Farmer Credit Delinquency in Southeastern US:

Factors and Behavior Prediction

Frederick Quaye, Valentina Haratrska and Denis Nadolnyak

Department of Agricultural Economics and Rural Sociology
Auburn University, AL, USA

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Abstract

This study examines the factors and behaviors that affect Southeast US farmers' ability to meet their loan payment obligations within the stipulated loan term. The study also estimates a credit risk model using farm-level financial information to determine the credit worthiness of various different farmers in different states and their possible repayment capabilities. The study uses a 10-year (2003-2012) pooled cross-sectional data from the USDA ARMS survey data (Phase III). A probit approach is used to regress delinquency against various borrower-specific, loan-specific, lender-specific, macroeconomic and climatic variables for the first part, whilst a logistic approach is used to regress farmers' coverage ratio (repayment capacity) on financial variables (liquidity, solvency, profitability, and financial efficiency) in addition with tenure, to determine how creditworthy the various kinds of farmers are, and in what particular states.

The results show that farmers with larger farms, farmers with insurance, farmers with higher net income, farmers with smaller debt to asset ratio, farmers with single loans and those that take majority of their loans from sources apart from commercial banks are those that are less likely to be delinquent. Temperature and precipitation increases also lowers farmer delinquency, unless in excessive quantities where certain thresholds are exceeded. The results for credit model also show which particular farmers and in what states are more likely to be creditworthy based on their financial variable information.

Keywords: Credit Delinquency · Agricultural Loans · Credit Model · Farmer Risk Analysis · Financial ratios

JEL classification: Q14, R51

1. Introduction

Agriculture is one of the high risk enterprises where farmers are continuously faced with a lot of uncertainties. These uncertainties mostly come in the form of shocks and may generate high costs, most at times in amounts which are not readily available to the farmer. These may include pest/ disease destruction, flood, hail or commodity price declines. Apart from these uncertainties, farmers may also require huge sums of money either at the start-up of the farm enterprise or when one needs to invest in machinery due to the ever changing nature of the industry (the fast development of new farming technology), labor capital, land and all other forms of resources. In all these instances, one of the key remedial actions that farmers take is to borrow the needed amount of money, with the expectation that they would be able to make profits within a specified period of time to make repayments. As to whether a farmer would be able to make the said repayment in the stipulated time depends on several factors which differ across farms, communities, regions as well as countries.

Apart from informal means, credit unions, life insurance companies and other financial institutions, agricultural loans in the US are mainly supplied either by commercial banks, or through the Farm Credit System (FCS) (Dodson *et al*, 2004). Though Ryan *et al* (1999) admit that there exist some form of direct competition between the FCS and commercial banks with regards to the agricultural credit market, they note that FCS lenders are more likely to serve larger, wealthier, and more established farmers as compared to commercial farms. The FCS refers to a nationwide network of borrower-owned lending institutions that are specialized in credit delivery. Established since 1916, the FCS provides loans, leases, and related services to farmers, ranchers, aquatic producers, timber harvesters, agribusinesses, and agricultural cooperatives, among a few

others. In addition to the aforementioned loan sources, quite a significant number of farmers in the US also receive credit from the Farm Service Agency (FSA). The various agricultural lending institutions need to arrange for a guarantee from FSA, in case the borrowing farmer defaults. The FSA provide these agricultural loan lenders with up to a 95% of the loss of principal and interest on a loan (Dixon *et al*, 1999). The mission of the FSA is to fill the gaps that exist in the commercial credit market where high-risk borrowers are unable to secure loans. In such instances, the FSA is mandated to provide the high-risk borrowers with direct loan (Escalante *et al*, 2006).

Although farm loans have the lowest delinquency rates in the country, maintaining the rates at a least minimum possible is essential for the growth of the financial credit market. Figure 1 shows the US loan delinquency rates from commercial banks over the last four decades.

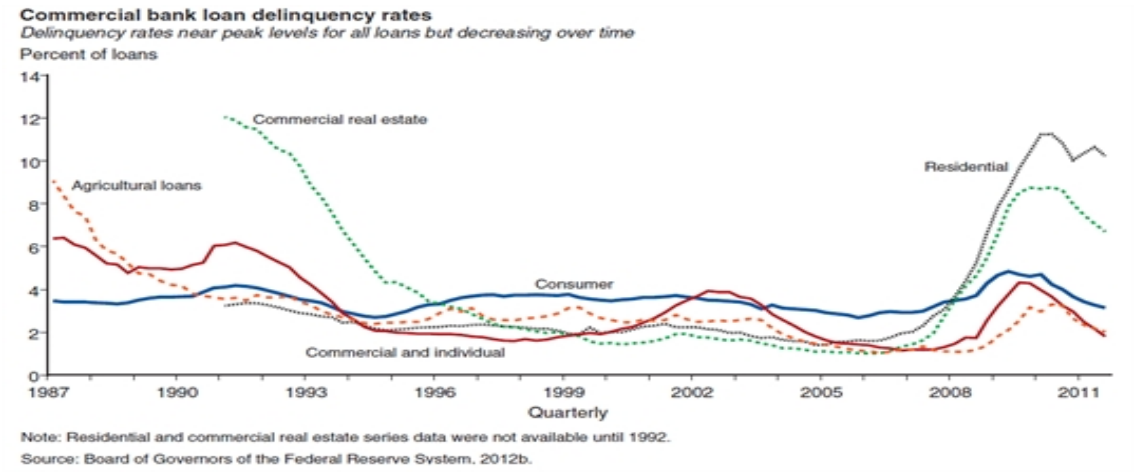

Figure1. Commercial banks loan delinquency rates

Though delinquency rates for most of the non-agricultural sectors experienced a sudden sky-rocketing rise, U.S. agriculture managed to sail through with the lowest increase whilst still maintaining the least delinquency rate. The question that needs to be asked is, can the rate be

further reduced? The answer would definitely be yes, only if the factors that cause farmers to be delinquent are known and the concerned stakeholders (farmers and agricultural lenders) consequently take ameliorating measures to avoid the instances of farmers becoming delinquent. According to the USDA, 2012, the decline in farm delinquency rates in 2010, coupled with high farm income in 2010 and in 2011, indicates that farm loan charge-off rates are moving back towards long term trend levels.

Factors that affect timely loan repayment vary across sectors and geographical locations, though there sure would be similarities across board. For instance some factors that affect mortgage loan repayment may be irrelevant for agricultural loans, whilst USA and African countries may face slight differences with respect to elements that influence loan delinquency. The factors affecting delinquency for the different sectors could generally be classified into four groups; borrower specific characteristics, lender specific characteristics, loan characteristics and country or regional specific variables of the economic environment. However, the specific factors under these groups may differ as mentioned. Aside these traditional factors, one other key variable emerging in the literature that is capable of affecting late repayment (or at worst default) is climate (Ayanda, 2012). This is because as mentioned, extreme erratic climatic conditions would reduce yield, which in turn would lower expected revenue, and thus increase the probability of farmer loan delinquency.

This study basically seeks to find out the factors that influence farmer loan delinquencies and defaults, specifically factors that make farmers relent on paying their loans on time. The paper also uses a credit-risk model to describe the behavior of default farmers, and under what circumstances they may be highly probable to miss their loan repayment deadlines. Unlike a recent study

(Hartarska *et al*, 2012) that explores the supply-side effect of climate on agricultural loans[1], this paper examines the specific factors that affect delinquency and default in the southeast US region, whilst incorporating climatic factors to explore any possible additional effects. Apart from the fact that this paper is the first to determine factors affecting farmer delinquent behaviors in the southeast region, it is also the foremost study that incorporates climatic factors with the traditional loan delinquency factors to explore their effects on southeastern US farmers. In addition, dissimilar to the uncountable number of loan default studies in the literature, those for delinquency are very few. This study (by incorporating delinquency) thus also attempts to narrow the wide gap between the studies of these two, because even though the factors that influence loan default automatically influences delinquency, the vice versa is not true.

The paper is henceforth structured as follows. Related studies are reviewed in the next section. The analytical framework and empirical model used for the analysis are then presented in the third section. Next, the data and estimation procedures are described in the fourth section, followed by the empirical results and subsequent discussion of the results. The results section has two main focuses; estimating the factors that affect farmer loan delinquency and the second exploring the behavior of delinquent farmers. Lastly, the paper ends with some concluding remarks.

2. Literature Review

Loan delinquency refers to the situation where an individual or corporation with a contractual obligation to make payments against a loan in a timely manner, such as an agricultural credit in this instance, fails to make the said payments on time. It represents the preceding stage for a loan

[1] The authors sought to determine the effects of climate, specifically the El Nino Southern Oscillation, on agricultural lending by commercial banks.

borrower to be default. The period between the delinquency stage and default is subjective, and specifically depends on the lender/ lending institution and its contractual agreement with the borrower. For most agricultural loans, the repayment terms vary according to the type of loan received, the collateral used (if any) in securing the loan, and the farmer's ability to repay.

Prompt repayment factors for loans are time and space subjective, and not necessarily the same among developing or developed countries. For instance with Armendariz *et al*'s (2005) study, they show that microfinance loan contracts with less frequent repayment face higher client default in Bangladesh. On the contrary, McIntosh (2007) in his study observed that fortnight loan repayment schedules saw a lower drop-out in participants and decreased default in Uganda. Contrary to both McIntosh's and Armendariz's studies, Field *et al*'s (2008) study about the repayment frequency and default in India's microfinance showed that switching from weekly to monthly installments did not affect client repayment capacity. Rather, and consistent with patterns observed among some other India bank's clients outside their experiment, there was no default changes among either the weekly or monthly clients. One must however note that all these studies were undertaken in developing countries, with two of them in the same continent and very near to each other in terms of geographical location. How much more differences could thus even be experienced in the factors for developed and developing countries? It must also be noted that though some factors may differ, some factors are almost constant, ceteris paribus, across space and time. Such factors include interest rate, loan-asset ratio, and loan-income ratio among a few others (Crook *et al*, 2012, Michael, 2011, and Oni *et al*, 2005). For such factors, smaller values would certainly imply a less likely probability of delinquency or default.

Loans in general, and including farm loans are granted based on a borrower's credit history or credit score. Borrowers that have defaulted in previous acquired loans have a lesser probability of securing another loan. For instance for FSA loans, the farmer needs to show that he/she has a good credit history, or if not must be able to show that the need to default was due to circumstances beyond his/her control. According to Featherstone *et al* (2006), the fundamental goal of a credit risk-rating system is to accurately estimate the credit risk of a specific transaction or portfolio of transactions/assets. They elaborate that its ultimate goal is to measure the expected and unexpected loss from investing in an asset and the capital required to support it. In estimating one's credit risk rating, Crouhy *et al* (2001) note that the estimations are mainly based on borrower attributes such as financial, managerial, earnings and cash flow, quality and quantity of assets, and liquidity of the firm. In so doing they observe that lenders tend to rely more heavily on repayment capacity, solvency, and loan security than on the borrower's profitability and financial efficiency. They go further to state that many risk-rating systems are weak and mostly do not provide the true repayment capability of borrowers because they are based on historical financial information generated under conditions that may not be applicable in the future. Walraven *et al* (2004) reviewed the prevalence of the use of risk ratings by commercial banks and they observed that majority of banks use credit score rating to determine the riskiness of the loan, with the exception of small banks.

Since Lyubov (2003) developed the first modern agricultural lending credit risk model, some few other studies have also tried to present much more improved and advanced credit risk-rating models that could be applied to agricultural loans. We must still bear in mind that agricultural credit models are likely to regional, and this must be factored into the models. For example, the

FCS recognizes regional differences by using region specific models to estimate borrower's credit score. This implies that each region has a single credit scoring model, which is typically representative of the farm type dominant in that region. Lubinda (2010) uses time series econometric forecasting techniques and risk simulation techniques to measure the credit risk as the probability of default. They observed that the probability of a farmer in the Free State province defaulting on a structured finance white maize production loan is 3.47%. With the purpose of developing credit models that meet capital requirements for agricultural lenders under the New Basel Capital Accord, Katchova *et al* (2005) bases their formulation on the Merton's option pricing model to develop their credit risk models. They develop a Credit Metric model and a Moody's KMV model, and by using farm financial data estimate the probability of default, loss given default and the expected and unexpected losses. Their study showed that the necessary capital for agricultural lenders under the new Basel Accord varied substantially depending on the riskiness and granularity of the loan portfolio. Odeh *et al* (2011) uses a multi-objective evolutionary optimization algorithm to develop a model they term a Fuzzy dominance based Simplex Genetic Algorithm to generate exact decision rules for predicting agricultural loan default while Yan *et al* (2009) attempts in their study to measure credit risk by using a seemingly unrelated regression (SUR) model to predict farmers' ability in meeting their financial obligations. They (Yan *et al*) use a simulation process in conjunction with the SUR model to predict the credit risk, in order to account for both the dependence structure and the dynamic feature of the structure model. Other recent studies include those of Katchova *et al* (2005) and Kim *et al* (2006). Studies that used the traditional models, especially the logit/probit models include Durguner *et al* (2007), Miller *et al* (1989) and Novak *et al* (1994).

As mentioned earlier, it is now evident to many that climate extremes have a high chance of reducing a farmer's ability to repay a loan. Studies are thus beginning to incorporate climate factors as factors that influence delinquency, and consequently default. Cai *et al* (2011) uses a dynamic optimization model to simulate how farm-level realized price/ profitability responses to yield change were induced by climate change. They observed that reduction in crop yields due to climate change results in reduced farm profitability for most of the states studied, which in turn increases the risk of defaulting on their payment. They further posit that the predicted climate change in the near future is more likely to pose a problem for agricultural production and profitability in the southern U.S. states as compared to the northern U.S. states. In their credit supply-side study titled 'El Nino and Agricultural Lending in the Southeastern U.S.A', Hartarska *et al* (2012) explained how changes in climatic conditions would affect the southeastern US region. They specifically study how inter-annual climate variability affects agricultural loan portfolios in agricultural banks serving agricultural producers. They observed that non-neutral El Nino Southern Oscillation years that typically have higher incidence of weather extremes are associated with smaller levels of non-performing. This result though deviant of basic economic reasoning, is explained as the result of support mechanisms put in place by complementary financial markets and support systems. Collier *et al* (2011) also examines the effects of extreme El Nino on the exposure of a lending institution in Peru. Among their findings, they observe that the correlated risk exposure of many small borrowers significantly affects the lender when a catastrophe or climate extreme occurs.

Insuring agricultural loans, and most loans in general is one of the efficient ways of avoiding the implications of default. Credit default swap, since its inception into the insurance market have had a share in the agricultural credit system. In an attempt to explore the problem of how to correctly

price South African weather derivatives (with multiple underlying) for crop farmers who buy agricultural insurance, Holemans *et al* (2011) established a weather derivative pricing equation to be used specifically in the South African market. Using a credit default swap pricing methodology, they demonstrate that an effective insured weather derivative could, in principle, help manage the unique weather risks faced by South African grape farmers. McKenzie *et al* (2009) examined the potential liquidity benefits of making available an Over-the-Counter Margin Credit Swap contract to grain hedgers. The MCS was developed as a financing tool that enables hedgers to draw on sources of capital outside the farm credit system to provide liquidity. They tried to obtain an explanation of elevator risk management and marketing problems related to increased margin risk, and possibly offer potential solutions. Overall, their simulation results showed that a MCS contract would provide significant liquidity benefits to hedgers during volatile periods. One moral hazard behavior faced mostly by agricultural insurance companies in such instances is the continued supply of credit to farmers even in high production risk areas (Smith *et al*, 2009). With the above financial instruments, lenders tend to reduce lender risks, enabling farms to adopt production technologies that on average may involve more income risk. Though these insurance companies therefore try their best to analyze every individual loan and its borrower pretty well, this still creates some amount of market failure in the agricultural credit market.

3. Method

The estimation procedures used are in two folds. The first part examines the key factors that influence loan delinquency and subsequent default of farmers, whilst the second part analyzes the delinquency/default behavior and its prediction for agricultural loan borrowers.

The study employs the Binary Probit model to determine the factors that affects farmer delinquency. It bases its analysis on the cumulative normal probability distribution. The probability P_i of a farmer being delinquent could be expressed in terms of the cumulative distribution of a standard normal random variable as;

$$P_i = prob\left[Y_i = 1 \mid X\right] = \int_{-\infty}^{x_i'\beta} (2\pi)^{-1/2} \exp\left(-\frac{t^2}{2}\right) dt$$

Where $P_i = \Phi\left(x_i'\beta\right)$

Y_i represents the independent variable (in this case whether a farmer is loan delinquent or not) whilst X represents the exogenous variables.

Marginal effects are used to interpret the relationship between a specific variable and the outcome of the probability.

For the continuous variables, the marginal effects while holding other variables constant is derived as; $\frac{\partial P_i}{\partial x_{ik}} = \phi\left(x_i'\beta\right)\beta_k$,

whilst the marginal effects for dummy variables (which represents the discrete changes in the predicted probabilities) could be derived as; $\Delta = \Phi\left(\bar{x}\beta,\ d = 1\right) - \Phi\left(\bar{x}\beta,\ d = 0\right)$.

Φ represents the cumulative distribution function whilst ϕ represents the probability density function. d represents the dummy.

Theoretically, credit delinquency/ default have been modeled as a function of individual characteristics that affect borrower repayment capacity, external shocks and macroeconomic variables.

The estimable equation could thus be formulated as;

$$\Phi^{-1}(P_{LD}) = \beta_i X_i = \beta_0 + \beta_1 B_i + \beta_2 L_i + \beta_1 Z_i + \beta_2 M_i + \beta_1 C_i + \varepsilon_i$$

Where LD represents loan delinquency, B_i contains borrower specific variables, L_i contains loan specific variables, Z_i contains lender specific variables, M_i contains macroeconomic variables, and C_i contains climate variables. β_i represents the estimable parameters whilst ε_i represents the error term, which is assumed to be distributed as standard normal and has a variance of 1.

The second part estimates the probability of delinquency using a credit risk model. Lubinda (2010) notes that when modelling credit risk in agricultural loans, the attributes of the agricultural sector and its borrowers must both be taken into account, a feature that is substantially different from the credit risk exposures in other sectors of the economy. However following Durguner's (2007) approach, this study also uses a farm-level data to measure creditworthiness instead of the conventional practice of using lender data. Other studies that have used farm-level data for such analyses include Novak *et al* (1994) and Escalante *et al* (2004). This study uses the model by Durguner *et al* (2011) in finding the credit riskiness of a borrowing farmer. These studies modeled the effect of financial ratios on farms' credit risk level, where credit risk level refers to repayment capacity. Higher repayment capacity implies a lower credit risk. Coverage ratio is used as a measure for repayment capacity. The choice of coverage ratio as the dependent variable is also justified (aside being used extensively in the literature) since the coverage ratio is the Farm Financial Standards Council's (FFSC-1997) recommended ratio measure for repayment ability.

With agricultural lenders being interested in a cut off between a high and low credit risk farmer and not in continuous ratios, farmers are considered to have low (high) credit risk if they have high (low) repayment capacity and a coverage ratio greater (less) than 1. The model is thus formulated as;

$$Y_t = \beta_0 + \sum_{i=1}^{5} \beta_i X_i + \sum_{j=1}^{3} \beta_j dummy\ j + \sum_{j=i}^{3} \sum_{i=1}^{5} \beta_{ji} dummy\ j * X_i$$

And is estimated as a logistic function, i.e.;

$$\log\left(\frac{Y_t}{1-Y_t}\right) = \beta_0 + \sum_{i=1}^{5} \beta_i X_i + \sum_{j=1}^{8} \beta_j dummy\ j + \sum_{j=i}^{8} \sum_{i=1}^{5} \beta_{ji} dummy\ j * X_i + \mu_t$$

The dependent variable, Y_t, refers to the coverage ratio. It is denoted as 1 if coverage ratio is ≥ 1 i.e. if the farm belongs to the low credit risk category, and zero otherwise. Though transforming the dependent variable into a discrete one may be associated with loss of information, previous studies have found that applying the logit model to the transformed variables does not underperform models where original continuous variables are used. The X_i represents the financial ratios. They are the working capital to gross return, debt-to-asset ratio, return on assets, asset turnover ratio, and tenure ratio. These financial ratios are used as proxies for liquidity, solvency, profitability, and financial efficiency and tenure respectively. Dummy *j* represents the farm type dummy i.e. either grains, cotton, tobacco, poultry, cattle, dairy products, fruits or vegetables. The use of coverage ratio as the dependent variable has been practiced by previous studies because of some distinct and peculiar attributes that the ratio has been observed to portray. Among these include its focus on the basic characteristics of a creditworthy farmer and the ability to meet cash obligations and make debt payments based on income (Durguner *et al*, 2011, Novak *et al*, 1997). It has however been noted that a disadvantage of the coverage ratio is its inability to distinguish between variations in profitability and debt levels.

The use of financial ratios as independent variables has also been practiced by studies such as Barry *et al* (2002), Katchova *et al* (2005) and Durguner *et al* (2011).

4. Data

As mentioned earlier, the Southeastern US was chosen as the study area because of two main reasons. First, due to the fact that its agriculture is mainly rain fed and second, based on the widely known conviction that the southeastern region might be the worst hit region as a result of climate variability. Farmers with only single loans are the main focus for the analyses, in order to eliminate money fungilibity issues with farmers with multiple loans. However, supplementary results are presented for farmers with multiple loans in order to observe any noticeable differences. The analyses are performed in two folds; one for farmers that have been delinquent within the past three years before the survey, and another for just farmers that received their loans within three years before the survey year. This is an approach widely used in the literature to reduce measurement errors and incorrect farmer information, since respondents tend to forget the exact years and tend to approximate the years. This also gives some amount of credibility to how the delinquency variable is constructed.

Apart from the climate and macroeconomic data, all other data were obtained from the Agricultural Resource Management Survey (ARMS) database (Phase III). ARMS is USDA's primary source of information on the financial condition, production practices, and resource use of America's farm businesses and farm households. A ten-year period (2003 – 2012) survey data of the ARMS are amalgamated into a pool-cross sectional data. This includes the borrower specific variables, loan specific variables and lender specific variables. Macroeconomic variables are county based. The rich farm-level information provided by the ARMS data provides a ground for detailed analyses

and much more reliable results. As stated by USDA, the ARMS is the only national survey that provides observations of field-level farm practices, the economics of the farm businesses operating the field and the characteristics of farm operators and their households, all collected in a representative sample. Although the Phase III survey is conducted from January through April, the variables do not need to be lagged to capture the exact year, since the survey questions are specifically asked in reference to the actual year i.e. farmers are asked to provide information for the specific year as at December, 31st. The ten-year annual climate data obtained from the Global Historical Climatology Network (GHCND) monthly summaries include the temperature, precipitation and databases under the National Climatic Data Center (NCDC). County levels of both climate data are used. Lastly, county unemployment rates and income data were obtained from the US Census Bureau. The 10-year pooled-cross sectional ARMS data (after observations without information to calculate their delinquent status are dropped) comprise of a total of 174,003 observations. 20,710 farmers had single loans, whilst 8,966 observations were used for the analyses, with regards to the restrictions given above. However, the entire sample of southeast farmers are used for the estimation of the credit model, since the calculation of delinquency does not affect the financial variables.

Table 1. Data Description for delinquency/default factor variables

Variable	Description	Measurement	Source	Apriori Sign
Borrower-specific variables				
Age	Five age groups; <35, 35-44, 45-54, 55-64 and >64	Years	ARMS	-
Gender	Gender of farm owner	Dummy (1 if male, 0 otherwise)	ARMS	
Education	Years of education	Years	ARMS	-
Farm size	Land size of farm	Acres	ARMS	-

Farming Years	Years primary operated began operating	Years		-
Farm income	Net farm income	US Dollars	ARMS	-
Debt	Total farm debt	US Dollars	ARMS	+
Debt-to-assets	Debt to assets ratio	Debt/Assets	ARMS	+
Assets	Value of farm physical assets	US Dollars	ARMS	-
Net worth	Net worth	US Dollars	ARMS	-
Loan Repayment	Maximum Loan Repayment Capacity	US Dollars	ARMS	-
Loan-specific variables				
Loan amount	Amount of loan	US Dollars	ARMS	+
Interest rate	Interest rate as at December, 31st	%	ARMS	+
Loan age		Years	ARMS	+
Loan term	Original term of loan	Years	ARMS	
Loan type	Type of loan		ARMS	
Balance on loan	Balance owed as at December, 31st	US Dollars	ARMS	+
Lender-specific variables				
Region			ARMS	
Ability to modify loan	Number of times loan is reprised		ARMS	-
Macroeconomic variables				
Unemployment rate	County unemployment rate as at December, 31st		Bureau of Labor Stats.	+
Per capita income	Per capita income	US Dollars	US Census Bureau	-
Climatic variables				
Temperature	Average Annual Temperature	Fahrenheit	NOAA	
Precipitation	Annual Precipitation	Inches/ Year	NOAA	

Because the data are annual and not monthly, delinquency variable is constructed by defining a delinquent farmer as one whose loan term is overdue by at least a year (i.e. if the loan was due the year before the ARMS Phase III survey) and yet still have not completed payments. This includes farmers that had their loans reconstructed or refinanced, with the prime definition focus being the inability to repay the loan within the initial stipulated term.

Table 2. Data Description for credit risk variables

Financial Ratios	Definitions	Expected sign
Repayment Capacity: Coverage Ratio	(Net Farm Income from Operations + Non-Farm Income + Depreciation + Interest on Term Debt + Interest on Capital – Income Taxes – Family Living Withdrawals) / (Annual Scheduled Principal + Interest Payments on Term Debt and Capital Leases)	
Liquidity: Working Capital to Gross Returns	(Current Assets - Current Liabilities) / Value of Farm Production	+
Solvency: Debt-to-Asset Ratio	Total debt / Total Assets (fair market value)	-
Profitability: Return on Assets	(Net Farm Income from Operations + Farm Interest Payments - Unpaid Labor Charge for Operator and Family) / (Average Total Farm Assets in terms of Fair Market Value)	+
Financial Efficiency: Asset Turnover Ratio	Value of Farm Production / Total Average Farm Assets (fair market value)	+
Tenure: Tenure	Owned Acres / Total Acres Operated	-

Table 1 and Table 2 present detailed descriptions of the data for the variables used whilst Table 3 present the summary statistics of the variables used. The summary statistics show a wide range between most of the farmer and farm characteristic variables, indicating a wide variety of sampled farms ranging from very small farms to significantly very large farms. There are however no significant outliers, and all the continuous predictor variables mainly show a normal distribution.

Table 3. Summary Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Age	53.5	11.3	21	90
Acres	764.6	1,673.1	1	48,730
Farm Age	24.2	13.7	0	83
Net Farm Income	160,148.3	1,277,229	-24,100,000	65,400,000
Debt	413,908.1	1,198,121	50	48,500,000

Debt to asset ratio	0.234	0.502	0.00016	24.31
Assets	2,438,859	11,100,000	2,500	719,000,000
Net Worth	2,046,222	10,900,000	-15,400,000	718,000,000
Loan Payment Capacity	206,852.1	997,618.7	0	53,600,000
Average Interest rate	6.66	4.93	0.02	100
Average Loan Term	10.53	7.8	1	50
Total balance	411,030	1,168,882	1	46,900,000
Number of Loans	1.59	1.01	1	5
Unemployment rate	8.77	3.16	2.5	20.7
Per-Capita Income	20,277.1	4,346.7	11,585	45,356
Temperature	61.6	5.02	29.8	76.98
Precipitation	50.63	10.7	15.36	100.84
Working Capital to Gross Returns	5.2	266.87	-16,795	44,968.5
Debt-to-Asset Ratio	19.73	1,499.64	0.00025	435,672
Return on Assets	18.17	5,861.94	-123,971.6	1,678,380
Asset Turnover Ratio	2.13	389.02	0.0000003	108,491
Tenure	1.10	17.36	0.000005	4,500

Further summary statistics show that out of the 5,433 farmer observations, 3.72% are classified as delinquent. 64.8% of the respondents have only one loan, whilst 21.62%, 6.97%, 2.64% and 3.96% have two, three, four and five different loans respectively. For those with only one loan, 2.78% of the farmers are delinquent. 4.04% and 1.95% are delinquent for those with two and three loans respectively, whilst 5.9% and 1.5% of farmers with four and five loans respectively are delinquent. Out of the 17 different sources of loans, the five main sources (making up approximately 94% of the sources) are Commercial banks (51.4%), Farm Credit System (29.9%), Implement dealers and financing corporations (IDFC) (6.7%), Savings and loan associations/ residential mortgage lenders (SLA) (3.1%), and lastly the Farm Service Agency (2.9%), in descending order. 3.8% of commercial bank borrowers were delinquent, 4.1% of FCS borrowers were delinquent, 0.8% of IDFC borrowers were delinquent, 3.0% of SLA borrowers were delinquent and 1.3% of FSA

borrowers were delinquent. Among those delinquent, farmers between the ages 55 – 64 are the most delinquent, followed by those between the ages 45 – 54, those between 35 – 44, those who are 65 and above and lastly those below 35 years. 1.5% of farmers below 35 years were delinquent, 3.9% of those between ages 35 – 44 were delinquent, 3.7% of those between ages 45 – 54 were delinquent, 4.2% of those between ages 55 – 64 were delinquent and 3.3% of those who are 65 years and above were delinquent. These cross tabulation summary statistics are shown in the appendix, in addition to those for the different states. The delinquent rates are approximately spread across the states, with the exception North Carolina and Kentucky which have very small number of delinquent farmers.

Results and Discussion

The regression results for the delinquency model are presented in two folds. First and of prime focus are the results shown in Tables 4 and 5. Table 4 presents the log odds whilst Table 5 presents the marginal effects. The first two columns of Tables 4 and 5 present the results for both crop and livestock farmers, whilst the last two columns present the results for only crop farmers. As explained earlier (in order to control for possible dependent variable measurement errors including money fungibility), the first and third columns include farmers that have either been delinquent for 3 years or less, whilst the second and fourth columns comprise of farmers that have been delinquent for 3 years or less, and also had their loans within the past three years before the survey. The Chi square tests show that each of the estimated models is jointly significant.

The results fail to ascertain whether age is a significant factor in predicting the delinquent behavior of farmers. Education, likewise does not show significant impacts with regards to which categories

of farmers are more likely to be delinquent than the other. However, it can be noted that farmers that have attended some college and those that completed are less likely to be delinquent compared with those without high school certificates respectively. This applies to the second and fourth columns only. The college educated farmers, either with or without certificates might be less likely to default due to the fact that they are more knowledgeable on how the credit system works, and might either try to refinance, reconstruct or get a bail-out. Both variables for farm size and farming experience generally meet the apriori expectation, where an increase in the number of acres operated reduces the probability of becoming delinquent, and likewise an increase in the years of farming experience also decreases the likelihood of being delinquent. Increases in net farm income as strongly expected reduces the probability of a farmer becoming delinquent, a key variable reflected in most of the variables used by agricultural credit institutions to access whether or not to grant loans to individual farmers.

Table 4. Probit Results of Delinquency model for farmers with single loans

	All		**Crop Only**	
delinquent	**+3**	**+3/-3**	**+3**	**+3/-3**
Age (Base = <35)				
35 – 44	0.199	0.591	0.439	0.595
	(0.243)	(0.555)	(0.312)	(0.734)
45 -54	-0.131	-0.246	-0.202	0.887
	(0.244)	(0.567)	(0.183)	(0.901)
55 – 64	-0.168	-0.137	-0.445	-0.829
	(0.256)	(0.608)	(0.232)	(0.639)
≥ 65	-0.373	-0.351	-0.436	-0.924
	(0.288)	(0.687)	(0.206)	(0.949)
Male	-0.0349	-0.0455		
	(0.221)	(0.487)		
Education (Base = HS or less)				
Completed High School	0.120	0.117	0.442	0.562
	(0.209)	(0.431)	(0.610)	(0.384)
Some College	0.106	0.264	0.259	-0.900**
	(0.218)	(0.448)	(0.632)	(0.409)
Completed College	0.355	-0.0976*	0.759	0.334
	(0.221)	(0.050)	(0.634)	(0.377)
Acres	-0.184***	-0.191*	-0.220**	0.379

	(0.0634)	(0.111)	(0.0971)	(0.271)
Farming Experience	- 0.0102**	0.00141	-0.0168*	-0.00999
	(0.00508)	(0.0119)	(0.0101)	(0.0232)
Farm Income	0.0846***	-0.148*	-0.0115**	-0.0120*
	(0.0201)	(0.065)	(0.00648)	(0.00809)
Financial Debt	0.204	1.513**	0.778***	0.416
	(0.130)	(0.608)	(0.284)	(1.264)
Debt-to-Asset ratio	0.0364	-0.482	-0.200	-3.322
	(0.218)	(0.528)	(0.392)	(2.379)
Rate of return	-0.00519**	-0.00129	-0.0146***	-0.0171*
	(0.00259)	(0.00434)	(0.00459)	(0.0103)
Net Worth	-0.0393	-0.691*	-0.451**	0.423
	(0.0511)	(0.363)	(0.188)	(0.950)
Insurance	-0.0552	0.282	-0.447*	-0.283**
	(0.126)	(0.237)	(0.253)	(0.085)
Maximum Repayment capacity	0.108	0.259	0.399	-1.326*
	(0.281)	(0.341)	(0.266)	(0.721)
Interest Rate on loan	0.00210	0.0526*	0.0309	0.194**
	(0.0304)	(0.0311)	(0.0762)	(0.024)
Prime bank loan rate	-0.0799	0.0316**	0.0293	0.192**
	(0.0636)	(0.0151)	(0.146)	(0.050)
Loan Term	-0.0270***	-0.0143***	-0.0315	-0.446***
	(0.00772)	(0.00217)	(0.0194)	(0.124)
Loan Outstanding	-0.271	1.590**	0.888**	2.349
	(0.193)	(0.670)	(0.368)	(1.546)
Lender (Base = Commercial banks)				
FCS	0.0979	-0.0430*	-0.310*	-0.0267
	(0.117)	(0.027)	(0.193)	(0.812)
FSA	-0.204	0.589	-0.149	-2.125*
	(0.300)	(0.579)	(0.688)	(1.223)
Purchase contract				0.552
				(0.687)
IDFC	-1.033**		-1.691***	
	(0.408)		(0.605)	
Co-Ops	0.594**	-0.463	0.129	
	(0.290)	(0.806)	(0.625)	
Other	-0.460	0.319		
	(0.519)	(0.816)		
Purpose (Base = Farm Improvement/ Rehabilitation)				
Purchase Feeder Livestock	0.840***	1.882***		
	(0.284)	(0.511)		
Other Livestock	-0.898*			-4.248*

	(0.463)			(2.419)
Operating Costs	-0.247*	0.418	-0.419	-3.649***
	(0.148)	(0.355)	(0.315)	(1.130)
Farm Equipment	-0.00370	0.740**	0.0967	-1.387
	(0.178)	(0.367)	(0.390)	(1.159)
Debt Consolidation	0.105	0.832		
	(0.219)	(0.522)		
Per capita income	-15.52	19.36	34.95	-87.97
	(16.41)	(34.34)	(27.42)	(85.56)
Unemployment	-0.0709**	0.0125	-0.129*	-0.547**
	(0.0297)	(0.0586)	(0.0712)	(0.236)
Temp	0.319	0.471	-0.821*	-2.304**
	(0.247)	(0.628)	(0.496)	(1.031)
Temp_sq	-0.00235	-0.00338	0.00637	0.0235**
	(0.00203)	(0.00503)	(0.00420)	(0.00941)
Preci	-0.0749**	-0.154*	-0.207***	-0.585***
	(0.0379)	(0.0794)	(0.0795)	(0.418)
Preci _sq	0.00687*	0.0152**	0.0197***	0.0155***
	(0.00356)	(0.00741)	(0.00711)	(0.00398)
$Temp_{t-1}$	0.0235	0.0479*	-0.0291	-0.108
	(0.0257)	(0.0307)	(0.0536)	(0.169)
$Temp_{t-1}$_sq	-0.000169	-0.000354*	0.000183	0.000624
	(0.000210)	(0.000189)	(0.000436)	(0.00133)
$Preci_{t-1}$	0.00817	-0.0216**	-0.0276*	-0.00237
	(0.00527)	(0.00968)	(0.0150)	(0.0191)
$Preci_{t-1}$_sq	0.00000246	0.000255**	0.000277*	0.0000656
	(0.0000587)	(0.000108)	(0.000166)	(0.000224)
$Temp_{t-2}$	0.00317	0.0390	-0.00889	0.399**
	(0.0201)	(0.0476)	(0.0449)	(0.179)
$Temp_{t-2}$_sq	-0.0000317	-0.000317	0.0000401	-0.00316**
	(0.000171)	(0.000402)	(0.000389)	(0.00144)
$Preci_{t-2}$	-0.00140	-0.00953	-0.0171	-0.0303
	(0.00528)	(0.0102)	(0.0127)	(0.0303)
$Preci_{t-2}$_sq	0.0000101	0.0000689	0.000118	0.000168
	(0.0000624)	(0.000123)	(0.000155)	(0.000347)
$Temp_{t-3}$	-0.00960	-0.0187	-0.00600	
	(0.0201)	(0.0636)	(0.0377)	
$Temp_{t-3}$_sq	0.0000719	0.000199	0.0000564	
	(0.000170)	(0.000509)	(0.000322)	
$Preci_{t-3}$	0.0169**	0.0672***	0.00219	
	(0.00746)	(0.0243)	(0.0126)	
$Preci_{t-3}$_sq	-0.000231***	-0.000765***	-0.0000580	
	(0.0000865)	(0.000273)	(0.000138)	
State (Base = Alabama)				
Florida	0.219	0.0499	-0.216	-0.898**
	(0.221)	(0.521)	(0.439)	(0.398)

Georgia	-0.492***	-0.0659	-0.763	-2.480
	(0.0325)	(0.564)	(0.703)	(1.575)
Kentucky	0.334		0.948*	
	(0.250)		(0.536)	
Mississippi	-0.0194	-0.489	-1.049**	
	(0.183)	(0.451)	(0.458)	
North Carolina	-0.514**	-0.110	-1.431***	-0.549*
	(0.209)	(0.506)	(0.494)	(0.396)
South Carolina	-0.772***			
	(0.263)			
Tennessee	0.438**	1.370***	0.317	2.384***
	(0.205)	(0.453)	(0.453)	(1.930)
Virginia	-0.0170	0.933*	-0.717	0.539***
	(0.225)	(0.517)	(0.560)	(0.0897)
Constant	-17.21**	-47.31**	-34.06	-67.42
	(7.759)	(21.96)	(28.9)	(95.07)
Observations	3268	1370	1041	477
Log likelihood	-402.8	-112.4	-116.6	-39.01
Pseudo R2	0.496	0.366	0.419	0.688
Model chi-square	196.7	129.7	167.9	172.2
Prob > Chi2	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Marginal Effects of the Delinquency model

Marginal Effects	All		Crops Only	
Delinquent	+3	+3/-3	+3	+3/-3
Age (Base = <35)				
35 – 44	0.0696	0.0189	0.0772	0.0142
	(0.0505)	(0.0209)	(0.0577)	(0.0195)
45 -54	-0.0434	-0.0107	-0.0452	0.0546
	(0.0720)	(0.0125)	(0.0609)	(0.0434)
55 – 64	-0.0500	-0.0621	-0.0579	-0.0487
	(0.0733)	(0.0720)	(0.0588)	(0.0319)
≥ 65	-0.0905	-0.0446	-0.0786	- 20.0642
	(0.0566)	(0.0542)	(0.0653)	(0.0591)
Male	-0.00764	-0.00189		
	(0.00686)	(0.00685)		
Education (Base = HS or less)				
Completed High School	0.0350	0.0549	0.00224	0.00142
	(0.0715)	(0.0816)	(0.0760)	(0.00279)
Some College	0.0279	0.0910	0.00122	-0.00148**

	(0.0765)	(0.0958)	(0.0421)	(0.000593)
Completed College	0.0130	0.00204*	0.00596	0.00381
	(0.0112)	(0.00153)	(0.189)	(0.0416)
Acres	-0.00686***	-0.00214*	-0.00865**	0.00539
	(0.00219)	(0.00138)	(0.00304)	(0.0729)
Farming Experience	-0.000328**	-0.000192	-0.000663*	-0.000205
	(0.000170)	(0.000189)	(0.000433)	(0.00362)
Farm Income	0.00154***	-0.000755*	-0.000473**	-0.000534*
	(0.000577)	(0.000441)	(0.000176)	(0.000323)
Financial Debt	0.00951	0.0112**	0.0309***	0.0218
	(0.00829)	(0.00808)	(0.00108)	(0.0767)
Debt-to-Asset ratio	0.00247	0.0644	-0.00834	-0.00924
	(0.00757)	(0.00402)	(0.0293)	(0.0251)
Rate of return	-0.000209**	-0.000125	-0.00576***	-0.00109*
	(0.0000845)	(0.0000865)	(0.000202)	(0.000721)
Net Worth	-0.00306	0.00313*	-0.0181**	0.00685
	(0.00243)	(0.00214)	(0.00634)	(0.00455)
Insurance	0.00475	0.0153	-0.0146*	-0.0186**
	(0.00418)	(0.00476)	(0.00819)	(0.00497)
Maximum Repayment capacity	0.0116	0.00730	0.0155	-0.0623*
	(0.00942)	(0.00872)	(0.0545)	(0.0405)
Interest Rate on loan	0.000746	0.000392*	0.000123	0.00854**
	(0.000997)	(0.000102)	(0.00431)	(0.00182)
Prime bank loan rate	-0.00226	0.00640**	0.00120	0.0528**
	(0.00211)	(0.00276)	(0.00423)	(0.00949)
Loan Term	-0.000852***	-0.00138***	-0.00125	-0.0462
	(0.000277)	(0.000460)	(0.0439)	(0.0383)
Loan Outstanding	-0.0121	0.00391**	0.0354**	0.0180
	(0.00644)	(0.00179)	(0.0124)	(0.0193)
Lender (Base = Commercial banks)				
FCS	0.00337	0.00452*	-0.00988*	-0.00124
	(0.00417)	(0.00235)	(0.0653)	(0.00118)
FSA	0.00901	0.0159	-0.00485	-0.00285*
	(0.0153)	(0.0199)	(0.0175)	(0.00180)
Purchase Contract				0.0358
				(0.0995)
IDFC	-0.0148**		-0.0245***	
	(0.00699)		(0.00478)	
Co-Ops	0.0292**	-0.00798	0.00571	
	(0.0103)	(0.00524)	(0.0199)	
Other	-0.00961	-0.00326		
	(0.00730)	(0.0105)		
Purpose (Base = Farm Improvement/				

Rehabilitation)				
Purchase Feeder Livestock	0.0740***	0.0488***		
	(0.00454)	(0.00381)		
Other Livestock	-0.0126*	0.000571		-0.0917*
	(0.00886)	(0.00902)		(0.0504)
Operating Costs	-0.00701*	-0.00984**	-0.0160	-0.0109***
	(0.00381)	(0.00490)	(0.0559)	(0.00170)
Farm Equipment	0.000403	-0.00422	0.00395	-0.0958
	(0.00590)	(0.00433)	(0.0139)	(0.548)
Debt Consolidation	0.00361	-0.00713		
	(0.00870)	(0.00496)		
Per capita income	-0.491	-0.402	0.138	-0.172
	(0.542)	(0.590)	(0.829)	(0.202)
Unemployment	-0.00226**	-0.00276	-0.00508*	-0.0148**
	(0.000993)	(0.0115)	(0.00378)	(0.00570)
Temp	0.00885	0.000558	-0.0325*	-0.0974**
	(0.00796)	(0.00960)	(0.0114)	(0.0195)
Temp_sq	-0.000633	0.00000612	0.000253	0.000845
	(0.000657)	(0.000790)	(0.000886)	(0.000368)
Preci	-0.00215**	-0.00369*	-0.00818***	-0.0158***
	(0.00109)	(0.00186)	(0.000287)	(0.00138)
Preci _sq	0.000193*	0.000343**	0.000781***	0.000589***
	(0.000112)	(0.000105)	(0.000274)	(0.0000965)
$Temp_{t-1}$	0.000907	0.00210*	-0.00113	-0.00468
	(0.000855)	(0.00118)	(0.0398)	(0.00858)
$Temp_{t-1}$_sq	-0.00000660	-0.0000161*	0.00000711	0.0000227
	(0.00000698)	(0.00000943)	(0.0000250)	(0.000874)
$Preci_{t-1}$	0.0000400	-0.000177**	-0.00108*	-0.00385
	(0.000172)	(0.000732)	(0.000780)	(0.00319)
$Preci_{t-1}$_sq	0.000000103	0.00000198**	0.0000109*	0.0000417
	(0.00000191)	(0.000000849)	(0.0000382)	(0.0000136)
$Temp_{t-2}$	0.000131	0.000580	-0.000356	0.0209**
	(0.000659)	(0.000950)	(0.00126)	(0.00873)
$Temp_{t-2}$_sq	-0.00000132	-0.00000373	0.00000164	-0.000638**
	(0.00000561)	(0.00000777)	(0.0000596)	(0.000128)
$Preci_{t-2}$	-0.0000558	-0.0000641	-0.000675	-0.00368
	(0.000173)	(0.000190)	(0.00237)	(0.00745)
$Preci_{t-2}$_sq	0.000000250	0.00000246	0.0000465	0.000487
	(0.00000204)	(0.0000224)	(0.000163)	(0.000496)
$Temp_{t-3}$	-0.000335	-0.00258	-0.000233	
	(0.000657)	(0.00514)	(0.000832)	
$Temp_{t-3}$_sq	0.00000248	0.0000627	0.00000220	
	(0.00000557)	(0.000482)	(0.0000782)	
$Preci_{t-3}$	0.000535**	0.00108***	0.0000863	
	(0.000242)	(0.000514)	(0.000307)	

Preci $_{t-3}$_sq	-0.00000734***	-0.0000627***	-0.00000229	
	(0.00000280)	(0.00000482)	(0.0000804)	
State (Base = Alabama)				
Florida	0.00807	0.00997	-0.00671	-0.0128**
	(0.0105)	(0.0175)	(0.0241)	(0.00504)
Georgia	-0.0102***	-0.00680	-0.00124	-0.0416
	(0.00386)	(0.00573)	(0.0463)	(0.0626)
Kentucky	0.0149		0.0156*	
	(0.0153)		(0.00739)	
Mississippi	-0.000193	0.00662	-0.0310**	
	(0.00597)	(0.00961)	(0.00108)	
North Carolina	-0.0115**	-0.00111	-0.0247***	-0.0166*
	(0.00654)	(0.00822)	(0.00484)	(0.00819)
South Carolina	-0.0140***			
	(0.00350)			
Tennessee	0.0213**	0.172***	0.00183	0.0414***
	(0.0101)	(0.0591)	(0.0615)	(0.00093)
Virginia	-0.000925	0.124*	-0.00134	0.0270***
	(0.00702)	(0.0781)	(0.0496)	(0.00197)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Southeastern farmers with higher rates of return have lesser probabilities of becoming delinquent. The results further show that farmers that made expenses on insurance have a lesser likelihood of becoming delinquent, an indicator that the credit markets are working quite efficiently as elaborated in the credit literature. Crop farmers with higher maximum repayment capability index are less likely to be delinquent, in accordance to the apriori. As expected, the interest rates on loans as well as the prime rates have a positive correlation with farmers' likelihood to be delinquent, whilst increases in the terms of loans for farmers increases their ability to repay (though not significant for only crop farmers). Farmers that borrow from FCS and FSA are less likely to be delinquent as compared to those that that borrow from commercial banks. Those that borrow from the IDFC are also less likely to be delinquent compared to their counterparts that borrow from commercial banks. With the assumption that farmers that have single loans use the loans for the

specific reasons for which they received the loan, the results show that farmers that took the loan to purchase feeder livestock are more likely to be delinquent compared with those that took the loans for farm improvement/ rehabilitation. On the other hand, farmers that took the loans for either purchasing other kinds of livestock or for paying for operational costs are less likely to be delinquent compared to those that used their loans for farm improvement/ rehabilitation.

As postulated, climate is a key determinant for farmer credit delinquency, supporting recent literature that precipitation and temperature levels are essential factors that determines farmers' ability to meet their loan obligations. Increases in annual rainfall levels decreases the probability of farmers not being able to pay their loans within the loan term. Likewise, temperature has a positive correlation with farmer delinquency. However, the results for both climatic variables suggest that extreme levels of either temperature or precipitation are factors that might reduce farm income and thus increase the probability of being delinquent.

Table 6 presents the model results for farmers with both single or multiple loans, focusing on those that received their loans within three before the survey and have been delinquent within three years. There exist some similarities in the results in comparison with Table 5 (for farmers with single loans). Consistently, age, gender and education do not generally affect farmer credit delinquency, with the exception of very few categories (age group 35 – 44 and some college educated farmers). Farm size and farm experience still do meet the apriori, both having a negative correlation with delinquency. The results further confirm that as farm income increases, farmers become less likely to be delinquent. Financial debt, as well as debt-to-asset ratio in this results depicts statistically significant impacts (for crops only and all farmers respectively), as well as an expected positive relationship with delinquency clearly showing that farmers that are already in

debt, or unable to pay off their by liquidating their assets are most likely to be delinquent when given additional loan.

Table 6. Probit Results of Delinquency model for farmers with multiple loans

	All (+3/-3)		Crops (+3/-3)	
Delinquent	Coefficient	M.E	Coefficient	M.E
Age (Base = <35)				
35 – 44	1.066*	0.0147*	0.861	0.0971
	(0.626)	(0.0310)	(0.829)	(0.134)
45 -54	-0.387	-0.0634	-0.949	-0.0792
	(0.627)	(0.125)	(0.792)	(0.0874)
55 – 64	-0.142	-0.0243	0.953	0.0888
	(0.668)	(0.108)	(0.769)	(0.0882)
≥ 65	-0.435	-0.0526	-0.618	-0.0991
	(0.814)	(0.0981)	(0.710)	(0.0882)
Male	0.409	0.0172		
	(0.588)	(0.0483)		
Education (Base = HS or less)				
Completed High School	-0.199	-0.00355	0.459	0.0383
	(0.495)	(0.00956)	(0.557)	(0.239)
Some College	0.349	0.00896	1.360**	0.0723**
	(0.514)	(0.0219)	(0.620)	(0.0403)
Completed College	-0.345	-0.00462	0.406	0.0406
	(0.609)	(0.00911)	(0.777)	(0.252)
Acres	-0.164**	-0.00309**	0.187	0.00904
	(0.0715)	(0.00105)	(0.163)	(0.578)
Farming Experience	0.0102	0.000192	-0.0440**	-0.00213**
	(0.0152)	(0.000366)	(0.0187)	(0.00136)
Farm Income	-0.157***	-0.00296***	-0.156	-0.0756
	(0.0196)	(0.000507)	(0.258)	(0.0483)
Financial Debt	0.00104	0.000271	0.00105*	0.0000841*
	(0.00661)	(0.000204)	(0.00613)	(0.0000504)
Debt-to-Asset ratio	0.885*	0.0166*	-1.569	-0.0760
	(0.685)	(0.00758)	(1.349)	(0.486)
Rate of return	0.00489	0.0000919	-0.0138	-0.000670
	(0.0563)	(0.000105)	(0.0100)	(0.00428)
Net Worth	-0.346	-0.00651	-0.886*	-0.0429*
	(0.544)	(0.0122)	(0.467)	(0.0274)
Insurance	-0.0196**	-0.00366**	-0.713*	-0.0264*
	(0.00779)	(0.00119)	(0.457)	(0.0171)
Maximum Repayment	0.276	-0.00520	0.535	-0.0259

capacity				
	(0.524)	(0.0119)	(0.607)	(0.166)
Average interest rate	0.206**	0.0388**	0.439*	0.0213*
	(0.111)	(0.0192)	(0.275)	(0.0136)
Prime bank loan rate	-0.0930	-0.00175	1.182***	0.0572***
	(0.199)	(0.00472)	(0.294)	(0.00366)
Average term	-0.199***	-0.0375***	-0.0621	-0.00301
	(0.0534)	(0.00564)	(0.0695)	(0.0192)
Total Loan Outstanding	0.268***	0.00504***	2.991**	0.145**
	(0.065)	(0.00162)	(1.321)	(0.0626)
Number of loans (Base = One loan)				
2 Loans	1.336***	0.0224***	1.860***	0.00766***
	(0.365)	(0.00158)	(0.437)	(0.00377)
3 Loans	2.074***	0.0226***	3.593***	0.0206***
	(0.463)	(0.00321)	(0.696)	(0.00608)
4 Loans	2.112***	0.0272***		
	(0.691)	(0.00154)		
5 Loans	2.955***	0.142***	3.423***	0.0251***
	(0.588)	(0.0310)	(1.007)	(0.00718)
Lender (Base = Commercial banks)				
FCS	-0.512	-0.00732	0.239	000165
	(0.343)	(0.0120)	(0.425)	(0.106)
FSA	0.287	0.00954	-2.652***	-0.0389***
	(0.698)	(0.0403)	(0.706)	(0.00142)
IDFC			4.858	0.352
			(5.128)	(0.477)
Co-ops	-1.112*	-0.0489*		
	(0.869)	(0.0323)		
Other	0.641	0.0469		
	(1.024)	(0.186)		
Per capita income	-34.82**	-0.655**	-232.6***	-0.113***
	(22.94)	(0.321)	(69.62)	(0.00720)
Unemployment	-0.00893	-0.000168	-0.673***	-0.0326***
	(0.0800)	(0.00151)	(0.164)	(0.00208)
Temp	0.0833	0.00157	-0.105	-0.00506
	(0.719)	(0.0139)	(0.827)	(0.0326)
Temp_sq	-0.0000807	-0.00000152	0.00191	0.0000927
	(0.0578)	(0.0000109)	(0.00655)	(0.0000593)
Preci	-0.195*	-0.00367*	-0.412***	-0.0199***
	(0.108)	(0.00195)	(0.136)	(0.00128)
Preci _sq	0.00206**	0.0000387**	0.00359***	0.0000174***
	(0.00103)	(0.0000186)	(0.00121)	(0.00000111)
$Temp_{t-1}$	-0.0513	-0.000965	0.00988	0.000479
	(0.0762)	(0.00189)	(0.0893)	(0.000310)

Temp $_{t-1}$_sq	0.0000414	0.00000779	0.0000775	0.000000528
	(0.0000618)	(0.0000154)	(0.0000709)	(0.0000244)
Preci $_{t-1}$	-0.0220*	-0.00414*	0.0273	0.0000132
	(0.0120)	(0.00346)	(0.0178)	(0.000845)
Preci $_{t-1}$_sq	0.0000255*	0.00000480*	-0.0000246	-0.00000178
	(0.0000136)	(0.00000175)	(0.0000191)	(0.0000762)
Temp $_{t-2}$	0.0940	0.00177		
	(0.0662)	(0.00279)		
Temp $_{t-2}$_sq	-0.0000818	-0.00000154		
	(0.0000551)	(0.00000241)		
Preci $_{t-2}$	-0.00661	-0.000124		
	(0.0112)	(0.000266)		
Preci $_{t-2}$_sq	0.0000313	0.00000589		
	(0.000136)	(0.00000426)		
Temp $_{t-3}$	0.0126	0.00237		
	(0.0896)	(0.00169)		
Temp $_{t-3}$_sq	0.0000408	0.00000767		
	(0.000709)	(0.0000134)		
Preci $_{t-3}$	0.0487*	0.000916*		
	(0.0258)	(0.000543)		
Preci $_{t-3}$_sq	-0.000566*	-0.0000106*		
	(0.000290)	(0.00000766)		
State (Base = Alabama)				
Florida	-0.417	-0.0450	-0.838	-0.0138
	(0.659)	(0.0806)	(0.848)	(0.0961)
Georgia	0.449	0.0201	0.126	0.0825
	(0.634)	(0.0609)	(0.781)	(0.0957)
Mississippi	-1.444**	-0.0211**	-1.789**	-0.0110**
	(0.619)	(0.00601)	(0.903)	(0.00667)
North Carolina	0.263	0.00722	-0.788	-0.0185
	(0.580)	(0.0238)	(0.929)	(0.121)
Tennessee	1.736***	0.0793***	3.972***	0.0225***
	(0.568)	(0.0108)	(0.894)	(0.00655)
Virginia	1.239**	0.240**	3.081***	0.0755***
	(0.625)	(0.0658)	(0.899)	(0.00255)
Constant	-25.69***		-2.395***	
	(2.73)		(0.239)	
Observations	1473		824	
R-squared	.		.	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Most notable and of prime significance is insurance. Both columns show that farmers that make insurance expenses are less likely to be delinquent, compared to those with no insurance. Interest rate on loans and total loan outstanding show a positive relationship with delinquency whilst loan term show a negative relationship. As expected, farmers with multiple loans are more likely to be delinquent than farmers with single loans, with the magnitude increasing as more loans are added. Precipitation increases still decreases the probability for farmers to be delinquent, until at very high levels when they become detrimental. However, temperature is not statistically for this results involving farmers with both single and multiple loans.

Tables 7 and 8 present the results for the credit model estimation. They seek mainly to determine how each different farmer (grains, cotton, poultry etc.) vary in terms of creditworthiness across the states. The results show that the creditworthiness of farmers that cultivate grains (corn, peanuts etc.) are significantly affected by all of the financial variables, with each of them meeting the apriori expectation. Compared to Alabama grains farmers, Florida grain farmers are more creditworthy, whist Mississippi and South Carolina grain farmers are less creditworthy. Similarly, the creditworthiness of cattle and poultry farmers are affected the same way as grain farmers, in terms of these financial ratios i.e. with the significant coefficients having the apriori signs. The only difference can be found in these farmers' behaviors across the states. Compared to Alabama cattle farmers, Florida, Kentucky, North Carolina and Tennessee cattle farmers are all more creditworthy. For poultry farmers, Georgia, Kentucky and Tennessee farmers are less creditworthy as compared to Alabama poultry farmers. Cotton, vegetables, fruits and dairy products farmers' creditworthiness are significantly affected by the same financial ratios. Their creditworthiness are negatively related to debt to asset ratio and positively related to both rate of return and asset

turnover ratio, as per the apriori. The differences in these groups of farmers can also be seen with respect to which state the farmer operates.

Table 7. Logistic Results of Credit Model Regressions for different farmers

cov_ratio	Grains	Tobacco	Cotton	Vegetables	Fruits	Dairy Pdts	Cattle	Poultry
capital_gross returns	0.285***	-0.0301	0.0356	0.0572	0.0087	0.0646	0.0248***	0.202**
	(0.0913)	(0.0267)	(0.125)	(0.0729)	(0.010)	(0.0431)	(0.0092)	(0.085)
debt_asset ratio	-0.0265***	-0.0681***	-0.0662***	-0.0290***	-0.063***	-0.0592***	-0.156***	-0.0429***
	(0.0042)	(0.009)	(0.0089)	(0.0069)	(0.0101)	(0.0086)	(0.0065)	(0.003)
Rate of return	0.160**	0.0058**	0.0646***	0.0086***	0.0201**	0.118***	0.0024*	0.118***
	(0.0177)	(0.0023)	(0.0102)	(0.0033)	(0.0079)	(0.0191)	(0.0013)	(0.0095)
Asset_turnover	1.726***	1.802***	4.368***	0.784**	2.154***	2.920***	10.08***	0.916***
	(0.280)	(0.696)	(0.524)	(0.317)	(0.725)	(0.839)	(0.431)	(0.098)
Tenure	-0.604**	0.0663	0.486	0.681	0.0781	-0.364	-0.713***	-0.0318
	(0.263)	(0.352)	(0.485)	(0.440)	(0.242)	(0.437)	(0.149)	(0.078)
Florida	0.535**	-0.432	-0.393	0.130*	2.150***	-1.365	0.684***	-0.606
	(0.156)	(1.188)	(0.996)	(0.082)	(0.564)	(0.838)	(0.222)	(0389)
Georgia	-0.183	0.134*	0.484**	-0.402	2.707***	-1.513*	0.282	-0.590**
	(0.710)	(0.033)	(0.063)	(1.089)	(0.783)	(0.885)	(0.211)	(0.245)
Kentucky	0.280	1.106*	-	-0.334	-	-0.820	0.724***	-1.097***
	(0.600)	(0.634)		(1.490)		(0.797)	(0.235)	(0.314)
Mississippi	-0.417*	-	-0.944*	-0.341	0.424	-1.439*	-0.0261	0.257
	(0.261)		(0.550)	(1.149)	(0.957)	(0.824)	(0.191)	(0.271)
North Carolina	-0.151	0.928*	-0.318**	-0.345	0.569	-0.0276	0.814***	0.352
	(0.560)	(0.562)	(0.196)	(1.060)	(0.635)	(1.013)	(0.227)	(0.248)
South Carolina	-0.312**	0.482	0.268	2.094***	1.908**	-0.782	0.563*	0.332
	(0.191)	(0.775)	(0.682)	(0.520)	(0.898)	(0.936)	(0.298)	(0.316)
Tennessee	0.299	-0.307**	-0.191	1.186	1.368	-1.487**	1.181***	-0.571*
	(0.589)	(0.161)	(0.607)	(1.451)	(1.211)	(0.732)	(0.233)	(0.316)
Virginia	-0.0415	-	-1.786*	-0.119	1.028*	-1.218	0.118	-0.170
	(0.628)		(1.080)	(1.179)	(0.638)	(0.755)	(0.182)	(0.299)
Constant	2.003***	2.183***	1.941***	1.858*	0.876	3.508***	1.523***	2.498***
	(0.538)	(0.577)	(0.472)	(1.063)	(0.559)	(0.814)	(0.176)	(0.214)
Observations	21,228	7,689	9,193	5,041	8,102	7,556	40,938	24,252
LR Chi^2	940.36	830.62	1941.0	675.30	1150.75	1408.13	9441.94	5351.62
Prob > Chi^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R^2	0.3924	0.3683	0.4882	0.2574	0.4044	0.2951	0.3805	0.4567

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Compared to Alabama cotton growers, Georgia cotton growers are more creditworthy whilst Mississippi, North Carolina and Virginia cotton farmers are less creditworthy. Also, the table show that Florida and South Carolina vegetable farmers are more creditworthy compared to Alabama vegetable growers. For fruits farmers, Florida, Georgia, South Carolina and Virginia farmers are more creditworthy as compared to Alabama fruits farmers. Lastly, Georgia, Mississippi and Tennessee dairy product farmers are all less creditworthy in comparison to Alabama dairy product farmers.

Table 8. Marginal Effects of Credit Model Regressions for different farmers

cov_ratio	Grains	Tobacco	Cotton	Vegetables	Fruits	Dairy Pdts	Cattle	Poultry
capital_gross returns	0.0005***	-0.001	0.0001	0.0013	0.0003	0.0037	0.0015***	0.0058**
	(0.0002)	(0.0009)	(0.0002)	(0.0007)	(0.0002)	(0.0025)	(0.0005)	(0.0024)
debt_asset ratio	-0.00004***	-0.0023***	-0.0001***	-0.0007***	-0.0019***	-0.0034***	-0.0096***	-0.0012***
	(0.0002)	(0.0005)	(0.00007)	(0.0007)	(0.0005)	(0.0006)	(0.0006)	(0.0001)
Rate of return	0.0003**	0.0002**	0.0001***	0.0002***	0.0006**	0.0068***	0.0001*	0.0034***
	(0.0001)	(0.0001)	(0.00006)	(0.0001)	(0.0002)	(0.0011)	(0.00008)	(0.0003)
Asset_turnover	0.0028***	0.0608***	0.0081***	0.0181**	0.0647***	0.1686***	0.6184***	0.0261***
	(0.0013)	(0.0179)	(0.0021)	(0.0079)	(0.0177)	(0.0433)	(0.0361)	(0.0028)
Tenure	-0.001**	0.0.0022	0.001	0.0157	0.0023	-0.021	-0.0437***	-0.0009
	(0.0006)	(0.0118)	(0.0011)	(0.0175)	(0.0072)	(0.0251)	(0.0091)	(0.0022)
Florida	0.0007**	-0.0178	-0.0009	0.0029*	0.0979***	-0.1267	0.0338***	-0.0228
	(0.0002)	(0.059)	(0.0027)	(0.0017)	(0.0431)	(0.1133)	(0.0087)	(0.0189)
Georgia	-0.0003	0.0043*	0.0008**	-0.0107	0.043***	-0.1564*	0.0157	-0.0207**
	(0.0014)	(0.0021)	(0.0005)	(0.035)	(0.0129)	(0.1096)	(0.0106)	(0.0105)
Kentucky	0.0004	0.0287*	-	-0.009	-	-0.0621	0.035***	-0.0509***
	(0.0008)	(0.0135)		(0.0478)		(0.0771)	(0.0087)	(0.0222)
Mississippi	-0.0008*	-	-0.0024*	-0.0091	0.0105	-0.1446*	-0.0016	0.0067
	(0.005)		(0.0013)	(0.0363)	(0.0194)	(0.1152)	(0.0119)	(0.0066)
North Carolina	-0.0003	0.0327*	-0.0007**	-0.0087	0.0137	-0.0016	0.0385***	0.0092
	(0.0009)	(0.0219)	(0.0003)	(0.0301)	(0.0127)	(0.0596)	(0.0082)	(0.006)
South Carolina	-0.0006**	0.0137	0.0004	0.0245***	0.0288**	-0.0622	0.0278*	0.0084
	(0.0003)	(0.019)	(0.0011)	(0.0057)	(0.0098)	(0.0986)	(0.0117)	(0.0071)
Tennessee	0.0004	-0.0118**	-0.0004	0.0175	0.0233	-0.1302**	0.0513***	-0.0209*
	(0.0008)	(0.0087)	(0.0013)	(0.0213)	(0.0121)	(0.061)	(0.007)	(0.0148)
Virginia	-0.0001	-	-0.0089*	-0.0029	0.0203*	-0.0967	0.0069	-0.0052
	(0.0011)		(0.0124)	(0.0302)	(0.0114)	(0.0794)	(0.0104)	(0.0098)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusion

This paper attempts to examine the factors and behaviors that affect Southeast US farmers' ability to meet their loan payment obligations within the stipulated loan term. The study further estimates a credit model using farm-level financial information to determine the credit worthiness of farmers and their possible repayment capabilities. These estimations are done with focus on the various types of farmers mainly found in the southeast (grains, poultry, tobacco, cotton etc.), whilst showing the different behaviors that occur among these farmers across the various states in the region. A delinquent farmer is defined as one whose loan term is overdue by at least a year and have yet still not finalized payments. The study uses a 10-year (2003-2012) pooled cross-sectional data from the USDA ARMS survey data. These years have similar variables to aid in calculating the delinquency variable, and also have common variables needed for the estimations. A probit approach is used to regress delinquency against various borrower-specific, loan-specific, lender-specific, macroeconomic and climatic variables for the first part. The second part uses a logistic approach to regress farmers' coverage ratio (repayment capacity) on certain financial variables (liquidity, solvency, profitability, and financial efficiency) in addition with tenure, to determine how creditworthy the various kinds of farmers are, and in what particular states.

The results on the whole show that age, education and gender are not very strong determinants of farmer credit delinquency. Farmers with bigger farms and those with more years of farming experience are both less likely to be delinquent. Expectedly, farmers with higher net farm income tend to pay their loans more on time comparatively. Farmers with insurance, and those with higher rates of return have a smaller probability of being delinquent. And of course the results show that farmers with higher debt to asset ratio are more likely to be delinquent. In addition, the results show that farmers with just a single loan are less likely to be delinquent compared with those with

multiple loans. Famers who acquire chunk of their loans from commercial banks are also in general more likely to be delinquent, compared with other borrowers. Rainfall and temperature both affect affect farmer's delinquent negatively, but excessive levels of these climatic factors tend to increase the probability of credit delinquency. Further, the estimations show some similarities and few differences for farmers' delinquent behaviors between crop and livestock farmers.

Furthermore, the results for the credit model show that compared to Alabama grain farmers, Florida grains farmers are more creditworthy, whist Mississippi and South Carolina grains farmers are less creditworthy. Compared to Alabama cattle farmers, Florida, Kentucky, North Carolina and Tennessee cattle farmers are all more creditworthy. For poultry farmers, Georgia, Kentucky and Tennessee farmers are all less creditworthy as compared to Alabama poultry farmers. Compared to Alabama cotton growers, Georgia cotton growers are more creditworthy whilst Mississippi, North Carolina and Virginia cotton farmers are less creditworthy. Florida and South Carolina vegetable farmers are more creditworthy compared to Alabama vegetable growers. For fruits farmers, Florida, Georgia, South Carolina and Virginia farmers are all more creditworthy as compared to Alabama fruits farmers. Lastly, Georgia, Mississippi and Tennessee dairy product farmers are all less creditworthy in comparison to Alabama dairy product farmers.

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Appendix

Farmers with a single loan	Frequency	Percent
1	4,474	21.60
2	4,936	23.84
3	11,297	54.56
Total	20,710	100.0

Operating Loans Term	Frequency	Percent
1	3,736	41.67
2	1,156	12.89
3	885	9.87
4	369	4.12
5	1,605	17.90
6	181	2.02
7	341	3.80
8	60	0.67
9	19	0.21
10	614	6.85
Total	8,966	100.0

Table 9. Summary Statistics by State

	AL		FL		GA	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	53.79	11.1	54.94	10.17	53.46	11.99
Acres	461.92	708.42	1,247.65	3,864.37	512.68	970.07
Farm Age	24	14.14	23.59	14.01	22.75	13.33
Farm Income	129,855.8	395,956.5	353,723.3	1,952,971	104,446.7	624,406.8
Debt	293,796	360,541	813,443.5	2,534,441	433,696.1	837,666.5
Debt to asset ratio	0.22	0.24	0.22	0.30	0.24	0.25
Assets	1,483,388	1,454,250	6,945,635	35,400,000	2,091,100	2,980,454
Net Worth	1,200,580	1,328,019	6,170,810	35,200,000	1,676,731	2,611,166
Insurance Expense	0.15	0.35	0.31	0.46	0.25	0.43
Loan Payment Capacity	150,725.1	321,138.6	441,498.4	1,639,053	144,137.9	421,874.5
Average Interest rate	7.04	5.39	6.5	3.58	6.72	4.68
Average Loan Term	10.71	7.62	12.18	8.95	10.44	7.41
Total balance	298,973.1	357,749.2	815,302	2,427,302	431,108	801,761.8
Number of Loans	1.58	0.96	1.44	0.94	1.46	0.85
Unemployment rate	7.57	3.55	7.89	3	8.77	2.86

Per-Capita Income	19,603.68	2,791.69	21,738.72	4,874.01	19,816.45	3,599.33
Temperature	62.19	3.23	68.7	4.92	62.33	4.77
Precipitation	54.83	10.92	53.77	9.83	50.41	11.21
Working Capital to Gross Returns	5.59	57.88	6.85	157.92	4.13	42.24
Debt-to-Asset Ratio	11.34	23.34	7.27	23.01	11.45	49.63
Return on Assets	-0.36	22.81	5.17	63.27	-6.23	145.72
Asset Turnover Ratio	0.47	0.71	0.45	1.45	0.8	5.92
Tenure	1.41	11.08	0.998	2.46	0.84	0.72

Table 9 Cont'd

	KY		MS		NC	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	50.67	11.48	52.62	11.18	53.97	11.07
Acres	735.31	1,256.64	1,091.12	1,862.3	600.12	1,068.32
Farm Age	23.35	13.27	21.33	13.2	25.6	14.16
Farm Income	145,339.3	598,506.9	127,920.9	1,070,694	155,393.8	767,534.8
Debt	330,230.4	585,383.6	495,553.8	1,953,769	324,135.7	538,954.9
Debt to asset ratio	0.20	0.19	0.32	0.94	0.21	0.23
Assets	1,936,493	3,019,821	1,848,102	4,206,431	2,013,642	4,204,165
Net Worth	1,623,413	2,625,072	1,384,594	2,713,209	1,707,805	4,059,475
Loan Payment Capacity	169,622.3	529,098.2	206,628.6	476,823.7	195,112.6	621,011.9
Average Interest rate	6.7	5.52	6.99	6.05	6.04	3.66
Average Loan Term	12.56	8.45	8.66	6.71	9.55	7.17
Total balance	332,872.6	542,329.5	441,245.8	1,867,424	332,165.9	697,482.2
Number of Loans	1.66	1.16	1.83	1.15	1.46	0.88
Unemployment rate	8.54	2.22	10.32	3.15	9.3	2.66
Per-Capita Income	19,661.62	3,271.12	17,101.22	3,378.01	20,919.73	3,803.3
Temperature	58.30	5.62	62.69	3.44	60.5	3.66
Precipitation	49.27	11.84	53.74	10.71	48.58	8.86
Working Capital to Gross Returns	2.15	12.73	1.42	8.14	3.45	36.89
Debt-to-Asset Ratio	10.38	35.24	41.95	1,061.15	9.01	18.71
Return on Assets	1.07	21.44	13.86	402.5	-1.27	131.48
Asset Turnover Ratio	0.39	0.99	3.31	93.29	0.75	10.36
Tenure	0.91	1.03	0.83	0.81	0.79	0.81

Table 9 Cont'd

	SC		TN		VA	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	54.11	11.2	52.71	11.6	55.06	10.65
Acres	863	1,356.81	978.43	1,590.84	629.68	870.25
Farm Age	24.66	13.8	26.51	14.29	26.82	12.55
Farm Income	356,365	3,656,081	127,834.5	541,344.3	78,610.43	703,224.2
Debt	391,202.7	992,477.7	410,874.6	751,985.5	295,577.4	535,155.1
Debt to asset ratio	0.18	0.2	0.23	0.29	0.25	0.95
Assets	2,440,004	4,272,593	2,208,393	4,362,132	2,266,071	3,923,183
Net Worth	2,068,122	3,681,227	1,819,385	3,996,711	1,985,067	3,557,265
Loan Payment Capacity	363,037.5	2,980,028	179,711.3	425,041.4	138,350.9	454,422.7
Average Interest rate	6.5	3.76	6.27	3.9	7.42	6.61
Average Loan Term	10.6	8.06	10.7	7.92	11.34	8.25
Total balance	363,699	870,110.9	424,816.9	740,201.3	319,514.2	668,544.6
Number of Loans	1.46	0.81	1.73	1.09	1.74	1.12
Unemployment rate	10.23	3.26	9.52	3	6.19	2.59
Per-Capita Income	20,426.38	3,427.39	20,146.42	3,635.29	24,189.2	6,071.1
Temperature	62.49	3.18	59.83	4.15	57.4	4.42
Precipitation	45.06	9.09	53.77	9.46	44.56	8.84
Working Capital to Gross Returns	1.36	6.74	5.30	57.98	2.17	20.55
Debt-to-Asset Ratio	7.13	16.18	12.83	89.62	10.28	54.11
Return on Assets	1.38	35.44	1.86	37.49	-2.81	42.21
Asset Turnover Ratio	0.50	1.58	0.31	0.84	0.33	1.23
Tenure	0.82	0.98	0.77	0.97	0.80	0.96

Table 10. Cross Tabulations

delinquent	Freq.	Percent								
0	8632	96.28								
1	334	3.72								
Total	8,966	100								
	Lender[2]									
delinquent	1	2	3	4	5	6	7	8	9	10
0	2568	259	36	56	266	4437	13	597	46	69
1	60 (2.2)	3 (1.1)	5 (12.1)	0	8 (2.9)	226 (4.9)	2 (13.3)	5 (0.8)	2 (4.2)	10 (12.7)
Total	2,678	262	41	56	274	4,613	15	602	48	79
	Lender									
delinquent	11	12	13	14	15	16	17	Total		
0	8	62	41	75	96	1	3	8,633		
1	0	2 (3.1)	0	7 (8.5)	1 (1.0)	2 (66.7)	0	333		
Total	8	64	41	82	97	3	3	8,966		
	Age class of primary operator									
delinquent	<35	35-44	45-54	55-64	>64		Total			
0	424	1,449	2,716	2647	1,396		8,633			
1	7 (1.6)	59 (3.9)	104 (3.7)	116 (4.2)	48 (3.3)		333			
Total	431	1,508	2,820	2,763	1,444		8,966			
			State							
delinquent	AL	FL	GA	KY	MS	NC	SC	TN	VA	Total
0	880	736	1,320	782	1,163	1,495	559	863	833	8,633
1	51 (5.5)	40 (5.2)	45 (3.3)	20 (2.5)	45 (3.7)	48 (3.1)	5 (0.9)	48 (5.3)	33 (3.8)	333
Total	931	776	1,365	802	1,208	1,543	564	911	866	8,966
	Years									
delinquent	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
0	243	285	1,173	828	42	849	1,026	917	1,111	2,159
1	3 (1.2)	1 (0.3)	93 (7.3)	81 (8.9)	11 (18.3)	38 (4.3)	14 (1.3)	28 (3.0)	31 (2.7)	33 (1.5)
Total	246	286	1,266	909	60	880	1,040	945	1,142	2,192
	Insurance									
delinquent	No	Yes	Total							
0	2,494	6,139	8,633							
1	234 (8.5)	99 (1.5)	333							
Total	2,728	6,238	8,966							

*Percentages in parentheses

[2] 1 = 'Farm Credit System' 2 = 'USDA Farm Service Agency (FSA)' 3 = 'Small Business Administration (SBA)' 4 = 'State and county government lending agencies' 5 = 'Savings and loan associations, residential mortgage lenders' 6 = 'Commercial Banks' 7 = 'Life Insurance Companies' 8 = 'Implement dealers and financing corporations' 9 = 'Input suppliers' 10 = 'Co-ops and other merchants' 11 = 'Contractor' 12 = 'Individuals-land bought under a mortgage or deed of trust' 13 = 'Individuals-land bought under a land purchase contract' 14 = 'Any other individuals' 15 = 'Any other lenders' 16 = 'Credit cards' 17 = 'Other debts (such as unpaid bills, etc.)'.