for which the coefficient of variation in per capita income increases by .01 can be expected to originate an additional $47,400 in guaranteed OL principal. For banks holding deposits in states for which the coefficient of variation in real farm assets rises by .01, the expected increase in OL loan obligations would be $12,310. Finally, significant and positive signs for *NDEF* and *MKTVAR* indicated that a higher expected rate of default for non-agricultural loans and greater market interest rate variability likely led guaranteed lenders to shift the investment of their portfolio away from these now riskier assets to safer OL guaranteed loans.

Beginning Farmer Guaranteed Loans

Results for the selection and regression equations of the guaranteed FO and loan usage models estimated for beginning farm borrower loans are displayed in table 2. The null hypotheses that all coefficients were equal to zero in each equation are rejected. The FO beginning farmer probit model predicted 97% of the observations correctly and the corresponding OL probit predicted 95% correctly. Identical results would have been obtained using a naïve approach that predicted all zero observations for the dependent variable. The R-squared coefficients for the FO and OL regression equations were .165 and .168, respectively. All four equations estimated for the guaranteed beginning borrowers contained a number of significant coefficient estimates which indicated explanatory power.

In the beginning farmer FO selection equation, four borrower demand variables were significant. They were *DSR*, *DAR*, *CVLB*, and *PCI*. Model results indicated a higher propensity of making beginning farmer FO loans for lenders holding deposits in states for which the debt servicing and debt-to-asset ratios as well as the coefficient of variation in real farm assets were rising, and the coefficient of variation in per capita income was falling. Thus, less repayment capacity in the farm sector as well as more variability in farm asset values were associated with higher probability of making a beginning farmer FO loan. More variability in general income levels resulted in a smaller chance of a bank making a beginning farmer FO loan. Higher debt servicing ratio and greater variability in farm asset values also significantly increased the likelihood of a bank making a beginning farmer guaranteed OL loan as well the volume of OL loan principal originated.

A higher expected rate of return on non-agricultural loans decreased the probability of a bank making a beginning FO loan, while greater variance in the market rate of interest increased this probability. The signage of these two variables was directly in line with the switching nature of the portfolio selection model. The strong positive significance of the lender characteristics (*LAR*, *MBHC*, *AGTL*, *MAJLDR*, and *ASSET*) continued in both the beginning farmer FO and OL selection models.

Only one variable (*CVLB*) in the FO regression equation for the beginning farmer sample was statistically significant at the 5% level, and none had significant marginal effects. The probable reason for so few significant coefficients in this equation is the large amount of idiosyncratic variation in the volume of FO loans originated. The state farm financial variables and regional binary variables do not fully account for the factors influencing bank intensity of use.

The list of variables found significant in the beginning farmer OL regression model and their respective signs is almost identical to that of the overall (table 1) OL regression model. In both the selection and regression models, lender characteristics are important. Larger banks (higher *ASSET*), those more specialized to agricultural lending (larger *AGTL*), and those with aggressive overall lending strategies (higher *LAR*) are likely to originate more OL loan principal to beginning farmers. Also, farm financial characteristics (*DSR* and *CVLB*) were important in determining the amount of OL loan volume originated to beginning farmers. Only two variables, *ARET* and *NDEF*, had marginal effects that were marginally significant (at the 10% level).

SDA Farmer Guaranteed Loans

The results for the SDA model are presented in table 3. The hypotheses that all coefficients in each equation were jointly zero are soundly rejected. The FO SDA and OL SDA farmer probit models predicted 98.9% and 98.4% of the observations correctly, almost the same as the sample proportions of zeros. The R-squared coefficients for the FO SDA and OL SDA regression equations were .209 and .179.

In both SDA loan selection equations, several coefficients were significant as were the marginal effects of these variables. The coefficients for *DSR*, *LAR*, *AGTL*, *MAJLDR*, *MKTVAR*, and *ASSET* were all significant at the 5% level with positive signs, while *VRA*, *CVFI*, *NRET*, and *ADEF* had statistically significant, negative coefficients. Similarly to all other estimated models, lenders with more aggressive lending strategies were more likely to pursue guaranteed lending. Higher expected rates of return for asset alternatives to guaranteed loans decreased the probability of guaranteed loan origination due to lenders switching away from the lower return asset to the higher return asset. Increases in the variance of the market interest rate were linked with significant increases in the likelihood of usage for both FO and OL guarantees, and *ADEF* significantly decreased the probability of guarantee usage.

Like *LAR*, *AGTL* appeared as a positive and statistically significant variable in all probit equations estimated in the study. Lenders with higher agricultural loan-to-total loan ratios likely face higher demand for agricultural loans in general and choose to specialize in agricultural loans. Such lenders would have greater opportunity to use guaranteed loans. Agricultural lenders may be savvier when it comes to making use of guaranteed agricultural loans, and it may even be the case that such banks have specialized personnel to originate such loans. Guaranteed lenders having originated significant numbers of guaranteed loans in the past year were more likely to issue guaranteed SDA loans. Increases in the variance of the market interest rate and larger bank asset size were associated with more banks making SDA loans.

FSA should expect fewer banks to originate SDA loans in years in which the percentage of agricultural loans made at a floating rate is higher as the negative signs of VRA in the probit equations confirm. Variable rate loans expose the lender to more uncertainty than do fixed rate loans as there are two sources of potential repayment difficulty for the borrower—that stemming from unfavorable project profitability and the chance that the rate of repayment exceeds the rate of return on the project. A .01 increase in *CVFI* also reduced the probability of making a guaranteed SDA OL loan by .00011. Lenders with higher expected rates of return on non-agricultural loans (*NRET*) were .00016 less likely to originate a SDA FO guarantee and .00029 less likely to originate a guaranteed SDA OL loan.

In the FO SDA loan volume model, only the estimated coefficient for *CVLB* was statistically significant. Its marginal effect was also significant. Two statistically significant coefficients (*DAR* and *LAR*) were found for the OL SDA loan volume model. However, the marginal effects for these two variables lacked significance. Thus, the estimated models were more successful in identifying those variables associated with lender propensity to issue SDA loans than those predicting the amount of SDA loan volume originated. This result is not surprising given that SDA loan origination is highly demand driven and geographically concentrated. In addition, the demand variables included in the equations characterized the financial position of the average farm borrower in a state rather than a select portion of the farm borrower population, i.e., those who would qualify for a SDA loan.

Implications for Policymakers

The signs and significance for the independent variables included in each of the estimated equations were much the same across loan type and samples. However, the characteristics associated with increased likelihood of making a guaranteed loan were not necessarily the exact same characteristics that led to higher amounts of principal obligated. This finding supported the choice of estimator for the study (double-hurdle vs. Tobit model). The similarities and differences between the estimated models have several implications for FSA as they consider program policy in the future.

For both FO and OL loans in the full lender model, there were distinct lender characteristics that indicated a higher probability of guaranteed loan origination. Lenders with larger asset size, higher loan-to-asset and agricultural loan-to-total loan ratios, and multi-bank holding company affiliation were more likely to use the FSA guaranteed loan program to serve their farm borrowers. If FSA is interested in expanding the number of banks making guaranteed loans in the future, then they should consider targeting lenders with these characteristics. However, if an overall volume expansion of the FSA guaranteed loan program is desired, it may be more efficient to target banks already making a high number of guaranteed loans. To expand the number of guaranteed loans originated, it might be most efficient to encourage banks currently making low numbers of loans per year to make more loans since such banks are familiar with the guaranteed loan process.

The significance of the lender variables in the selection and regression equations combined with current trends in banking can be used to forecast future use of guaranteed loans. The coefficients for *ASSET* had positive signs in all equations. Banks are continuing to increase in size as banks merge or are acquired by larger banks. If current trends continue, FSA should expect those banks to begin or continue to make guaranteed loans in the future. Also, those banks using guaranteed loans will continue to make larger volumes of FO and OL loans—not necessarily larger volumes of these types of loans to beginning and SDA farmers—but certainly larger volumes to guaranteed borrowers in general. Since FSA is mandated to target lending to beginning and SDA farmers, it may be appropriate to include lender level characteristics such as asset size, loan-to-asset ratio, and agricultural loan-to-total loan ratio as criteria for which banks FSA should target. Together with FSA's Preferred Lender program (PLP) which reduces the amount of paperwork involved to originate a guaranteed loan and gives commercial lenders more control of the process, FSA has the potential to increase the efficiency of guaranteed loan delivery.

As expected, results in most equations indicated that banks originating large numbers of guaranteed loans in the past had higher probabilities of originating guaranteed loans in the future. Major guaranteed lenders also originated a higher volume of principal. However, major lender status did not necessarily indicate that banks would lend more principal to beginning and SDA farmers. In general, the lack of significance of bank-specific variables in the beginning FO and SDA models points toward these types of lending being primarily demand driven. That is to say, a bank may be inclined to make guaranteed loans, but if no potential borrowers fitting these criteria enter their applicant pool, they cannot make a loan that fits these categories.

The significance of the expected return and default rates indicates that banks consider the general lending climate (including alternative investment opportunities) when deciding whether to make guaranteed loans. Banks treated the decision as a portfolio problem choosing to invest in an asset when returns were expected to rise (default rates were expected to fall) or switch to an alternative when returns were expected to decline (default rates were expected to rise). The widespread significance of these relationships in the selection models supports the theoretical specification as a portfolio selection model.

Some borrower loan demand characteristics were significant. Debt servicing ratio and coefficient of variation in the value of real farm assets were significant in several of the estimated models. In addition, the coefficients of the state-level variables debt-to-asset ratio, variation in net farm income and per capita income exhibited noticeable significance. These results also indicate that broad forces beyond the control of FSA affect guaranteed loan usage.

LIST OF REFERENCES

Dixon, B. L., B. L. Ahrendsen and S. M. McCollum. *Models of FSA Guaranteed Loan Use Volume and Loss Claims Among Arkansas Commercial Banks*. Arkansas Agricultural Experiment Station, University of Arkansas Division of Agriculture, Fayetteville, Bulletin 962, November 1999.

Dodson, C. B. and S. R. Koenig. "Explaining County-Level Variability in Farm Service Agency Farm Loan Programs." *Agricultural Finance Review* 63(2003): 193-212.

Greene, W. H. *Econometric Analysis*, 3rd edition. Prentice-Hall, Inc. 1997. Upper Saddle River, NJ.

Heckman, J. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1979):153-161.

Humphrey, D. B. and L. B. Pulley. "Banks' Responses to Deregulation: Profits, Technology, and Efficiency." *Journal of Money, Credit and Banking* 29(February 1997):73-93.

Koenig, S. R. and P. S. Sullivan. Profile of Participants in FmHA's Guaranteed Farm Loan Programs. Washington, DC: USDA/ERS, Dec. 1991.

Pederson, G. D. "Agricultural Bank Portfolio Adjustments to Risk." *American Journal of Agricultural Economic* 74(August 1992):672-681.

Santomero, A. M. "Fixed Versus Variable Rate Loans." *Journal of Finance* 38(December 1983):1363-80.

Settlage, L. A. *Examining the Use of Farm Service Agency Guaranteed Loans by Commercial Banks*. Unpublished Ph.D. dissertation, Purdue University, December 2005.

Settlage, L. A., B. L. Dixon, B. L. Ahrendsen and S. R. Koenig. *Models of Farm Service Agency Guaranteed Loan Loss Claim Rates in the U.S. for 1990-1998*, Arkansas Agricultural Experiment Station, University of Arkansas Division of Agriculture, Fayetteville, Bulletin 966, June 2001a.

Settlage, L. A., B. L. Dixon, B. L. Ahrendsen and S. R. Koenig. "Estimating Principal Outstanding Models for Farm Service Agency Guaranteed Loans." Selected Paper presented at the AAEA Annual Meetings, Chicago, IL, Aug. 5-8, 2001b.

Sullivan, P J. and W. M. Herr. "The Effect of FmHA Guaranteed Farm Loans on Rural Credit Markets." *The Review of Regional Studies* 20(1990):50-59.

Tobin, J. "Estimation of Relationships for Limited Dependent Variables." *Econometrica* 26(1958):24-36.

Turvey, C. G. and A. Weersink. "Credit Risk and the Demand for Agricultural Loans." *Canadian Journal of Agricultural Economics* 45(1997):201-217.

Table 1. Estimated FO and OL Guaranteed Loan Usage Models

Independent Variable	FO Probit Coefficients	Marginal Effects˜	FO Regression Coefficients	Marginal Effects˜	OL Probit Coefficients	Marginal Effects˜	OL Regression Coefficients	Marginal Effects˜
Constant	-2.743***	-0.362***	-5.257***		-2.989***	-0.674***	-3.230***	
VRA	-0.127	-0.017	-0.030	0.095	-0.182	-0.041	0.072	0.086
VRN	0.127	0.017	1.212	1.087	0.893*	0.201*	2.348***	2.281***
DSR	1.690***	0.223***	-0.181	-1.841**	1.720***	0.388***	0.601	0.471
DAR	1.112***	0.147***	2.067***	0.975	-0.280	-0.063	-0.643*	-0.622*
CVFI	-0.105	-0.014	-0.082	0.021	-0.057	-0.013	0.065	0.069
CVLB	0.858***	0.113***	4.251***	3.408***	0.740***	0.167***	1.287***	1.231***
PCI	-2.709***	-0.357***	-3.257**	-0.596	1.492**	0.336**	4.853***	4.740***
LAR	1.586***	0.209***	2.153***	0.595	1.136***	0.256***	1.000***	0.914***
FOGRET	-2.101**	-0.277**	-4.677***	-2.613				
OLGRET					-0.297	-0.067	1.345**	1.368**
ARET	-1.721	-0.227	5.804**	7.494***	0.138	0.031	3.157*	3.146*
NRET	-1.879***	-0.248***	-1.338***	0.508	-2.559***	-0.577***	-0.434***	-0.241
FODEF	-2.256*	-0.298*	-0.752	1.464				
OLDEF					-0.641	-0.145	1.630*	1.678*
ADEF	-0.049	-0.006	-0.686**	-0.638*	-0.430***	-0.097***	-0.800***	-0.768***
NDEF	-0.102*	-0.013*	0.452***	0.553***	-0.054	-0.012	0.382***	0.386***
MBHC	0.063***		0.080***		0.043***		0.042**	
AGTL	2.199***	0.290***	1.958***	-0.202	3.028***	0.683***	0.642***	0.413*
MAJLDR	1.334***		1.468***		2.069***		0.955***	
SRET	1.178**	0.155**	1.530*	0.372	1.063**	0.240**	-0.115	-0.195
MKTVAR	0.060*	0.008*	0.163***	0.104	0.107***	0.024***	0.137***	0.129***
ASSET	0.030***	0.004***	0.035***	0.005	0.030***	0.007***	0.012***	0.010***
IMR			1.156***				0.093	
Overall Model Results†:	χ^2: 10,026.22*** % Correct: 90.71		F: 33.28*** R^2: .114 Adjusted R^2: .111		χ^2: 18,753.99*** % Correct: 83.29		F: 127.65*** R^2: .213 Adjusted R^2: .212	

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. † "% correct" is the percent of observations in sample correctly classified by the probit model. ˜Marginal effects are not valid for binary variables because they are not continuous.

Table 2. Estimated FO and OL Beginning Farmer Guaranteed Loan Models

Independent Variable	FO Probit Coefficients	Marginal Effects˜	FO Regression Coefficients	Marginal Effects˜	OL Probit Coefficients	Marginal Effects˜	OL Regression Coefficients	Marginal Effects˜
Constant	-3.121***	-0.123***	-15.197		-4.043***	-0.245***	-3.783***	
VRA	-1.031***	-0.041***	-3.526	0.453	-1.326***	-0.080***	-0.413	0.238
VRN	0.839	0.033	3.288	0.051	1.572**	0.095**	1.951***	1.178
DSR	1.098**	0.043**	3.932	-0.308	1.708***	0.103***	1.429***	0.590
DAR	1.764***	0.070***	7.685	0.877	0.426	0.026	-0.033	-0.243
CVFI	-0.159	-0.006	-0.628	-0.014	-0.096	-0.006	-0.065	-0.017
CVLB	1.557***	0.061***	9.031**	3.023	1.327***	0.080***	0.889***	0.237
PCI	-5.238***	-0.207***	-20.118	0.101	0.932	0.057	1.032	0.573
LAR	1.366***	0.054***	5.492*	0.220	1.109***	0.067***	0.803***	0.258
FOGRET	-3.029**	-0.119**	-13.798	-2.107				
OLGRET					1.401	0.085	1.032	0.344
ARET	1.595	0.063	7.831	1.675	3.717**	0.225**	4.761***	2.934*
NRET	-1.203***	-0.047***	-4.086	0.557	-2.062***	-0.125***	-1.034***	-0.020
FODEF	-0.235	-0.009	6.046	6.955				
OLDEF					-0.651	-0.039	0.202	0.521
ADEF	-0.516*	-0.020*	-1.974	0.016	-0.731***	-0.044***	-0.566***	-0.207
NDEF	0.123	0.005	0.671	0.197	0.293***	0.018***	0.282***	0.138*
MBHC	0.067***		0.253	-0.006	0.064***		0.042***	
AGTL	1.291***	0.051***	4.685*	-0.297	2.016***	0.122***	1.022***	0.031
MAJLDR	1.099***		3.997*	-0.246	1.442***		0.721***	
SRET	0.913	0.036	3.910	0.385	1.889***	0.114***	0.930*	0.002
MKTVAR	0.155***	0.006***	0.587	-0.010	0.197***	0.012***	0.128***	0.031
ASSET	0.028***	0.001***	0.105*	-0.004	0.026***	0.002***	0.014***	0.001
IMR			4.316*				0.557***	
Overall Model Results†:	χ^2: 3,001.83*** % Correct: 97.40		F: 13.02*** R^2: .165 Adjusted R^2: .152		χ^2: 7,269.67*** % Correct: 95.34		F: 25.06*** R^2: .168 Adjusted R^2: .162	

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. † "% correct" is the percent of observations in sample correctly classified by the probit model. ˜Marginal effects are not valid for binary variables because they are not continuous.

Table 3. Estimated FO and OL SDA Farmer Guaranteed Loan Models

Independent Variable	FO Probit Coefficients	Marginal Effects˜	FO Regression Coefficients	Marginal Effects˜	OL Probit Coefficients	Marginal Effects˜	OL Regression Coefficients	Marginal Effects˜
Constant	-3.572***	-0.053***	-10.973		-3.457***	-0.070***	-16.045**	
VRA	-1.381***	-0.021***	-1.959	0.813	-1.119**	-0.023**	-1.925	1.347
VRN	1.556	0.023	4.062	0.939	1.722	0.035	7.117	2.081
DSR	1.256*	0.019*	3.999	1.477	2.487***	0.050***	7.205*	-0.066
DAR	2.888***	0.043***	8.479	2.683	1.204**	0.024**	6.171**	2.650
CVFI	-0.716***	-0.011***	-2.116	-0.679	-0.557***	-0.011***	-1.727*	-0.099
CVLB	0.830**	0.012**	6.380***	4.714	0.018	0.000	0.069	0.015
PCI	-4.040***	-0.060***	-10.142	-2.033	0.274	0.006	4.736	3.936
LAR	1.556***	0.023***	3.633	0.510	0.850***	0.017***	2.906**	0.420
FOGRET	-1.590	-0.024	-5.721	-2.529				
OLGRET					-0.891	-0.018	0.068	2.672
ARET	-1.652	-0.025	4.295	7.612	-4.028	-0.082	-5.035	6.742
NRET	-1.065***	-0.016***	-1.500	0.637	-1.415***	-0.029***	-3.864*	0.274
FODEF	0.582	0.009	2.696	1.528				
OLDEF					0.393	0.008	-1.001	-2.151
ADEF	-1.328***	-0.020***	-3.193	-0.526	-0.703**	-0.014**	-1.499	0.557
NDEF	0.265**	0.004**	1.118*	0.587	0.019	0.000	0.119	0.065
MBHC	0.020		0.105		0.036		0.062	
AGTL	1.034***	0.015***	1.495	-0.581	1.235***	0.025***	3.484*	-0.128
MAJLDR	1.011***		2.023		1.182***		3.269*	
SRET	0.935	0.014	1.424	-0.453	1.290*	0.026*	3.155	-0.617
MKTVAR	0.257***	0.004***	0.472	-0.044	0.231***	0.005***	0.551	-0.124
ASSET	0.027***	0.000***	0.053	-0.002	0.023***	0.000***	0.061*	-0.006
IMR			2.197				3.218*	
Overall Model Results†:	χ^2: 1,639.09*** % Correct: 98.90		F: 7.19*** R^2: .209 Adjusted R^2: .180		χ^2: 2,631.72*** % Correct: 98.42		F: 8.70*** R^2: .179 Adjusted R^2: .158	

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. † "% correct" is the percent of observations in sample correctly classified by the probit model. ˜Marginal effects are not valid for binary variables because they are not continuous.