Credit Delivery Analyses and Climate Impact Issues: The Case of Ghana and Southeastern US

by

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Abstract

The first paper examines the impact of the microfinance sector on small/ micro enterprises in Ghana. The study uses 2007 BEEPS data and employs the financing constraints approach to study if the presence of microfinance institutions has been successful in alleviating financing constraints associated with small enterprises. This is done by comparing investment sensitivity to internally generated funds (cash flow) in enterprises with and without access to microfinance institutions. The study also uses a Propensity Score Matching method to reinforce/ support the results obtained from the financing constraints approach. The results obtained from the analyses indicate that small/ micro enterprises in areas with adequate MFIs have investment less sensitive to the availability of internal funds due to the fact that they have better access to external funds, and thus imply that the microfinance sector is alleviating financing constraints in the country.

The second paper uses the Ricardian (Hedonic model) approach to determine the impact of climate change on agricultural farmland values for the southeastern United States. The analyses employ a 5-year pooled cross-sectional data from the ARMS database, climate data from the GHCND and soil data from the SSURGO database. Marginal effects and climate impact projections for 2100 from the three Atmospheric Oceanic General Circulation Models (Hadley CM3, ECHO-G and NCAR PCM) are used in calculating the impacts on the regional farmland values. The Ricardian regression results show that farmland values increase with higher winter and summer temperatures but fall with higher spring and fall temperatures. Winter and summer temperatures have a positive but declining impact on farmland values, whereas spring and fall temperatures have negative and increasing impacts. The results also show that an increase in spring precipitation increases

farmland values whilst increases in winter, summer and fall precipitations tend to decrease farmland values. Spring precipitation has a positive but declining impact on farmland values, whereas precipitation in the winter, summer and fall have negative and increasing impacts. The marginal effects indicate that higher annual temperature is beneficial for farmland values throughout the region with the exception of Florida and Mississippi. Increases in annual precipitation are detrimental to most of the states except Alabama, Mississippi and Tennessee. The marginal effects for the seasonal temperature and precipitation also varied significantly across the states. Lastly, the projections show that the aggregate farmland value for the entire Southeast US is likely to decrease under the three model scenarios considered in the analyses.

The third paper examines the factors and behaviors that affect Southeast US farmers' ability to meet their loan payment obligations within a 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 older farmers, 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 the credit model also show which particular farmers and in what states are more likely to be creditworthy based on their financial variable information.

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List of Abbreviations

MFI	Microfinance institution
BEEPS	Business Environment and Enterprise Performance Survey
RCB	Rural and Community Banks
FNGO	Financial non-governmental organization
ROSCA	Rotating savings and credit association
ASCA	Accumulating savings and credit association
BoG	Bank of Ghana
GHAMFIN	Ghana Microfinance Institutions Network
ARB	Association of Rural Banks
GCSCA	Ghana Co-operative of Susu Collectors Association
MFT	Microfinance Transparency
SAT	Sinapi Aba Trust
FASLL	First Allied Savings and Loans Limited
ICFS	Investment cash-flow sensitivity
PSM	Propensity Score Matching
CIA	Conditional Independence Assumption
ARMS	Agricultural Resource Management Survey
USDA	United States Department of Agriculture
SECC	Southeast Climate Consortium
EPA	Environmental Protection Agency

PMM	Passel, Massetti and Mendelsohn
Hadley CM3	Hadley Centre Coupled Model, Version 3
ECHO-G	Global coupled atmosphere-ocean climate model
NCAR PCM	National Center for Atmospheric Research - Parallel Climate Model
GHCND	Global Historical Climatology Network
NCDC	National Climatic Data Center
SSURGO	Soil Survey Geographic Database
FIPS	Federal Information Processing Standard
OLS	Ordinary least Squares
FCS	Farm Credit System
FSA	Farm Service Agency
SUR	Seemingly unrelated regression
MCS	Margin Credit Swap
FFSC	Farm Financial Standards Council
NOAA	National Oceanic and Atmospheric Administration

Introduction

Climate change consequences and credit issues, especially microfinance has been key research topics for many researchers over the past few decades. This is due to how critical the impacts and consequences of these activities have been found out to be. Climate change has partly been a hot issue lately due to the controversial and conflicting impacts associated to it by various scientists, scholars, and policy makers. Intergovernmental Panel on Climate Change (IPCC) and the National Academy of Sciences have reported that most of observed warming is likely due to the results of human activities such as Greenhouse gas emission and warned that warming will be a serious threat in near future. On the other hand, policy-makers and media argued that climate change is highly uncertain (Oreskes, 2004). Credit delivery topics are also very key because the literature affirms that availability of funds (either internally or externally) is a good premise for firm growth. For instance in agriculture, where farmers are faced with numerous forms of uncertainty, it is believed that availability to credit is a great tool in managing production shocks such as pest/ disease destruction, flood, hail or commodity price declines.

The main objectives of this dissertation can be categorized into three. First, to determine the joint impact of microfinance on small enterprises (in this case for the Ghanaian economy). Second, to determine the impact of climate variation on southeastern US farmers and lastly to examine the factors and behaviors that influence southeastern farmers' repayment capabilities (by using credit delinquency and credit worthiness).

The first paper studies the investment impact of MFIs on small/ micro enterprises in Ghana with the emphasis being on the entire nation. Previous microfinance impact studies have either focused on the evaluation of specific microfinance institutions or on particular parts of the country. The focus of this paper is to determine whether the operations of the MFIs in Ghana as a whole have impacted enterprises positively in investment terms. The paper employs the financing constraints approach to evaluate the impact of microfinance through investment in Ghana. This methodological approach avoids the typical challenges associated with impact assessment studies where MFI clients serve as a treatment group with other individuals or enterprises that are not clients serving as a control group (Hartarska et al, 2008). The effectiveness of the MFIs in the country is judged by the sensitivity of small/ micro enterprises' investment to availability of internal funds. The paper further uses a Propensity Score Matching procedure in determining the effect of credit access on investment.

The second paper uses a Hedonic model to examine the impact of climate change on agricultural farmland values. Also in the paper, projected effects of climate change in the future are made using predicted climate change data from three Atmospheric Oceanic General Circulation Models that predict future climate values. Most previous climate change studies in the US are county based and thus the individual farmer-based ARMS data are averaged by county in this study to provide a well detailed analysis as per the effects on individual locations with particular characteristics. This to the best of my knowledge and search is the first study on just the entire southeastern region with regards to weather variability/ climate change sensitivity on farmland values. Since farmland value per acre of each farmer is directly related to the present value of future net revenues from farming activities, this study seeks to provide farmers in the Southeastern region an idea of how variable their farm revenue/ farmland value would be in the wake of a significant climate change.

The third paper finally examines the factors that influence farmer loan delinquencies, 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. This paper examines the specific factors that affect delinquency 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.

Chapter 1. Investment Impact of Microfinance Credit Delivery in Ghana

Abstract

This research paper examines the impact of the microfinance sector on small/ micro enterprises in Ghana. The study uses 2007 BEEPS data and employs the financing constraints approach used by several other researchers in the study area to study if the presence of microfinance institutions has been successful in alleviating financing constraints associated with small enterprises. This is done by comparing investment sensitivity to internally generated funds (cash flow) in enterprises with and without access to microfinance institutions. The study also uses a Propensity Score Matching method to reinforce/ support the results obtained from the financing constraints approach. The results obtained from the analyses indicate that small/ micro enterprises in areas with adequate MFIs have investment less sensitive to the availability of internal funds due to the fact that they have better access to external funds. This result thus shows that the microfinance sector is alleviating financing constraints in the country.

Keywords: Microfinance · Financing Constraints · Cash flow sensitivity · Investment · Internal funds

JEL classification: G21

Introduction

The impact that microfinance has in expanding businesses in Ghana is a key subject due to the amount of importance the country currently attaches to the microfinance sector. This is because such as many other countries, Ghana recognizes the importance that small enterprises place on the economy. As observed by Hartarska *et al*, 2006, Berkowitz *et al*, 2002 and McMillan *et al*, 2002, small enterprises are very important for economic growth.

Microfinance primarily involves the provision of financial services including savings, micro-credit, micro insurance, micro leasing and transfers in relatively small transactions by microfinance institutions (MFIs) designed to be accessible to micro-enterprises and low-income households that lack access to banking and related services due to the high transaction costs associated with serving these client categories. Microfinance could thus be seen as a critical financial tool which can be a remedy for the poor in overcoming poverty, and hence could play a key role in the development of a country such as Ghana. Asiama, 2007 lists the key effects microfinance plays as helping very poor households meet certain basic needs and protect them against risks, improving household economic welfare and helping to empower women by supporting women's economic participation. Otero, 1999 also notes that microfinance creates access to productive capital for the poor, which together with human capital, addressed through education and training, and social capital, achieved through local organization building, enables people to move out of poverty.

Microfinance in Ghana is not anything new and dates back to the colonial era. As stated by Asiama, 2007, evidence suggests that the first credit union in Africa was established in Northern Ghana in 1955 by Canadian Catholic missionaries. Over the years, the microfinance sector has thrived and developed into a well-organized and nationally coordinated commercial sector in the country regardless the numerous challenges it has faced and this has been made possible by the various financial sector policies and programs undertaken by different governments since independence (Gallardo et al, 2005). Among these are the provision of subsidized credits in the 1950s, the establishment of the Agricultural Development Bank in 1965 specifically to address the financial needs of the fisheries and agricultural sector, the establishment of Rural and Community Banks (RCBs) and the introduction of regulations such as commercial banks being required to set aside 20% of total portfolio to promote lending to agriculture and small scale industries in the early 1980s, among some few others (Steel et al, 2003). Problems that the microfinance sector has faced over the years include very high interest rates, information asymmetry and lack of access to credit by the MFIs themselves.

Microfinance in Ghana can be categorized into three main groups (Asiama, 2007). These are formal suppliers such as savings and loans companies, rural and community banks, as well as some development and commercial banks, semi-formal suppliers such as credit unions, financial non-governmental organizations (FNGOs), and cooperatives and lastly informal suppliers such as susu[1] collectors and clubs, rotating and accumulating savings and credit associations (ROSCAs and ASCAs), traders, moneylenders and other individuals. The Bank of Ghana (BoG) which is the central bank oversees all the operations of MFIs in the country. The government observes that the overall policy framework for microfinance is informed by the poverty reduction strategy, which seeks to balance growth and macroeconomic stability with human development and empowerment

[1] The informal microfinance sector is largely made up of Susu collectors and the term Susu refers to an informal means by which Ghanaians securely save and access their own money, and might also gain limited access to credit from the Susu collectors.

in such a way as to positively impact the reduction of the country's poverty levels in the medium term (Government of Ghana, 2005).

There exist over 300 formal MFIs and an unspecified higher expected number of informal MFIs operating across the length and breadth of the country (Kyereboah-Coleman, 2007). Among these figures, 90 institutions are registered with the Ghana Microfinance Institutions Network (GHAMFIN[2]) and serve over 500,000 clients across the country (from MFT data). The main activities of these institutions are savings, micro-credit delivery and financial consulting for individuals and small enterprises.

This paper studies the investment impact of MFIs on small/ micro enterprises in Ghana with the emphasis being on the entire nation. There have been few studies in the microfinance sector in Ghana and the researchers who have delved into the sector have focused on topics such as factors which affect the operations of MFIs, regulations governing the sector, challenges that the sector continues to face and most importantly as related to this paper, impact studies. These impact studies however either focus on the evaluation of specific microfinance institutions or on particular parts of the country. The focus of this paper is to determine whether the operations of the MFIs in Ghana as a whole have impacted enterprises positively in investment terms. The paper employs the financing constraints approach to evaluate the impact of microfinance through investment in Ghana. As stated by Hartarska et al, 2008, this methodological approach avoids the typical

[2] GHAMFIN was established in the year 1998 with the aid of the World Bank to regulate and the keep the database of MFI's in Ghana. In addition to this, Gallardo et al, 2005 lists the activities of GHAMFIN as the microfinance institutional body undertaking policy advocacy and representation, accessing resources for and implementing institutional and staff capacity building programs, and offering a platform for the dissemination and exchange of best practices in microfinance.

challenges associated with impact assessment studies where MFI clients serve as a treatment group with other individuals or enterprises that are not clients serving as a control group. The effectiveness of the MFIs in the country is judged by the sensitivity of small/ micro enterprises' investment to availability of internal funds. Other studies which employed this approach include Budina et al, 2000 and Hartarska et al, 2006. The paper further uses a Propensity Score Matching procedure in determining the effect of credit access on investment.

The review of current literature is discussed in the next section. The analytical framework and empirical model used for the analysis are then presented in the third section. Afterwards the data and estimation procedures are described in the fourth section followed by the empirical results and the subsequent discussion of the estimation. The paper ends with some concluding remarks which might be very helpful for policy implications.

2. **Literature Review**

As stated earlier, previous researches regarding microfinance have focused on factors which affect the operations of MFIs, regulations governing the sector, challenges that the sector faces and impact analyses of the MFIs but with the impact analyses focusing on specific areas and specific MFIs. For instance, Anim, 2009 studied the sensitivity of loan size to lending rates in the countrys' microfinance sector and found out that there exist pronounced variations in the responsiveness of loan size to interest rate changes at different percentiles in the country. Gallardo, 2001 studied the framework for Regulating MFIs in Ghana and the Philippines and structured out the similarities and differences that exist between the sectors of the two economies. His paper primarily sought to provide a framework for addressing regulatory issues which impact the operations and the institutional development of MFIs. Gallardo et al, 2005 also worked on the comparative review of microfinance regulatory framework issues in Benin, Ghana and Tanzania also with the objective of suggesting how the sector must be regulated.

Basu et al., 2004 estimated that in Ghana only about 6 percent of the entire population have access to formal financial services, with the majority being denied access and these individuals and enterprises therefore tend to rely largely on informal sources such as friends, relatives, suppliers and money lenders for their financial needs. Provision of loans to individuals and small enterprises has been found as a great remedy in reducing or alleviating poverty, particularly when used judiciously to generate some form of a long-term source of income. In this light, Adjei et al, 2009 confirms that the provision of financial services to individuals or households helps them to better manage their existing asset base or to reduce their liabilities. This loan accessibility they claim provides a security or fallback position if difficulties are encountered.

The impact analyses of MFIs include studies by Nanor (2008), Afrani (1997), Onyina *et al* (2011), Gyamfi (2011) and Adams *et al* (2010). Nanor, 2008 studied the impact of microfinance on selected districts in the Eastern region of Ghana. Focusing on four districts and basing his sample on household units, the results of the study indicated that microfinance had positive impact on the household income of the respondents from two districts whilst there was no impact on the household income for the other two districts. Afrani, 1997 undertook an impact study of the operations of Sinapi Aba Trust[3] (SAT) as a contribution to an International Transformation Research carried out by the OI Research Group. His work sought to assess the nature and degree of changes that clients have experienced in their businesses since they started benefiting from the credit scheme of SAT, and to further examine the extent to which these changes in their businesses

[3] Sinapi Aba Trust is one of the MFIs in Ghana that provides microfinance services to entrepreneurs in small and micro enterprises with the objective of improving their business and enhancing income generation opportunities in order to alleviate poverty, improve their standard of living, and consequently positively transform their lives.

have affected other aspects of their lives. The results of the study showed that an improvement in the conditions of the clients occurred following the receipt of credit. Similar to Afrani's study, Onyina *et al*, 2011 also performed an assessment of the impact of microfinance on clients who received loans from the Sinapi Aba Trust of Ghana. With a more detailed finding, the results show that old clients are more likely to acquire assets, improve their businesses, and spend larger amounts on their children's education than new clients. Gyamfi, 2011 performed a case study of the First Allied Savings and Loans Limited (FASLL) with the aim of analyzing the impact of microfinance on poverty reduction for the company's clients. With a random sample of small/ micro enterprises drawn from different districts, the study revealed that despite two main problems faced by FASLL (payment default and inadequate capital to sustain and cater for the growing number of clients), the company has been successful in improving the economic livelihood of the respondents. Adams *et al*, 2010 analyzed the impact of microfinance on maize farmers in the Brong-Ahafo region with their results showing positive impacts of microfinance on both the social and economic well beings of the clients.

In another interesting study, Kyereboah-Coleman, 2007 examined the impact of capital structure on the performance of MFIs. Using a 10-year period panel data with both fixed and random effect techniques, the study finds out that most of the MFIs examined employ high leverage and finance their operations with long term as against short term debt. The results also indicated that highly leveraged MFIs perform better by reaching out to more clientele, enjoy scale economies and are better able to deal with moral hazard and adverse selection, thus enhancing their ability to deal appropriately with risk. Just recently, Alhassan *et al* (2013) assessed the impact of MFI's institutional capacity on advocacy for women empowerment in the Northern region. They mainly observed that MFIs covered in their study were bereft of plausible advocacy strategies capable of influencing policy reforms that can engender women empowerment. They also observed that the employees of these MFIs lack the requisite advocacy skills and there are no short or long term strategies put in place to equip employees with the necessary expertise.

Several studies have clearly pointed out the importance and positive effects associated with microfinance in alleviating poverty. However, various studies have likewise questioned these positive impacts across regional boundaries and suggests from theory that microfinance works differently in different regions due to variations in population density, attitudes to debt, group-cohesion, enterprise development, financial literacy and financial services provision (Rooyen *et al,* 2012). This is because some studies have indicated much more mixed impacts, whilst other studies have also identified certain flaws and drawbacks associated with this developmental tool. Such negative instances could be seen in countries where microfinance institutions have recorded high default rates with thousands of poor entrepreneurs being over-indebted.

Rooyen *et al*'s (2012) systematic review of the microfinance impact literature in Sub-Saharan Africa identifies two main findings based on quality, relevant and reliable microfinance impact studies in the sub-region. First, what has been the impact on financial outcomes? It is observed that microfinance has both positive and negative impacts on the incomes of poor people, whilst in some instances there are no impacts at all. It is also observed that microfinance clientele tend to invest more but it is uncertain whether these additional investments lead to greater profit levels. In addition, they observe that microfinance services increase both expenditure and the accumulation of assets. It is worth-noting though that while these businesses initially accumulate more assets, this asset accumulation reduces/ stops over time. Second, what are the impacts on non-financial outcomes? Evidence suggests that microfinance generally have a positive impact on the health of poor entrepreneurs and this is comparatively observed based mainly on the number of days they are unable to work due to sickness. Majority of evidence also suggests that microfinance have a positive impact on food security and nutrition, but this is however not the same across all regions.

Evidence on the impact on both education and women's empowerment suggest both positive and negative impacts whilst impact on housing generally has positive results. There is however very little evidence that suggests a positive impact on job creation whilst there is no evidence concerning the impacts on child labor and social cohesion.

Investment as defined by the Oxford dictionary is referred to as putting money into something with the expectation of gain, that upon thorough analysis, has a high degree of security for the principal amount, as well as security of return, within an expected period of time. Whether or not a loan received by an individual or a small enterprise would yield positive investment results depends on so many factors. The most important of these factors is the reason behind the acquisition of the loan. Individuals that acquire loans for personal effects and to meet emergent financial needs are definitely not those being considered in this study. Investment impacts can occur when the motive behind the acquisition of a loan by an individual or small enterprise is primarily to start a new business, recuperate a dying business or to expand an already operating business.

One key factor that determines the performance of MFIs is the capital structure of the enterprise. Even though Modigliani and Miller (1958) object to this assertion on the basis of the assumptions including existence of perfect capital market, homogenous expectations, absence of taxes and no transaction cost, Kyereboah-Coleman, 2007 notes that this is unrealistic since the real world market is not characterized by such assumptions. Other studies that have debunked Modigliani and Miller's proposition include Jensen and Meckling (1976), Grossman and Hart (1982) and Harris and Raviv (1990). Morduch (2000) notes that MFIs that follow the principles of good banking will be able to grow without the constraints imposed by donor budgets and would also be those able to alleviate the most poverty which is the primary objective of MFIs. The benefits acquired from the operations of MFIs could be observed in both economic and social terms (Hartarska et al, 2008), but due to how subjective the social criterion is, only the economic term is looked at in this paper in the form of the additional investment the enterprise made.

In the presence of asymmetric information and high transaction costs, loans are either rationed or available at a premium (Stiglitz *et al*, 1981; Carreira *et al*, 2010; Hartarska *et al*, 2008). When this happens external financing and internal financing are no longer perfect substitutes as hypothesized by Modigliani *et al*, 1958. This does not allow enterprises to raise the necessary amounts to fulfill their investment and growth goals. Information asymmetry also creates a situation where MFIs tend to finance projects with higher risks causing sub-optimal allocation of credits to enterprises. As stated by Carreira *et al* (2010), this leads to the tendency of firms avoiding external finances since they know how risky a particular project might be.

The financing constraint method is used in many other fields which incorporate economics in their studies. Carreira *et al* (2010) outlined among other stylized results of financing constraint's studies the following. Financial constraints are more severe for younger and smaller enterprises because there is not enough information about these enterprises and thus lenders cannot measure the extent of risk associated with lending to such enterprises. This is also because the problems with asymmetric information in capital markets (Adverse Selection and Moral Hazard) are more severe for small and young enterprises and these problems, particularly the former, are found to restrict enterprises' ability to raise external funds needed to take advantage of investment opportunities. Also Start-ups/new entrepreneurs appear to be financially constrained and thus Start-up capital has been found to negatively affect start up success. In addition, financial constraints are decisive for enterprise survival, the greater the financial constraints the more likely it is that an enterprise would not survive over time.

The current literature has repeatedly stated that financing constraints is a key determinant of the impact MFIs have on their target population or clients. Kaplan *et al*, 1997 defined a firm as being financially constrained if there exists a wedge between the costs of using external and internal funds but Carreira *et al*, 2010 argues that with such a definition, all firms could then virtually be classified as such. They thus define financial constraints as the inability of a firm or a group of firms to raise the necessary amounts (usually due to external finance shortage) to finance their optimal path of growth. This study henceforth adopts this definition. Kerr et al, 2010 asserts to the fact that financing constraints are one of the biggest concerns impacting potential entrepreneurs around the world and further observes that alleviating financing constraints for would-be entrepreneurs is a very important goal for policymakers worldwide.

Using cash flows as a measure for investment has generated an intense debate in recent literature with several arguments both in favour and against the topic. For instance, Kaplan *et al*, 1997 argue that cash flow is not a good measure of the existence of financing constraints because for investment cash-flow sensitivity (ICFS) measure to be meaningful and consistent, it is necessary to make assumptions that may not be verified on the curvature of the cost function of acquiring external funds. They explain also that further inconsistencies may arise with this measure due to precautionary savings and excessively risk-averse management. In their study, they thus classified firms according to information obtained from company annual reports and their results concluded that constrained firms are less sensitive to cash flow. Almeida *et al*, 2001 also tried to show that ICFS is not the best of approaches. They show that when firm's investments and use of external finance are endogenously related, investment-cash flow sensitivities increase as credit constraints are relaxed. This is in contrast to the established view that investment-cash flow sensitivities increase with the degree of financial constraints. They conclude with the prediction that sensitivities will decrease with financial constraints, so long as firms are not entirely unconstrained. Allayannis *et al*, 2004 however present an explanation for these arguments and argue that investment is more sensitive to cash flow for more constrained firms. They explain that

Kaplan–Zingales' results are driven more by a few influential observations in a small sample which results in their conclusion. In the ensuing debate, several other studies have supported the use of the ICFS as an appropriate measure which when used effectively ensures a good measure for investment studies. Such studies include Erickson *et al*, 2000, Gomes, 2001, Cummings *et al*, 2006 and Alti, 2003. Alti, 2003 for instance analyzed the sensitivity of a firm's investment to its own cash flow in the benchmark case where financing is frictionless. He found out that the investment-cash flow sensitivities that were obtained in the frictionless benchmark were very similar, both in magnitude and in patterns they exhibit, to those observed in the data and thus concluded that in particular, the sensitivity is higher for firms with high growth rates and low dividend payout ratios.

Adding to the current literature, Cleary *et al*, (2007), Lyandres (2007) and Povel *et al* (2002) create a new dimension to the ongoing debate on cash flow sensitivities. Their findings point to the fact that the investment cash-flow relationship is U-shaped. This relationship and the rationale behind it are summarized by Carreira *et al*. They explain that below a certain level of internal funds there exists the risk of firms defaulting payment and as long as the revenues which would be derived from the investment are large enough to allow the lender to be willing to provide larger amounts in order to mitigate the risk of defaulting, a decrease in internal funds would lead to an increase in investment. At the same time, for higher levels of internal funds the decrease in internal funds would lead to a decrease in investment in order to avoid the costs of resorting to larger amounts of external finance due to higher expected liquidation losses.

3. **Analytical Framework and Empirical Model**

As stated earlier, the study employs the financing constraints approach used frequently in recent literature with regards to impact studies in the microfinance sector. Abiola, 2011 presents a very similar study which also employs this approach in a study titled, "Impact Analysis of Microfinance in Nigeria". The similarities between these two West-African neighbours in terms of their microfinance sectors give a green light that this tool or approach could be appropriately applied to the Ghanaian system. With this approach, it is imperative to determine which variable measures the improvement made by the MFIs. In this study, investment is the measure for improvement. One relevant aspect of this approach as noted earlier is the inclusion of a control group and thus it is important to identify a control group that is closely identical to the treatment group. A unique feature in this study which is very similar to that employed by Hartarska et al, 2008 is the focus of this approach. As stated earlier, the impact evaluation is performed on the entire microfinance sector and not on individual MFIs as estimated in other studies. This as noted by Hartarska *et al,* 2008 does not focus on the impact on income or other socioeconomic outcomes but rather determines whether microfinance has been able to alleviate financing constraints in the specific region.

The theoretical basis of the financing constraints approach stems from recent literature such as the study by Cleary, Povel and Raith (2007) which shows that for positive or slightly negative levels of enterprise wealth, investment is positively related to internal finance. Theoretically, since financing constraints do not affect all firms/ enterprises uniformly, the extent of effective financing constraints that different enterprises face provides information on the ability of the financial system to cater for these firms' financial needs (Hartarska *et al*, 2008). This makes investment in enterprises with limited or no access to credit markets (due to the absence or poor functioning of credit markets) more dependent on internal funds than enterprises with better functioning credit markets. The financing constraints approach was first used by Fazzari *et al* (1988). This approach basically tests for differences in the sensitivity of investment to internal funds in enterprises with different levels of informational opacity by splitting a sample of enterprises into sub-samples which are defined according to theoretical priors that characterize constrained and unconstrained enterprises (Hartarska *et al*, 2008). A reduced-form investment equation is then estimated for each sub-sample where investment is modeled as a function of the enterprise's internal funds. These are also done for the control group and a statistically significant difference in the investment sensitivity to internal funds across the sub-samples signifies a group being more credit constrained than the other.

A Tobit regression approach is used in estimating the model. Tobit analysis as used in extensive literature is a great tool for estimating data that are censored. McDonald *et al* (1980) explains that, for data that are clustered at a limiting value, usually zero, the Tobit technique gives best results since it uses all observations both those at the limit and those above the limit. The data used in this study are of such nature with several enterprises recording an investment (being the dependent variable) lower limit amount of zero. This is because the nature of the survey question does not allow respondents to record negative investments.

The Tobit model in this case is formulated as;

$$Inv = \begin{cases} X_t \beta + u_t \\ 0 \end{cases} \text{if} \begin{cases} X_t \beta + u_t > 0 \\ X_t \beta + u_t \leq 0 \end{cases} \quad \text{for} \quad t = 1,2,\ldots,\text{N} \tag{1}$$

Where N represents the number of observations and *Inv* i.e. the dependent variable represents the amount of investment made during the previous year. *X* represents a vector of independent variables, β is a vector of unknown coefficients whilst ε is an independently distributed error term assumed to be normal with zero mean and constant variance.

Variables used in estimating the model are similar to the ones used by Hartarska et al, 2008 and these include investment in the past year before the survey, cash flow, investment opportunity, number of employees, age of the enterprise, gender of the enterprise owner, educational level of the entrepreneur, the type of business i.e. whether the enterprise falls into the manufacturing, trade or service category, number of hours worked per week and power generator usage during power outages.

The cash flow variable caters for the internal funds available to the enterprise. For the investment opportunity variable, it is assumed that enterprises would hire part-time workers when they foresee opportunities in investment and enterprise growth and thus part-time worker hiring would be used as a proxy for investment opportunity. As estimated by Abiola, 2011, investment opportunity would be estimated as a dummy variable where enterprises that hired part-time workers during the previous year are seen as having investment opportunities whereas enterprises that recorded zero values for part-time hiring are seen not to be having investment opportunities.

The estimated Tobit model is thus specified as;

$$Inv = \beta_0 + \beta_1 IF + \beta_2 IO + \beta_{3-8} Z \qquad (2)$$

Where;

IF = internal funds capital variable (Cash flow)

IO = investment opportunity variable

Z = a vector of variables that capture various characteristics of the enterprise

Internal funds capital is separated from investment opportunity because enterprises without investment opportunities would not invest even if they had capital.

The hypothesis being tested in this study is that;

> H_0: Small enterprises with access to MFIs have no investment sensitivity to the availability of internal funds due to the fact that they have better access to external funds through the presence of The MFIs.
>
> H_A: Small enterprises without access to MFIs face more significant financial constraints since they rely more on their internal funds for investment.

This hypothesis could be traced back to the study conducted by Modigliani *et al* (1958) which states theoretically that external finance and internal finance are perfect substitutes. Thus when external financing constraints exist, small/ micro enterprises have no choice but to resort to their internal funds.

In addition to the financing constraint approach, a Propensity Score Matching (PSM) approach is employed to match enterprises according to their covariate propensity scores based on access to credit. This helps to determine the effect of microcredit access on the small/ micro enterprises with the counterfactual being that what would have happened to the unconstrained group if they actually had no access to credit like the control group. This procedure (PSM) also helps eliminate any kind of selection bias which might be associated with the data.

The investment choice (i.e. the amount of investment made in the previous year) as the 'outcome variable' is justified since it obeys the Conditional Independence Assumption (CIA), which assumes that given a set of observable covariates *X,* which are not affected by treatment, the potential outcome(s) should be independent of treatment assignment i.e. $Y(0), Y(1) \amalg D \mid X$ where $Y(0)$ and $Y(1)$ are the outcomes for the treatment and control groups respectively.

Given that CIA holds and assuming additionally that there is an overlap between both groups (as was suggested by Heckman *et al*, 1998), the propensity score matching estimator for the 'average treatment for the treated' (ATT) as was formulated by Caliendo *et al*, 2005 can be written as:

$$\tau_{ATT}^{PSM} = E_{P(X)|D=1}\left\{E\left[Y(1)D=1, P(X)\right] - E\left[Y(0)D=0, P(X)\right]\right\} \tag{3}$$

This study adopts the Mahalanobis metric matching procedure due to its acclaimed properties (Sianesi, 2001).

4. **Data**

Cross-sectional data of the small and microenterprises were obtained from the Ghana Business Environment and Enterprise Performance Survey which is part of the Business Environment and Enterprise Performance Survey (BEEPS) series of the World Bank for the year 2007. This was conducted by the Ghana Statistical Service, the public institution authorized by the government that has the sole responsibility of conducting national statistical surveys and population and housing surveys. The data consist of enterprises from the Production (Manufacturing), Service and Trade sectors and thus the sampling reduction bias issues raised by Carreira *et al* (2010) are excluded in this study. This makes the financing constraint approach appropriate to be used for this data without generating any bias with subsequent conclusions. Studies that have also used cross-sectional data in determining the impact of microfinance on various economies include articles by Deloach *et al*, 2011, Abiola, 2011, Hartarska *et al*, 2008 and Devi *et al*, 2011. The questionnaire has a section which asks detailed questions on individual or group enterprises including their business activities over the previous year. The data also have information about enterprises' MFI usage and the metropolises from where the enterprises are located.

This paper analyzes enterprises with less than 20 permanent employees[4]. This means the analysis includes both micro enterprises (enterprises with less than 5 employees) and small enterprises (enterprise with 5-19 employees). Enterprises are either classified as unconstrained or constrained based on the enterprise's self-acknowledgement, a procedure referred to as 'direct elicitation' as used in studies such as Quisumbing (2006) and Simtowe *et al* (2006). The paper uses a survey question that asks respondents whether access to finance is a constraint to their operations. Enterprises that acknowledge access to finance is either a little a no obstacle are classified as unconstrained whilst enterprises that say access to finance is either a moderate, major or a very severe obstacle are classified as constrained.

In order to differentiate this study from that of an impact study on all financial institutions, only enterprises that had received credit from MFIs are analyzed in this paper[5]. Constrained enterprises that had received credit only from banks are not dropped because, small/ micro enterprises that admit that access to finance is a constraint would as well have no access to microfinance. It is however arguable that some of the unconstrained enterprises dropped may never have received any credit from MFIs but might as well not necessarily be constrained to microfinance access. This argument notwithstanding, it is expected that dropping such observations would not influence the results since only 2 observations that have never had any credit from a microfinance institution are

[4] The survey defines small enterprises as those with 5-19 employees, medium enterprises as those with 20-99 employees and large enterprises as those with 100 and more employees.

[5] Since the paper distinguishes unconstrained enterprises from constrained enterprises by the access to finance question, enterprises that have received credit from banks only and not MFIs are excluded in order to specifically analyze the impact that the MFI sector has had and not the finance sector in general.

dropped. This is because most of the enterprises that have taken credit from MFIs have also at a point in time taken credit from banks. However, this does not present a shortfall for the paper in distinguishing between credit from MFIs and that from banks since most of the banks themselves sell microfinance products for their small enterprise clients causing the overlap. A final sample of 489 enterprises operating in the Accra, Tema, Takoradi, Kumasi and Tamale metropolises is used for the estimation. This comprises of 100 unconstrained observations (representing 20.45% of the sample) and 389 constrained observations (representing 79.55% of the sample). The variable measuring cash flow is obtained by subtracting total costs from total sales for the year 2006. A positive relationship is therefore expected between cash flow and investment sensitivity to internally generated funds. Investment opportunity as stated earlier is estimated using 2006 part-time worker hiring as a proxy.

Table 1 presents the summary statistics of the variables used in the analysis. These are grouped into two in terms of whether enterprises are constrained or unconstrained with respect to access to microcredit from MFIs. The entire sample comprising both constrained and unconstrained enterprises is also summarized alongside the individual groups. Continuous variables have mean values whilst dummy variables are summarized by their percentages. In addition, standard errors for continuous variables and proportions for the categorical variables are presented in parentheses. The apriori expectations are stated based on economic reasoning and theories from previous studies.

Table 1.1. Summary Statistics

Variable	Description	Measurement	Total Sample	Unconstrained	Constrained	Apriori Sign
Inv	Amount of investment made in previous year	Continuous (GH₵1000)	2.04 (8.44)	3.41* (15.57)	1.64* (5.22)	
Cash flow	Total revenue less total costs	Continuous (GH₵1000)	23.71 (124.19)	56.74*** (240.48)	7.04*** (50.30)	+
Invoppor	Investment Opportunity	Dummy (1 if enterprise hired part-time worker, 0 otherwise)	18.94% (93)	15% (15)	20.1% (78)	+
permemploy	Permanent number of employees	Continuous	6.82 (4.15)	7.21 (4.49)	6.74 (4.07)	+
Entage	Enterprise Age	Continuous (Years)	11.15 (8.63)	10.54 (8.33)	11.33 (8.72)	+
Manufac	Manufacturing Sector	Dummy (1 if manufacturing enterprise, 0 otherwise)	41.75% (205)	34%* (34)	44.0%* (171)	+/-
Trade	Trade Sector	Dummy (1 if trade enterprise, 0 otherwise)	33.6% (165)	36% (36)	32.7% (127)	+/-
Service	Service Sector	Dummy (1 if service enterprise, 0 otherwise)	24.64% (121)	30% (30)	23.4% (91)	+/-
Education	Years of Formal Education	Continuous	4.44 (1.63)	4.76** (1.44)	4.35** (1.67)	+
Female	Female	Dummy variable (1 if female, 0 otherwise)	47.86% (234)	52% (52)	46.8% (182)	+/-
Working hours/week	Number of Hours worked per week	Continuous	51.92 (17.0)	57.56 (12.02)	63.65 (13.33)	+
Generator Usage	Generator usage during power outage	Dummy (1 if enterprise owns a working generator, 0 otherwise)	7.33% (35)	13% (13)	5.66% (22)	+

Parentheses have standard errors for continuous variables and proportions for dummy variables
***, **, * implies statistically significant mean differences at the 1%, 5% and 10% levels respectively

The summary statistics of the two groups show that the data conform to theory to a good extent. This can be seen from the fact that unconstrained enterprises averagely invested higher amounts into their fixed assets compared to the constrained ones. More so, the unconstrained enterprises had averagely higher amounts of cash flow than constrained enterprises. It is observed that over fifty percent of unconstrained enterprises for both groups are females whilst over forty-five percent of constrained enterprises are females with an average for the entire sample being 47.9%. This shows that small/ micro enterprise owners are almost evenly represented in terms of gender indicating that enterprises could be run by both sexes so far as they have the required skills and know-how. In addition, Table 1 shows that majority of the enterprises are mainly into production whilst the least proportion are in the service sector i.e. more than forty percent of total sample are in the production sector. Unconstrained enterprises also do have averagely more number of permanent workers than do constrained enterprises with a ratio of about seven to six.

The data however deviate from theory in terms of enterprise's age since the recorded enterprise age averages for unconstrained enterprises are lesser than those of the constrained enterprises. This is because it is expected from theory that older enterprises would have much access to finance since potential lenders are more able to observe the amount of the risk associated with the investment of older enterprises than that of younger enterprises. This deviation may have been caused by the establishment of MFIs much farther away from older enterprises than from younger enterprises, a situation which would probably not have been deliberate. In addition, the average number of years of formal education for unconstrained enterprise owners is slightly higher than that of constrained enterprise owners though the difference is not much. This could be attributed to the fact that much better educated enterprise owners are able to use their knowledge to strategically position themselves in securing funds more as compared to their less educated compatriots. It can however be seen from the summary that education is a problem among the entrepreneurs with a total sample average value of about 4.4 years of formal education.

5. **Results and Discussion**

Table 2 presents the Tobit regressions by group of the unconstrained and constrained micro/ small enterprises. The Tobit function in Stata by default reports the coefficients which are the marginal effects on the latent dependent variable (Newton *e al*, 2000). Its marginal effect function reports four different forms of marginal effects at the means of the independent variables. These include the β coefficients themselves which are the changes in the mean of the latent dependent variable, the changes in the unconditional expected value of the observed dependent variable, the changes in the conditional expected value of the dependent variable and the changes in the probability of being uncensored. All four marginal effects for both unconstrained and constrained enterprises are reported in the appendix (Tables 5 and 6). In addition to the regression results presented in Table 2, the sample consisting of enterprises with credit from banks only is also analyzed and the results presented in the fourth and fifth columns. This is a robust check to determine if dropping such observations had significant implications on the results. As expected, dropping such minute number of observations did not cause any significant changes in the results. It can be observed that columns 3 and 5 in Table 2 are the same since no constrained observation was dropped.

As stated earlier, a statistically significant difference in investment-cash flow sensitivity between the two groups would indicate how efficient MFIs have been to small/ micro enterprises in Ghana. In conformance to the apriori expectation, the cash flow variable is positive and

Table 1.2. Tobit regression by group for Constrained and Unconstrained enterprises

Investment	Unconstrained	Constrained	Unconstrained (With Banks)	Constrained (With Banks)
Cash flow	0.0195*	0.0317***	0.0191*	0.0317***
	(0.0112)	(0.00789)	(0.0107)	(0.00789)
Inv Opportunity	8.133	6.433***	7.820	6.433***
	(8.341)	(1.143)	(8.100)	(1.143)
Entage	2.123*	-0.0819	2.101*	-0.0819
	(1.099)	(0.181)	(1.068)	(0.181)
$(\text{Entage})^2$	-0.0509*	-0.00158	-0.0504*	-0.00158
	(0.0301)	(0.00498)	(0.0293)	(0.00498)
Education	0.873	0.416	0.945	0.416
	(2.971)	(0.419)	(2.852)	(0.419)
Female	11.83	-3.050	10.68	-3.050
	(22.59)	(2.829)	(21.52)	(2.829)
Female*Educ	-4.314	0.0638	-4.068	0.0638
	(4.651)	(0.595)	(4.427)	(0.595)
Trade	6.184	-0.176	5.626	-0.176
	(8.370)	(1.235)	(7.898)	(1.235)
Service	11.25	0.319	11.16	0.319
	(8.100)	(1.320)	(7.875)	(1.320)
Permanent employees	0.719	0.423***	0.705	0.423***
	(0.795)	(0.130)	(0.769)	(0.130)
Working hours/week	0.699***	0.177***	0.648***	0.177***
	(0.240)	(0.0365)	(0.199)	(0.0365)
Generator Usage	-14.75	1.275	-13.96	1.275
	(10.07)	(1.946)	(9.357)	(1.946)
Constant	-77.22***	-18.31***	-73.76***	-18.31***
	(24.16)	(3.477)	(21.40)	(3.477)
_se	23.21***	7.630***	22.61***	7.630***
	(2.643)	(0.436)	(2.508)	(0.436)
Observations	100	389	102	389
Log Likelihood	-218.3	-666.3	-226.5	-666.3
LR Chi^2	25.27	116.99	26.76	116.99
Prob > Chi^2	0.0136	0.000	0.0084	0.000
Pseudo R^2	0.0747	0.1007	0.0758	0.1007

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

statistically significant for both constrained and unconstrained enterprises. As seen in Table 2, investment-cash flow sensitivity for unconstrained enterprises is 0.0195 as against 0.0317 for unconstrained enterprises. This shows that in the Ghanaian setting, constrained enterprises rely more on their internal funds (cash flow) than do unconstrained enterprises in accordance to the theoretical literature.

A t-test was conducted to determine if sensitivity difference between the two groups are statistically significant. The null hypothesis of equality between the two coefficients was rejected at the 5% significance level indicating that unconstrained enterprises are indeed slower in using their internal funds for investment than constrained enterprises. With such results, statistical inferences could thus be made that MFIs in Ghana have alleviated financing constraints faced by small/ microenterprises to a good extent. The level of alleviation may not be very huge since many small enterprises still face challenges with funds, but the results show that they are in the process and with time, hopefully poverty could be alleviated to a very large extent, all things being equal.

Furthermore, the results for constrained enterprises show that as compared to enterprises without investment opportunities who did not hire part-time labour, those with investment opportunities are able to make an investment average of over six thousand Ghana cedis. The results however show a statistically insignificant value for unconstrained enterprises. Also for constrained enterprises, the number of permanent employees that an enterprise has is very important and imperative in determining the amounts of investment made, this observed from the fact that an additional permanent employee increases investment by over four hundred Ghana cedis. Number of hours worked per week shows statistical significant results for both unconstrained and constrained enterprises with unconstrained enterprises having a higher magnitude. It is observed that an additional hour of work per week increases investment by over six hundred Ghana cedis for unconstrained enterprises whilst that of constrained enterprises increases by about one hundred and seventy Ghana cedis. The results also indicate that unconstrained enterprises invest more as their enterprises grow. An additional year of enterprise age of an unconstrained enterprise increases investment by over two thousand Ghana cedis. As expected, when the enterprise matures and exceeds a certain age, it starts to experience reduction in investment for every additional year, and this might be due to the economic theory of diminishing returns. Finally, it could be seen that the result in column 4 are very similar to those in column 2 indicating that the observations dropped did not cause any significant change in the results.

The Propensity Score Matching analyses are illustrated below. Table 3 presents the regression estimates whilst Table 4 presents the results for the Mahalanobis procedure.

The results show that the Average Treatment for the Treated (ATT) is about GH₵3,412 whilst that of the constrained group is about GH₵ 1,922 indicating a difference of about GH₵ 1490 between the amount of investments made by unconstrained and constrained small/ micro enterprises. This result show that even though unconstrained enterprises are less sensitive in terms of cash flow-investment sensitivity, they tend to make higher amounts of investment confirming the hypothesis that they acquire such funds from external sources due to their access to MFIs.

As per the estimation results, the microfinance sector is seen to have positively impacted on enterprise performance as indicated in the literature and thus confirms the importance of MFIs in alleviating financing constraints for small enterprises as noted by studies such as Devi *et al*, 2011, Adjei *et al*, 2009, Abiola, 2011 among others.

Table 1.3. Probit Regression Estimates for the Propensity Score Matching Analysis

Variables	Credit Access Variable (Constraint)
Cash Flow	0.0033***
	(0.0009)
Investment opportunity	-0.2577
	(0.1645)
Enterprise Age	-0.0051
	(0.0084)
Education	0.0871**
	(0.0449)
Female	0.1868
	(0.1367)
Permanent Employees	0.0123
	(0.0166)
Working hours/ week	0.0188***
	(0.0048)
Constant	-0.2272***
	(0.3897)
Number of Obs	489
Log Likelihood	-227.9
LR chi^2	39.68
Prob > chi^2	0.000
Pseudo R^2	0.1001

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

Table 1.4. Estimates for the Mahalanobis Matching Procedure

Variable	Sample	Treated	Controls	Difference	S.E.
Investment	Unmatched	3.412	1.648	1.764	0.945
	ATT	3.412	1.922	1.490	1.694

Treated = 100
Untreated (Control) = 389

6. **Conclusion**

This paper uses the financing constraints approach to study the impact of microfinance on credit access for microenterprises in Ghana. A statistically significant difference in cash flow between unconstrained and constrained enterprises indicates how efficient MFIs have been to small/ micro enterprises in Ghana. From the financing constraints theory, a smaller magnitude of the cash flow variable for unconstrained enterprises indicates a lesser sensitivity to internal funds compared to constrained enterprises. The study uses a 2007 World Bank Enterprise data conducted by the Ghana Statistical Service (a cross-sectional survey data from five different metropolises namely the Accra, Tema, Kumasi, Takoradi and Tamale metropolises) in analyzing the sector. The Tobit regression procedure was used to assess the impact of microfinance on financially constrained and unconstrained enterprises by determining respondents' sensitivity to internal funds. Enterprises were classified either as unconstrained or constrained based on self-selection (direct elicitation). A Tobit model was used due to the censoring nature of the data in terms of investment (which is the independent variable) since many enterprises had a lower investment limit of zero.

The results recorded showed statistically significant cash flow estimates for both unconstrained and constrained enterprises. More so, unconstrained enterprises had a lower cash flow magnitude than that of constrained enterprises implying that investment sensitivity with regards to internal funds is indeed lesser for unconstrained enterprises. This shows that MFIs have to some extent alleviated financing constraints in the country even at a time when the sector was not very well established. The study further employs the Propensity Score Matching analysis to match farmers according to their covariate propensity scores based on access to credit. This helps to determine the effect of microcredit access on the small/ micro enterprises in terms of investment amounts made. With investment being the outcome variable, it was observed that unconstrained enterprises make higher amounts of investment (average treatment for the treated) compared to constrained enterprises indicating that even though unconstrained enterprises are less sensitive in terms of cash flow-investment sensitivity, they tend to make higher amounts of investment confirming the hypothesis that they acquire such funds from external sources due to their access to MFIs.

What needs to be done is for all stakeholders to join hands and resources to continue making the microfinance sector in Ghana one of the leading and big-league microfinance sectors in the African sub-region. One drawback of this study is that the 2007 BEEPS data used for the analysis does not provide information on household/ community income and does not also provide information on the specific locations and addresses of the enterprises. These variables have been used in some studies that classified firms/ enterprises as constrained or unconstrained using proximity of enterprises to MFIs. However, this does not affect this study since the self-selection procedure was used. Subsequent researchers with much integrated data might add more variables in estimating the impact of the MFI sector.

Chapter 2. Effects of Climate Variability on Agriculture in the South-Eastern US

Abstract

This study uses the Ricardian (Hedonic) approach to determine the impact of climate change on agricultural farmland values for the southeastern United States. The analyses uses a 5-year pooled cross-sectional data from the ARMS database, climate data from the GHCND and soil data from the SSURGO database. Marginal effects and climate impact projections for 2100 from the three Atmospheric Oceanic General Circulation Models (Hadley CM3, ECHO-G and NCAR PCM) are used in calculating the impacts on the regional farmland values.

The Ricardian regression results show that farmland values increase with higher winter and summer temperatures but fall with higher spring and fall temperatures. Winter and summer temperatures have a positive but declining impact on farmland values, whereas spring and fall temperatures have negative and increasing impacts. The results also show that an increase in spring precipitation increases farmland values whilst increases in winter, summer and fall precipitations tend to decrease farmland values. Spring precipitation has a positive but declining impact on farmland values, whereas precipitation in the winter, summer and fall have negative and increasing impacts.

The marginal effects indicate that higher annual temperature is beneficial for farmland values throughout the region with the exception of Florida and Mississippi. Increases in annual precipitation are detrimental to most of the states except Alabama, Mississippi and Tennessee. The marginal effects for the seasonal temperature and precipitation also varied significantly across the states. Lastly, the projections show that the aggregate farmland value for the entire Southeast US is likely to decrease under the three model scenarios considered in the analyses.

Keywords: Climate Change · Southeast US · Ricardian Model · Farm land Values · ARMS Data

JEL classification: Q54

Introduction

It has been established from the weather pattern data and researches on global warming that greenhouse gas emissions (which is generated from the day-to-day activities of humans) cause the depletion of the ozone layer which would consequently lead to higher temperatures and decreased precipitation as the years go by. Due to the direct effect of temperature and precipitation on farming activities, it has been predicted that the agricultural sector would be affected the most (Deschenes and Greenstone, 2007). The effects would vary according to the type of production (e.g. livestock production would be affected more by temperature than precipitation) and the specific cultivation type (e.g. rice could adapt much more to increased precipitation than could maize).

The United States Department of Agriculture (USDA) notes that climate change poses a big challenge to U.S. agriculture with agriculture existing as a complex web of interactions between agricultural productivity, ecosystem services and climate change. This is due to the fact that agricultural production is susceptible to climate change through its direct (abiotic) effects on crop and livestock development, as well as through the indirect (biotic) effects arising from changes in the severity of pest pressures, availability of pollination services, and performance of other ecosystem services that affect agricultural productivity. Adaptive actions are thus very imperative to manage the effects of climate change by altering patterns of agricultural activity to capitalize on emerging opportunities while minimizing the costs associated with negative effects.

Agriculture serves a significant role in the Southeastern region with crop production ranging from vegetables, cotton, citrus fruits, strawberries, rice, peanuts, corn, sugar cane, wheat, tobacco, and soybeans. Crops such as cotton and vegetables are extremely important for the southeastern region accounting for about 22% of cotton and over 50% of fresh-winter vegetables in terms of the share of national production. Also, with the vast economic importance of agriculture in the region (having more than 400,000 farms and contributing hugely to revenue in the Southeast region e.g. being a prominent industry in Alabama and contributing almost $5 billion to the state's economy), and regarding the direct effect weather has on agricultural productivity, distortions as a result of global warning would strongly affect revenue in the region. In reference to the varied number of crops cultivated, it is thus unarguable that changes in the climate would alter production of these commodities if sufficient adaptive measures are not put in place. Because of the long and low-lying nature of the Southeast's coastline and its exposure to sea level rise and hurricanes, it has been estimated that the region may be one of the most vulnerable to climate change in the United States (Smith, 2004; Karl et al., 2009).

Climate change data already documented in the Southeastern region however show that precipitation over the past decades have slightly decreased whilst average temperature for the region have also increased slightly over the past century (a situation that has occurred only in very few parts of the earth). Researchers have carefully noted that this trend should not be interpreted to imply a permanently downward trend for the region since climate is very unpredictable, with Robinson *et al* (2002) and Kunkel *et al* (2006) attributing the trend to changes in sea surface temperatures and internal dynamics respectively. Nevertheless, whether the region experiences a decrease in temperature or an expected increase (since other studies including Melillo *et al* (2009) notes that the average temperature is averagely expected to increase by 4-9% across states in the US), both situations calls for strategic adaptive measures in order not to distort the agricultural processes going on in the region, and even if it does should be very mild and controllable. Though the importance of adaptation is undisputable, very recent studies have cautioned the sole reliance on adaptation as a remedy for climate change. Studies by Ackerman *et al* (2013) and Takle *et al* (2013) note that adaptation to warmer and drier conditions is necessary but not sufficient for tackling the entire effects of climate change on agriculture.

Due to the importance of accurate scientific forecasting and adaptation to climate change in the Southeastern US region, the Southeast Climate Consortium (SECC) was formed to use advances in climate sciences, including improved capabilities to forecast seasonal climate and long-term climate change, to provide scientifically sound information and decision support tools for agricultural ecosystems, forests and other terrestrial ecosystems of the Southeastern USA. Consisting of a multidisciplinary, multi-institutional team (comprising 8-member universities[6]), the SECC is tasked with a goal of developing a climate information and decision support system for the Southeastern USA that will contribute to an improved quality of life, increased profitability, decreased economic risks, and more ecologically sustainable management of agriculture, forestry, and water resources. Just as the SECC does, this paper uses climatic data (temperature and precipitation), coupled with soil data and southeastern farm characteristics, to determine and identify areas where climate change impacts on agricultural land values would be significant.

This study uses the Ricardian (Hedonic) approach to identify the impact of climate change on agricultural farmland values. Also in the paper, projected effects of climate change in the future are made using predicted climate change data from the three Atmospheric Oceanic General Circulation Models that predict future climate values. Most previous climate change studies in the US are county based and thus the individual farmer-based ARMS data are averaged by county in this study to provide a well detailed analysis as per the effects on individual locations with

[6] Auburn, Clemson, Florida, Florida State, North Carolina State, Alabama (Huntsville), Georgia and Miami universities make up the SECC

particular characteristics. To the best of my knowledge and search, an entire study on just the southeastern region with regards to weather variability/ climate change sensitivity on farmland values has not yet been done and this study would be the first. Since farmland value per acre of each farmer is directly related to the present value of future net revenues from farming activities, this study seeks to provide farmers in the Southeastern region an idea of how variable their farm revenue/ farmland value would be in the wake of a significant climate alteration.

The paper is henceforth structured as follows. The literature review including recent debates is discussed in the next section. The analytical framework and empirical model used for the analysis are then presented in the third section. Afterwards 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; the first focus being the Ricardian analysis/ marginal effects estimation and the second focus uses simulations from predicted climate data to make projections. The paper ends with some concluding remarks which would be very helpful for policy implications.

Literature Review

The potential effects of climate change on agriculture have well been documented to a large extent across different geographical locations. The United States have not been left out and there are a huge number of studies including nationally, regionally and state-based that seek to identify the possible outcomes (with regards to agriculture) of significant changes in the climate over time. With the earlier highlights of the importance of agriculture in the Southeastern region and its susceptibility to climate variability, researches about the region have focused on a wide range of topics such as impact issues, adaptive measures and forecasting/projections either on the entire farming sector or on individual crop/ livestock productions.

There exist different approaches used in the literature in determining the impact of climate change on farming activities. However the two main approaches involve using either agronomic models or economic models. Agronomic studies focus on the yield as the outcome variable. Because of the pertained complexity of such studies, theoretical models are used to simulate yields given daily weather inputs, nutrient application and initial soil conditions (Schlenker and Roberts, 2008). This is done by using empirical or experimental production functions to predict the effect of the change in climate with the estimates largely relying on crop-yield models. Studies that have adopted such models include those by Adams *et al* (1990), Easterling *et al* (1991), Rosenzweig *et al* (1994), Mearns *et al* (2001) and Stockle *et al* (2003), among several others. Economic studies have mainly used the Ricardian approach (Hedonic models) to measure the sensitivity of farmland value per acre to climatic, geographic, economic and demographic factors, with farmland values representing the expected future present value of future rents. This approach assumes that farmers wish to maximize to profit and thus would choose inputs of each land unit that would maximize farm revenue. Ricardian studies that have sought to estimate the impact of climate change on farmland values include Mendelsohn *et al* (1994), Schlenker *et al* (2005), Schlenker *et al* (2006), Timmins (2006), Kabubo-Mariara *et al* (2007) and Seo *et al* (2008) among several others.

Both the weaknesses and strengths of these two approaches have been highlighted by different researchers and the choice of a particular approach is based on a study's focus and how well the study intends to face challenges and explore its advantages. Schlenker and Roberts (2008) note that one obvious advantage of simulation models is the way they incorporate the whole distribution of weather outcomes over the growing season unlike regression-based approaches that typically use average weather outcomes or averages from particular months. Its weaknesses have been found to include its inability to fully capture the adaptation and mitigation strategies of farmers in the face of climate change (Schlenker *et al*, 2006), misspecification and omitted variable bias issues (Sinclair *et al*, 2000, Long *et al*, 2005), its uncertainty about the physiological process (functional form) and the number of parameters in the models (Schlenker *et al*, 2008) and lastly its inherent bias that tends to overestimate the negative impact of climate changes (Mendelsohn *et al*, 1994). Mendelsohn *et al* (1994) explain that this bias is caused by the failure of the agronomic approach to allow for economic substitution as climate conditions change, and thus by not permitting a complete range of adjustments, such studies tend to overestimate the damages from environmental and climatic changes. Unlike agronomic models, hedonic models are able to account for the entire agricultural sector rather than a single crop at a time. Hedonic models have also been found to account for behavioral response or adaptation. Schelenker *et al* (2006) notes also that the advantage of the hedonic approach is its ability to rely on cross-sectional variation to identify the implicit choices of landowners regarding the allocation of their land among competing uses, rather than modeling their decision directly. The hedonic model approach has its own challenges mostly involving econometric issues. These include the hedonic approach being thought of as a partial equilibrium analysis (since it assumes agricultural prices are held constant) (Schlenker *et al*, 2005), unrobust results across different weighting schemes and its inability to estimate adjustment costs (Quiggin *et al*, 1999) as well as variable issues concerned with irrigation and how is treated in the model. Also just like most regression analyses, there have been concerns of omitted variable bias associated with the hedonic model.

The proposed impacts of climate change by different studies across different regions in the US/ the US as a whole have been varying and in some cases contradictory, thus raising concerns about the accuracy and precision of such findings. Studies such as Adams *et al* (1995), Easterling *et al* (1991) and Kaiser *et al* (1993) predicted huge losses to the agricultural industry during the next century should climate predictions materialize. Meanwhile, studies such as Schlenker *et al* (2008), Kelly *et al* (2005) and Schlenker *et al* (2005) have projected mild negative impacts of climate change as a result of global warming. On the other hand, Deschenes *et al* (2007) found out that climate change in essence would be beneficial to US agriculture. For Schlenker *et al* (2006) and Mendelsohn *et al* (2011) studies, they each observe in their analysis that climate change would affect each region or state differently ranging from mild gains to huge losses. This therefore calls for improved methods as the practice of science requires, to build on previous methods and arrive at robust results which would help prevent extreme farm losses in future as a result of climate change. It is also in this view that this study analyses just the Southeast region using highly valuable individual data to determine additional individual effects.

Following the introduction of the Ricardian model by Mendelsohn *et al* (1994), some researchers have raised pertinent concerns which they believe to cause irregularities with the model. In their follow-up paper, Quiggin *et al* (1999) observe that, just as Mendelsohn *et al* (1994) says the 'dumb-farmer scenario' in agronomic studies implicitly assumes infinite adjustment costs and therefore yields an upper-bound estimate, the Ricardian approach likewise implicitly assumes zero adjustment costs which therefore yields a lower-bound estimate of the costs of climate change. They further explain that the main costs of global warming are almost sure to be adjustment costs and thus economic analyses of global warming must focus on the rate of temperature change, not temperature levels. Such an analysis, they intimate would give a more accurate picture of the impact of climate change rather than the model estimated by Mendelsohn *et al* which in their opinion is not well-behaved. In another follow-up and strong rebuttal, Kaufmann (1997) in his paper notes that the instability of the regression coefficients among models and the lack of consistency with the physiology and economics of grain production completely the credibility of the model reported by Mendelsohn *et al* (1994). They opine that the lack of consistency within models estimated with data weighted by cropland and crop revenues implies complete inconsistency across all models. An earlier response to the Mendelsohn *et al*'s (1994) paper by Cline (1996) also indicates that the Ricardian approach suffers from being a partial-equilibrium analysis that assumes relative prices are unchanged. This partial-equilibrium framework as he notes is particularly misleading with respect to water availability for irrigation. In summary states that the regressions weighted by crop value, which heavily feature irrigated fruit and vegetable crops, are particularly likely to understate the adverse effects of global warming.

In the wake of these very constructive criticisms of Mendelsohn *et al*'s (1994) Ricardian model, aftermath studies that use the model for analytical purposes tend to carefully do that using certain revised additions. Seo *et al* (2008) estimated a Ricardian analysis of the impact of climate change on South American farms taking into account farmer adaptations. In order to also check for consistency, they tested several econometric specifications and estimated five different models comparing them to see any significant changes across the distinctions. They observed that both small and large farms are vulnerable to climate change with small firms being more vulnerable. Treating irrigation in their model also showed that both rainfed and irrigated farms would both loose more than half of their revenues by the year 2100. In Schlenker *et al*'s (2006) impact study of global warming on US agriculture, they linked farmland values to climatic, soil and socioeconomic variables for US counties east of the 100^{th} meridian. This is because the 100^{th}

meridian has been found to be the boundary in the US where states east of this meridian could successfully farm without irrigation. And thus, there was no evident need for the lack of irrigation in their model to bias the results. Also observing that the relationship between climatic variables and plant growth is highly nonlinear, they econometrically show that degree days give a more improved result, further performing sensitivity checks to show the robustness of their results across specifications. Schlenker *et al* (2005) whiles using a similar approach but accounting for irrigation, estimates the Ricardian model making sure that the results are robust across different weighting schemes and models. They observed from their analysis that it was not prudent to pool both irrigated and dryland counties in a single regression, and suggest evidently that these two must be differently assessed. Mendelsohn and Dinar (2003) also with a refined approach to Mendelsohn *et al*'s (1994) Ricardian model explored the interaction between climate, water, and agriculture. They tested whether surface water withdrawal helps to explain the variation of farm values across the United States and whether adding these variables to the standard Ricardian model changes the measured climate sensitivity of agriculture. They observed that the value of irrigated cropland is not sensitive to precipitation and increases in value with temperature. They also noted that gravity and especially drip systems help to compensate for higher temperatures, and also concluding from their results that irrigation can help agriculture adapt to global warming.

In a new dimension but similar[7] to the hedonic model, Deschenes *et al* (2007) propose the use of the profit function in estimating the impact of climate change on agriculture citing the farmer adaptation and omitted variable weaknesses associated with the production function approach and the hedonic approach respectively as the basis of their alternate choice. By estimating the impacts of temperature and precipitation on agricultural profits and then multiplying the estimates by the

[7] Similar because the hedonic model is itself derived from the farm profit function.

predicted change in climate, they sought to exploit the random year-to-year variation in temperature and precipitation to estimate whether agricultural profits are higher or lower in years that are warmer and wetter. Confirming the robustness of their estimation, their results indicated a 4% increase in annual profits as a result of climate change, an outcome that was different from many previous studies.

Not being left out in the literature are adaptation issues and measures that need to be put in place in order curtail any huge farm losses as a result of climate change. A 2010 U.S. EPA Southeast Climate Change Adaptation Planning workshop explained that the two main policies to promote adaptation to climate change include; first, policies that would discourage risky behavior (e.g. building in vulnerable coastal areas which could be threatened by sea level rise) and second, policies that encourage retreat from vulnerable areas. In a study by Crane *et al* (2011), they examine the performance of agriculture in the context of climate adaptation and explain two different examples. In a first example, they explore how technical aspects of climate adaptation in Mali are situated within the enactment of ethnic identities and political struggles between farmers and herders. In a more local setting, their second example shows how farmers in southeastern United States approach climate variability and climate forecasts as risk management tools. They notice substantial differences between approaching adaptation as a dynamic process that is socially embedded and approaching adaptation as a set of modeled responses to anticipated future conditions. Their conclusion suggest that building a synergistic relationship between promises to be a better than either one them. In another recent by study, Bartels *et al* (2012) describes ongoing interactions, dialog, and experiential learning among the network's diverse participants. They show how participatory tools have been used in a series of workshops to create interactive spaces for knowledge coproduction. And presenting findings from these workshops related to participants' perspectives on climate change and adaptation, they suggest that the thoughtful design of stakeholder engagement processes can become a powerful social tool for improving decision support and strengthening adaptive capacity within rural communities. Other studies concerning adaption issues include Cammarano *et al* (2012), Royce *et al* (2012) and Cabrera *et al* (2009).

Analytical framework

The Ricardian Approach (also referred to as the Hedonic analysis) is employed to explore the effect of weather variability on farmland values. Due to the careful nature of how the hedonic model was recently applied by Van-Passel, Massetti and Mendelsohn (2012) (henceforth PMM) and how they particularly address its associated flaws, this paper follows suit since both studies basically have the same objectives, with geographical location being the main distinction. As indicated earlier, the Ricardian model assumes that farmland value per acre of each farmer i in County c is equal to the present value of future net revenues from farming activities, modeled as;

$$V_i = f(P_c,\ Q_{i,c},\ X_{i,c},\ Z_c, M_c)$$

Where P_c is the market price of each crop at county c, $Q_{i,c}$ is the output of each crop for farm i at county c, $X_{i,c}$ is the vector of inputs for each crop at farm i (except land), M_c is a vector of input prices at county c and Z_c is a vector of exogenous variables at county c (including climate and soil variables).

As previous studies (such as Massetti and Mendelsohn (2011), Seo *et al* (2008) and Schlenker *et al* (2006) among several others) have established, the response of temperature and precipitation to farm value is nonlinear. Many studies such as Mendelsohn and Dinar (2003) and Seo *et al* (2008) have observed that farmland value per acre is sensitive to seasonal precipitation and temperature, making the approach viable and meaningful. This study thus follows PMM (2012) in estimating the hedonic model as;

$$\ln V_i = \alpha + \beta_{T,m} T_{c,m} + \gamma_{T,\mathrm{m}} T_{c,\mathrm{m}}^2 + \beta_{R,m} R_{c,m} + \gamma_{R,\mathrm{m}} R_{c,m}^2 + \eta S_c + \theta G_c + \vartheta H_c + ST + \varepsilon_{ic}$$

Where T represents Temperature, R represents rainfall, G is a vector of geographic variables, H is a vector of individual farm socioeconomic and demographic variables, S is a vector of soil variables and ST represents a State dummy. The model implicitly accommodates the adaptation to climate as producers in different areas adjust to their specific climate (Deschenes *et al*, 2007).

The expected marginal impact of seasonal temperature on farmland value per acre is given as;

$$E \frac{\partial V_i}{\partial T_m} = \mathrm{E}\left[\mathrm{V_{i,c}}\right]\left(\beta_{\mathrm{T,m}} + 2\gamma_{\mathrm{T,m}} \mathrm{T}_m\right)$$

with the marginal impact of seasonal temperature on farmland value percentage being derived as;

$$ME_{Tr} = \frac{\partial V_i / V_i}{\partial T_{c,m}} = \beta_{\mathrm{T,m}} + 2\gamma_{\mathrm{T,m}} \mathrm{E}\left[\mathrm{T_{c,m}}\right]$$

where the marginal impact of seasonal precipitation is also measured similarly. Unlike the study by PMM (2012), weights are not assigned to the individual locations. This in no way affects the analysis since the authors of PMM (2012) admit that the weighting factor did not alter their results in any significant way.

The predicted impact of climate on an individual farmland value per acre by the year 2100 is given as;

$$\Delta W_i = E\left[V_i\right] T_1, W_1 - E\left[V_i\right] T_0, W_0$$

The first component ($E\left[V_i\right]T_1, W$) is the estimated farmland value under the new temperature and precipitation by the year 2100, and the second component ($E\left[V_i\right]T_0, W_0$) is the estimated farmland value under present climatic conditions. These estimates are then aggregated to obtain the predicted loss or gain in farmland values by the year 2100.

The prediction uses three different model scenarios, as used by PMM (2012) and these are the Hadley CM3, ECHO-G and NCAR PCM.

The analyses assume that the expected changes in farm output prices as a result of global warming in the Southeastern region are expected to be small and insignificant due to the impact of the global food market. Estimations are also done for irrigated farms and for rainfed farms only in order to capture any significant differences.

Data

Farm level data from the Southest US were obtained from the Agricultural Resource Management Survey (ARMS) database (Phase III). A pooled-cross sectional analysis is performed by combining of a 5-year (2007-2011) dataset of the ARMS Survey data. Climate data were obtained from the Global Historical Climatology Network (GHCND) monthly summaries which is a temperature, precipitation and snow database under the National Climatic Data Center (NCDC). Soil data were obtained from the Soil Survey Geographic Database (SSURGO), specifically SSURGO 2.2.6 being the most current soil database of USDA as at the time this study was being undertaken. Climate data were classified by cities, but since the land value model used in this study is at the county level, these cities are individually matched with their respective counties. Lastly, county population and income data were obtained from the US Census Bureau. Since some counties in different states bear the same name, the five digit FIPS (Federal Information Processing Standard) county codes for each county were used in merging the climate/ soil data to the rest of the ARMS data in order not to generate conflicts with these different counties having the same names. The 5-year pooled-cross sectional ARMS data comprise of a total of 103,560 observations. Averaging by county, a total of 647 observations across 9 Southeastern US states are used for the estimation. The farm level observations make the data richer even though they are averaged consequently.

Table 1 gives a detailed description of the data obtained whilst Table 2 shows the summary statistics of the variables used.

Table 2.1. Data Description

Variable	Description	Measurement	Source	Apriori Sign
Farmland Value	Estimated market value of farmland	Dollar/acre[8]	ARMS	
Acres Operated	Total Size of land under operation	Acre/acre	ARMS	
Land Owned	Acres of farmland owned	Acre/acre	ARMS	
Land Rented	Acres free rented + acres share rented + acres cash rented	Acre/acre	ARMS	
Average County Specific Climate Variables				
Winter Temp	Winter mean air temperature, 1981-2010	^oF	GHCND	+/-
Spring Temp	Spring mean air temperature, 1981-2010	^oF	GHCND	+/-
Summer Temp	Summer mean air temperature, 1981-2010	^oF	GHCND	+/-
Autumn Temp	Autumn mean air temperature, 1981-2010	^oF	GHCND	+/-
Winter Preci	Winter mean cumulative precipitation, 1981-2010	cm/ season	GHCND	+/-
Spring Preci	Spring mean cumulative precipitation, 1981-2010	cm/ season	GHCND	+/-
Summer Preci	Summer mean cumulative precipitation, 1981-2010	cm/ season	GHCND	+/-
Autumn Preci	Autumn mean cumulative precipitation, 1981-2010	cm/ season	GHCND	+/-
Average County Specific Soil Characteristics				
Total Sand	Mineral particles 0.05-2.0mm in equivalent diameter as a weight percentage of the less than 2mm fraction	% Weight	SSURGO	-
Total Silt	Mineral particles 0.002-0.05mm in equivalent diameter as a weight percentage of the less than 2mm fraction	% Weight	SSURGO	-
Total Clay	Mineral particles <0.002mm in equivalent diameter as a weight percentage of the less than 2mm fraction	% Weight	SSURGO	-
Organic Matter	Weight of decomposed plant and animal residue expressed as a weight percentage of the less than 2mm soil material	% Weight	SSURGO	+
ph	Soil ph level	-	SSURGO	+/-
Salinity	Soil Electrical Conductivity	-	SSURGO	-
Soil Erodibility	Susceptibility of soil particles to detachment by water (KW factor)	-	SSURGO	-
Average County Specific Geographic Variables				
Slope Gradient	Difference in elevation between two points, expressed as a percentage of the distance between those points	%	SSURGO	+/-
Miles to town	Number of Miles from farm to the nearest town with a population of 10,000+	Miles	ARMS	-
Per Capita Income	Average County Per Capita Income	US Dollars	US Census Bureau	+
Mean Elevation	Mean elevation above sea level	Km	GHCND	-
Latitude	Decimated degrees with northern hemisphere values > 0 and southern hemisphere values < 0	Degrees	GHCND	+/-
Longitude	Decimated degrees with western hemisphere values < 0 and eastern hemisphere values > 0	Degrees	GHCND	+/-

[8] The 'per acre' variables are divided by the acres utilized, even though this makes no difference because the total acres operated and the acres utilized recorded by the survey all had the same values across the observations.

Table 2.2. Summary Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Average County Specific farm variables				
Land Value ($)	2588055	3499199	6322	43700000
Land Value/acre ($/ac)	7054.687	7910.768	500	150888.9
Acres Operated (ac)	682.6293	956.8856	2	13728.87
Acres Owned (ac)	367.906	738.3325	0	13467.7
Acres Owned/acre (ac/ac)	0.5864	0.2134	0	5.7059
Acres Rented (ac)	329.6228	440.1119	0	4814.929
Acres Rented/acre (ac/ac)	0.440	0.1955	0	1.04
Average County Specific Climate Variables				
Winter Temp (^{0}F)	45.6364	7.8365	29.78	69.7641
Spring Temp (^{0}F)	61.6789	5.3466	44.24	76.3255
Summer Temp (^{0}F)	78.0609	3.0549	64.5082	93.7664
Autumn Temp (^{0}F)	63.3853	5.7099	42.98	79.1315
Winter Preci (10mm)	27.4550	7.2286	10.6454	64.8
Spring Preci (10mm)	30.1118	5.8243	0	51.465
Summer Preci (10mm)	36.6846	9.9164	14.13	84.899
Autumn Preci (10mm)	27.2296	3.9356	5.79	44.2124
Average County Specific Soil Characteristics				
Total Sand (%wgt)	55.2984	20.9932	4.6043	90.6708
Total Silt (%wgt)	28.9778	17.6452	0.8051	76.9717
Total Clay (%wgt)	13.8809	6.1629	1.6282	37.8823
Organic Matter (%wgt)	3.5488	3.4041	0.6773	29.1429
Ph	5.3462	0.3808	4.6778	7.57
Salinity	0.1567	0.7977	0	18.4074
Soil Erodibility	0.2308	0.0923	0.0244	0.471
Average County Specific Geographic Variables				
Slope Gradient (%)	8.7145	7.0375	0.6071	42.8788
Miles to town (mi)	10.5621	8.1106	0	120
Income Per Capita ($)	22813.91	4983.15	10925	490001
Mean Elevation (mi)	106.498	112.344	1.222	670.211
Latitude (^{0})	33.9092	2.9773	25.0026	39.1430
Longitude (^{0})	-82.7697	3.5779	-91.3605	-75.7230

Table 2 shows a very wide difference in the estimated average land value per acre with some farmers estimating a market value as low as $500 whilst in some areas, an acre of land could cost as high as $150000. This confirms the nature of the land market in the US where an acre of land could be bought for some few thousands or less in certain states, but cost as high as a million dollars in other states too. The data show very high land value estimates in states such as North Carolina and Virginia whilst relatively low figures are recorded for other states such as Mississippi and Alabama and this is even slightly evident in the land value mean values as categorized by states in the appendix (Table 6). Table 2 also shows from the data, a county average of $22814 for income per capita in the Southeastern US region, which is slightly below the actual average of about $24580. This is because as is well known, agriculture predominantly occurs in relatively poorer areas, and thus there were some few rich counties that had no data on farming activities therefore making the average a little smaller. Just like the farmland value per acre values, table 6 shows that relatively richer states such as Virginia and Florida have higher income per capita averages.

Results and Discussion

Table 3 presents the log-linear regression results of the Ricardian model. The first column shows the coefficients of the model for all the variables. The second and third columns present the results of the estimated model when state dummies and all other variables except those for climate are exempted in order to determine the stability of the model, by observing any vast significant differences across the coefficients.

Almost all the variables are statistically significant implying their importance on Southeastern US farmland value. Only the longitude, latitude and slope gradient variables are not significant.

Table 2.3. Southeastern US Ricardian Regression

lnLandValue	OLS			Median Regression		
	All Variables	Without State Dummies	Only Climate Variables	All Variables	Without State Dummies	Only Climate Variables
wintertemp	0.3695***	0.3600***	0.2139***	0.2111***	0.2256***	0.0527
	(0.0290)	(0.0275)	(0.0349)	(0.0370)	(0.0265)	(0.0375)
wintertempsq	-0.0044***	-0.0044***	-0.0014***	-0.0031***	-0.0035***	-0.0013***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)
springtemp	-0.5627***	-0.5018***	-0.2631***	-0.3118***	-0.3780***	-0.4432***
	(0.0726)	(0.0708)	(0.0933)	(0.0928)	(0.0684)	(0.1005)
springtempsq	0.0048***	0.0043***	0.0026***	0.0027***	0.0030***	0.0027***
	(0.0006)	(0.0006)	(0.0008)	(0.0008)	(0.0006)	(0.0008)
summertemp	1.4213***	1.6966***	1.0734***	0.7036***	0.8697***	0.4580***
	(0.1044)	(0.1050)	(0.1315)	(0.1334)	(0.1015)	(0.1416)
summertempsq	-0.0097***	-0.0115***	-0.0084***	-0.0047***	-0.0063***	-0.0047***
	(0.0007)	(0.0007)	(0.0009)	(0.0009)	(0.0007)	(0.0009)
autumntemp	-0.0861*	-0.1436*	0.0824	-0.3774***	-0.3130***	0.1314
	(0.0744)	(0.0760)	(0.1024)	(0.0950)	(0.0735)	(0.1103)
autumntempsq	0.0008*	0.0014***	-0.0009	0.0039***	0.0037***	-0.0012
	(0.0006)	(0.0006)	(0.0008)	(0.0008)	(0.0006)	(0.0009)
winterpreci	-0.1352***	-0.0732***	-0.0336***	-0.1765***	-0.0735***	-0.0847***
	(0.0056)	(0.0047)	(0.0061)	(0.0072)	(0.0045)	(0.0066)
winterprecisq	0.0021***	0.0010***	0.0000	0.0029***	0.0010***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
springpreci	0.0148*	0.0117	0.0532***	0.0709***	0.0694***	0.0611***
	(0.0077)	(0.0076)	(0.0102)	(0.0099)	(0.0073)	(0.0110)
springprecisq	-0.0003**	-0.0003**	-0.0010***	-0.0010***	-0.0011***	-0.0011***
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
summerpreci	-0.0630***	-0.0695***	-0.1481***	-0.0220***	-0.0655***	-0.1499***
	(0.0040)	(0.0038)	(0.0043)	(0.0051)	(0.0036)	(0.0046)

summerprecisq	0.0008***	0.0009***	0.0017***	0.0003***	0.0008***	0.0016***
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)
autumnpreci	-0.0342***	0.0035	-0.0931***	-0.1389***	0.0111	-0.0588***
	(0.0075)	(0.0076)	(0.0101)	(0.0095)	(0.0073)	(0.0109)
autumnprecisq	0.0008***	0.0001	0.0022***	0.0025***	0.0001	0.0015***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
percapitaincome	0.0489***	0.0494***		0.0466***	0.0470***	
	(0.0007)	(0.0007)		(0.0009)	(0.0007)	
elevationmean	0.0024***	0.0028***		0.0031***	0.0028***	
	(0.0001)	(0.0001)		(0.0001)	(0.0001)	
latitudemean	-0.0387	-0.0800		-0.0668	-0.0954	
	(0.0090)	(0.0080)		(0.0115)	(0.0077)	
longitudemean	0.0199	0.0270**		0.0389	0.0419*	
	(0.0038)	(0.0030)		(0.0049)	(0.0029)	
slopegradient	-0.0074	-0.0074*		-0.0077	-0.0066*	
	(0.0010)	(0.0010)		(0.0013)	(0.0010)	
soilerodibilityfactor_kw	-1.7767***	-1.8599***		-1.9099***	-1.4916***	
	(0.1157)	(0.1154)		(0.1478)	(0.1116)	
organicmatter	0.0114***	0.0088***		0.0142***	0.0326***	
	(0.0018)	(0.0018)		(0.0022)	(0.0017)	
totalsand	-0.0318***	-0.0328***		-0.0394***	-0.0673***	
	(0.0015)	(0.0016)		(0.0020)	(0.0015)	
totalsilt	-0.0211***	-0.0230***		-0.0296***	-0.0595***	
	(0.0016)	(0.0017)		(0.0021)	(0.0016)	
totalclay	-0.0220***	-0.0300***		-0.0429***	-0.0769***	
	(0.0019)	(0.0019)		(0.0024)	(0.0018)	
ph	-0.0946***	-0.0270*		0.1037***	0.0100	
	(0.0156)	(0.0151)		(0.0199)	(0.0146)	
salinity	0.0411***	0.0225***		0.0450***	0.0111***	
	(0.0038)	(0.0039)		(0.0049)	(0.0038)	
milesfromtown	-0.0058***	-0.0088***		-0.0081***	-0.0103***	

	(0.0004)	(0.0004)		(0.0005)	(0.0004)	
acresowned_acre	1.1494***	1.1615***		1.5778***	1.2932***	
	(0.0530)	(0.0548)		(0.0676)	(0.0530)	
acresrented_acre	1.3014***	1.2690***		1.6689***	1.3140***	
	(0.0553)	(0.0572)		(0.0707)	(0.0553)	
Florida	0.7221***			0.7332***		
	(0.0223)			(0.0284)		
Georgia	0.4214***			0.5178***		
	(0.0170)			(0.0217)		
Kentucky	-0.0801***			-0.1453***		
	(0.0286)			(0.0365)		
Mississippi	-0.0262			-0.0333		
	(0.0177)			(0.0226)		
North Carolina	0.2915***			0.3351***		
	(0.0231)			(0.0295)		
South Carolina	0.2236***			0.1935***		
	(0.0231)			(0.0295)		
Tennessee	-0.1082***			-0.2907***		
	(0.0193)			(0.0247)		
Virginia	-0.0014			-0.1832***		
	(0.0293)			(0.0375)		
Constant	-34.274***	-42.832***	-29.201***	-23.0970***	-25.4358***	-21.7678***
	(2.1465)	(2.1509)	(2.4618)	(2.7415)	(2.0799)	(2.6502)
Observations	647	647	647	647	647	647
R-squared	0.6878	0.686	0.5491	0.4525	0.4295	0.3364
Adj. R-squared	0.6873	0.6682	0.5487			
F test	154.0.0	172.3.0	127.5.0			
Prob (F-statistic)	0.000	0.000	0.000			

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

This shows that farmlands are mainly not priced due to the geographical location of the farms, but rather due to the climatic, soil and economic characteristics associated with the location where the farm is situated. Most important are the significances of the climatic variables, showing that the amount of temperature and precipitation at any point in time during the farming cycle is very essential for higher farm values.

The statistical significance of all the squared temperature and squared precipitation coefficients imply and support most of the climate change studies that climate indeed has a nonlinear effect on farmland value. Approximate peak average temperature and cumulative precipitation levels for the southeast US could be calculated by dividing the linear coefficient of each climate variable with twice its corresponding squared coefficient. The peak temperature levels for the winter, spring, summer and autumn seasons are thus 41.99^0F, 58.61^0F, 73.26^0F and 53.81^0F respectively whilst the peak cumulative precipitation levels are 32.19cm, 24.67cm, 39.38cm and 21.38cm respectively for the winter, spring, summer and autumn seasons. The results further show that farmland values increase with warmer winter and summer temperatures but however fall with warmer spring and autumn temperatures. This finding could partly be because most vegetables and other crops (including beans, beets, broccoli, cabbage, carrots, corn, tomatoes etc.) grown in the southeastern part of the US have their flowering during the winter and summer seasons, and thus require larger amounts of sunshine to develop. It must however be noted and as seen from the results, these winter and summer temperatures have positive but declining impacts on farmland value (having negative squared values), and thus excess temperatures beyond the peak levels would be detrimental to farm growth and thus lesser farm values. Average spring and autumn temperatures have negative and increasing impacts on farmland value. The results show that only an increase in spring precipitation increases farmland value. For winter, summer and autumn seasons, increases in average monthly precipitations tend to decrease farmland value. Spring precipitation has a positive but declining impact on farmland values, whereas winter, summer and autumn precipitations have negative and increasing impact on farmland values.

Increases in sand, silt and clay reduces farmland value. This is so because as it is widely known, high of amounts of these soil particles are detrimental to plant growth and thus reduce the land values. Organic matter on the other hand increases the value of farmlands. Increases in the soil pH level reduce the farmland value. Higher elevation also increases the value of farmland, a finding which contradicts some studies, such as PMM (2012). This may be because, since some parts of the southeastern region already has a relatively higher elevation, farmers who farm at these areas may have been able to adapt to the conditions over the years and tend to have higher productivity than farming at lower elevation levels. This may also be to the fact that lower elevation farms might be more susceptible to certain negative occurrences such as flooding since the southeast does not have too many elevated areas. The state dummies also indicate that compared to Alabama, average farmland values are higher in Florida, Georgia, North Carolina and South Carolina whereas they are comparatively lesser in Kentucky, Mississippi, Tennessee and Virginia.

The regression results in the second and third columns of Table 3 show very similar coefficients like the one in the first column. These regressions were mainly run as a robustness check if the coefficients are stable. The signs on the coefficients are almost all the same with just little variation in the magnitude of the coefficients. In order to check for heteroskedasticity due to the nature of the data, robust standard errors are estimated for the regressions. Another robustness check was done by using a median regression approach to estimate the same models in the first three columns of Table 3, instead of the OLS estimator in order to verify again if there could be any significant deviations in the coefficients and the their corresponding signs. The results are presented in the last three columns of Table 3, and these do not show any wide variation in the coefficients. Table 8 in the appendix presents the Ricardian regression results using the mean deviations of temperature and precipitation. A mixed model is further run using non averaged observations (where various farmers are matched with corresponding counties) to find out if averaging by county imposes significant effects to our results. The signs and magnitudes are very similar, thus the analyses are proceeded using the OLS results.

Table 7 in the appendix presents the Ricardian regression results for rainfed farms only, irrigated farms, crop farms only and lastly livestock farms only. The signs and the magnitudes on the coefficients differ slightly across the sub-groups with some of the variables losing their statistical significance. For instance winter and spring temperatures have no effect on crop only farms because of their statistical insignificance, whilst autumn temperature unlike for the entire sample has a hill-shaped distribution, having a negative squared coefficient rather than the positive one the entire sample. Autumn temperature also tends to have no impact on livestock only farms. Apart from these however, all the other climate variables are statistically significant. But as noted, some other control variables have no effect on farmland value either for the rainfed only, irrigated, crop only or livestock only farms.

Table 4 presents the marginal effects of the estimation with respect to changes in farmland values due to changes in seasonal climate variables across the southeastern US states. This represents the percentage change in farmland value as a result of a marginal increase in temperature and precipitation by season and for the entire year. The marginal effect values are estimated for each state as seen in Table 4.

Table 2.4. Marginal Effects for Temperature and Precipitation

State	Annual Temp	Annual Preci	Winter Temp	Spring Temp	Summer Temp	Autumn Temp	Winter Preci	Spring Preci	Summer Preci	Autumn Preci
Alabama	0.0234	0.0019	-0.0380	0.0412	-0.1166	0.0683	0.0185	-0.0069	-0.0098	0.0111
Florida	-0.0128	-0.0004	-0.1441	0.1065	-0.1581	0.0875	-0.0403	-0.0002	0.0219	0.0130
Georgia	0.0227	-0.0031	-0.0490	0.0459	-0.1124	0.0691	-0.0067	-0.0024	-0.0096	0.0136
Kentucky	0.0335	-0.0032	0.0511	-0.0237	-0.0418	0.0521	-0.0190	-0.0060	-0.0159	0.0133
Mississippi	-0.0229	0.0041	-0.0388	0.0474	-0.1271	0.0687	0.0310	-0.0081	-0.0096	0.0092
North Carolina	0.0295	-0.0033	0.0022	-0.0024	-0.0541	0.0581	-0.0261	-0.0026	-0.0075	0.0117
South Carolina	0.0242	-0.0048	-0.0342	0.0345	-0.1129	0.0662	-0.0237	-0.0009	-0.0068	0.0143
Tennessee	0.0310	0.0002	0.0248	-0.0074	-0.0524	0.0556	0.0044	-0.0076	-0.0156	0.0108
Virginia	0.0347	-0.0068	0.0455	-0.0377	-0.0075	0.0501	-0.0415	-0.0023	-0.0164	0.0132

The marginal effects were estimated using the Ricardian regression coefficients in Table 3 which included all the variables. These values vary significantly across the southeastern US, and this is due to the fact that the underlying average climates of these states differ. Annual temperature is beneficial to Alabama, Georgia, Kentucky, North Carolina, South Carolina, Tennessee and Virginia whilst it is detrimental to Florida and Mississippi. Virginia has the highest marginal benefit from annual temperature of about 3.5% whilst Georgia has the lowest marginal benefit 3.8%. On the other hand, annual precipitation is detrimental to all the states except Alabama, Mississippi and Tennessee. Virginia once again has the highest marginal loss from annual precipitation of about 0.68% whilst Florida has the least marginal loss from annual precipitation of about 0.04%.

Seasonally, winter temperature is detrimental to Alabama, Florida, Georgia, Mississippi and South Carolina whilst it is beneficial to Kentucky, North Carolina, Tennessee and Virginia. Spring temperature is beneficial to all the states except Kentucky, North Carolina and Tennesee. As is mostly the case (PMM, 2012 among others), summer temperature is detrimental to all the states. Virginia however faces the least loss from summer temperature. This is because Virginia relatively has the lowest temperature and its average summer temperature is just like the average spring/ autumn temperature for the other states. Autumn temperature is however beneficial to all the states. Winter, spring and summer precipitations are mostly detrimental to almost all the states with exception of a very few. Meanwhile, autumn precipitation is beneficial to all the states in the southeastern US region.

The first two columns of Table 5 show the current farmland values and the aggregated farmland values for all the states as well as the entire southeastern US region whilst the remaining columns show the change in farmland value per acre and the corresponding aggregated total farmland values. As mentioned earlier, three different model scenarios are used for predicting the welfare gains or losses by the year 2100. This is achieved by using the coefficients from the Ricardian model in Table 3 to estimate the non-marginal changes in climate, in order to determine the predicted consequences based on the different scenarios. As explained, the difference is found between the future expected farmland value and the present farmland value in order to determine the loss or gain in welfare. This study assumes just like other studies (e.g. Seo *et al* (2008)) that all other factors remain constant with just the variation in climate variables as predicted by the models. The forecasts do not include likely changes of technology, prices, capital investments, infrastructure, and population and thus the analysis show the role climate change might play by the 2100 and not specifically how farming or farmland values will change. However, it inherently accommodates adaptation since we assume that producers in different climate areas have already adopted their technology or farm practices in order to adapt to climatic conditions in those areas. Hadley CM3 and ECHO-G models relatively have a much higher prediction compared to the

NCAR PCM model. Hadley CM3 predicts a 4.4^{0}C increase in temperature[9] and an accompanying 27.3cm decrease in annual precipitation[10] whilst ECHO-G predicts a 4.3^{0}C increase in temperature and an accompanying 16.8cm decrease in annual precipitation. The NCAR PCM model however predicts much lesser temperature and precipitation values of a 2.8^{0}C increase and a 4.2cm decrease respectively. The analyses were made by taking into account both predicted changes in temperature and precipitation rather than a partial analysis.

Table 2.5. Welfare Change per Acre and Total Welfare Change for the Southeastern US region

	Present		Hadley CM3 (by 2100)		ECHO-G (by 2100)		NCAR PCM (by 2100)	
	Land Value/ acre	Total land Value (mil $)	Impact/ acre	Total Impact (mil $)	Impact/ acre	Total Impact (mil $)	Impact/ acre	Total Impact (mil $)
AL	3728	33555.96	-210.802	-2124.13	-207.52	-2094.55	-126.71	-1367.23
FL	16185	149711.00	-6803.08	-71180.3	-6608.42	-69379.7	-3942.51	-44720
GA	5815	59025.49	-493.49	-5817.99	-463.03	-5508.82	-258.92	-3437.02
KY	3870	53798.70	1085.14	16957.31	1068.97	16732.51	653.50	10956.95
MS	2729	31113.22	-194.92	-2454.97	-195.82	-2465.27	-123.69	-1642.95
NC	6042	50751.71	873.87	8136.18	870.47	8107.60	542.21	5350.26
SC	4506	21630.24	-166.50	-961.95	-142.83	-848.29	-65.17	-475.5
TN	4575	49871.10	920.39	11323.95	899.15	11092.37	541.82	7197.19
VA	6067	49141.24	1937.49	17442.06	1921.83	17315.18	1188.69	11376.95
SeUS	7055	606028.00	-339.1	-3186.65	-317.47	-3005.44	-176.75	-1862.37

[9] Fahrenheit temperature equivalents are used for the analyses.
[10] The annual precipitation model predictions are divided by twelve in order to obtain the average monthly precipitation for the analyses.

For the entire southeastern US region, farmland value per acre and the aggregated values decrease for all the three model scenarios. Farmland value per acre decreases by $339, $317 and $177 as predicted by the Hadley CM3, ECHO-G and NCAR PCM models respectively. These are relatively less impacts representing a decrease of about 4.81%, 4.49% and 2.51% respectively compared to some huge estimated losses for some other countries and sub-regions in various studies (Adams *et al*, 1995, Kaiser *et al*, 1993, etc.). The aggregated total farmland values in the southeast region also decrease by $3.187 billion, $3.005 billion and $1.862 billion for the Hadley CM3, ECHO-G and NCAR PCM models respectively. These represent a decrease of about 0.53%, 0.49% and 0.31%. These results are consistent with the modest impact estimates in other studies.

Under the three different scenarios (Hadley CM3, ECHO-G and NCAR PCM models), the farmland per acre and total impact trends are the same for each state. That is, states either benefit or loose in terms of farmland value as a result of global warming across all the models. The magnitudes just differ as is rationally expected. Alabama, Florida, Georgia, Mississippi and South Carolina are likely to make losses in farmland values by the year 2100, with Florida getting the worst hit. South Carolina on the other hand is expected to face the least loss. Kentucky, North Carolina, Tennessee and Virginia are likely to make gains in farmland values due to the changes in climate conditions by the year 2100. Virginia would probably face the highest gain whilst North Carolina makes are expected to make the least gain.

Unlike the assertion by Deschene *et al* (2007) study, the results from the Hedonic model used in this study are robust and any large positive or negative deviations are not likely. Also, though they claim that the US agriculture in general would likely gain from climate change, this study shows that Southeast US agriculture alone would likely loose. This finding however does not debunk their result, since other parts of the US may gain and thus offset the losses faced by the Southeast.

The results are similar to that of Schlenker *et al* (2005), where losses in US agriculture are likely to occur, but not very huge as estimated by earlier agronomic studies.

Conclusion

This study uses the Ricardian (Hedonic) approach to determine the impact of climate change on agricultural farmland values for the southeastern US states. Southeastern US farm data for the analyses are obtained from the Agricultural Resource Management Survey (ARMS) database. A pooled-cross sectional analysis is performed by combining of a 5-year (2007-2011) dataset of the ARMS Survey data. Climate data for the estimations were obtained from the Global Historical Climatology Network (GHCND) Monthly Summaries whilst soil data were obtained from the Soil Survey Geographic Database (SSURGO), specifically SSURGO 2.2. The Ricardian model for the entire sample is estimated using the OLS estimator for the entire variables, all variables excluding country dummies and climate variables only. Using the same format, a median regression is also used to estimate these models in order to determine if the OLS estimates are consistent. Another regression is done using the deviations of temperature and precipitation. Using the coefficients from the Ricardian model, marginal effects representing the percentage change in farmland value as a result of a marginal increase in temperature and precipitation are estimated by season and for the entire year. The paper further makes climate impact projections on farmland values using predicted climate change data from three Atmospheric Oceanic General Circulation Models (Hadley CM3, ECHO-G and NCAR PCM).

The Ricardian regression results show that farmland values increase with warmer winter and summer temperatures but fall with warmer spring and autumn temperatures. Winter and summer temperatures have positive but declining impacts on farmland values whilst spring and autumn temperatures have negative and increasing impacts on farmland values. The results showed an increase in spring precipitation increases farmland value whilst increases in winter, summer and autumn average monthly precipitations tend to decrease farmland value. Spring precipitation has a positive but declining impact on farmland value whereas winter, summer and autumn precipitations have negative and increasing impacts on farmland values. The marginal effect results show that annual temperature is beneficial to Alabama, Georgia, Kentucky, North Carolina, South Carolina, Tennessee and Virginia whilst it is detrimental to Florida and Mississippi. On the other hand, annual precipitation is detrimental to Florida, Georgia, Kentucky, North Carolina, South Carolina and Virginia whilst being beneficial to the rest of the states. The marginal effects for the seasonal temperature and precipitation also varied significantly across the states. Lastly, the projections showed that farmland value per acre and the aggregated values for the entire southeastern US region will decrease for all the three model scenarios. Average farmland value per acre will decrease by $339, $317 and $177 as predicted by the Hadley CM3, ECHO-G and NCAR PCM models respectively representing a decrease of about 4.81%, 4.49% and 2.51% respectively. The aggregated total farmland values also decrease by $3.187 billion, $3.005 billion and $1.862 billion for the Hadley CM3, ECHO-G and NCAR PCM models respectively. These represent a decrease of about 0.53%, 0.49% and 0.31%. The seasonal projections also vary widely across the individual states.

As noted earlier on, this estimation is a comparative analysis and do not take into account the likely changes which might occur in technology, prices, capital investments, infrastructure, and population. As noted by PMM (2012), a major advantage of the Ricardian approach is how structural changes and farm responses are implicitly taken into account. Even though this study mentioned about the inherent adaptation options that farmers use to cushion themselves against changing climatic conditions, it does not go further to analyze the specific farmer behavior. It is therefore for further researches to be directed towards finding ways to incorporate adaptation into the Ricardian model.

Chapter 3. Farmer Credit Delinquency in Southeastern US: *Factors and Behavior Prediction*

Abstract

This study examines the factors and behaviors that affect Southeast US farmers' ability to meet their loan repayment 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 older farmers, 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 lower 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

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 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.

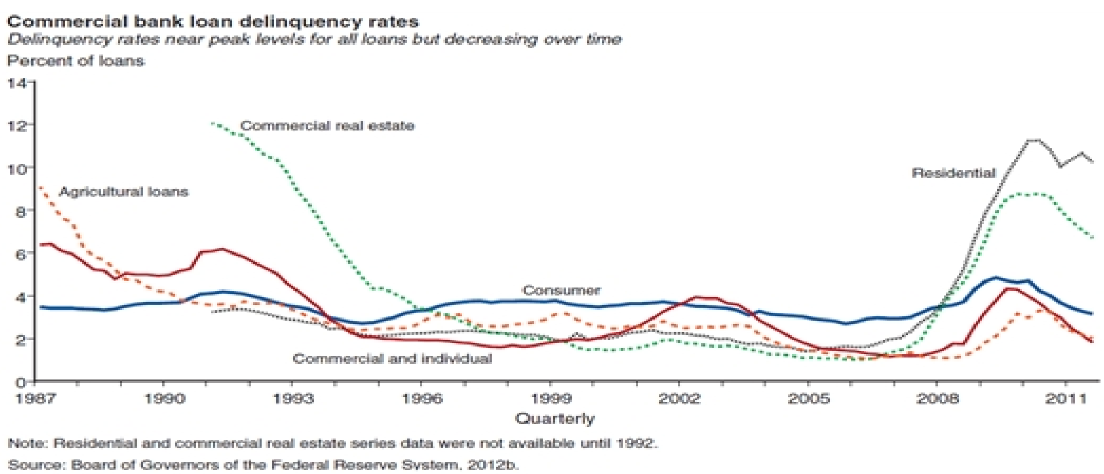

Figure 3.1. Commercial banks loan delinquency rates

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. 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. Next, the paper uses a credit-risk model to describe the behavior of 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[11], this paper examines the specific factors that affect delinquency and default in the southeast US region, whilst

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

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, research studies with regards to credit delinquency are very few. This study (by incorporating delinquency) thus also attempts to narrow the wide gap between credit default and delinquency, 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.

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 payments on time. It represents the preceding stage for a loan 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 Zech (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 be 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) base 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. 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 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 not as expected, 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.

Method

The estimation procedures used are in two folds. The first part examines the key factors that influence loan delinquency, 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, in order to estimate the probability of a farmer being delinquent. Marginal effects are used to interpret the relationship between a specific variable and the outcome of the probability.

Theoretically, credit delinquency/ default have been modeled as a function of individual characteristics that affect borrower repayment capacity, external shocks and macroeconomic variables. At each point in time, delinquency status is a function of account characteristics, customer characteristics, economic environment, and past delinquency history up to the present time (Banerjee *et al*, 2013). 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. Following Durguner's (2007) approach, this study 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;

$$Y = \beta_0 + \sum_{i=1}^{5} \beta_i X_i + \sum_{j=1}^{8} \beta_j dummy\ j + \sum_{j=i}^{8} \sum_{i=1}^{5} \beta_{ji} dummy\ j * X_i + dummy\ S$$

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

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

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.

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 for 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 combined 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.

There is no variable that would allow to directly identify delinquent or restructured loans or loans in default. Instead, I employ the following construction: I focus on medium term loans (with a term of 10 years or less and on loans smaller than 3 years). I first construct the year in which the loan must be repaid using the origination year and the term of the loan. Next, I establish if the loan was repaid or still has balance in the current year, if the current year is after the due date. If there is such balance I call that loan a loan in default. I first analyze farmers that have been delinquent within 3 years as at the survey year, in order not to capture those that were delinquent several years back, but have been in good standing for recent years. I further create an even more restricted group and only focus on loan with a term of 3 or less than 3 years and only use that variable as delinquent. This procedure would miss loans that were given within past 3 years and are delinquent but might have been restructured and are still being paid off.

Table 3.1. 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	

Table 3.2. 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 3.3. 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 3.4. 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)
Assets	-0.0263*	-0.0139*	-0.0312**	-0.0221**
	(0.147)	(0.00713)	(0.0113)	(0.00907)
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)
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 3.5. 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)
Assets	-0.00304*	-0.00174*	-0.00249**	-0.00126**
	(0.0017)	(0.00087)	(0.00107)	(0.00054)
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)
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.

Additionally, Table 11 presents the results for a probit heckman selection model, taking into consideration that farmers that had access to loans may themselves be selected. This is done to examine if the results presented in Table 4 might significantly change. The estimations are performed for only crop farmers. The selection variables used include farm income, farmer age, organic matter content of soil (for soil quality), financial debt, farm size and acres. The results generally present similar magnitude and significance levels, with few differences in some of the variables, with age being the mainly affected one. In this results, we realize that older farmers are less likely to be delinquent than younger farmers. Aside these, most of the results are similar. Tables 12 and 13 provide results when using only the first lag, second lag, no lag or both lags with coverage ratio. Coverage ratio is used to check its effect on delinquency, since it is used subsequently for the credit risk model. It is significant and negative as expected.

Table 3.6. Probit Results of Delinquency model for farmers with multiple loans

Delinquent	All (+3/-3)		Crops (+3/-3)	
	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)
Assets	-0.0209	-0.0144	-0.0452**	-0.0311**
	(0.176)	(0.0231)	(0.0196)	(0.0128)
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 capacity	0.276	-0.00520	0.535	-0.0259
	(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)		
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	1370		477	
R-squared	0.536		0.662	

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 3.7. 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 3.8. 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 education and gender are not very strong determinants of farmer credit delinquency. When corrected for selection the results show that age is a significant factor and older farmers are less likely to be delinquent than their younger counterparts. 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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Appendices

Appendix 1

Table 1.5. Marginal effects (dF/dx) for Unconstrained enterprises

Variable	Latent Variable	Unconditional Expected Value	Conditional on being Uncensored	Probability Uncensored
Cash flow	0.0195*	0.0056*	0.0051*	0.0003*
	(0.0112)	(0.0033)	(0.0029)	(0.0002)
Invoppor#	8.133	2.7417	2.2930	0.1273
	(8.341)	(2.4425)	(2.1791)	(0.1236)
Entage	2.123*	0.6217*	0.5547*	0.0314*
	(1.099)	(0.3218)	(0.2871)	(0.0163)
$Entage^2$	-0.0509*	-0.0149*	-0.0133*	-0.0008*
	(0.0301)	(0.0088)	(0.0078)	(0.0004)
Education	0.873	0.2558	0.2281	0.0129
	(2.971)	(0.8699)	(0.7761)	(0.0440)
Female#	11.83	3.4474	3.0849	0.1730
	(22.59)	(6.6143)	(5.9009)	(0.3346)
Female*Education	-4.314	-1.2631	-1.1269	-0.0639
	(4.651)	(1.3618)	(1.2150)	(0.0689)
Trade#	6.184	1.8942	1.6543	0.0932
	(8.370)	(2.4508)	(2.1866)	(0.1240)
Service#	11.25	3.6982	3.1297	0.1736
	(8.100)	(2.3718)	(2.1160)	(0.1199)
Permemploy	0.719	0.2105	0.1825	0.0106
	(0.795)	(0.2328)	(0.2077)	(0.0118)
Working hours/ week	0.699***	0.2046***	0.1825***	0.0103***
	(0.240)	(0.0702)	(0.0626)	(0.0036)
Generator Usage#	-14.75	-3.2661	-3.3674	-0.1857
	(10.07)	(2.9490)	(2.6310)	(0.1492)
Constant	-77.22***	-22.6129***	-20.1741***	-1.1439**
	(24.16)	(7.0734)	(6.3106)	(0.3578)

(#) dF/dx is for discrete change of dummy variable from 0 to 1
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.6. Marginal effects (dF/dx) for Constrained enterprises

Variable	Latent Variable	Unconditional Expected Value	Conditional on being Uncensored	Probability Uncensored
Cash flow	0.0317***	0.0103***	0.0088***	0.0015***
	(0.00789)	(0.0026)	(0.0021)	(0.0004)
Invoppor#	6.433***	2.7185***	2.0918***	0.3205***
	(1.143)	(0.3717)	(0.3158)	(0.0539)
Entage	-0.0266	-0.0266	-0.0226	-0.0039
	(0.181)	(0.0588)	(0.0499)	(0.0085)
Entage^2	-0.00158	-0.0005	-0.0004	-0.0001
	(0.00498)	(0.0016)	(0.0014)	(0.0002)
Education	0.416	0.1352	0.1148	0.0196
	(0.419)	(0.1363)	(0.1158)	(0.0198)
Female#	-3.050	-0.9807	-0.8377	-0.1423
	(2.829)	(0.9198)	(0.7813)	(0.1335)
Female*Education	0.0638	0.0207	0.0176	0.0030
	(0.595)	(0.1934)	(0.1643)	(0.0281)
Trade#	-0.176	-0.0569	-0.0485	-0.0083
	(1.235)	(0.4016)	(0.3412)	(0.0583)
Service#	0.319	0.1050	0.0887	0.0151
	(1.320)	(0.4291)	(0.3645)	(0.0623)
Permemploy	0.423***	0.1374***	0.1167***	0.0199***
	(0.130)	(0.0423)	(0.0359)	(0.0061)
Working hours/ week	0.177***	0.0576***	0.0489***	0.0084***
	(0.0365)	(0.0119)	(0.0101)	(0.0017)
Generator Usage#	1.275	0.4494	0.3686	0.0620
	(1.946)	(0.6325)	(0.5273)	0.0918
Constant	-18.31***	-5.9728***	-5.0567***	-0.8639***
	(3.477)	(1.1303)	(0.9601)	(0.1640)

(#) dF/dx is for discrete change of dummy variable from 0 to 1
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2

Table 2.6. Summary Statistics by States

Variable	AL	FL	GA	KY	MS
Average County Specific farm variables					
Land Value ($)	1673182 (1848726)	4929977 (7031723)	1980980 (1363791)	1669562 (1627406)	2550589 (2745102)
Land Value/acre ($/ac)	3728.44 (1764.34)	16184.92 (13744.91)	5815.01 (5581.16)	3870.41 (4827.28)	2729.23 (1611.99)
Acres Operated (ac)	520.09 (372.79)	1081.185 (1879.67)	530.89 (518.05)	590.54 (476.97)	911.17 (962.08)
Acres Owned (ac)	276.44 (203.55)	780.12 (1649.90)	308.27 (249.62)	307.61 (178.59)	353.77 (248.16)
Acres Owned/acre (ac/ac)	0.61 (0.23)	0.67 (0.18)	0.66 (0.16)	0.61 (0.20)	0.60 (0.26)
Acres Rented (ac)	256.16 (282.11)	328.06 (417.61)	234.87 (336.93)	295.76 (359.83)	577.60 (832.80)
Acres Rented/acre (ac/ac)	0.41 (0.22)	0.36 (0.18)	0.37 (0.16)	0.41 (0.20)	0.43 (0.26)
Average County Specific Climate Variables					
Winter Temp (^{0}F)	45.67 (3.01)	59.74 (4.66)	47.13 (3.99)	36.34 (1.96)	46.65(2.82)
Spring Temp (^{0}F)	62.46 (2.22)	70.57 (2.57)	63.01 (3.17)	56.29 (2.09)	63.73 (1.73)
Summer Temp (^{0}F)	79.0 (1.24)	81.64 (0.85)	78.88 (2.19)	75.76 (2.09)	79.92 (0.95)
Autumn Temp (^{0}F)	63.70 (2.29)	73.11 (3.19)	64.33 (3.15)	57.77 (1.86)	64.67 (1.76)
Winter Preci (10mm)	36.58 (3.23)	22.60 (8.45)	30.59 (5.41)	27.66 (3.81)	39.57 (3.48)
Spring Preci (10mm)	36.21 (3.62)	25.03 (4.50)	28.71 (4.31)	34.65 (3.06)	38.17 (3.75)
Summer Preci (10mm)	33.27 (5.21)	53.07 (7.09)	33.38 (5.76)	29.41 (2.63)	33.38 (5.86)
Autumn Preci (10mm)	28.84 (3.79)	26.54 (4.82)	25.73 (4.51)	26.18 (2.94)	31.24 (1.53)
Average County Specific Soil Characteristics					
Total Sand (%wgt)	49.33 (13.55)	81.15 (11.20)	65.56 (12.86)	20.67 (6.14)	39.92 (13.05)
Total Silt (%wgt)	33.06 (10.30)	4.89 (6.64)	20.81 (9.47)	57.98 (6.04)	43.11 (10.77)
Total Clay (%wgt)	17.19 (4.03)	4.39 (2.08)	13.10 (4.35)	21.23 (2.85)	16.48 (6.23)
Organic Matter (%wgt)	1.63 (0.59)	8.14 (4.35)	1.91 1.43	2.33 (1.23)	1.85 (0.81)
Ph	5.19 (0.18)	5.67 (0.54)	5.21 (0.17)	5.74 (0.34)	5.35 (0.38)
Salinity	0.03 (0.12)	0.56 (0.90)	0.01 (0.04)	0.0001 (0)	0.02 (0.13)
Soil Erodibility	0.26 (0.04)	0.09 (0.04)	0.21 (0.05)	0.36 (0.03)	0.34 (0.05)
Average County Specific Geographic Variables					
Slope Gradient (%)	7.82 (2.74)	2.44 (1.04)	8.08 (5.45)	11.47 (4.47)	6.51 (2.36)
Miles to town (mi)	13.56 (11.27)	6.70 (5.63)	9.71 (5.93)	15.45 (12.51)	15.34 (7.09)
Income Per Capita	21971.58 (3036.51)	24232.83 (4715.04)	22251.78 (4821.03)	21341.03 (3960.22)	19628.01 (3553.31)
Mean Elevation (mi)	97.55 (44.44)	14.69 (8.57)	112.48 (84.9)	133.86 (39.2)	58.32 (22.78)
Latitude (^{0})	33.11 (1.20)	28.65 (1.34)	32.92 (1.35)	37.47 (0.59)	32.75 (1.14)
Longitude (^{0})	-86.64 (0.82)	-82.38 (1.35)	-83.60 (0.94)	-85.76 (1.58)	-89.62 (0.67)

Mean values with standard errors in parentheses

Table 2.6 Cont'd

Variable	NC	SC	TN	VA
Average County Specific farm variables				
Land Value ($)	2049835 (1240177)	2133790 (1306817)	2440160 (1981635)	2309005 (2302898)
Land Value/acre ($/ac)	6041.87 (3327.59)	4506.30 (2614.06)	4575.33 (2417.44)	6066.82 (4106.73)
Acres Operated (ac)	528.95 (525.28)	831.57 (700.66)	769.69 (811.40)	551.57 (477.29)
Acres Owned (ac)	239.62 (371.14)	379.61 (363.74)	294.56 (226.17)	266.28 (222.08)
Acres Owned/acre (ac/ac)	0.50 (0.16)	0.52 (0.19)	0.51 (0.20)	0.56 (0.36)
Acres Rented (ac)	301.47 (291.92)	456.91 (442.27)	484.18 (650.13)	301.27 (387.15)
Acres Rented/acre (ac/ac)	0.52 (0.16)	0.49 (0.19)	0.51 (0.20)	0.49 (0.18)
Average County Specific Climate Variables				
Winter Temp (^{0}F)	42.03 (2.86)	45.84 (1.99)	39.16 (1.40)	36.61 (2.11)
Spring Temp (^{0}F)	58.77 (2.79)	62.24 (1.59)	57.90 (1.62)	54.39 (2.27)
Summer Temp (^{0}F)	76.53 (2.82)	79.12 (1.19)	76.12 (1.84)	73.56 (2.19)
Autumn Temp (^{0}F)	60.40 (2.92)	63.49 (1.71)	59.13 (1.42)	56.34 (2.60)
Winter Preci (10mm)	25.98 (4.32)	26.54 (3.43)	33.23 (2.96)	22.32 (3.55)
Spring Preci (10mm)	29.03 (4.86)	26.24 (2.69)	37.41 (3.86)	28.49 (3.53)
Summer Preci (10mm)	34.66 (5.77)	35.12 (4.91)	29.66 (3.00)	29.11 (3.88)
Autumn Preci (10mm)	28.15 (3.54)	24.81 (2.96)	29.21 (2.96)	26.23 (3.79)
Average County Specific Soil Characteristics				
Total Sand (%wgt)	58.76 (8.70)	69.74 (8.15)	24.08 (7.80)	45.78 (10.24)
Total Silt (%wgt)	27.02 (6.30)	18.24 (5.85)	54.74 (8.83)	37.16 (8.19)
Total Clay (%wgt)	14.11 (3.38)	11.85 (2.89)	20.77 (3.14)	16.95 (2.68)
Organic Matter (%wgt)	3.85 (3.02)	2.09 (0.99)	2.02 (1.56)	1.85 (0.81)
Ph	5.16 (0.25)	5.24 (0.22)	5.39 (0.25)	5.32 (1.17)
Salinity	0.11 (0.57)	0.09 (0.25)	0.000 (0.00)	0.28 (2.24)
Soil Erodibility	0.22 (0.04)	0.20 (0.05)	0.34 (0.05)	0.26 (0.03)
Average County Specific Geographic Variables				
Slope Gradient (%)	10.43 (8.87)	5.76 (4.20)	12.54 (5.44)	15.56 (7.07)
Miles to town (mi)	8.07 (5.65)	10.51 (4.19)	12.12 (7.49)	17.16 (10.06)
Income Per Capita	23327.66 (3650.07)	22476.91 (4255.49)	22348.38 (3987.60)	27747.01 (6914.93)
Mean Elevation (mi)	136.10 (152.64)	66.98 (59.78)	166.0 (78.96)	187.84 (131.62)
Latitude (^{0})	35.56 (0.49)	34.06 (0.55)	35.91 (0.46)	37.60 (0.77)
Longitude (^{0})	-79.44 (1.72)	-80.80 (1.06)	-86.27 (1.95)	-79.11 (1.55)

Mean values with standard errors in parentheses

Table 2.7. Ricardian Regression of Only Rainfed, irrigated, crops and livestock farms

lnLandValue	Only Rainfed	Irrigated Farm	Crops Only	Livestock Only
wintertemp	0.5846***	0.1182***	-0.0643	0.3982***
	(0.1177)	(0.0329)	(0.0516)	(0.0476)
wintertempsq	-0.0068***	-0.0011***	0.0008	-0.0046***
	(0.0014)	(0.0004)	(0.0006)	(0.0006)
springtemp	-1.8903***	-0.6550***	-0.1084	-0.9082***
	(0.2963)	(0.0840)	(0.1294)	(0.1184)
springtempsq	0.0154***	0.0057***	0.0007	0.0078***
	(0.0025)	(0.0007)	(0.0011)	(0.0010)
summertemp	3.2890***	1.0266***	0.9169***	1.3095***
	(0.4539)	(0.1189)	(0.1800)	(0.1771)
summertempsq	-0.0209***	-0.0071***	-0.0063***	-0.0089***
	(0.0029)	(0.0008)	(0.0012)	(0.0011)
autumntemp	-1.0979***	0.5851***	0.4762***	-0.1169
	(0.3095)	(0.0844)	(0.1354)	(0.1203)
autumntempsq	0.0090***	-0.0046***	-0.0031***	0.0012
	(0.0026)	(0.0007)	(0.0011)	(0.0010)
winterpreci	-0.0732***	-0.0906***	-0.0473***	-0.0990***
	(0.0247)	(0.0064)	(0.0109)	(0.0089)
winterprecisq	0.0014***	0.0013***	0.0009***	0.0015***
	(0.0004)	(0.0001)	(0.0002)	(0.0001)
springpreci	0.0681*	0.0609***	0.0359**	0.0020
	(0.0352)	(0.0088)	(0.0146)	(0.0119)
springprecisq	-0.0010**	-0.0009***	-0.0005**	-0.0001
	(0.0005)	(0.0001)	(0.0002)	(0.0002)
summerpreci	-0.0356*	-0.0910***	-0.0865***	-0.0555***
	(0.0183)	(0.0045)	(0.0075)	(0.0061)
summerprecisq	0.0005**	0.0012***	0.0011***	0.0008***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
autumnpreci	-0.1605***	-0.0448***	-0.0715***	-0.0257**
	(0.0374)	(0.0082)	(0.0137)	(0.0120)
autumnprecisq	0.0027***	0.0010***	0.0012***	0.0006***
	(0.0007)	(0.0001)	(0.0002)	(0.0002)
percapitaincome	0.0409***	0.0565***	0.0655***	0.0478***
	(0.0030)	(0.0008)	(0.0012)	(0.0011)
elevationmean	0.0022***	0.0025***	0.0027***	0.0017***
	(0.0004)	(0.0001)	(0.0002)	(0.0001)
latitudemean	-0.0134	-0.0046	-0.0380**	0.0127
	(0.0380)	(0.0104)	(0.0170)	(0.0139)
longitudemean	-0.0010	0.0380***	0.0202***	0.0352***
	(0.0160)	(0.0044)	(0.0074)	(0.0060)
slopegradient	-0.0192***	-0.0083***	-0.0121***	-0.0039***
	(0.0044)	(0.0011)	(0.0019)	(0.0014)
soilerodibilityfactor_kw	-0.7971	-2.1331***	-3.1507***	-0.5767***
	(0.5249)	(0.1326)	(0.2067)	(0.1896)

Table 7 Cont'd

organicmatter	0.0006	0.0202***	0.0234***	-0.0092**
	(0.0085)	(0.0020)	(0.0028)	(0.0036)
totalsand	-0.0200***	-0.0344***	-0.0439***	-0.0078***
	(0.0071)	(0.0018)	(0.0025)	(0.0029)
totalsilt	-0.0082	-0.0186***	-0.0233***	0.0011
	(0.0074)	(0.0019)	(0.0027)	(0.0030)
totalclay	-0.0012	-0.0226***	-0.0289***	0.0018
	(0.0085)	(0.0022)	(0.0031)	(0.0035)
ph	0.1224*	-0.0751***	-0.0216	-0.0358
	(0.0642)	(0.0179)	(0.0273)	(0.0254)
salinity	-0.0549	0.0468***	-0.0286***	0.0627***
	(0.0449)	(0.0043)	(0.0065)	(0.0065)
milesfromtown	-0.0043***	-0.0065***	-0.0024***	-0.0073***
	(0.0010)	(0.0005)	(0.0006)	(0.0005)
acresowned_acre	0.6594***	1.2764***	0.3532***	1.1860***
	(0.0457)	(0.0604)	(0.0220)	(0.0493)
acresrented_acre	0.6479***	1.3006***	0.3553***	1.3903***
	(0.0660)	(0.0625)	(0.0328)	(0.0562)
Florida	0.3549***	0.6215***	0.7417***	0.6034***
	(0.0998)	(0.0253)	(0.0446)	(0.0343)
Georgia	0.4080***	0.3648***	0.3644***	0.4050***
	(0.0690)	(0.0196)	(0.0363)	(0.0253)
Kentucky	-0.1192	-0.1340***	-0.0413	-0.2281***
	(0.1134)	(0.0327)	(0.0551)	(0.0435)
Mississippi	-0.1446**	0.0760***	0.0352	0.0306
	(0.0689)	(0.0204)	(0.0363)	(0.0271)
North Carolina	0.8592***	0.2348***	0.6085***	0.1566***
	(0.0953)	(0.0267)	(0.0454)	(0.0356)
South Carolina	0.5411***	0.2296***	0.3509***	0.1466***
	(0.0906)	(0.0268)	(0.0442)	(0.0363)
Tennessee	0.1084	0.0229	-0.0410	-0.0210
	(0.0755)	(0.0223)	(0.0401)	(0.0290)
Virginia	0.5024***	-0.1791***	0.2446***	-0.3379***
	(0.1204)	(0.0336)	(0.0559)	(0.0455)
Constant	-47.4769***	-31.5340***	-35.9820***	-22.2063***
	(9.4040)	(2.4507)	(3.6432)	(3.7301)
Observations	647	647	647	647
R-squared	0.5344	0.7545	0.7941	0.6045
Adj. R-squared	0.5264	0.7539	0.7930	0.6029
F test	66.31	1164	738.4	363.7
Prob (F-statistic)	0.000	0.000	0.000	0.000

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.8. Regression Results using Deviations for Temperature and Precipitation

lnLandValue	All Variables	Without State Dummies	Only Climate Variables	Continuation		
wintertemp	-0.0595***	-0.0744***	0.0395**	organicmatter	0.0159***	0.0107***
	(0.0159)	(0.0153)	(0.0182)		(0.0019)	(0.0019)
wintertempsq	-0.0018***	-0.0021***	-0.0014***	totalsand	-0.0323***	-0.0310***
	(0.0004)	(0.0003)	(0.0004)		(0.0016)	(0.0016)
springtemp	0.0506***	0.0464***	0.0641***	totalsilt	-0.0155***	-0.0160***
	(0.0074)	(0.0075)	(0.0092)		(0.0017)	(0.0017)
springtempsq	0.0065***	0.0051***	0.0026***	totalclay	-0.0209***	-0.0253***
	(0.0006)	(0.0006)	(0.0008)		(0.0020)	(0.0020)
summertemp	0.1946***	0.2131***	0.0303	ph	-0.0231	0.0596***
	(0.0230)	(0.0232)	(0.0266)		(0.0165)	(0.0157)
summertempsq	-0.0081***	-0.0084***	-0.0084***	salinity	0.0426***	0.0251***
	(0.0007)	(0.0007)	(0.0009)		(0.0040)	(0.0041)
autumntemp	-0.0149**	-0.0147**	-0.0232***	milesfromtown	-0.0071***	-0.0104***
	(0.0066)	(0.0064)	(0.0080)		(0.0005)	(0.0004)
autumntempsq	0.0032***	0.0029***	-0.0009	acresowned_acre	1.1389***	1.1210***
	(0.0006)	(0.0007)	(0.0008)		(0.0563)	(0.0577)
winterpreci	-0.0058***	-0.0114***	-0.0331***	acresrented_acre	1.2288***	1.2029***
	(0.0017)	(0.0016)	(0.0015)		(0.0587)	(0.0602)
winterprecisq	0.0015***	0.0008***	0.0000	Florida	0.6107***	
	(0.0001)	(0.0001)	(0.0001)		(0.0235)	
springpreci	0.0047***	0.0036**	-0.0046**	Georgia	0.3707***	
	(0.0018)	(0.0017)	(0.0020)		(0.0180)	
springprecisq	-0.0008***	-0.0008***	-0.0010***	Kentucky	-0.0986***	
	(0.0001)	(0.0001)	(0.0002)		(0.0301)	
summerpreci	-0.0186***	-0.0172***	-0.0455***	Mississippi	-0.0267	
	(0.0016)	(0.0014)	(0.0015)		(0.0188)	
summerprecisq	0.0011***	0.0011***	0.0017***	North Carolina	0.2892***	
	(0.0000)	(0.0000)	(0.0001)		(0.0245)	

autumnpreci	0.0134***	0.0169***	0.0392***
	(0.0014)	(0.0014)	(0.0016)
autumnprecisq	0.0013***	0.0016***	0.0022***
	(0.0001)	(0.0001)	(0.0002)
percapitaincome	0.0563***	0.0564***	
	(0.0008)	(0.0008)	
elevationmean	0.0023***	0.0028***	
	(0.0001)	(0.0001)	
latitudemean	-0.0323	-0.0969*	
	(0.0096)	(0.0084)	
longitudemean	0.0422	0.0589*	
	(0.0041)	(0.0031)	
slopegradient	-0.0066*	-0.0057***	
	(0.0010)	(0.0011)	
soilerodibilityfactor_kw	-2.0750***	-1.9914***	
	(0.1228)	(0.1215)	
South Carolina	0.2496***		
	(0.0245)		
Tennessee	-0.0108		
	(0.0204)		
Virginia	-0.1096***		
	(0.0311)		
Constant	5.1937***	8.2075***	4.6058***
	(0.5795)	(0.4927)	(0.3649)
Observations	647	647	647
R-squared	0.7605	0.7436	0.5491
Adj. R-squared	0.7599	0.7431	0.5487
F test	135.1	155.3	127.5
Prob (F-stat)	0.000	0.000	0.000

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.9. Southeastern US Ricardian Mixed Model Regression

ln_landvalue	Estimate	Standard Error
wintertemp	0.3707***	0.02898
wintertempsq	-0.00444***	0.000342
springtemp	-0.5733***	0.07262
springtempsq	0.004856***	0.000605
summertemp	1.4412***	0.1044
summertempsq	-0.00981***	0.000674
autumntemp	-0.1031***	0.07435
autumntempsq	0.001325***	0.000618
winterpreci	-0.1347***	0.005627
winterprecisq	0.002101***	0.000089
springpreci	0.01415***	0.007722
springprecisq	-0.00027*	0.000113
summerpreci	-0.06218**	0.003961
summerprecisq	0.000773***	0.000044
autumnpreci	0.03328***	0.007476
autumnprecisq	-0.00041***	0.000132
percapitaincome	0.04891***	0.000725
population	0.000656***	0.000014
elevationmean	0.002377***	0.000092
latitudemean	-0.04024***	0.009036
longitudemean	0.02074***	0.003844
slopegradient	-0.00754***	0.000986
soilerodibilityfactor_kw	-1.7929***	0.1157
organicmatter	0.01156***	0.001751
totalsand	-0.03182***	0.001548
totalsilt	-0.02086***	0.001644
totalclay	-0.02203***	0.001889
ph	-0.09465***	0.01559
salinity	0.04149***	0.003802
milesfromtown	-0.00581***	0.000430
acresowned_acre	1.1523***	0.05295
acresrented_acre	1.3040***	0.05532
Florida	0.7238***	0.02225
Georgia	0.4224***	0.01697
Kentucky	0.07309***	0.02858
Mississippi	0.02587*	0.01768
North Carolina	0.2907***	0.02308
South Carolina	0.2244***	0.02310
Tennessee	0.1040***	0.01934
Virginia	-0.01367	0.02935
Constant	-34.1211***	2.1467

Observations	103,560	
R-squared	0.776	
Adj. R-squared	0.743	
F test	11.57	
Prob (F-statistic)	0.000	

Appendix 3

Table 3.9. 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 3.9 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 3.9 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 3.10. Cross Tabulations

delinquent	Freq.	Percent
0	8633	96.28
1	333	3.72
Total	8,966	100

		Lender[12]									
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							
		Loan Term (Years)									
delinquent		1	2	3	4	5	6	7	8	9	10
0		4,069	1,110	663	255	1,370	174	313	59	19	601
1		193 (4.53)	46 (3.98)	22 (3.21)	8 (3.04)	35 (2.49)	7 (3.87)	8 (2.49)	1 (1.67)	0 (0)	13 (2.1)
Total		4,262	1,156	685	263	1,405	181	321	60	19	614

*Percentages in parentheses

[12] 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.)'.

Farmers with a single loan	Frequency	Percent
1 – One year or less	4,474	21.60
2 – Non-real estate loans >1 year	4,936	23.84
3 – Real Estate loans	11,297	54.56
Total	20,710	100.0

Operating Loans Term	Frequency	Percent
1	4,262	47.53
2	1,156	12.89
3	685	7.64
4	263	2.93
5	1,405	15.67
6	181	2.02
7	321	3.58
8	60	0.67
9	19	0.21
10	614	6.85
Total	8,966	100.0

Table 3.11. Probit Heckman Selection Model for Delinquency

	Crops Only			
delinquent	**+3**	**M.E**	**+3/-3**	**M.E**
Age (Base = <35)				
35 – 44	0.389	0.0268	0.383**	0.0218**
	(0.680)	(0.0412)	(0.161)	(0.0101)
45 -54	-0.407	-0.0527	-0.355*	-0.0219*
	(0.473)	(0.0617)	(0.185)	(0.0161)
55 – 64	-0.877*	-0.0608*	-0.373*	-0.0417*
	(0.497)	(0.0399)	(0.207)	(0.0311)
≥ 65	-0.163***	-0.0118***	-0.350*	-0.0108*
	(0.0477)	(0.00174)	(0.210)	(0.00616)
Male	0.0350	0.00682	0.0496	0.00312
	(0.0506)	(0.00710)	(0.0986)	(0.00635)
Education (Base = HS or less)				
Completed High School	-0.695	-0.0821	-0.117	-0.0214
	(0.795)	(0.108)	(0.776)	(0.0287)
Some College	0.173	0.0126	0.174	0.0235
	(0.345)	(0.0417)	(0.112)	(0.0922)
Completed College	0.526	0.0401	0.535	0.0317
	(0.392)	(0.0320)	(0.900)	(0.0523)
Acres	-0.0915	-0.00638	-0.372**	-0.0247**
	(0.120)	(0.00963)	(0.174)	(0.0102)
Farming Experience	-0.0112*	-0.00203*	-0.0627*	-0.00663*
	(0.00891)	(0.00139)	(0.0480)	(0.00415)
Farm Income	-0.0108**	-0.00185**	-0.0288***	-0.00186***
	(0.00672)	(0.000726)	(0.0032)	(0.000530)
Financial Debt	0.672**	0.0418**	0.102	0.0117
	(0.330)	(0.0169)	(0.0920)	(0.0213)
Debt-to-Asset ratio	0.103**	0.0226**	0.103*	0.0158*
	(0.0465)	(0.00107)	(0.0557)	(0.00821)
Rate of return	-0.00714	-0.000527	-0.0182**	-0.00148**
	(0.00533)	(0.000635)	(0.00515)	(0.000610)
Assets	-0.0869**	-0.00532**	-0.0270***	-0.00234***
	(0.0382)	(0.00236)	(0.0106)	(0.000852)
Net Worth	-0.662**	-0.0615**	-0.221	-0.0341
	(0.331)	(0.0291)	(0.337)	(0.0296)
Insurance	-0.532**	-0.0412**	-0.390***	-0.0539***
	(0.263)	(0.0207)	(0.054)	(0.00367)
Maximum Repayment capacity	0.0688	0.00612	0.103	0.0255
	(0.680)	(0.0573)	(0.101)	(0.0476)
Interest Rate on loan	0.445	0.0326	0.318*	0.0309
	(0.545)	(0.0412)	(0.214)	(0.0168)
Prime bank loan rate	0.0911***	0.00512***	0.0142*	0.00217*
	(0.0153)	(0.00105)	(0.00738)	(0.000716)

Loan Term	-0.0335***	-0.00312***	-0.0341**	-0.00185**
	(0.00480)	(0.000111)	(0.0167)	(0.000443)
Loan Outstanding	0.350**	0.0289**	0.775*	0.0610*
	(0.116)	(0.0105)	(0.443)	(0.0375)
Lender (Base = Commercial banks)				
FCS	-0.549**	-0.0211**	-0.542	-0.0887
	(0.225)	(0.0102)	(0.436)	(0.0699)
FSA	-0.140**	-0.0104**	-0.238*	-0.0197*
	(0.0611)	(0.00444)	(0.141)	(0.0116)
Purchase contract	-0.218**	-0.0305**	-0.245	-0.0168
	(0.0881)	(0.0166)	(0.174)	(0.0169)
IDFC	-0.0444	-0.00369	-0.103	-0.0302
	(0.0463)	(0.00421)	(0.0835)	(0.0669)
Co-ops	0.553	0.0356	0.389	0.0147
	(0.806)	(0.0845)	(0.241)	(0.436)
Any Other lenders	-0.0695	-0.00305	-1.488*	-0.265*
	(0.0890)	(0.00844)	(0.763)	(0.188)
Purpose (Base = Farm Improvement/ Rehabilitation)				
Purchase Feeder Livestock	-0.0819*	-0.00445*	-0.0142	-0.00337
	(0.0492)	(0.00296)	(0.0877)	(0.00557)
Other Livestock	-0.130**	-0.0108**	-0.0151	-0.00203
	(0.0532)	(0.00532)	(0.0905)	(0.00680)
Operating Costs	-0.112***	-0.0101***	-0.162*	-0.0205*
	(0.0294)	(0.000812)	(0.0942)	(0.0121)
Farm Equipment	0.164***	0.0315***	0.164*	0.0099*
	(0.0403)	(0.00154)	(0.0981)	(0.00513)
Debt Consolidation	-0.146***	-0.0191***	-0.152	-0.0164
	(0.0489)	(0.00222)	(0.104)	(0.0213)
Per capita income	26.501*	0.881*	31.648	0.339
	(18.261)	(0.461)	(35.795)	(0.463)
Unemployment	-0.361*	-0.0256*	0.0588	0.00625
	(0.196)	(0.0113)	(0.124)	(0.0314)
Temp	-0.206**	-0.0439**	-0.302*	-0.0369*
	(0.0959)	(0.224)	(0.118)	(0.0263)
Temp_sq	0.00202	0.000107	0.00244	0.000365
	(0.00377)	(0.000302)	(0.00509)	(0.000449)
Preci	-0.302***	-0.0403***	-0.0806**	-0.00441**
	(0.0780)	(0.00399)	(0.0303)	(0.00203)
Preci _sq	0.0385**	0.00163**	0.0560**	0.00367**
	(0.1721)	(0.000665)	(0.0290)	(0.0119)
$Temp_{t-1}$	0.0850	0.00639	-0.0761	-0.00552
	(0.0629)	(0.00668)	(0.0773)	(0.00439)
$Temp_{t-1}$_sq	-0.0000728	-0.0000066	0.0000600	0.00000416
	(0.0000512)	(0.0000550)	(0.0000642)	(0.0000942)

Preci $_{t-1}$	-0.0185	-0.00106	-0.0191	-0.00265
	(0.0859)	(0.00365)	(0.0219)	(0.00249)
Preci $_{t-1}$_sq	0.000199	0.0000336	0.00194	0.000310
	(0.000921)	(0.0000620)	(0.00239)	(0.000488)
State (Base = Alabama)				
Florida	-0.194***	-0.00863***	-0.0604	-0.00417
	(0.0529)	(0.00125)	(0.0960)	(0.00633)
Georgia	-0.458	-0.0235	0.0250	0.00171
	(0.530)	(0.0433)	(0.112)	(0.0164)
Kentucky	0.298*	0.02558*	0.131**	0.00719**
	(0.184)	(0.0138)	(0.0722)	(0.00383)
Mississippi	-0.159	-0.0326	-0.233	-0.0207
	(0.301)	(0.0418)	(0.173)	(0.0362)
North Carolina	-1.103***	-0.501***	-0.647*	-0.0393*
	(0.365)	(0.00179)	(0.401)	(0.0171)
South Carolina	-0.389	-0.0118	-0.0880	-0.00498
	(0.392)	(0.0307)	(0.105)	(0.00554)
Tennessee	0.130	0.00993	-0.395*	-0.0211*
	(0.365)	(0.0164)	(0.212)	(0.0139)
Virginia	0.669	0.0417	-0.0435**	-0.00423**
	(0.438)	(0.0523)	(0.0118)	(0.00197)
Observations	1370		477	
R-Squared	0.528		0.764	

Table 3.12. Delinquency Probit Regression Models

Delinquent	With No Climate Lags	With only the First Lag	With only the Second Lag	With Coverage Ratio
Age (Base = <35)				
35 – 44	0.453	0.595	0.522	0.539
	(0.635)	(0.518)	(0.624)	(0.555)
45 -54	-0.238	0.186	-0.587	-0.366
	(0.421)	(0.242)	(1.001)	(0.624)
55 – 64	-0.221	-0.0979	-0.520	-0.688
	(0.394)	(0.1036)	(0.563)	(0.898)
≥ 65	-0.359	-0.199	-0.539	-0.245
	(0.547)	(0.168)	(0.639)	(0.737)
Male	-0.0547	-0.0398	0.0411	-0.0263
	(0.163)	(0.0965)	(0.106)	(0.233)
Education (Base = HS or less)				
Completed High School	-0.188	-0.0826	0.379	-0.784
	(0.403)	(0.456)	(0.596)	(0.772)
Some College	0.0773	0.376	0.1314*	0.1443**
	(0.400)	(0.452)	(0.0673)	(0.0703)
Completed College	-1.180**	-0.802	-0.875	0.232
	(0.523)	(0.605)	(0.794)	(0.771)
Acres	-0.0832***	-0.0857***	-0.144***	-0.142***
	(0.0110)	(0.0130)	(0.0161)	(0.0270)
Farming Experience	-0.00763**	-0.0179**	0.0270	-0.0989**
	(0.00114)	(0.00541)	(0.0362)	(0.0394)
Farm Income	-0.0595***	-0.0446***	-0.0908***	-0.0628***
	(0.00157)	(0.00166)	(0.0199)	(0.00472)
Financial Debt	0.557	0.883*	0.503	0.298*
	(0.445)	(0.514)	(0.627)	(0.185)
Assets	-0.0192**	-0.0599	-0.0264	-0.0204*
	(0.00794)	(0.0383)	(0.440)	(0.0131)
Debt-to-Asset ratio	0.0213	0.0976	0.0388	0.0747*
	(0.266)	(0.673)	(0.0862)	(0.0424)
Rate of return	-0.00361*	-0.00754	-0.00214	-0.00285
	(0.00205)	(0.00589)	(0.00626)	(0.0132)
Net Worth	0.362	0.451	-0.129	-0.414
	(0.251)	(0.321)	(0.422)	(0.649)
Insurance	-0.0890***	-0.0654*	-0.0899**	-0.0604***
	(0.00313)	(0.0379)	(0.0397)	(0.00686)
Maximum Repayment capacity	-0.266	0.280	-0.553	-0.673
	(0.443)	(0.458)	(0.511)	(0.977)
Interest Rate on loan	0.0114*	0.0290**	0.0229*	0.0240**
	(0.00792)	(0.00601)	(0.0102)	(0.00580)
Prime bank loan rate	-0.0394**	-0.0538***	-0.0472**	-0.0873**

	(0.0159)	(0.0199)	(0.0228)	(0.0380)
Loan Term	-0.181***	-0.205***	-0.252***	-0.560***
	(0.0462)	(0.0549)	(0.0626)	(0.175)
Loan Outstanding	1.240	0.454*	0.963*	-0.624
	(0.435)	(0.279)	(0.0520)	(0.701)
Lender (Base = Commercial banks)				
FCS	-0.0214*	0.0723	-0.0572	-0.568
	(0.0109)	(0.375)	(0.434)	(0.724)
FSA	-0.688*	-1.098	-0.0727	-0.692**
	(0.382)	(0.707)	(0.921)	(0.263)
Purchase contract	1.975	5.967	3.345	5.731
	(1.261)	(5.911)	(9.033)	(4.362)
Purpose (Base = Farm Improvement/ Rehabilitation)				
Other Livestock	-0.458*	0.497	-0.197	-1.080*
	(0.238)	(0.823)	(0.884)	(0.649)
Operating Costs	-1.144***	-1.416***	-1.529***	-2.567**
	(0.314)	(0.396)	(0.508)	(1.072)
Farm Equipment	-0.472	-0.447	-0.893*	-2.491**
	(0.362)	(0.477)	(0.534)	(1.155)
Per capita income	-16.74	-25.77	13.53	-47.49
	(31.53)	(40.76)	(40.70)	(63.06)
Unemployment	-0.377**	-0.182**	-0.304***	-0.290*
	(0.161)	(0.0891)	(0.107)	(0.171)
Temp	-0.366*	-0.537*	-0.138	-0.518**
	(0.167)	(0.319)	(0.829)	(0.226)
Temp_sq	0.00253*	0.00475*	0.00201	0.0137*
	(0.00118)	(0.00230)	(0.00671)	(0.00804)
Preci	-0.126*	-0.353***	-0.415***	-0.416***
	(0.0758)	(0.112)	(0.139)	(0.0258)
Preci _sq	0.00117*	0.00311***	0.00413***	0.00683***
	(0.000681)	(0.000992)	(0.00130)	(0.00228)
$Temp_{t-1}$		-0.150**		-0.264**
		(0.0755)		(0.130)
$Temp_{t-1}$_sq		0.000108*		0.000191*
		(0.0000594)		(0.000100)
$Preci_{t-1}$		-0.0189		-0.0759***
		(0.0152)		(0.0293)
$Preci_{t-1}$_sq		0.0000169		0.0000704**
		(0.0000165)		(0.0000307)
$Temp_{t-2}$			0.232**	0.317
			(0.101)	(0.134)
$Temp_{t-2}$_sq			-0.000183**	-0.00264
			(0.0000612)	(0.00101)
$Preci_{t-2}$			-0.0190	-0.0351

			(0.0180)	(0.0412)
Preci $_{t-2}$_sq			0.000116	0.000201
			(0.000215)	(0.000339)
State (Base = Alabama)				
Florida	-0.654	-0.319	-0.498	-0.502
	(0.594)	(0.809)	(0.790)	(0.433)
Georgia	-1.210	-0.347	-0.601	-1.037
	(1.482)	(0.667)	(0.692)	(1.352)
North Carolina	-1.352**	-0.791	-2.275**	-1.908
	(0.647)	(0.807)	(0.942)	(1.312)
Tennessee	0.974**	2.146***	1.752***	5.203***
	(0.451)	(0.672)	(0.650)	(1.513)
Virginia	0.525	1.961***	0.224	4.902***
	(0.507)	(0.753)	(0.778)	(1.710)
Coverage ratio				-0.189**
				(0.0609)
Constant	-12.29*	-38.11**	-59.33**	-45.80*
	(8.3)	(18.7)	(23.4)	(29.9)
Observations	477	477	477	477
Log likelihood	-43.7	-50.2	-57.3	-36.6
Pseudo R^2	162.6	161.7	185.6	191.3
Model chi-square	104.9	80.11	169.03	147.91
Prob > Chi2	0.000	0.001	0.000	0.000

Table 3.13. Marginal Effects for Table 3.12

Delinquent	With No Climate Lags	With only the First Lag	With only the Second Lag	With Coverage Ratio
Age (Base = <35)				
35 – 44	0.0809	0.010	0.0596	0.0623
	(0.0606)	(0.0662)	(0.0765)	(0.0664)
45 -54	-0.0666	0.00991	-0.0251	-0.0650
	(0.0590)	(0.0806)	(0.0435)	(0.0494)
55 – 64	-0.00764	-0.00999	-0.0243	-0.0690
	(0.0566)	(0.01073)	(0.0486)	(0.0514)
≥ 65	-0.0131	-0.0150	-0.0605	-0.0905
	(0.0291)	(0.0217)	(0.0748)	(0.292)
Male	-0.00356	-0.00418	0.00511	-0.00368
	(0.00937)	(0.0109)	(0.0224)	(0.00563)
Education (Base = HS or less)				
Completed High School	-0.00776	-0.00271	0.0168	-0.0188
	(0.0350)	(0.00369)	(0.0993)	(0.0906)
Some College	0.00352	0.0168	0.0251*	0.0632**
	(0.0158)	(0.0223)	(0.0130)	(0.0290)
Completed College	-0.0316**	-0.0161	-0.0181	-0.0415
	(0.0142)	(0.0221)	(0.109)	(0.202)
Acres	-0.00363***	-0.00291***	-0.0458***	-0.0168***
	(0.0000163)	(0.000398)	(0.00277)	(0.000806)
Farming Experience	-0.000333**	-0.000608**	0.000862	-0.00126**
	(0.000107)	(0.000226)	(0.00520)	(0.000604)
Farm Income	-0.00849***	-0.000835***	-0.00289***	-0.00218***
	(0.000784)	(0.000114)	(0.000175)	(0.00107)
Financial Debt	0.00243	0.0300*	0.0160	0.00925*
	(0.109)	(0.0107)	(0.0968)	(0.00443)
Assets	-0.000839**	-0.00203	-0.000840	-0.00612*
	(0.000376)	(0.0276)	(0.00525)	(0.00396)
Debt-to-Asset ratio	0.000928	0.00331	0.00124	0.000342*
	(0.0416)	(0.00451)	(0.0746)	(0.000164)
Rate of return	-0.000157*	-0.000256	-0.000682	-0.000170
	(0.0000706)	(0.000347)	(0.00412)	(0.000814)
Net Worth	0.0205	0.0153	-0.0410	-0.00934
	(0.0316)	(0.0208)	(0.248)	(0.0449)
Insurance	-0.00274***	-0.00156*	-0.00201**	-0.000801***
	(0.000124)	(0.000713)	(0.000721)	(0.0000377)
Maximum Repayment capacity	-0.0116	0.00950	-0.0176	-0.0843
	(0.0519)	(0.0129)	(0.106)	(0.0404)
Interest Rate on loan	0.00498*	0.000983**	0.00129*	0.00355**
	(0.00226)	(0.000334)	(0.000741)	(0.00106)

Prime bank loan rate	-0.00172	-0.000183	-0.0000151	-0.000528
	(0.0771)	(0.0248)	(0.000909)	(0.0253)
Loan Term	-0.0290***	-0.0195***	-0.00804***	-0.0250***
	(0.000354)	(0.000945)	(0.000485)	(0.00120)
Loan Outstanding	0.105	0.0154*	0.0307*	-0.00992
	(0.506)	(0.00729)	(0.0186)	(0.0475)
Lender (Base = Commercial banks)				
FCS	-0.000918*	0.00262	-0.00172	-0.0407
	(0.000532)	(0.0355)	(0.0109)	(0.199)
FSA	-0.0836*	-0.0338	-0.0269	-0.0427**
	(0.04923)	(0.365)	(0.172)	(0.0148)
Purchase contract	0.148	0.385	0.155	0.125
	(0.407)	(0.873)	(0.877)	(0.850)
Purpose (Base = Farm Improvement/ Rehabilitation)				
Other Livestock	0.0400*	0.0450	-0.0426	-0.0917*
	(0.0264)	(0.0561)	(0.268)	(0.0549)
Operating Costs	-0.0869***	-0.161***	-0.256***	-0.137**
	(0.00347)	(0.0187)	(0.0132)	(0.0613)
Farm Equipment	-0.0137	-0.0267	-0.0137*	-0.0410**
	(0.0636)	(0.0334)	(0.00837)	(0.0108)
Per capita income	-0.730	-0.874	0.431	-0.520
	(3.274)	(1.189)	(0.526)	(0.490)
Unemployment	-0.0773**	-0.00617**	-0.00968***	-0.0236*
	(0.0347)	(0.00239)	(0.000584)	(0.0113)
Temp	-0.0160*	-0.0182*	-0.0441	-0.0249**
	(0.00716)	(0.0100)	(0.267)	(0.00919)
Temp_sq	0.000110*	0.000161*	0.000339	0.000146*
	(0.0000695)	(0.000719)	(0.00386)	(0.0000700)
Preci	-0.0548*	-0.0120***	-0.0132***	-0.0152***
	(0.0346)	(0.00163)	(0.000798)	(0.00229)
Preci _sq	0.000509*	0.000106***	0.000132***	0.000120***
	(0.000228)	(0.0000144)	(0.00000794)	(0.0000577)
$Temp_{t-1}$		-0.0509**		-0.0152**
		(0.0292)		(0.00558)
$Temp_{t-1}$_sq		0.0000366*		0.0000301*
		(0.0000198)		(0.0000190)
$Preci_{t-1}$		-0.000642		-0.00517***
		(0.000873)		(0.00333)
$Preci_{t-1}$_sq		0.00000572		0.00000490**
		(0.0000778)		(0.0000167)
$Temp_{t-2}$			0.00738**	0.0175**
			(0.00345)	(0.00597)
$Temp_{t-2}$_sq			-0.0000358**	-0.000401
			(0.0000120)	(0.00101)

Preci $_{t-2}$			-0.000605	-0.00112
			(0.00365)	(0.00236)
Preci $_{t-2}$_sq			0.00000369	0.000417
			(0.0000223)	(0.00108)
State (Base = Alabama)				
Florida	0.0310	-0.0703	0.0453	-0.0467
	(0.0541)	(0.0180)	(0.0656)	(0.0666)
Georgia	-0.0713	-0.0706	-0.0643	0.109
	(0.328)	(0.0989)	(0.0526)	(0.520)
North Carolina	-0.0284**	-0.0143	-0.0347**	-0.0646
	(0.00630)	(0.0199)	(0.00103)	(0.310)
Tennessee	0.0519**	0.0203***	0.0455***	0.0236***
	(0.0252)	(.000774)	(0.000699)	(0.000764)
Virginia	0.0464	0.0249***	0.0110	0.0369***
	(0.189)	(0.00010)	(0.0654)	(0.00149)
Coverage ratio				-0.0486**
				(0.0133)