Essays on Farmer Consumption Choices, Beginning Farmers Credit Constraints and Exit

by

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A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
December 10, 2016

Keywords: food safety, household utility, beginning farmers/ranchers, farm survival, climate risk, liability of adolescence

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Abstract

The dissertation is divided into three chapters, the first concerning the choice of food safety in Ghana, the second on Beginning farmer credit constraints, and the last on beginning farmer survival.

Chapter 1 uses linear and logistic regression to show household composition's impact on food safety choices for subsistence households in the Ashanti region of Ghana. Three biomarkers act as proxies for the consumption of aflatoxin contaminated groundnuts. OLS regression and a test for endogeneity verify that the impact of consumer-to-worker ratio is robust and unbiased overall. All models show that both the number of children attending school and the number of children under 10 are household composition variables that are significantly associated with contamination levels, and thus food safety decisions. (Key words: aflatoxin, consumer worker ratio, food safety, groundnut safety, household composition, peanut toxin, utility of food safety. JEL Classification: Q1, Q10, Q12, I10, I15).

Chapter 2 seeks to answer how capital constraints influence the profitability of beginning farmers and ranchers (BFRs). Using propensity score matching with nearest neighbor and mahalanobis distance algorithms, we confirm that there is a negative treatment effect of between \$4,700 and \$35,400 for credit constrained beginning farmers and ranchers (BFRs). This represents a -14% to -77% loss with similar per acre losses in the value of production. Constrained BFRs are younger, less liquid, more likely to lease, and concentrated in the South compared to their unconstrained peers. The high variance in the differential value of production shows the breadth of diversity and the challenges in classifying BFR credit needs. (Key words:

propensity score matching, beginning farmer rancher, credit constraints, finance, family farm. JEL Classification: Q00, Q14, G02, D13, D14, D24).

Chapter 3 uses a 1992-2012 Agricultural Census panel of beginning farmers and ranchers from which we estimate a probit model with marginal effects. We find evidence that climate variation affects farmers, especially seasonal rainfall variation. Farmer scale in terms of sales and assets does decrease exit, but we find no evidence that government payment intensity does the same. We find weak support for the liability of adolescence hypothesis and observe a slowing increase of failure risk when comparing those farming 8 to 10 years with those less than 7. (Key words: beginning farmer rancher, survival, hazard, liability of adolescence, risk, climate. JEL Classification: Q00, Q12, Q14, Q50, D00).

Acknowledgments

I am grateful for all of the time and support of all of my committee members, faculty, and staff at Auburn University who helped me achieve this labor. I would like to thank Dr. Valentina Hartarska for her leadership of this process as well as Dr. Curtis Jolly for all of his support through the years. I extend my gratitude to Dr. Mark Carpenter for the many hours we spent on statistical methodology. I would like to thank Dr. Kinnucan and Randy Beard for their rigorous instruction of micro economic theory. Thank you Dr. David Curry of the Crummer Graduate School of Business for inspiring me to pursue economics at the highest academic levels. Also from Central Florida I would like to thank Dr. Keith Whittingham and Jonathan Baker, S.V.P. for gifting me with practical skills in data analytics. For those who supported my professional development, I thank Dr. Deacue Fields, Dr. Overtoun Jenda, Dr. Jocelyn Vickers, and Dr. Ansley Abraham. I would not be where I am without the support of Dr. Paul Mohr, Alabama Commission on Higher Education. Of the many who stood out in facilitating a difficult research undertaking, Dr. Denis Nadolnyak, Claudine Jenda, and all of the staff at Agricultural Economics and Rural Sociology Department -- thank you. I would like to give a special thanks to the staff of the USDA without whom this research would not be possible; the ERS and NASS staff in Washington DC and the NASS staff in Athens, GA. My family supported me through these difficult years and I wish to thank my wonderful mother, father, my older brother who was always there to lend a hand, and all of my relatives, past and present. To the above and anyone that I left out, thank you all.

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List of Abbreviations

AFB1	Alfatoxin Blue-1
BFR	Beginning Farmers and Ranchers
EFR	Experience Farmers and Ranchers
LOA	Liability of Adolescence
NASS	National Agricultural Statistical Service
USDA	US Department of Agriculture
ERS	Economic Research Service
OMB	Office of Management and Budgets
BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
NOAA	National Oceanic Atmospheric Administration

Chapter 1: Essays on Farmer Consumption Choices, Beginning Farmers Credit Constraints and Exit

1.1 Problem

The study has dual purposes: the first is to discover how household composition, income, and other socio-economic and demographic factors affect food safety decisions in rural Ghana; the second is to explore how the findings can add to already established policy interventions. It is taken for granted that households of lower socio-economic status relative to a given population may consume food of an inferior quality that is less nutritious and in some cases less safe. Family income and the number of dependents determine the effective income of the household, and may move the household towards more (less) safe food. There exists some work on income and less food safety preference for higher income individuals in developed countries. Baker and Crosbie (1993) observed that having a higher income increased the probability of price sensitivity to intervention while Patil et al. (2005) found individuals who were engaging in riskier consumption (raw milk, raw meat, etc.) tended to have higher than average income. These findings are counter-intuitive but not uniform. Dosman et al. (2001) hypothesized that wealthier consumers perceive food to be less risky because they have better access to safe foods while Knight and Warland (2004) believe that perceived vulnerability to risk is influenced by socio-demographics. Some earlier works affirm the conventional wisdom that income is positively related to a consumer's willingness to pay to avoid risk and concern about health (McDaniels et al. 1992; Hamilton 1985a, 1985b). The latter study was conducted in Canada while the formers were conducted in the US. Stated consumption preferences in developed countries may not be good predictors of decision behavior in developing countries where income is significantly lower and where dependency ratios are much higher. Yet the existing food safety literature is rather narrow, instead focusing more on trade and toxicology (see Athukorala and Jayasuriya, 2003; Otsuki, 2001; Wagacha and Muthomi, 2008 and others). What is missing from the food safety literature is how socio-demographic variables (e.g. consumer-to-worker ratios) of households in developing countries affect the real socio-economic condition of those households and their subsequent food safety decisions. This is the first paper to directly address the role of household composition on food safety decisions in rural Ghana. The first part of the paper includes a review of the literature on aflatoxin, Ghanaian rural society, and household production and consumption. The discussion then moves to modeling household utility. The third part describes the data, the fourth part describes the methodology, the fifth part presents the results, and the paper concludes with a discussion of the findings and recommendations for future research.

1.2 Literature

Mycotoxins are the ubiquitous toxic by-products of fungi such as molds. One particular mycotoxin, aflatoxin B1 (AFB1), is one of the most potent liver carcinogens known. Aflatoxin is the by-product from the mold species, aspergillus flavus, which commonly grows in groundnuts, maize, cocoa, dried fruits, and other agricultural products (Bankole and Adebanjo, 2003). The diet of rural Ghanaians and other peanut and/or maize consuming Africans places them at risk for consuming tainted staples. The World Health Organization and other researchers acknowledge that 20 parts per billion is generally the upper limit for safe human consumption (Wu, 2006). Consuming high levels of aflatoxin is associated with stunted growth, immunosuppression, productivity loss, liver cancer, toxicosis (diseased condition), and in severe cases death (Bankole and Adebanjo, 2003; Turner et al., 2003; Wang et al., 2001). It is also known that the interaction of aflatoxin with Hepatitis B (HBV) greatly increases the likelihood that an individual will develop liver cancer (Wogan et al. 2004). The survey used for this study finds that 17% of those sampled were HBV carriers. This compares to less than 1% of the population in Western Europe and North America (WHO, 2008).

A Risky Climate. Shank et al. (1972), show how the mean and variance of aflatoxin contamination greatly increase during the wet seasons and very dry seasons. In a geostatic analysis of toxin producing fungi, Cotty and Jaime-Garcia (2007) confirm that fungal growth is more prevalent in climates that are both warm and humid as well as dry and irrigated. They identify two phases of aspergillus growth: the first occurring when crops are stressed by drought; the second occurring post-harvest due to warmth and humidity. Figure 1-1 shows the study area, Ejura-Sekyedumase, which is located in the central west region of Ghana. Figure 1-2 shows the departure from the mean monthly rainfall and temperature. Variation in both rainfall and temperature has increased. This can cause plant stress and promote fungal growth as identified by Cotty and Jaime-Garcia. Ghana's natural climate is a major risk factor for aflatoxin contamination. There are other important risk factors such as consumption preferences, resource constraints, and groundnut production practices, as the ensuing literature highlights.

Ghanaian Rural Society. The state of Ghana is home to 24.8 million people with 56% of the labor force employed in the agricultural sector. (CIA World Factbook, 2005). Most of those employed in agriculture live in rural areas and earn $.14 per hour compared to the $.26 national average. The most common crops produced are cocoa, rice, cassava, maize, shea nuts, bananas, and groundnuts. The Ghanaian Living and Standards Survey (2008) reports that in 2000, the average household size was 5.1 and the size of rural households were 5.4. It is estimated that 80% of Ghanaians consume groundnuts while 32% consume groundnuts more than three times a week (Jolly, et al 2008). The strong cultural preference for groundnut consumption places the population at risk for aflatoxin exposure, unless steps are taken to mitigate that risk.

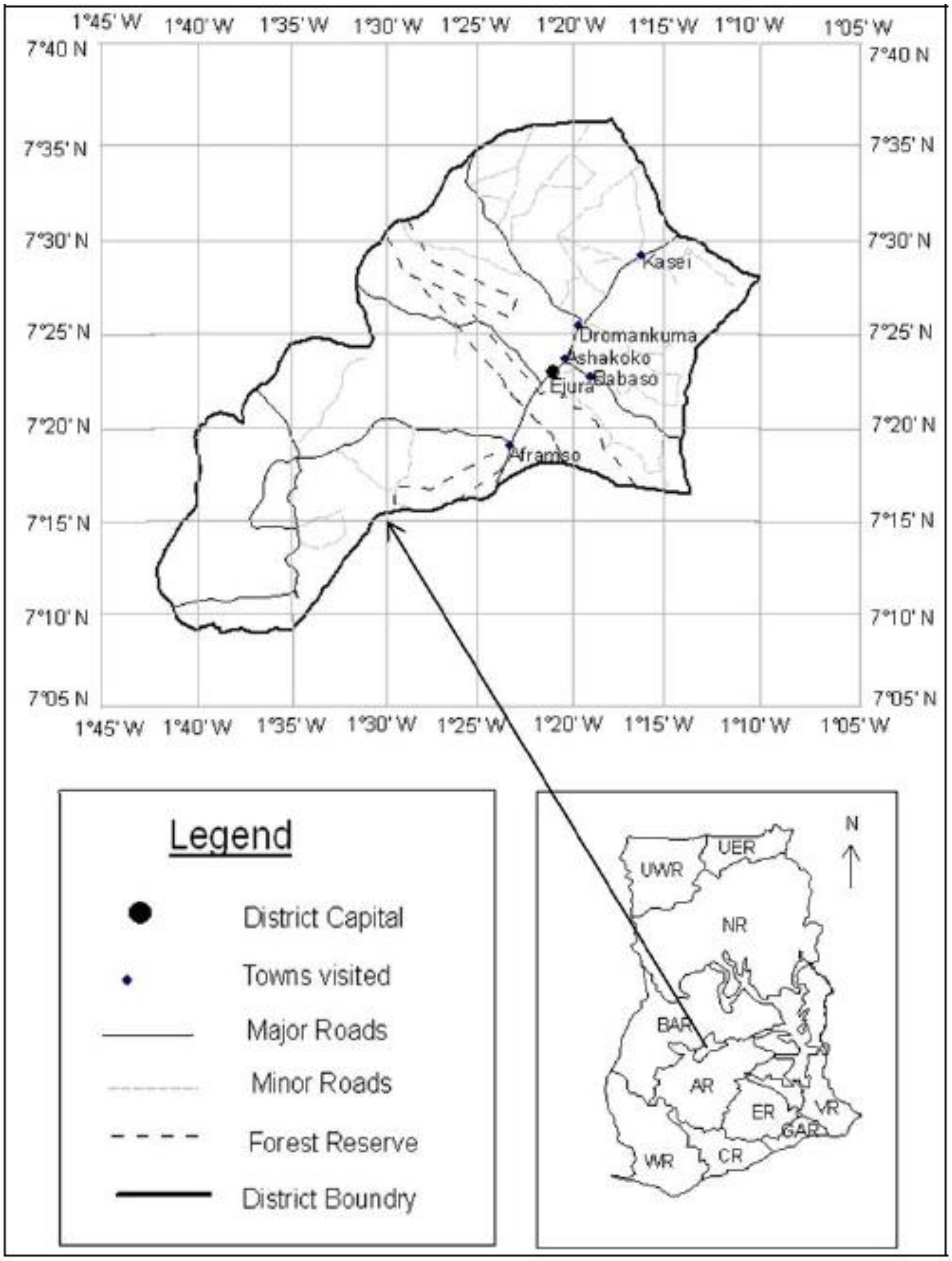

Figure 1-1 A Map of Ejura-Sekyedumase District, Ghana (www.arpnjournals.com)

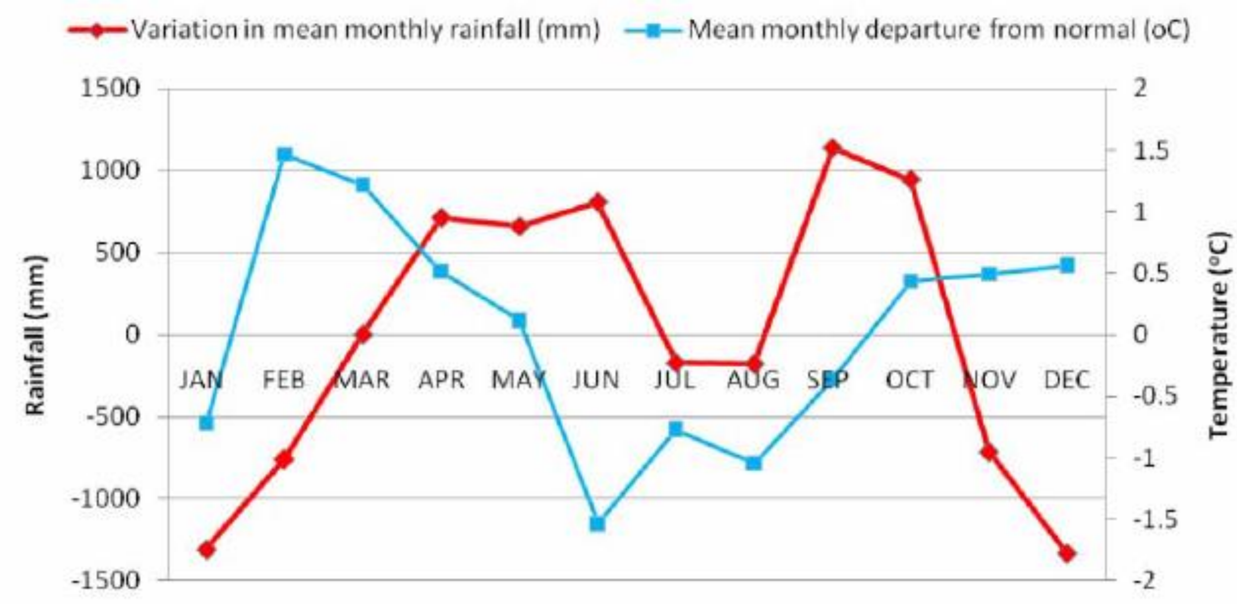

Figure 1-2 Mean monthly temperature and rainfall departure, 1993-2006. (Baselines for rainfall and temperature are 1430 mm and 26.3° C, respectively).

Mitigating Risk. *Why do people choose not to manage these risks more effectively?* Actively managing food safety at both production and consumption stages is essential for reducing the risk and impact of these toxins. The FAO and WHO (2003) and the University of Maryland Extension (2000) also assert that good hygienic and manufacturing processes reduces the appearance of fungi, thereby reducing toxin formation. There have been numerous other studies on post-harvesting activities in Ghana and other developing countries (see Kitinoja et al., 2011; Amoako-Attah et al. 2007). All reports indicate that current post-harvest practices are insufficient to prevent spoilage and losses. Improper storage and handling practices that fail to dry pods, do not control humidity, and leave groundnuts exposed to pests and the environment can all lead to mold infestation. Sorting groundnuts is also an important supply chain activity. Although the vast majority of surveyed market participants across Ghana reported that they sorted their peanuts, only half of marketers and processors sorted their produce. Ninety percent of respondents had no conception of what aflatoxin is or its associated dangers (Awuah et al.

2008). This suggests both a knowledge barrier to food safety as well as unconscious mitigation under the auspices of quality improvement. In many cases quality mirrors food safety decisions (e.g. sorting and drying to prevent mold growth and improve taste). When households and subsistence farmers are poor, food safety may suffer.

Household Production. A joint report from the Food and Agricultural Organization and the World Food Program (FAO-WFP, 2001) highlights important aspects of Ghanaian agricultural production, including risks and productive constraints. The 40% average interest rate, high fertilizer prices, and limited availability of productive capital such as tractors and oxen, all result in suboptimal input use, inefficient production, and lower yields for the multitude of small farmers. In resource constrained households, it is typical for the entire family, even children, to be engaged in production. Mull and Kirkhorn (2005) report that 39.7% of rural Ghanaian children participate in the economy with 73.6% of them working in agriculture. The corresponding figures for their urban peers are only 19.8% and 21.5%. Part V sections 87 and 89, and 90 of the Ghana Children's Act (1998), forbid the "exploitative" labor of all children, while allowing for "light" work at the age of 13, and formal employment at the age of 15.[1] Due to financial hardships and poor enforcement mechanisms, Mull and Kirkhorn are skeptical of the Act's effectiveness. Households may choose to exploit children through labor in order to expand production. Households that have many dependents and cannot expand production due to lack of resources or inputs may self-exploit by foregoing spoilage discard, purchasing inferior quality groundnuts, and in other ways lowering the acceptable safety level of consumption. This "safety

[1] Labor is "exploitative" of a child if it deprives the child of its health, education or development and "light" work constitutes work which is not likely to be harmful to the health or development of the child and does not affect the child's attendance at school or the capacity of the child to benefit from school work. See http://www.law.yale.edu/rcw/rcw/jurisdictions/afw/ghana/ghana_childrens_act.pdf for the entire Act.

rationing" ensures that the most hazardous food is produced and consumed by the most stressed households.

Safety Rationing. Chayanov (1966) and Ellis (1993) believe that peasant households have the capacity to self-exploit when burdened by many consumers and insufficient produce or income. When household labor is flexible, the self-exploitation takes the form of lowering the subjective wage to achieve higher output. Figure 1-3 shows the Chayanov peasant production model.[2] A better term than "peasant" might be "subsistence" which Chamberlin (2008) considers synonymous with smallholder i.e. owning 2-10 ha. This definition seems appropriate since the FAO-WFP (2001) reports that the average Ghanaian land holding is less than 2 ha. Notice how an increase in consumers relative to workers increases labor (reduces leisure) to L_2 in order to meet the new minimum subsistence level Y_2. This new tradeoff between leisure and output is characterized by the transformation of I_1 to I_2. When household labor is treated as optimally fixed according to household composition, self-exploitation may take the form of safety rationing: the production and consumption of less safe food due to resource constraints. There has been some research on socio-economics and food safety with Wagacha and Muthomi (2008) noting that many sub-Saharan Africans are exposed to mycotoxins because of their socio-economic status. Resource constraints and lack of education prevent climate controlled storage and proper post-harvest handling. Low income and large households make consuming substandard produce necessary. This is supported by Mintah and Hunter (1978) and Kpodo et al.(2000) finding aflatoxin present in over half of the groundnut samples taken in Accra, as well

[2] The assumptions of Chayanov's model are: 1) no market for labor outside of the household, 2) farm output can be either retained for home consumption or sold at the market price, 3) all peasant households have flexible access to land for cultivation, and 4) each peasant community has a social norm for the minimal acceptable consumption level.

as by Jolly et al.'s (2006) finding that the majority of study participants had aflatoxin present in their urine and blood.

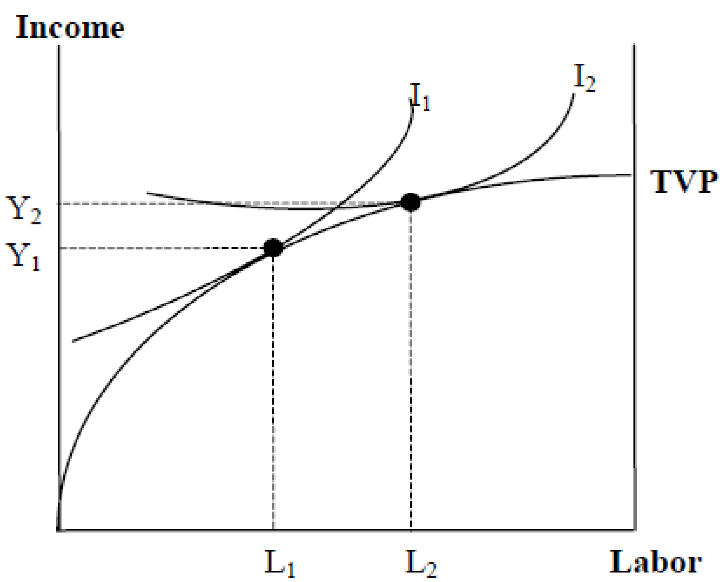

Figure 1-3 The Subsistence Household Utility Function and Production Constraint

1.3 Model and Methodology

Suppose a household has a utility function that captures the food safety at issue and subsistence household production as follows:

(1) $$U(Y_b, Y_g), = (\beta Y_b)^{\delta} + (\gamma Y_g)^{\delta}.$$

The production technology is concave and represented by:

(2) $$Y_b = B(l), \text{ and}$$

(3) $$Y_g = G(l).$$

Both consumption (utility) and production are subject to:

(4) $$l_0(w) \geq l,$$

(5) $$Y_0(c) \leq Y_b + Y_g.$$

Where Y_b is unsafe produce; Y_g is safe produce; β and γ are parameters associated with the relative utility from consuming each, where $\gamma > \beta$. The additive components of utility represent substitutability between the two with an imposed independent marginal utility of consumption. That leaves δ, where $0 < \delta < 1$, which allows for decreasing marginal utility of consumption, l_0 is the maximum amount of labor available as a function of *w* workers in the household, and Y_0 is the minimum acceptable level of consumption as determined by *c* consumers in the household. It can be shown that the system of equations (1) - (5) will have a reduced form of:

(6) $$R^* = G^*(c,w)/B^*(c,w)$$

See the appendix for the full derivation. A weakness of this approach is that it assumes that marginal utility is the same for all household members. A member who is sick or has mold allergies may have a rapidly declining marginal utility of tainted consumption. An important characteristic of this formulation is that it evaluates the safety ratio at the subsistence level i.e. at the level of zero utility.

The choice for food safety, R^* is modeled in two different ways: The first uses continuous biomarkers as dependent variables while the second approach uses limited dependent variables based on the medians of each biomarker. The first approach models safety as a continuous variable which is linear in household composition and characteristics.

(7) $$R^s = \alpha_0 + \sum_{j=1}^{j} \alpha_j{}^s X_j + \varepsilon^s$$

Where R is a given household's chosen safety level, *s* is a superscript for the food safety proxy being tested, α_0 is the intercept, and α_j is the j^{th} coefficient for independent variable X_j and ε^s is a normally distributed error term. OLS is first used to estimate the predictors' effects on all of the biomarkers.[3] Empirically we estimate the equation:

$$R^{*} = \beta_0 + \beta_1 cw + \beta_2 cw\_part + \beta_3 net\_cw + \beta_4 IncPerCap + \beta_5 BilMthCap + \beta_6 Age + \beta_7 Gender + \beta_8 FormalEd + \beta_9 HBSurfaceAG + \beta_{10} loc2 + \beta_{11} loc3 + \varepsilon \quad (8)$$

Where *cw* is ratio of consumers to workers, *cw_part* removes children under 9 as workers from cw, and net_cw removes children in primary and secondary school as workers.

The primary hypothesis that will be tested are:

h1: $$\frac{\partial R^{*}}{\partial cw} \equiv \beta_2 < 0$$

Allowing for off-farm wage opportunities at some prevailing rate, output generated from on-farm activities and wage labor will be aggregated under:

$$I = Y_b + Y_g + wl, \quad (9)$$

Which is similar to Michael and Becker's Full income.[4] This way, labor can be traded for wages to purchase food, or for food itself. Income is normalized by dividing I by the number of household members. This yields:

h2: $$\frac{\partial R^{*}}{\partial I} \equiv \beta_4 > 0, \text{ and}$$

where *I* is household income per capita. (h1) states that food safety level decreases (increases) with each additional consumer (worker) and captures the hypothesized impact of changes in the consumer-to-worker ratio (*cw*). (h3) recognizes that 1) opportunities may exist for off-farm or extra-household work and 2) unsafe food is an inferior good. We use *cw, net_cw,* and *cw_part* in accordance with the role of children in household production and the capacity for households to

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[3] The strength of this approach is that it does not rely on the often varying or even absent medical consensus on what constitutes a "safe" level of a given biomarker as long as they're monotonically increasing in harm. The drawback is that biological markers may not be linearly related to every variable.

[4] Michael and Becker (1973) summarize an approach to New home economics where household necessities could be produced from time *T* and market commodities *x*, $Z = f(x_i, T_i)$. They go on to define full income as: $F = w\sum T_i + \sum p_i x_i$ where *w* and *p* are the market wage rate and the price of input, respectively.

self-exploit (Mull and Kirkhorn, 2005; Ellis, 1993; Chayanov, 1966). Additional variables we use are *IncPerCap* and *BilMthCap* to account for full per capita income and expenses (Michael and Becker, 1973). *Gender, Age,* and *FormalEd* were all determinants of mitigating aflatoxin exposure via sorting (Awuah et al., 2009). *HBSurfaceAG* is a dummy for presence of Hepatitis B and was chosen because HBV inhibits the removal of AFB1 (Kew, 2003). Village dummies *loc1* (Nkwanta), loc2 *(*Hiawoanwu), and *loc3 (*Dromankuma) were chosen to account for geographical differences in aflatoxin exposure.

For the second approach we use a maximum likelihood estimator to maximize the likelihood of having higher than median biomarker level which is also evidence of consuming less safe food. The limited dependent variables are *HiAFB1* for higher than median AFB1, *HiBil* for higher Bilirubin, and *HiAST/ALT* for higher AST/ALT. This approach may be useful because an agreed upon low or "normal" amount of AFB1 is hard to find in the literature, the standards for bilirubin are varied, and all proxies, including AST/ALT, are positively skewed.[5] To this end the binomial choice of food safety is modeled by adapting a food quality choice model laid out by Cicia, Del Giudice, and Scarpa (2002):

(10) $$U^s_{R,i} = v^s_{R,i} + \varepsilon^s_{R,i} = \sum_{j=1}^{j} \beta^s_j X_{p,R,i} + \varepsilon^s_{R,i}$$

where, *S* is a superscript for the safety proxy, $U_{R,i}$ is the utility household *i* receives from safety choice *R*, $v_{j,i}$ is the observable component of utility, $\varepsilon_{R,i}$ is the unobservable component of utility, $X_{p,R,i}$ is household *i's* preference *p*, for choice *j*. The probability of observing decision *R* will be a function of the probability that the utility of choice *R* is greater than the utilility of the other choice. Dropping the s superscript *S* the decision rule is:

(11) $$P(U_{R,i}) = P(U_{R,i} \geq U_{\neq R,i}),$$

[5] Normal is not agreed upon but human adult ranges are 0-1.9 depending on individual health and circumstances. For more information see LSU Sciences Center, WebMd, and Medline Plus online health references.

For every food safety proxy. The corresponding binomial logistic function for a given utility of choice is:

$$\frac{P(U_{R,i})}{1-P(U_{R,i})} = \frac{\exp(\beta_0 + \beta_j x_{p,R,i})}{1+\exp(\beta_0 + \beta_j x_{p,R,i})} \tag{12}$$

To make the estimation more tractable, the model is often transformed via natural log into a logit:

$$\text{logit}(U_{R,i}) = \beta_0 + \beta_j x_{p,R,i}\,, \tag{13}$$

Where β_j now corresponds to changes in the log probability of having a higher biomarker i.e. unsafe food consumption, and *X* is a vector of previously defined predictors. Before estimating the model the key household composition variables are constructed.

Figure 1-4 shows a scatter plot depicting *cw* and AFB1. The relationship looks linear, but a formal regression is needed for confirmation.

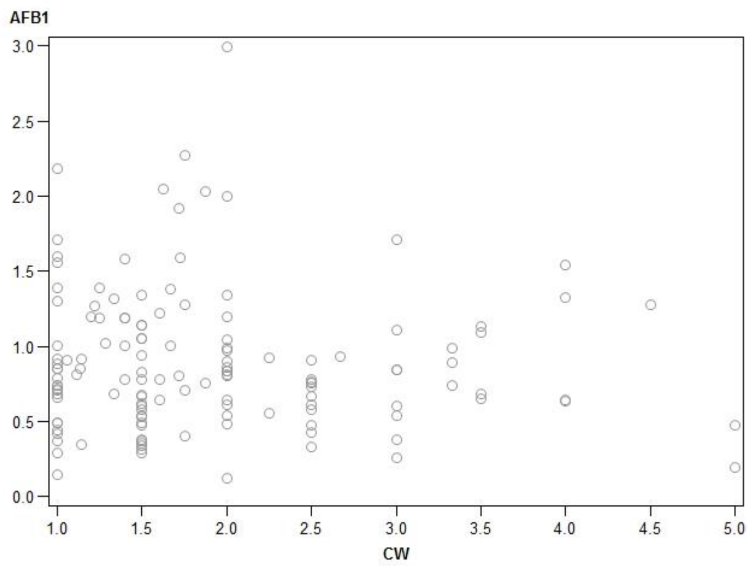

Figure 1-4 Scatter plot for AFB1 vs. consumer-to-worker ratio

1.4 Data

The data comes from a cross-sectional survey conducted in the Ejura Sekyedumase district (Ashanti region) of Ghana during the summer of 2002. Although nearly 10 years old, this survey provides the most recent dataset available that captures a comprehensive set of information including food safety, health, and socio-demographic variables. Ejura Sekyedumase's heavy reliance on groundnuts and potential vulnerability to unsafe consumption made the district an excellent candidate for support from the Peanut Collaborative Research Support Program (CRSP), a program under the USAID.[6] The district has two rainy seasons which occur in early Summer (April to May) and then from September to November (Jolly et al., 2006). From June to August 2002, a cross-sectional field survey was administered to three villages in order to obtain the villagers' health status, health history, consumption patterns, and demographic and socio-economic information. The areas surveyed were: Nkwanta, Hiawoanwu, and Dromankuma.[7] The Ejura District Health Director facilitated the study by introducing the investigators to potential study participants and community leaders in each area. The study's purpose was explained, questions were answered, and times and places were chosen for survey completion and sample collection.

A total of 162 participants volunteered to participate and field agents administered the survey and tests. Questions on socio-demographic variables were asked such as: monthly income, monthly expenses, age, gender, number of household members, the number of children, the number of children attending primary and secondary school, the number of children younger than nine, the level of education of the respondent, and awareness of aflatoxin. Table 1-1 gives

[6] The survey was funded in part by USAID grant LAG-G-00-96-90013-00. USAID has in its mission to advance food security, improve global health, and promote economic prosperity. The CRSP recognizes peanut as an important crop for developing countries and supports the advancement of research that fulfills USAID's mission.
[7] Key medical information in Kasei was unable to be collected thus 20 observations were dropped.

a description of the socio-demographic variables. The average household size in this area is 7.3, which is much larger than the Ghanaian rural average size of 5.4. In terms of income, this area is very poor.[8] In terms of 2007 USD, monthly per capita income is approximately $5.68 on average and per capita expenses are approximately $2.72[9]. Of the respondents 23%, 28%, and 49% came from Nkwanta, Hiawoanwu, and Dromankuma, respectively. The average respondent is 40 years of age and the mean household size is 7, including the person being interviewed. Slightly less than half of the population has had more than primary education. Less than 10% are aware of the dangers of aflatoxin specifically. Most people are subsistence farmers producing groundnuts, yams, cassava, beans, tobacco, cotton, maize, and vegetables. Selected population characteristics of the district are reported in Appendix 1 to save space. Males only represent 49% of the sample which is 2.7% less than the 2000 population census. Out the district's estimated 81,115, approximately .2% were surveyed, all of whom lived in rural areas compared to the 51.2% of the population that lives in rural areas. The Population's 50.5% children-youth would only be representative of the sample if in addition to the head of the household, one or two of the seven members were adult. The sample may not accurately represent the entire district but it likely captures similar rural dynamics including large numbers of dependents and perhaps better job opportunities for males in the urban areas. From the 162 respondents, answers were intermittently omitted.

[8] World factbook reports that the 2009 Ghanaian GDP per capita was $2,600 even after adjusting for purchasing power parity. Current figures show Ghana GDP per capita ranked 169 in the world. Ejura's annualized income of $68 per capita places it well below both Ghanaian and international average income.

[9] The previous Ghanain currency (New Cedi) was terminated after July 2007. Since our data are in "New" Cedi within a time –constant crossection, we round the old exchange rate of 9,600 /USD to 10,000/USD for simplicity. For more details see: https://en.wikipedia.org/wiki/Ghanaian_cedi#Exchange_rate_history

Table 1-1 Description of Socio-Demographic Variables

Variable	Mean	N	Description
HouseholdNo	7.31	137	Number of persons in household of survey participant
IncPerCap	5.68	107	Total monthly income divided by HouseholdNo
BilMthCap	2.72	104	Total monthly bills divided by HouseholdNo
ChildLtNine	1.81	135	Number of children in household ≤9 years of age
ChildtoFift	0.89	135	Number of children in aged 10-15
ChildPrim	1.34	134	Number of children in primary school
ChilSec	0.17	135	Number of children in secondary school
Children	2.56[a]	142	Number of persons ≤15 years of age
Age	40.31	140	Age of respondent
Gender	0.49	142	Gender of survey respondent (1=M)
FormalEd	0.46	140	Education of respondent (1=more than primary education)
HBSurfaceAG	0.17	141	Hepatitis B antigen presence (1=present)
loc1	0.28	142	Nkwanta Village
loc2	0.28	142	Hiawoanwu
loc3	0.49	142	Dromankuma
HeardAflatoxin	0.09	122	Awareness of what aflatoxin is (1 = aware)

[a] The sum of the means for ChildLtNine and ChildtoFift sum to 2.696, which is slightly higher than the mean 2.56 children reported due to 7 respondents with no children leaving questions on children age category missing.

Only 142 samples of blood were collected while 91 people submitted urine samples the morning following blood collection. The blood and urine samples were processed by the Kumasi center for collaborative research, Tropical Medicine, School of Medical Sciences, at the Kwame Nkrumah University of Science and Technology. There, the blood was separated into plasma and peripheral blood mononucleotides, they were frozen at -80 ° Celsius via liquid nitrogen, and then shipped to the University of Alabama at Birmingham for analysis. The medical information collected enabled the measurement of levels of biomarkers such as AFB1 albumin adduct, bilirubin, aspartate aminotransferase (AST), alanine aminotransferase (ALT), and the presence of Hepatitis B virus (HBV).

Measuring Aflatoxin Exposure. Much literature on human pathology is devoted to measuring unsafe consumption and health. Tests such as radioimmunoassays were conducted in controlled laboratories to detect trace amounts of substances of interest such as AFB1 adducts in the blood, bilirubin in the blood and urine, and AST to ALT ratio in the blood (Jolly et al. 2006).[10] AFB1 offers the most direct measure of unsafe groundnut consumption. There are still challenges associated with using AFB1 as a proxy: 1) it only measures exposure for up to 3-4 months after tainted consumption, 2) it is correlated with eating contaminated food but the exact aflatoxin content of the food cannot be determined 3) people with different genotypes may process the toxin differently. In order to get a holistic picture of unsafe consumption choices, bilirubin and AST/ALT are used as additional pathways or proxies.

Table 1-2 provides summary statistics on the proxies. The means of *AFBl* and *Bilirubin* suggest that there was previous exposure to either unsafe foods or health adversity; ideally both markers would be near zero. Sheth et al. (1998) found that in patients with Hepatitis C an AST/ALT ratio larger than one (>1.06) was significantly associated with greater risk for cirrhosis of the liver.[11] The AST/ALT ratio should not deviate far from unity in general, yet the sample's mean AST/ALT is 2.68.

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[10] The RIA is used to measure minute hormones such as the AFB1-albumin adduct that is covalently bound in peripheral blood albumin (Jolly, 2006).

[11] Sheth et al. looked at the interaction of AST/ALT ratio and Hepatitis C virus with cirrhosis of the liver. They found AST/ALT< .60 and HVC are not associated with cirrhosis while the WHO Expert Committee on Biological Standardization found AST/ALT<1 is still associated with viral Hepatitis. Hence the 2 observations with AST/ALT< are assumed to be good examples of biomarker-hepatitis virus interactions

Table 1-2 Summary Statistics for Measures of Aflatoxin Exposure

Variable	Obs	Mean	Std. Dev.	Min	Max
AFB1	140	0.89	0.46	0.12	2.99
Bilirubin	134	0.52	0.24	0.10	1.70
AST/ALT	138	2.68	1.29	0.48	11.27

1.5 Results

Table 1-3 shows the results of the least squares model. The model specification and coefficients for the key variables are briefly discussed here. All models except for *Bilirubin* are jointly significant at the 5% level. *Cw* is the least restrictive definition of the consumer to worker ratio. It is not significant for *AFB1*, the most direct biomarker, but it is significant for *Bilirubin.* In absolute value the magnitudes of *cw*'s coefficients are smaller than those of either *cw*_part or *net_cw*, meaning that the *cw* effect may be overpowered by the other two. Functional form misspecification is possibly an issue. A Ramsey RESET test for omitted variable bias was run and the results are reported in the appendix. As expected both *AFB1* and *AST/ALT* are correctly specified, but *Bilirubin* are not, meaning that the negative *cw* coefficients (as well as the others) may be biased[12]. A test for endogeneity was administered to all models in order to see if the misspecification of *Bilirubin* was a result of residual correlation with *cw*. Figure 1-1 shows the results of using the residual of *cw*, regressed on the other exogenous variables along with *growtoconsume* added for identification. The *cw* residual is not significant, which is evidence that the *Bilirubin* model suffers from omitted variable bias. With this in mind, the results for the other key variables are reported.

[12] We also tested for self-selection and did not find any so OLS should provide unbiased estimates.

Table 1-3 OLS Results

VARIABLES	AFB1	Bil	AST/ALT
incpercap	-0.00	0.00	-0.06**
	(0.008)	(0.006)	(0.026)
bilmthcap	-0.03	-0.01	0.17***
	(0.018)	(0.013)	(0.055)
age	0.01***	0.00	0.00
	(0.003)	(0.002)	(0.009)
gender	0.07	0.01	-0.14
	(0.083)	(0.058)	(0.232)
formaled	0.07	0.07	-0.23
	(0.094)	(0.064)	(0.260)
loc2	0.22**	0.00	0.21
	(0.099)	(0.067)	(0.276)
loc3	0.28**	-0.02	0.86***
	(0.110)	(0.077)	(0.307)
heardaflatoxin	0.13	-0.02	-0.51
	(0.152)	(0.101)	(0.422)
hbsurfaceag	0.11	0.04	0.16
	(0.113)	(0.081)	(0.326)
cw	-0.08	-0.07*	0.08
	(0.064)	(0.043)	(0.178)
*cw*_part	0.20*	0.26***	-0.25
	(0.115)	(0.077)	(0.319)
net_cw	0.36***	0.08	0.10
	(0.090)	(0.062)	(0.258)
Constant	-0.47	0.08	2.36***
	(0.311)	(0.216)	(0.867)
Observations	93	87	91
r2	0.337	0.199	0.230
Adjusted R-squared	0.237	0.069	0.112
F	3.383	1.533	1.943
Prob > F	0.0005	0.1315	0.0415

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

*Cw*_part is significant for AFB1 at the 10% level. It has a positive sign meaning that a change in *cw*_part by one yields an increase of AFB1 by .20, which is approximately .40 standard deviations. *Cw_part* also affects Bilirubin presence by .26 (albeit dubiously), which is more than a standard deviation. This effect is significant at the 1% level. *Net_cw* is a stronger food safety predictor with respect to AFB1, because its coefficient of .36 is significant at 1%. It is not a significant predictor of Bilirubin or AST/ALT biomarkers

Income and bills per capita are only significant for *AST/ALT* and the coefficients have the correct sign. This implies that an increase of approximately 1 USD per capita decreases AST/ALT ratio by .06. Per capita expenses increase this amount at an even greater rate of .17 per USD. Location is a determinate of AFB1, with both locations increasing AFB1 content relative to living in loc1 (Nkwanta). The primary difference between the two locational dummies is that *loc3* (Dromankuma) has larger and more significant coefficients meaning that those living in Dromankuma have a higher risk of eating contaminated food relative to both Nkwanta and Hiawoanwu (loc2). Gender, formal education, and Hepatitis B variables are all not significant for any model. Age is only significant for the *AFB1,* marginally increasing each by approximately .01.

The first attempt to run the *Bilirubin* logistic model was met by a quasi-separation of data points. Given the small number of survey participants and an even smaller number of complete observations, the data is primed for separation problems. The probability of observing separation dramatically decreases with sample size and increases with dichotomous predictors (Heinze and Schemper, 2002). The removal of the collinear variable *net_cw_part* solved the separation problem. The Maximum Likelihood Estimates (MLs) are presented in Table 1-4. Monthly income and bills were significant for *HiAST/ALT* and the have the hypothesized signs.

Table 1-4 Logistic Results in Odds Ratios

VARIABLES	HiAFB1	HiBil	HiAst/Alt
incpercap	-0.0436	0.00381	-0.121*
	(0.0637)	(0.0577)	(0.0675)
bilmthcap	-0.156	-0.0267	0.331**
	(0.129)	(0.114)	(0.129)
age	0.0393*	0.0319*	0.0163
	(0.0211)	(0.0190)	(0.0200)
gender	1.157**	0.125	-0.503
	(0.540)	(0.512)	(0.543)
formaled	-0.0319	1.050*	-0.112
	(0.584)	(0.588)	(0.610)
loc2	1.793***	0.431	0.762
	(0.683)	(0.583)	(0.634)
loc3	1.611**	-0.335	2.406***
	(0.750)	(0.674)	(0.752)
heardaflatoxin	1.180	-0.517	-1.138
	(1.123)	(0.962)	(0.950)
hbsurfaceag	0.584	-0.604	1.012
	(0.724)	(0.766)	(0.774)
cw	-0.139	-0.345	-0.866*
	(0.396)	(0.388)	(0.493)
*cw*_part	0.763	1.244*	0.369
	(0.715)	(0.734)	(0.858)
net_cw	1.599**	0.0218	0.949
	(0.730)	(0.555)	(0.614)
Constant	-6.271***	-3.331*	-2.073
	(2.238)	(1.996)	(2.116)
Observations	93	88	91
Log likelihood	-51.21	-53.81	-48.96
chi2	24.68	12.74	27.96
Prob > chi2	0.0164	0.3880	0.0056
Pseudo R2	0.194	0.106	0.222

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

An approximately 1 USD increase in household per capita income reduces the likelihood of the respondent having a high AST/ALT by .12; per capita expense significantly increases the likelihood of a high AST/ALT by.33. *Cw* and *cw_part* are significant at 10% for *HiAST/ALT* and *Bilirubin*, respectively, however Bilirubin fails to reject its null hypotheses of independence at 5%. The impact of the regressors for *Bilirubin* is jointly no different than zero. *Net_cw* increases the likelihood of having a high AFB1 at 5% significance level. A one unit increase in the net consumer-to-worker ratio increases the likelihood of having a higher AFB1 1.6. Location is highly significant across models and follows the same pattern as the linear model with one exception. As before, *loc3's* impact is higher and more significant than *loc2's* in all models, the exception being *HiAFB1* where *loc2* is slightly higher and more significant. This is likely due to the difference in the distribution of contamination. The OLS model is impacted by the means of the locations while the logistics model is dominated by the medians of the locations.

1.6 Discussion

The modeling and the evaluation of different food safety proxies show that Socio-demographics and income play an important role in food safety decisions. Until now many studies focused on hypothetical measures of risk aversion for high income nations and completely neglected family composition and low income nations. One unexpected result was the asymmetrical effects of income and expenses on AST/ALT. The negative impact of expenses on contamination level outweighed the positive effect of income by several times. Behaviorally, this is interesting because food safety choices may be more sensitive to income losses than income gains. Additionally, the fluctuation of family income coupled with the lack of savings accounts and credit may reduce safe consumption in less developed countries. Both the number of children younger than 10 and the number of children attending school, pressure households toward unsafe consumption. *AFB1* as a proxy for food safety is robust while the indirect measures *Bilirubin* is biased and hence not a good proxy for food safety decisions.

These results indicate the complexity of household decision making, especially when national and international development objectives may conflict with a household's immediate needs. It could be that as more children are sent to primary and secondary school, education related expenses and reduced time spent laboring reduces the family's effective income. This reduced income is offset by consuming low safety produce. All tests of joint significance reveal that the aggregate effects of these household characteristics are more than random variation. Yet the effects of the *Bilirubin* pathway is still ambiguous due to unobserved influences.

Going forward, policy makers and food safety advocates should incorporate household characteristics into the design of food safety interventions. At the time of this writing, mycotoxin contamination of food is still a global concern. The analysis was conducted on one of the most complete survey of its type and the behavioral results of this study are likely not sensitive to time. Absent preventative measures, poorer households will consume less safe food relative to their better off counterparts. Households with higher proportions of children under 10 or attending school are effectively poorer, at risk for nutritional disparities and unsafe consumption, and should be given priority for intervention. Intervention can take the form of command and control or incentives (Unnevehr and Hirschhorn, 2000). National and local efforts to control the groundnut AFB1 content in the supply chain may be less effective due to difficulty in enforcement, especially for local markets. An incentive based intervention called "School Meals Program" administered by the World Food Program incentivizes poor parents in developing countries to send their children to school by feeding the children, and in some cases allowing the children to bring home staples. (World Food Program, 2011). Such programs alleviate some of the burden of younger, less productive members of the household. The nutrition curriculum taught to local teachers and enrolled children can be augmented to include food safety awareness and increase cultural preferences for safe consumption. The food safety literature until now has ignored household dynamics in developing countries as well as the effect of household composition on a family's socio-economic status. This study answers how a particular household dynamic in Ghana affects the nutritional choice of aflatoxin consumption.

There is room for additional research on gender composition, missing or imperfect labor markets, and economic participation. It would be interesting to see if the additional on-farm time and non-farm household production that socially marginalized household members face, results in a better (worse) safety of consumption. Lastly, the predictive ability of this framework can be made much more accurate if medical innovators develop better, more general proxies and indexes for food safety. Ideally, multiple proxies might capture the net effect of eating contaminated food instead of narrow, one-dimensional proxies.

Chapter II: The Role of Credit Constraints on the Profitability of Beginning Farmers and Ranchers

2.1 Problem

The USDA defines BFRs as farm operators who have operated a farm or ranch for less than 10 years. These BFRs account for 22% of all farms and 10% of the value of production (Ahearn, 2013). This subset of farmers represents the renewal of the family farm model which is firmly rooted in American culture, history, and warrants special attention. Obstacles to this class of adolescent farm enterprises may determine financial performance and ultimately success or failure. One particular challenge to family farms is obtaining timely credit which continues to be an issue among beginning farmers (Mishra et al., 2008; Hartarska and Nadolnyak, 2012). This paper seeks to clarify the role that credit constraints have on BFR profitability.

Beginning farmers are more likely to have trouble accessing credit than farmers that are already established. Hartarska and Nadolnyak (2012) found that among the newest farmers in Alabama, BFRs for whom collateral was either a moderate or major obstacle, both were more likely to apply for credit and to be denied. The experienced farmers and ranchers (EFRs) in the US tend to be older on average than the US population in general and workers in particular. Nearly 1/3 of BFRs are *under* the age of 55 while 2/3 of EFRs are *over* the age of 55 (Ahearn and Newton, 2009). For this reason within the next 20 years it is likely that operators over the age of 65 may retire leaving a new crop of operators who are younger on average; a subset of whom will have little to no experience farming and are thus referred to as beginning farmers and ranchers (BFRs). The paper is organized as follows: First is a review of literature on financial constraints and performance, next we model the propensity of being credit constrained.

2.2 Literature

Identifying credit constrained households. Some authors have used self-identified constrained households in their analysis (Japelli, 1990; Feder et al., 1985; Feder et al., 1990; Briggeman, 2009). Others have used an estimated excess demand via a partial equilibrium credit model with demand shocks (Petrick, 2005). Since loans are typically cheaper than savings and equity, there is likely an interaction between credit demanded for consumption and that needed for investment in production. In this case the value of marginal output may be equated to some exogenous interest rates (Carter and Wiebe, 1990; Sial and Carter, 1996). Carter (1989) and Wiebe (1990) and several others investigated the shadow interest rates through their use of structural production function, reduced formed models, and output supply equation with a selectivity correction (Feder et al., 1990; Petrick, 2004a; Sial and Carter, 1996).

Equity. Bierlen and Featherstone (1998) show how farm equity is important in difficult times. They base their study on a panel of individual U.S. farm data. The authors distinguished periods with or without credit rationing as well as subgroups of farms that were more or less likely to be constrained. Their selection criteria were farm individual level of assets, debt-to-asset ratio, age of operator, and certain business cycles.

Credit rationing. Petrick and others note that rural households may make riskier investments, have less collateral, and subsequently be less likely to receive credit (Petrick, 2004; Binswanger and Rosenzweig, 1986; Hoff and Stiglitz, 1993). Household assets and relative riskiness of counties can possibly be used to identify credit constrained farm households. Zeller (1994) looked at formal and informal credit institutions in Madagascar and found that debt-servicing obligations and income were the main criteria for credit rationing. Duong (2002) found that *education* of a borrower was a statistically significant determinant of credit rationing by institutions while *age* had an ambiguous effect. One casual observation of a credit constrained farm is that the value of the marginal product of a credit-constrained input (VMP) will be > 0, implying a suboptimal use of input due to credit (presumably). Likewise, credit rationing may exacerbate this problem if productive inputs compete with household consumption for a share of the credit constrained budget. This suggests that capital and credit are substitutes for land input for a given unit of output.

There is likely a relation between farm size and experience through the credit rationing process. Loans to small farmers may be viewed as riskier by lenders as well as loans to farmers without sufficient collateral. As land and equipment can be sources of collateral and BFRs tend to be smaller, this implies an endogeneity between farmer experience and the ability to obtain credit (Carter, 1989; Eswaran and Kotwal, 1989). Due to a lack of prior saving these same farmers are more likely to demand credit especially, if they are in an expansive phase of the farm life cycle. Dong et al. (2012) found that in North China more dependents translated into less probability of being credit constrained while age increased the odds of being credit constrained. As expected savings decreased the odds of being credit constrained. The effects of age and number of dependents may be counter-intuitive until one considers the role that external income from wages may play in credit determination thus the number of wage earners and the employability of the borrower.

Lack of credit. Many studies since the 1960's have found that a lack of available credit is a major impediment to young farmers' survival and growth (Patrick and Eisgruber, 1968; Epperson and Bell, 1970). Petrick and others note that commercial credit institutions typically do not serve farm households due to lack of collateral and transaction costs (Binswanger and Rosenzweig, 1986; Hoff and Stiglitz, 1993; Petrick, 2005). There are several key barriers to entry among BFRs: training, education, technical assistance, land, capital and credit, markets. (Sureshwaran and Ritchie, 2011). A necessary input for BFRs to begin operations is land which can either be purchased or leased; the latter requiring more credit and upfront collateral. Ahearn observed that BFRs are more likely to lease land than established farmers as well as purchase land from non-relatives (Ahearn, 2013). There is conflicting literature on land, access to credit, and farm survival. Richardson, et al (1983) found that taking out loans to purchase land and equipment had a negative impact on profitability and survival rather than leasing the same. In an earlier dynamic simulations Patrick and Eisgruber (1968), found that long-term loan limits negatively influence both farm growth and family consumption, especially in the early years of the operation. It may be that the lifecycle of the farm households determines the marginal effect of access to credit. It would certainly determine credit terms, hence profitability, assuming that collateral increases with years on farm. Petrick (2004a) found that the marginal effect of land on output decreases with access to capital as well as credit. Rizov (2004) looked how credit constraints affected firm profits in a transition economy. Both Dong and Rizov used switching regression to account for the inherent endogeneity of the probability of being credit constrained and productive capability. The issue is that both developing economics are emerging from systems without freehold land rights.[13]

Off-Farm work. Economic literature has documented the exodus from farms as a result of modern returns to education and skills (Huffman, 1980); this approach has been indirectly exploited to measure the impact of production shocks on both household labor allocation and participation in local labor markets. This phenomenon can be either partial; in terms of hours spent on farm or completely prohibitive; like deciding to exit farming or deciding not to enter. Several studies show that off-farm labor can be used to supplement on farm investment, and

[13] For more on freehold law see: http://en.wikipedia.org/wiki/Freehold_%28law%29

consumption especially fertilizer (Huffman (1980), Lamb (2003). One interesting hypothesis from Lamb (2003) is that an increase in positive weather (rain) deepens the off-farm labor market and increased labor supplied. The results are obtained from rural India, so the off-farm labor is likely performed on farms with positive production shocks by members of those with negative shocks. Also since fertilizer is a ubiquitous input in conventional agriculture in developed countries, complementarity between off-farm labor and on farm investment and consumption may more easily be identified. A common theme is that farm household needs, e.g. consumption and investment, can drive the decision to pursue off-farm employment. Huffman finds that a determinant of off-farm labor demand is the *size of farm output*. Farm output is identified using a profit maximizing average production function; the output rate is the instrument. Gross farm output is measured as: as the *value of farm sales, home consumption, rental value of farm dwellings, government farm program payments, and net increase in farm inventories.*[14] Huffman finds positive association of off-farm labor with operator wage, education, and variance in farm size, while negative coefficients for non-operator wage (spouse). Kimhi, and Lopez (1999) found that years spent doing off-warm work is significantly associated with attitudes associated with a farmer's succession decision.

Performance. The prevailing argument is that access to credit can have a positive effect on productivity and conversely farms without access to credit suffer in profits and productivity (Dong et al.,2012; Duong and Izumida, 2002; Freeman et al., 1998; Sial and Carter, 1996; Feder et al., 1990). The exact performance pathway is however ambiguous. Barham et al. (1996) estimate a positive impact of credit on profitability using micro-level data. Feder et al. (1990) argue that suboptimal input levels may result from lack of access to credit. Naidu et al. (2013)

[14] Huffman measures farm labor input as on-farm work days X education index. Total on-farm work = annual household work + expenditure on hired labor. Size distribution is measured as the variance of the natural log of the county distribution of farm sales.

argue that reasons for low productivity in Indian agriculture stem from lack of irrigation and timely inputs and that credit could remedy this. They also found that credit had a significant impact on yield, although their results were likely confounded from a rather ad hoc approach.[15] Duong and Izumida (2002) employ a switching regression and found that total value of livestock and farming area squared were positive determinants of borrowing. Lastly they find that liquidity positively impacts output via cultivated land. In this case the value of marginal output may be equated to some exogenous interest rates (Carter and Wiebe, 1990; Sial and Carter, 1996; Demirguc and Maksivmovic, 1998). Ciaian and Swinnin (2009) show how credit market imperfections influence the distribution of subsidies [sic profit] via ownership to the fixed assets of production i.e. land. They also cite Feder (1985) and Carter and Wiebe (1990) for introducing the farm credit constraint.

On growth, Demirguc and Maksivmovic (1998) look at excess growth made possible by external financing, while Oliveira and Fortunato (2006) found that that the growth of both smaller firms and younger firms were more sensitive to capital constraints in the form of cash flow than their larger more mature counterparts. Many Researchers have found that small firms that are poised to grow may not due to unfavorable financing options and a reliance on retained earnings; the most expensive source of capital (Oliveira and Fortunato, 2006; Binks and Ennew, 1996; Butters and Lintner, 1945). When measuring the impact of credit constraints many notable works assume exogenous prices and use the value of output in their analyses which is the likely scenario for most BFRs (Buyinza et al., 2013; Briggeman et al., 2009; Duong and Izumida, 2002). Kumr et al (2013) used other proxies for performance such as input use, physical and

[15] Naidu et al (2013) used a series of linear regressions to account for national credit flow's impact on yield, production, and area planted. Joint determinations of the different regressands are not accounted for opening the door to misspecification bias.

human capital formation, consumptive smoothing and wage seeking. Whatever the measure, literature holds that access to credit positively effects performance.

Land and credit. Land is by far the most critical input for a conventional farmer and Ahearn (2013) observed that BFRs are more likely to lease land than to purchase while Mishra et al. (2009) observed that Non BFRs had roughly twice the amount of assets as BFRs, largely reflecting the difference in land tenure. Feder et al. (1990) note that farms with larger land holdings are more likely to receive credit than those without. Williamson and Katchova (2013) showed that land ownership can represent a general investment strategy in addition to a productive asset. Research has shown that land tenure indeed influences the distribution of government program benefits and thus farm profitability. This is especially true to the extent that landowners can capture conservation and the commodity payments on the acres they rent or leave them idle for conservation. What is unclear is how financial capital constraints influence BFRs profitability through the various pathways.

2.3 Model and Methodology

In order to capture the intertemporal tradeoff between investment and household consumption we model the utility of the farm household as a two-period production model: Following Briggeman et al. (2009) we can write a two-period farm household consumption model as:

(1) $$\max_{c_0 > 0, c_1 > 0, B \geq 0} u(c_0, c_1; z^h)$$

Where z^h is a vector of exogenously determined household characteristics. X is a vector of input variables purchased during period 0 at prices *w* used to produce output vector Y in period 1 through the relationship, $Y = f(X, Z^y)$. Z^y is a vector of fixed production factors i.e. land and machinery. Note that input prices and value of the marginal product are normalized by output price P which is subsequently omitted. Both household consumption and production function are bound by:

(2) $$W_0 + \mathrm{wx} - \mathrm{c}_0 - B = 0, \text{ and}$$

(3) $$f(x, z^y) + O - c_1 - (1+r)B = 0$$

The first expression means that money borrowed during period 0 is used for both consumption and the purchase of non-fixed factors of production; the second expression indicates that funds borrowed in period 0 must be repaid with interest in period 1 through production and other sources of income O. Finally there is a borrowing constraint:

(4) $$\bar{B}\left(z^{\mathrm{h}}, z^{y}\right) \geq B,$$

which is a function of observed household and production characteristics. Solving for the first order necessary conditions of the Lagrangian we have:

(5) $$L_x := \frac{\partial f(.)}{\partial x} - w \cdot \frac{(1+r)\eta}{\lambda} = 0$$

(6) $$L_\lambda : \bar{B} - \frac{f(x; z^y) + O - c_1}{1+r} = 0$$

(7) $$L_\eta : \bar{B} - c_0 - wx + a = 0$$

The F.O.N.C. indicates that the produce must be discounted by the interest rate since there is a one period lag between purchase of inputs and production of outputs. Since the value of production is log normally distributed the output that we are interested in is the logged value of production (*LVPRODTOT*) and its per acre value (*LVPRODPA*). Similar to Briggeman et al. (2009) we determine the likelihood of being credit constrained by using the natural log of Household Income (*LHHI*), Farm Net worth (*FNW*), Working Capital/Monthly Expenditures (*WC2E*), Total operator spouse labor on-farm labor hours (*ONFARM*), total weeks spent by operator and spouse working away from the business (*WKSOFF*), Number of years owning and operating the business (*TENURE*), Households head age (*AGE*), Number of dependents

(*DEPENDENTS*), Full time employee equivalents (*FTE*), Number of loans (*NUMLOANS*), Expected sales price of dwelling (*HOMEVALUE*), No college for operator and spouse (*NOCOLLEGE*), Household head is single (*SINGLE*), and finally Loan to Asset Ratio (*LTA*). Briggeman et al (2009) identified the aforementioned variables as both economically and statistically valid for identifying credit constrained farm enterprises.

In order to account for the correlation of the probability of being credit constrained and the outcome we use a propensity score matching algorithm similar to Briggeman et al. (2009), the main differences being that they employ a Epanechnikov Kernel whereas we do not. First the likelihood of being credit constrained will be estimated using a logistic regression. Next, both a nearest neighbor match and a mahalanobis match will be used to account for constrained and non constrained BFRs not having a common support. Finally, two sample t-tests will be performed to see if there is a difference in farm performance after accounting for propensity score and/or mahalanobis distance. From Briggeman et al. (2009) we can write the difference between constrained and unconstrained performance $Y_{1,0}$ as:

(8) $$E(Y_0) \text{ and } E(Y_1),$$

with our hypothesis being:

(9) $$E(Y_0) > E(Y_1) \text{ or } E(Y_0 - Y_1) > 0.$$

Now we only observe Y_1 when D=1 and Y_2 when D=0, so we rewrite () as:

$E(Y_1 - Y_0)$, also referred to as the average treatment effect (ATE). We are more concerned with

(10) $$E(Y_1 - Y_0|D=1) = E(Y_1|D=1) - E(Y_0|Z,D=1),$$

which is the Average Treatment Effect of the Treated. Note the second expression on the right-hand side. This can be thought of as the average on the untreated if they had been treated. Since we know,

(11) $E(Y_1)| D=1) - E(Y_0 | D=0)$

$= E(Y_1|D=1) + \{E[Y_0|D=1]-E[Y_0|D=1]-E[Y_0|D=0]\}$,

or as Angrist and Pischke (1999) describes it, ATET + Bias.

The counterfactual framework is well established (Rosenbaum and Rubin, 1983; Angrist and Pischke, 1999; Harding, 2003). Matching by propensity score is valid only if outcome Y_i is independent of selection (Rosenbaum and Rubin, 1983). Following closely the work of Maddala (1986) and Duong and Izumida (2002) we can write the Probability of being credit constrained as P(D =1) as P(B* >0), where $B^* = \gamma Z + u_i$. The probability of being credit constrained is:

(12) $P(D=1) = P(Y>B^*)$, where $Y = X\beta+\varepsilon$. Then we have:

(13) $P(D=1) \equiv P(-X\beta - \varepsilon > B^*)$.

Estimating Credit constraint. Briggeman et al. (2009) and use a logistic function such that:

(14) $$Logit(X\beta) = \frac{P(D=1)}{P(D=0)} = \frac{1}{1+ e^{X\beta}}$$

Solving for probability we get: $E[P(D=1|X\beta)]$ which is substituted into (10) for Y_1 and Y_0 leaving us an expression estimable by maximum likelihood estimation.

Japelli (1990) believed that credit constrained businesses could self-identity on survey and that self-identification would adequately separate truly constrained proprietors from those that were not. He used a probit model to identify individuals likely to be credit constrained while Briggeman et al (2009) used a logit model with a kernel matching algorithm.[16] This allows a more efficient estimation of the credit constraint because it imposes orthogonality on B_j and B_k, $j \neq k$, and as such eliminates correlation between the covariates.

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[16] For thoroughness, we compare logistic classification with results with those from a linear discriminant function which is reported in Appendix 2.

Turning to figure 2-2, a casual glance at the histograms reveal that the LVPRODTOT distribution both constrained and non-constrained populations look similar. Yet it may be beneficial to control for even weak sample section and the issue of population heterogeneity is only partially answered when analysis is restricted to univariate methods such as propensity score matching. Thus we add clusters based on principal components to the probit model to uncover natural groupings of BFRs, unburdened by the correlation among predictors. The clusters are determined by taking principal components from the regressors in the literature and running a hierarchical clustering algorithm that randomly creates *n* centroids (cluster means) and then assigns each observation to the nearest cluster, recalculates the centroid, and then repeats until the either the algorithm converges on the procedure exceeds the maximum number of iterations.[17]

2.4 Data

This project uses individual data from the 2005 ARMS PhaseIII. For the logistic model and discriminant model the variables of interests are described in table 2-1. Using a similar sample from Briggeman et al. (2009) we see 5184 total sole proprietors in 2005 with 3.95% of all farmers being credit constrained.[18]

[17] We use PROC FASTCLUS in SAS to achieve this; see Johnson and Winchern (2007) for more details. . Findings from the Principal Component analysis, Clustering analysis are reported in Appendix 2.

[18] The number of farmers and ranchers comes from all farmers that answered the Cost and Returns Report(CRR) in the ARMS PhaseIII survey. This number is adjusted by removing both farms not legal organized as sole proprietorships and famers that classify themselves as non-family farms.

Table 2-1 Description

Outcome Variables	
CONSTRAINED	Was denied credit at some time or selected out
LVPRODPA	The Log of the total value of production per acre operated
LVPRODTOT	The Log of the total value production operated
Common support Variables	
HHI	Household Income
LHHI	The Log of Household Income
WC2E	Working capital, excluding net positive
FNW	Farm net worth, to operator household
LFNW	Log of farm net worth
WKSOFF	Total operator and spouse weeks spent doing paid off-farm work
TENURE	Number of years operating a farm
AGE	Age of survey respondent
DEPENDENTS	Total members of household <18
FTE	Full time employee equivalent of all operator hours
NUMLOANS	number of outstanding loans
HOMEVALUE	Market value of principal operators dwelling
NOCOLLEGE	1 if Neither Operator nor Spouse have college education
SINGLE	1 if Operator is not married
REGION	Dummies for Midwest, South, or West -- base is Northeast
PRODUCERTYPE	Dummies for GrainOil, Dairy, Hog, Poultry, or Beef-- Base is Other

However table 2-2 shows that 5.82% of BFRs are constrained.[19] The difference in farmer constraint by tenure itself suggest that there may be difference in BFRs' access to credit; perhaps even an underlying difference in the distribution of those credit constrained and those who are not.

[19] A means of the key variables indicates that about 3.95% of all farmers and 5.82% of BFRs are credit constrained i.e. answered "yes" to at least one of the credit denial questions. See appendix for credit questionnaire. The gross number of credit constrained farmers is 208, with 27 being outliers. 181 being constrained. Of these 181 nearly 75 were able to get credit at a different creditor or at a different time. This question's whether or nor these BFRs are actually constrained. There's no easy answer because it may be the case receiving credit late or on undesirable terms can have a negative impact on farm performance.

Table 2-2 BFRS

Variable	N	Means	STDDEV	STDERR
CONSTRAINED	791	0.0582	0.2342	0.0083
LHHI	575	10.7819	1.1007	0.0459
LVPRODTOT	676	10.5596	2.4378	0.0938
LVPRODPA	676	5.9876	2.3610	0.0908
WC2E	790	0.1942	2.1831	0.0777
LFNW	775	12.5973	1.2707	0.0456
WKSOFF	791	52.3723	45.0636	1.6023
ONFARM	791	2413	1892	67
FTE	791	1.237	1.012	0.036
TENURE	791	5.425	2.541	0.090
AGE	789	45.257	12.993	0.463
DEPENDENTS	791	1.228	1.635	0.058
NUMLOANS	775	0.997	1.204	0.043
HOMEVALUE	791	86575	114528	4072
NOCOLLEGE	791	0.096	0.295	0.010
Single	791	0.169	0.375	0.013
Midwest	791	0.210	0.407	0.014
South	791	0.508	0.500	0.018
West	791	0.187	0.390	0.014
GrainOil	791	0.131	0.338	0.012
DAIRY	791	0.105	0.307	0.011
Hog	791	0.019	0.136	0.005
Poultry	791	0.111	0.315	0.011
Beef	791	0.255	0.436	0.016

Figure 2-1 shows a histogram of level Value of Production and Household income. The distribution of both variables for constrained (1) and unconstrained (0) heavily skewed to the right and thus hard to compare.

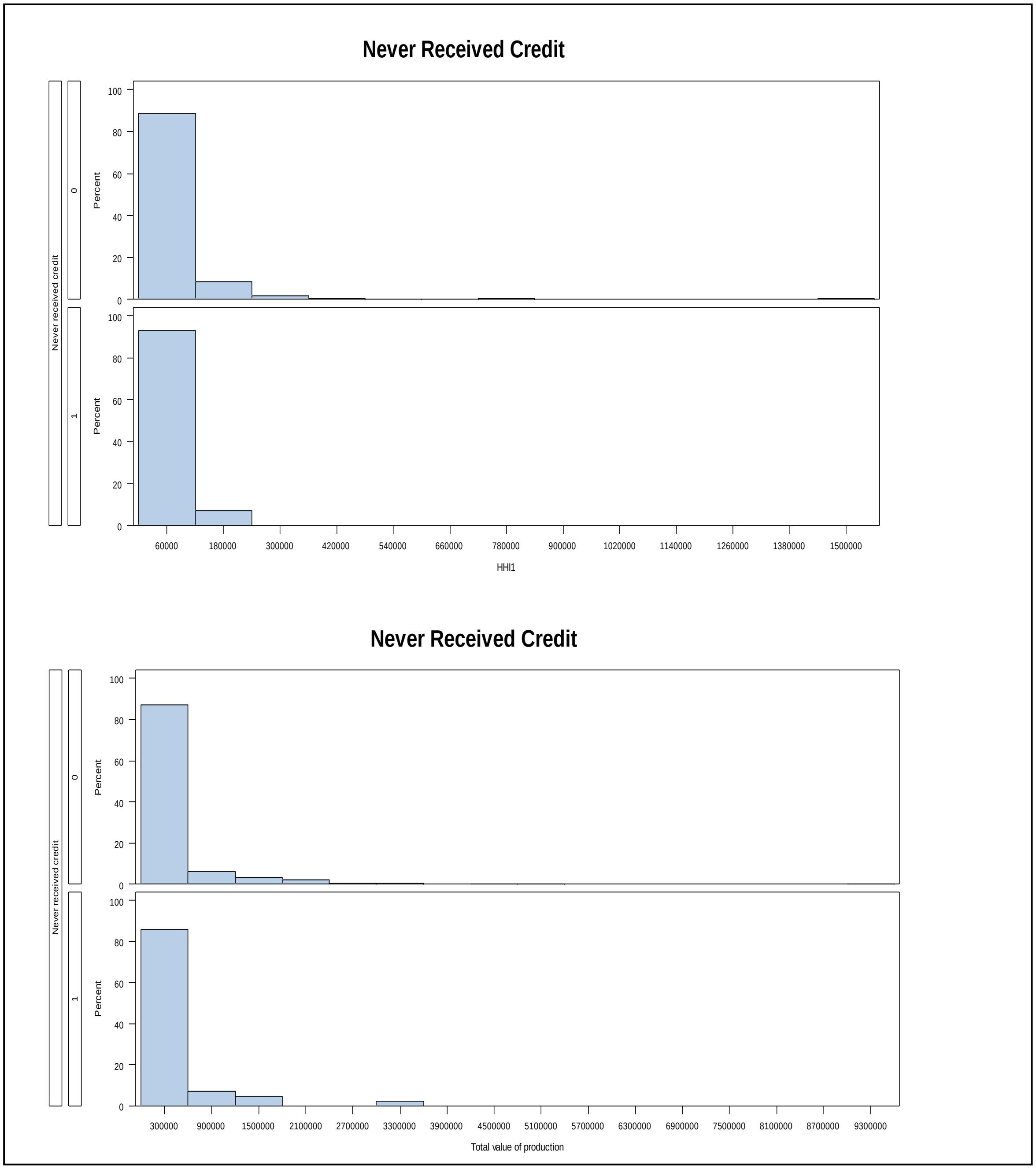

Figure 2-1. Histogram of Level Income and VPRODTOT

Figure 2-2 lists the same two variables in natural log form. Logged HHI appears approximately normal while logged VPRODTOT is somewhere between normally and uniformly distributed along a relevant range of output, providing further evidence that the log VPRODTOT may be a better measure of performance.[20]

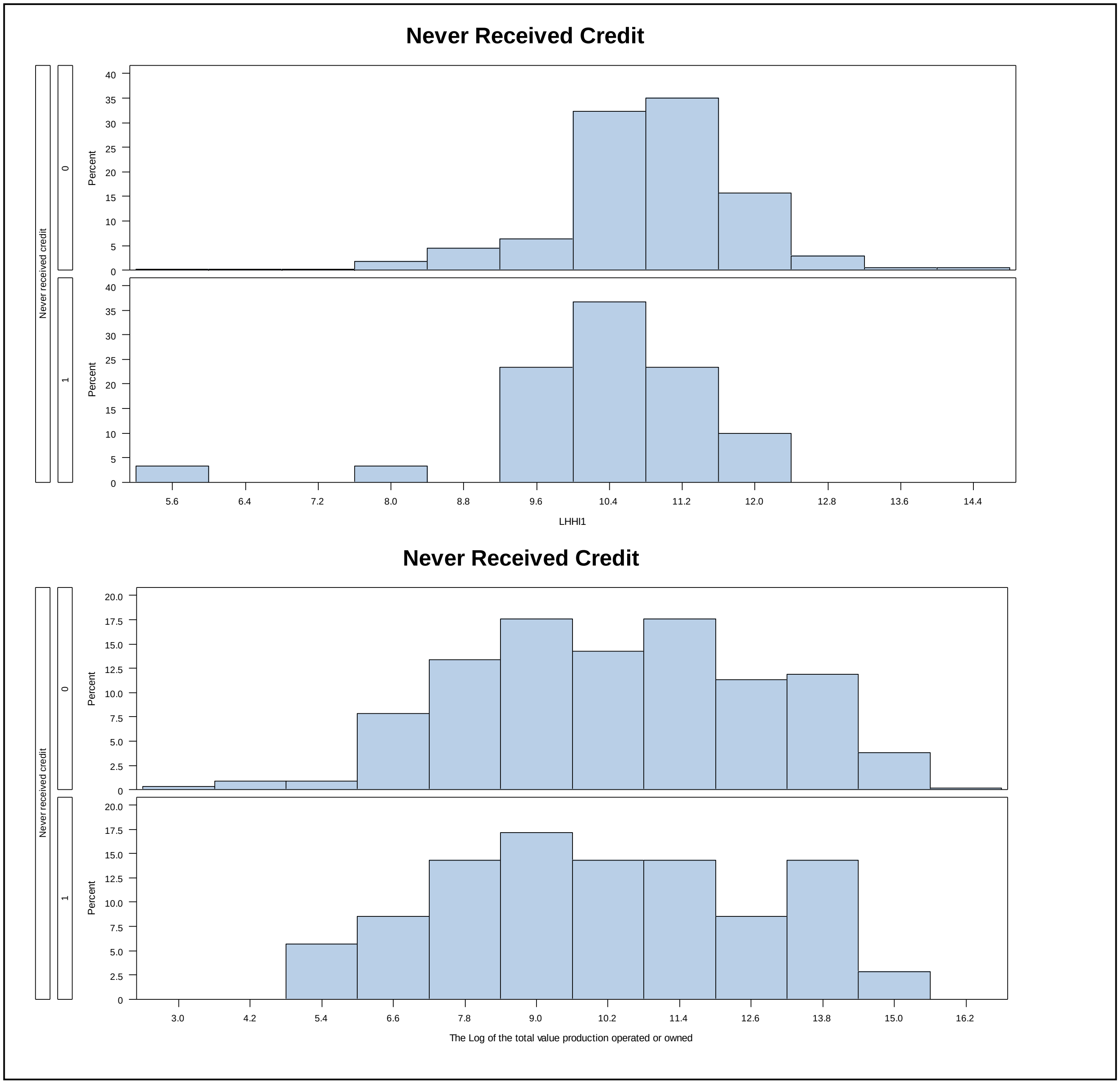

Figure 2-2. Histogram of Log Income and VPRODTOT

We also see the weighted sample of BFRs in table 2-2. Note that approximately 51% of the BFRs in the sample are from the Southern region, while 21% and 19% are from the West and

[20] We checked the distribution of acres operated and also found them to right skewed as acres tend to be associated with the value of production.

Midwest and the respectively; the remaining 9% are in the Northeast. The enterprise breakdown consists of 13%, 10.5%, 2%, and 25.5% of farmers being in GrainOil, Dairy, Hog, Poultry, and Beef respectively; the remaining ≈49% are in other enterprises.[21] Outside of elucidating the regional and enterprise distributions of the raw sample, the unweighted means do not reflect the response bias of many farmers, especially smaller ones, so table 2-3 shows the weighted means of both farm characteristics and performance variables.[22] Total Value of Production (*VPRODTOT*) $33,125 for these BFRs and with average operated acres 154.92, which is less than half of what experienced farmers operate. Only 85.75 acres are owned implying that BFRs lease as many acres as they own. Household income is ≈ $70,745 while farm net worth is $340,207. The average BFR has been operating 4.71 years while their age is 47 years old; the average age all farmers in the sample are 55 years old on average. Collectively principal operator and spouse spend an average of 74 weeks off-farm and have one dependent. The household has .73 loans on average and only 7% of farm household have neither operator nor spouse with at least some college. The .55 BFR monthly Working capital to equity ratio compared to a .82 ratio for all farmers in general. The average FTE for the BFR sample is .81 with an average of 37.7 weeks spent off-farm between operator and spouse.[23] BFRs on average are have ≈1 dependent, likely reflecting an early stage in the life-cycle. We added three clusters as explanatory variables based on principal components analysis and Cubic Clustering Criterion the predictors. The resulting BFR subset yields 551 observations, 35 constrained farmers, and two dummy variables for clusters 2 and 3. Although 35 observations is small, it represents a

[21] "Other" enterprises include vegetables, fruit, tobacco, cotton/cottonseed, nurseries, Christmas trees, grasses, sheep, equine, aquaculture, bees, rabbit, and other niche enterprises.
[22] The survey weights correspond to a total population of approximately 307,741 BFRS in 2005 while the 2002 and 2007 Census of Agriculture report 583,000 and 593,000 BFRs, respectively. The differences are likely due to the subset farmers that both answered the Cost and Returns Report(CRR) and whose had less than 10 years of operating.
[23] FTE only includes labor for the principal operator, spouse, and other operators. Non operator seasonal labor and contract labor are not included.

larger proportion of constrained BFRs compared to all farmers. Additionally the sample size is large enough to yield unbiased results for the two-sampled t-test performed as reported in the results section.

Table 2-3 BFRs Ummatched

	.	0	1	Diff (0-1)	Pvalue
N	791	745	46		
LVPRODTOT	8.91	8.93	8.43	0.5*	0.10
LVPRODPA	4.78	4.83	3.99	0.83***	0.00
LHHI	10.82	10.85	10.43	0.42***	0.03
WC2E	0.55	0.57	0.13	0.44	0.51
LFNW	12.05	12.05	11.93	0.12	0.91
WKSOFF	74.29	74.58	69.32	5.26*	0.07
TENURE	4.71	4.69	5.08	-0.39	0.13
AGE	47.49	47.78	42.5	5.28**	0.02
DEPENDENTS	0.95	0.91	1.62	-0.71***	0.00
FTE	0.81	0.8	0.98	-0.18***	0.03
NUMLOANS	0.73	0.71	1.06	-0.36***	0.03
HOMEVALUE	90,987	92,232	69,595	22,637	0.41
NOCOLLEGE	0.07	0.07	0.01	0.06	0.25
SINGLE	0.18	0.18	0.26	-0.08	0.20
Midwest	0.27	0.27	0.21	0.06	0.61
South	0.5	0.49	0.57	-0.08	0.11
West	0.17	0.17	0.18	-0.01	0.36
GrainOil	0.08	0.08	0.08	0	0.88
Dairy	0.04	0.04	0.04	0	0.68
Hog	0.01	0.01	0	0.01	0.62
Poultry	0.02	0.02	0	0.01	0.60
Beef	0.35	0.36	0.32	0.04	0.77
LTA	0.18	0.18	0.19	0.01	0.66

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

2.5 Results

Probit Results. Next we report the results from the probit regression. Table 2-4 lists the results from modeling the mean probability of being credit constrained (treated) as a function of the three clusters and other predictors.

Table 2-4 Probit Results

Parameter	Estimate	Pr > ChiSq
Intercept	-3.1991 (3.131)	0.3069
LHHI	-0.0921 (0.190)	0.628
WC2E	-0.2573 (0.195)	0.1866
LTA	-1.3153 (1.625)	0.4183
LFNW	-0.0529 (0.174)	0.7607
WKSOFF	-0.00067 (0.006)	0.9164
ONFARM	-0.00015 (0.001)	0.8825
FTE	0.5632 (2.022)	0.7806
TENURE	0.0808 (0.068)	0.2364
AGE	-0.0142 (0.021)	0.4987
DEPENDENTS	0.333** (0.163)	0.0413
NUMLOANS	0.3777 (0.266)	0.156
HOMEVALUE	0.009*** (0.003)	0.0009
NOCOLLEGE	-1.4255 (1.182)	0.2278
Single	0.9064 (0.620)	0.1436
Midwest	0.2327 (0.790)	0.7683
South	0.9114 (0.843)	0.2796
West	0.4415 (0.815)	0.5882
GrainOil	-0.3075 (0.637)	0.6291
DAIRY	-1.791** (0.745)	0.0163
Hog	-2.1394 (3.563)	0.5482
Poultry	-2.4958 (1.802)	0.1661
Beef	-0.4828 (0.519)	0.3525
CLUST2	-10.2*** (2.564)	<.0001
CLUST3	2.04*** (0.634)	0.0013

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

Table 2-4 (continued) Goodness of fit

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Square	*DF*	Pr > ChiSq
Likelihood Ratio	38465.07	24	<.0001
Score	30855.27	24	<.0001
Wald	137492.7	24	<.0001
Association of Predicted Probabilities and Observed Responses			
Percent Concordant	64.6	Somers' D	0.335
Percent Discordant	31.1	Gamma	0.35
Percent Tied	4.4	Tau-a	0.041
Pairs	18540	c	0.668
Discriminant Analysis Based on Principal Components *Error Count Estimates for CONSTRAINED*			
	0	1	*Total*
Rate	0.3379	0.3056	0.3217
Priors	0.5	0.5	

DEPENDENTS, *HOMEVALUE*, *DAIRY*, *CLUSTER1*, and *CLUSTER2* are all significant determinants of being credit constrained.[24] Each additional dependent increases the probability of being constrained by .33 standardized units (z) from the mean probability. The *HOMEVALUE* coefficient indicates that for every $100,000 of home value one is .932 z units more probable to be constrained.[25] This is counterintuitive until one accounts for the financial diversity of BFRs, including farmers with large home value who may have large mortgages, other financial obligations, or whose demand for credit simple outstrips lenders willingness to accommodate i.e. lender rationing. Production type, specifically dairy corresponds to being less credit constrained while being in cluster 3 increases the probability of being constrained by 2.03 standard units. As no one in cluster 2 is credit constrained discussing the magnitude of its

[24] Nearly every regressors is highly significant before the replicate weight are added.
[25] Of course the Probit coefficients are approximately linear in the neighborhood of X, so accurate and accuracy diminishes as we move away from mean of HOMEVALUE.

coefficient adds no value to the discussion. The Probit model fit statistics show that the regression is jointly significant which gives us confidence that there is some treatment selection occurring. The percent concordant is .668 which is greater than the pedagogical coin toss, yet it is far from a deterministic model of BFR credit access. An alternative method to classify BFRs using a discriminant function was also used, but the results only yielded an increase in treatment of approximately 1%, so we report this in the Appendix and rely on the probit model for the propensity score matching.

Matching Results. The results are based on using three nonhierarchical clusters as predictors of being credit constrained. The results are based on Nearest Neighbor (NN) and Mahalanobis (MH) matching algorithms respectively. Table 2-5 compares NN and MH results to the unmatched treatment means. The first thing noticeable is that the matched VPRODTOT means are lower than the unmatched means. This is almost wholly due to the constrained groups performing less than the unconstrained groups in every match.[26] You can see unmatched VPRODTOT is not significant, likely due to outliers on the high side. The logs of VPRODTOT and VPRODPA are normally distributed indicating significance of VPRODPA in the unmatched and mahalanobis (MH) matched samples; this corresponds to loss in production of $4,700 and $35,430 respectively. The per acre treatment effect is significantly different across all specifications and corresponds to treatment effects of $52 (Unmatched), $127 (NN), and $146 (MH). The magnitude of the treatment effect both terms is the largest in MH sample.[27] The differences in the magnitude of treatment effect are also explained by the difference in samples

[26] The differences between constrained and unconstrained total and net value of production among all matches is mainly due to the constrained groups, but this difference is not significant due to high between group variance.
[27] *VPRODPA* is calculated by dividing *VPRODTOT* by acres operated after matching to get results that are both consistent with individual VPRODTOT and acre estimates as well as outliers.

arising from matching methods, namely the difference in criteria between NN's exclusive use of propensity score and MH's addition of mahalanobis distance.

Table 2-5 Comparison of Matched Group Means by Treatment

		Group Means by Treatment			
			Control	*Credit Constrained*	*Difference*
Unmatched	N	791	745	46	
	VPRODTOT	$ 33,125	$ 33,384	$ 28,682	$ 4,703
	VPRODPA	$ 214	$ 217	$ 165	$ 52*
Nearest Neighbor	N	72	36	36	
	VPRODTOT	$ 17,264	$ 23,450	$ 12,704	$ 10,747
	VPRODPA	$ 110	$ 196	$ 69	$ 127**
Mahalanobis	N	70	35	35	
	VPRODTOT	$ 25,599	$ 46,053	$ 10,621	$ 35,432*
	VPRODPA	$ 126	$ 204	$ 57	$ 147***

Table 2-6 summarizes the findings into a table of average treatment effects (ATT). The signs of ATT are now negative and in percentages in order to emphasize the loss that credit constrained BFRs face. Depending on how weak the credit selection effect i.e. subsample, the loss in value of production can be anywhere between -15% and -77%. The per-acre loss is even more pronounced for unmatched and NN matched samples at -24% and -65%. When choosing between matching methods we tend to favor the mahalanobis match. Although the treatment effect is larger than the total famer sample, the MH match bifurcates the BFRs sample into high and low producers while accounting for individual producer characteristics. It is important to note that treatment effect of the logged VPRODTOT and VPRODPA are all highly significant. This suggest that despite difficultly with small sample precision, there still remains a substantial loss in farm revenue for constrained BFRs whether one accounts for endogenous determinants of credit constraints or not.

Table 2-6 Average Treatment Effect of Treated

	Credit constrained (-) unconstrained			
	VPRODTOT	%	VPRODPA	%
Unmatched	$ (4,703)	-14%	$ (52)	-24%
Nearest Neighbor	$ (10,747)	-46%	$ (127)	-65%
Mahalanobis	$ (35,432)	-77%	$ (147)	-72%

2.6 Discussion

Propensity score matching using nearest neighbor and mahalanobis distance algorithms confirms that there is a negative treatment effect for constrained BFRs. One finds between -14% and -77% lost value of production from constrained beginning farmers and ranchers. Admittedly the gap in the difference of the treatment effects has revealed is that BFRs are diverse group of farmers and as such multivariate matching techniques such as mahalanobis distance may populated different untreated subject than univariate measures such as the lone propensity score. Some explanation in the bifurcation of the sample may be due to the BFRs reason for farming in the first place. Farmers who recently started farming through inheritance or hobby might be less prone to invest in production, have a smaller demand for credit, and cause more variance with in the performance of unconstrained BFRs. Meanwhile the constrained BFRs who are 3.8-5.3 years younger on average may still be in the growth stage of the family enterprise, seek more credit for investment or consumption, and wind up denied access to as much credit as they seek. The divergent forces within farmer intent and life-cycles likely exacerbates the between group differences in value of production.

Beginning farmers and ranchers represent a diverse yet important subset of the single family farming population and understanding their financial needs is paramount to any public attempts to maintain this institution. We have shown that even after controlling for farm characteristics and the likelihood of being credit constrained, these constraints are still associated with lower revenues from farming. One variable that we could not control for was the reason why the operator started farming in the first e.g. life-style, inheritance, tax purposes, or to grow a business; such detailed information is rarely captured both on a farm enterprise level with both detailed financial information and with a sizable sample allowing s sophisticated techniques on subsamples In addition to larger BFR sample and better instruments for famer intent, it also may be insightful to explore other methods of classifying BFRs by other financial instruments such as working capital indices; comparing internally generated measures of capital constraints to self-identification would provide invaluable information on farmer propensity to be credit constrained.

Expanding land purchase loans to BFRs and offering support to new women principal operators may increase the long-term performance and viability of these enterprises. Likewise helping these farmers to acquire program acres may save farmers lost revenue share in leases, provide leasing income of their own. Other targeted interventions can provide liquidity as in the FSA microloans for small and beginning operators producing for local markets. In this case careful attention must be paid regional differences in BFR credit needs.

Chapter 3: Survival of Beginning Farmers under Profit Risk and Climate Change

3.1 Problem

Little is known about what causes beginning farmers and ranchers (BFR) to exit before reaching maturity. Nor is there much literature on this risk posed to BFRs from a changing climate. This paper seeks to uncover previously unstudied risks to BFR survival and maturity. According to the quinquennial Census of Agriculture, the number of BFRs has decreased by 21% over the last decade. But should we expect risks associated with failure to be constant in terms of maturity? We also propose a method of testing whether the Liability of Adolescence of Hypothesis (LOA) is applicable to BFRs. The paper is organized as follows: First is a discussion of literature of BFR Exit, Partial Exit, and how profitability and climate affect the aforementioned decisions; next we model farmer exit as limitedly dependent on value; then we review the data on BFRs, divisional climate variation; in the methodology section we explore hypotheses on implied value via observed outcomes both as a whole and by farmer experience; next we list the results from the different specification, and finally we discuss those results and their implications for further BFR research.

3.2 Literature

The literature on determinants of beginning farmer survival is scarce with most focusing on larger, more established farms. We review relevant works on farmer exit and firm exit which may apply to BFRs unique condition such as size and earnings. For instance Igami (2013) found that entry of big firms do not necessarily drive out small firms. In the case of Tokyo grocery stores small grocers did better when larger firms entered; it is other large and medium size firms that exit at higher rates. But are these findings generally applicable to agricultural businesses? As figure 3-1 shows, from 2002 to 2012 the share of farmers with sales < $250,000 decreased from 93% to 88%, while the share of farmers with sales >$1,000,000 increased from 1% to 4%. Even the midsize farms ($250,000-$999,999) experienced growth from 6% in 2002 to 8% in 2012.[28] In fact, every subclass among the < $250,000 sales class experience a decline in farmers except the 5,000-9,999 class which saw a modest increase (.8%). Facially speaking, sales growth among large farms and midsized farms is associated with a decline in small farm membership.

There are several approaches to modeling firm net exit/entry. One such approach is the use of count models, the properties of which have been thoroughly explored (Chappell et al 1990; Breshnahan and Reiss, 1991; Asplund and Sandin, 1999). Asplund and Sandin (1999) note that there is a relation between market size, intensity of competition, and the number of firms via a sunk cost of entering or remaining in a given market.[29] Ahearn and Katchova (2016) found yearly exit rates of 4% for BFRs with between 6 and 10 years farming the percent difference of beginning farm date counts between census years. Still there are known issues with estimations using count model such as assumptions on mean and variance equality, scale, and how to treat zero values of entry and exit. Survival via the linked farms approach models offer an alternative approach. Table 3-1 compares exit rates from the Griffin-Hartarska (GH) estimate of exit rates and the Katchova-Ahearn (KA) estimate. The KA rates are similar in 2007-2012 period but differ in 1997-2007 likely due to methodology.[30]

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[28] Every subclass among the < $250,000 sales class experience a decline in farmers except the 5,000-9,999 class which saw a modest increase (.8%). Facially speaking, sales growth among large farms and midsized farms is associated with a decline in small farm membership.

[29] They find that the minimum market size per unit of capacity needed for entry is increasing in the number of firms

[30] One concern noted in Katchova and Ahearn (2016) was the lag between BFRs beginning year and first Census Report which the exit rates could potentially be inflated. As any measurement error is on the left side we believe we will still get unbiased predictor estimates.

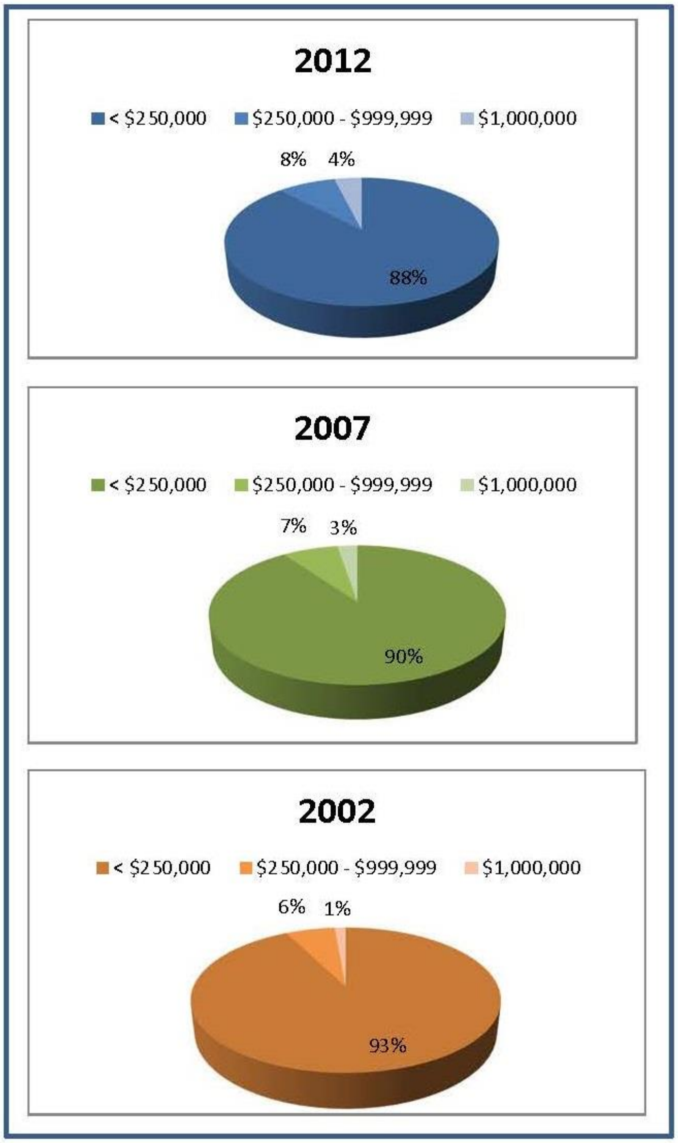

Figure 3-1. Farms by Market Value of Agricultural Products Sold

Table 3-1 Comparison of Farmer Exit Rate by Experience

		Exit	
		GH	KA
All Farmers	1992-1997	8.5%	.
	1997-2002	7.2%	8.7%
	2002-2007	7.0%	8.2%
	2007-2012	8.5%	8.5%
BFRs	1992-1997	9.7%	.
	1997-2002	7.5%	9.1%
	2002-2007	7.8%	9.0%
	2007-2012	9.8%	9.7%
Experienced	1992-1997	8.0%	.
	1997-2002	7.0%	7.9%
	2002-2007	6.6%	7.7%
	2007-2012	8.0%	8.0%

That leaves the question of which variables are economically relevant for BFR survival. Several authors have noted that farmer age and experience play a role in firm survival (Key, 2013; Key and Roberts, 2006; Mahmood 2000; Pietola et al., 2003). Mahmood (2000) notes that immaturity or "adolescence" contributes to firm failure, although not linearly. He and others have noted that substantial fixed costs in the form of sunk costs can reduce exits from a given industry (Dixit, 1989; Hoppenhayan, 1992).

Off-farm work and scaling back. Participation in farming need not be viewed as a binary choice; alternative approaches can include the number of hours worked on-farm, size of operation, etc. Igami (2011) models entry and exit as an ordered probit adding the decisions to expand or shrink to the explicit decisions to enter or exit. The literature on the effects of off-farm labor and exit is ambiguous. Among counties losing farms, off-farm income contributed to farmer exit and can compete with maize intensification in small holder farms (Goetz and

Debertin, 2001; Mathenge et al., 2015). Yet off-farm labor can also be used to supplement on farm investment, and consumption, especially fertilizer Huffman, 1980; Lamb, 2003. Still among a set of beginning farms these effect is even less well studied. An interesting hypothesis from Lamb (2003) is that an increase in positive weather (rain) deepens the off-farm labor market and increased labor supplied.[31] Also since fertilizer is a ubiquitous input in conventional agriculture in developed countries, complementarity between off-farm labor and on farm investment and consumption may more easily be identified. By the same token off-farm wages can be used to transition out of farming and the literature on external wages is far from unanimous. Using panel data, Ahituv and Kimhi. (2002) found that off-farm labor supply and capital were negatively associated. A common theme is that farm household needs e.g. consumption and investment, can drive decisions to pursue off-farm employment, regardless of enterprise the money is to be spent. Huffman finds that a determinant of off-farm labor demand is the size of farm output. Huffman finds positive association of off-farm labor with operator wage, education, and variance in farm size, while negative coefficients for non-operator wage (spouse).[32]

Government Payments. Recent works have found that government payments have a negative effect on farm failure rate (Key and Roberts 2006; Mishra et al. 2014). Total government payments tend to be correlated with size and has a positive effect on farmer survival and is positively correlated with farmer experience and age (Audretsch and Mahmood, 1995; Mahmood, 2000; Disney et al., 2000; Key and Roberts, 2006). Also a larger share of the government payments to sales ratio corresponded to a significantly longer lifespan in years

[31] Lamb (2003) result's were obtained from rural India, so the off-farm labor is likely performed on farms with positive production shocks by members of those with negative shocks.
[32] Farm output is identified using a profit maximizing average production function; the output rate is the instrument. Gross farm output is measured as: the value of farm sales, home consumption, rental value of farm dwellings, government farm program payments, and net increase in farm inventories.

across all sales classes. It turns out that larger debt to asset ratio is associated with an increased hazard rate (Key and Roberts 2006). Kazukauskuas et al. (2013) found that decoupling government payments from production resulted in a decreased exit overall, but an increase in disinvestment i.e. land and machines. This results indicate that government payments can both allow an optimal (de)rescaling of production overall while facilitating aging or failing businesses to exit. They also create a farm subsidy dependency ratio as the share of direct payments to total output and look at intensity of disinvestment.   Figure 3-2 shows the government payment intensity by sales class for 1992-2012. What the graph shows is that payment intensity is actually the largest among low sales BFRs, which goes against the conventional narrative of government payments accruing to larger farmers.

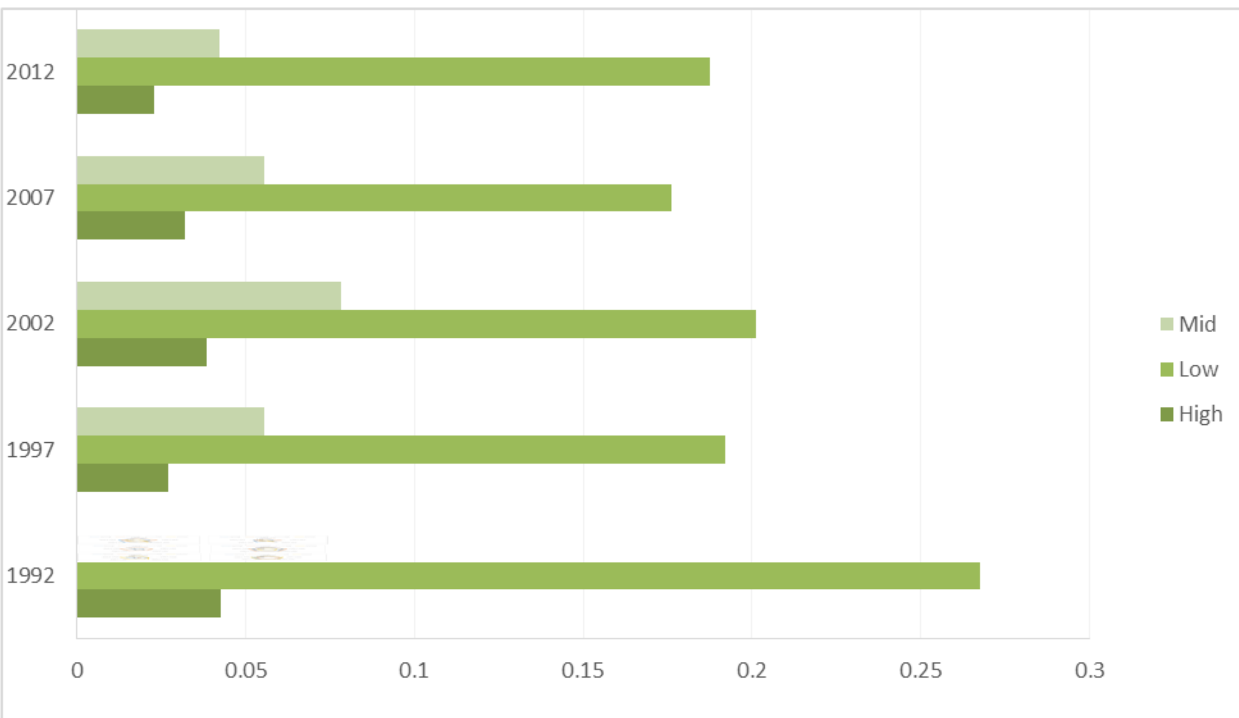

Figure 3-2. Government payments intensity by sales class

Profitability and risk. Uncertainty and risk drives the use of labor, fertilizer, pesticide, machine, land, usage, even discrete decisions such as shutting down which BFRs as whole are more likely to do. Most farms that make less than $50 thousand in revenue have losses and the average farmer making more than $50K has more than $1.9 million in assets (Ahearn and Newton, 2009). Assets such as land and machines are also associated with liabilities i.e. so highly leveraged BFRs can find themselves at risk of revenue fluctuation, default, and exit. One source of risk is the fluctuation in input and output prices between production and marketing. Gillespie and Fulton (2001) looked at hog farmers and found that the higher the output/input price ratio the lower the exit rate and the more likely that smaller firms would survive. Farmer performance can affect exit rates and the literature is replete with evidence of farm size and age positively affecting farmer performance (Key, 2013; Pflueger and Russek, 2013; Wang et al 2014; Audrestch and Mahmood, 1995). For example, Mahmood and Audrestch find that ownership status and firm size influence subsequent firm survival, while the macro environment both influence firm survival and hazard rates. Pflueger and Russek note the negative relationship between productivity and farm exit across different European countries.[33]

Climate variability. The challenges that BFRs face are likely to increase as climate variability adds risk, reduces yields, profits, debt repayment capacity, and farm survival (Dell et al. 2012; Tol, 2002). The literature is divided on the near term effects of climate change on determinants of agricultural of profitability. Schlenker et al. (2009) found in a panel study of three crops that temperatures below 32 C^0 (89.6 F^0) increased yields while temperatures above this threshold dramatically decreased yields, namely due to slow historical adoption of new seed varieties and management practices. Some researchers have found downward bias in climate

[33] Their framework uses a productivity lottery not known by entrants until shortly after entering in which a "bad draw" implies a return insufficient to stay in business, hence failure at adolescence.

impact due to technological adaption, crop mix, and insurance (Kaminski et al., 2013; Fleischeret al., 2011; Scheel and Hinnerichsen, 2012). There is a growing consensus that the farmers who are able will adapt to a changing climate, and as such, there may be a divergence in the performance of better adapters with that of the worse. Given farmers in similar geography experience similar weather, part of the difference in farmer profitability geospatially systemic. Others looked at how crops yields are sensitive to precipitation's annual, seasonal, and spatial distribution of rainfall (Mjelde et al 1998; Ogallo et al. 2000; Igelsias and Quiroga, 2007). Deschenes and Greenstone (2007) also find that using climate normals in the form of total degree days and total precipitation for the growing season provides a scientific way of assessing the impact of climate on agricultural profits.

3.3 Model and Methodology

To estimate model we start with a value function that maximizes the present value of future utilities, but also makes this utility function subject to a labor constraint (Pietola et al.1999; Blundell and MaCurdy 1999; Kimhi and Bollman, 1999). From this they derive a value function.

(1) $$V_t = \sum \gamma_{\tau|t} \left(C_\tau, L_\tau\right)$$

Where C is consumption, L_τ is leisure, $\gamma_{\tau|t}$ is the discount factor from period τ to t. The intertemporal budget constraint is:

(2) $$\sum r_{\tau|t}\, C_\tau = \sum r_{\tau|t}\left(w_\tau(1 - L_\tau) + F_\tau\right) + A_\tau$$

Where A_t is the net value of assets at time t, F_τ the gross farm income, w_τ is the off-farm wage rate, $r_{\tau|t}$ is the market discount rate from period τ to t. Lastly, Kimhi and Bolman define $W_t = V^E_t - V^S_t$ as the tendency to exit in period t, the net effect of on farm and off-farm income and utility.

(3) $$W_t = \eta X_t + \varepsilon_i$$

The exit decision rule is:

$$E_t = \begin{cases} 1 \ \ if\ farmer\ decides\ to\ exit\ in\ period\ t \\ \qquad\qquad 0\ if\ otherwise \end{cases}$$

The probability of observing BFR exit can be modeled as:

(4) $$E^* = \boldsymbol{X}_i'\beta + \varepsilon_i,\ \mathrm{E} = 1 \text{ if } E^* > 0, \textit{ otherwise } 0.$$

Where, $X \ni$ (**PROFITABILITY, RISK, SIZE, CHARACTERISTICS, ECONOMY, CLIMATE, TIME**)

Where $\mathbf{PROFITABILITY_t}$ is a vector consisting of ROA_t and $GPAYINT_t$, $\mathbf{SIZE_t}$ consist of $LNASSETS_t$, $MIDSALES_t$, *and* $HIGHSALES_t$, $\mathbf{ECONOMY_{tc}}$ consists of $NONAGSHARE_{ts}$, $UNEMPRATE_{tc}$, $WRKOFF_t$; $\mathbf{RISK_t}$ consists of $OISTDEV_t$, $\mathbf{CLIMATE_{td}}$ consists of $SPRING\_HDD_{td}$, $SUMMER\_HDD_{td}$, $FALL\_HDD_{td}$, $WINTER\_CDD_{td}$, $SPRING\_CDD_{td}$, $FALL\_CDD_{td}$, $SPRING\_SP3_{td}$, $SUMMER\_SP3_{td}$, $FALL\_SP3_{td}$, $WINTER\_SP3_{td}$, $SUMMER\_HDD_{td}$, $FALL\_HDD_{td}$, $WINTER\_CDD_{td}$, $\mathbf{CHARACTERISTICS_t}$ consists of AGE_t, $LIVESTOCK_t$, $FAMILY_t$, $MINORITY_t$, **REGION** consists of *AP, CB, DLT, LS, MTN, NTE, NP, PAC, SP*, and **TIME (t)** is *CYEAR* and is measured in 5 year increments from 1992 to 2012.

The error ε_i is distributed as a standard normal random variable with a log likelihood function of:

(5) $$ln\mathrm{l} = \sum_{n=1}^{N}(E_t \ln[1 - \Phi(-X_n\beta)] + (1 - E_t)\ln\Phi(-\mathrm{X}_n\beta)),$$

where ϕ is the cumulative distribution for a standard normal random variable and β is a vector of parameters to be estimated. The goal is to estimate changes in the probability of exit. We do so by implicitly using the value of exit W_t from eqn (3) which is conditioned on X_{jt} such that:

(6a) $$\frac{\partial w}{\partial x} > 0 \Rightarrow \partial V^E - \partial V^S > 0 \text{ , while}$$

(6b) $$\frac{\partial w}{\partial x} > 0 \Rightarrow \partial V^E - \partial V^S < 0 \text{ in general.}$$

We use the linked-farms approach for measuring exits. We take final census year that the beginning farmer responds and input EXIT=1, unless the year is 2012 the final year of our sample, in which case we exclude the observation.[34] This leaves us with the predictors for the years the BFRs responded including the year of their final response.

Looking at the literature in choosing our predictors, sales, firm size, age, and experience tend to affect farmer exit so we add two dummy variables for sales level (*MIDSALES*, *HIGHSALES*), Log of Assets (*LnASSETS*), and three failure time dummies (*FAILEARLY*, *FAILMID*, *FAILLATE*) for BFRs failing at 2 years or less, between 3 and 7 years, or between 8 and 10 years respectively. Since profitability influences firm failure we measure it using gross return on assets (*ROA*) as well as Government payment intensity (*GPAYINT*), we also measure risk in the form of the standard deviation of National Agricultural input-to-output ratio (*OISTDEV*). The literature also found that opportunities for off-farm income goes into decisions to either scale back farming or to supplement on farm activity and household consumption, thus we add an off-farm work dummy (*WRKOFF*), county unemployment rate (*UNEMPRATE*), and nonagricultural share of *GDP* (*NONAGSHARE*). In order account for differences in principal operator and operation characteristics we include dummies for livestock enterprises (*LIVESTOCK*), family farms (*FAMILY*), and minority operators (*MINORITY*). To account for regional and time differences in observations we include a time variable for the census year of the observation (*CYEAR*) and dummy variables for the 10 production regions: Southeast (*SE*), Appalachia (*AP*), CornBelt (*CB*), Delta (*DLT*), Lake States (*LS*) Mountains (*MTN*), Northeast (*NTE*), Northern Plains (*NP*), Pacific (*PAC*), and Southern Plains (*SP*). See the data section for a description of all the variables.

[34] Between 1992 and 2002 only a subset of famers received the "long form" questionnaire containing questions on farm assets. Subsequently all farmers received the assets questions. This does not affect overall exit rate but may affect weighted means of variables.

Since the literature shows that climate variability negatively affects profit measures and debt repayment capacity we include climate in the form of seasonal sum of heating degree days, SPRING_HDD, SUMMER_HDD, and FALL_HDD; seasonal sum of cooling degree days WINTER_CDD, SPRING_CDD and FALL_CDD; seasonal rainfall index SPRING_SP3, SUMMER_SP3, FALL_SP3, and WINTER_SP3. In order to account for lack of rainfall we use the monthly Standardized Precipitation Index (SPI) as well as the heating degree days (HDD), and cooling degree days (CDD), all from the National Oceanic and Atmospheric Administration (NOAA) which are captured at the divisional level (Deschenes and Greenstone,2007; Schlenker et al., 2009; Dell et al., 2012).[35] Whereas the HDD and CDD are the five-year averages of the 3-month period for that season, the reported sp3 is the variance of the index of observing a given amount of rainfall for the 3 months of the season.[36] Mannocchi et al. (2009) used a drought index based on cumulative soil moisture drought on yield and economic net benefit therefore we use the NOAA Climate division three-month precipitation index (SP3) to control from rainfall's effect on profitability expectation and exit.

But should we assume the rate of hazard to stay constant throughout the life cycle of the farmer? The common thread among the literature is that industry exit is affected by the firm's life cycle shifter and should be modeled accordingly (Freeman et al., 1983; Audretsch and Mahmood, 1995 Mahmood, 2000; Pietola et al., 2003). We use intensity of government

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[35] We were able to match US counties with divisions using the NOAA climate prediction center. It is important to note that not every county rests entirely in a single Division. To solve this problem we took the approach that if at least 10% of a county's area appear to lie within more than one division, we assign it to the division where most of the area lies and then add a flag for multi division. In the case of close proportions, we randomly assign its divisional membership. http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/CLIM_DIVS/states_counties_climate-divisions.shtml

[36] For SP3 a zero index value reflects the median of the distribution of precipitation, a -3 indicates a very extreme dry spell, and a +3 indicates a very extreme wet spell. "Degree days are the absolute difference between 65°F and the average temperature (daily high - daily low)/2, days that are higher than 65 are called cooling days and days lower than 65 are called cooling days on account of the need to heat(cool) the home respectively (National Weather Service, url: http://www.srh.noaa.gov/key/?n=climate_heat_cool)

payments as a proxy for government policy which plays a role in the timing of exits (Pietola et al., 2003) and ROA to proxy the scale of existing farmers as well as profitability (Igami, 2011). Mahmood extends the works of Freeman et al. (1983). In particular they allow flexibility in the rate of change of institutional mortality and derive expressions for both max failure times and max failure rates.[37]

We test the Liability of Adolescence hypothesis (LOA) by creating dummies for three distinct "adolescent" groups of BFRs: FAILEARLY for farmers that failed in 2 years or less, FAILMID for those that failed between 3 and 7 years inclusive, and FAILLATE for failures during years 8 or 9. With these we test for decreasing Exit probability over the experience horizon. FAILEARLY are farmers with 2 years or less of farming, F2t7 are farmers with at least 3 and less than 7 years of farming, and FAILLATE is at least 8 years of farming and less than 10 years. Since only BFRs are in the scope of the study, we drop FAILEARLY giving the two explicit linear hypotheses:

(7a) FAILMID = FAILLATE, and

(7b) FAILMID = FAILLATE = 0.

If hypotheses (7a) and (7b) are rejected then the parameters are non zero, unequal, and the individual parameters are significant. We can then compare their magnitudes to the base case which gives us the two implicit hypotheses:

(7c) FAILMID > FAILEARLY, FAILLATE > FAILEARLY,

and finally if, and only if, (7a) – (7c) are all true, then we can test:

(7d) FAILMID > FAILLATE ≡ FAILEARLY < FAILMID > FAILLATE, i.e. exit hazard peaks at the middle of adolescence, ceteris paribus, which is equivalent to the LOA hypothesis.

[37] See appendix for Mahmoods's the full derivation.

3.4 Data

The data comes from the US Census of Agriculture. We construct a panel of farmers responding to the census from 1992 – 2012. The maximal number of records are constrained in 1992-2002 where only a subsample of farmers were surveyed on assets.[38] The regression is run on ~112,000 of these records which means on average, ~28,000 BFRs per year. We also use rainfall and temperature estimates from NOAA to account for systemic risks stemming from climate. Employment information and wages are available at the BEA and profitability for state and national inputs and outputs are published by ERS.[39] State GDP comes from BLS. What follows is a brief description of variables.

For exits rate we define it as the final census year that the beginning farmer responds. Table 3-2 shows 5-year regional exit rates. All regions experienced a decrease in 5-year exit rates between 1992 and 2012.

Table 3-2 Beginning Farmer Exit by Region (pct)

Region	1992	1997	2002	2007
AP	40.5	34.6	31.4	35.0
CB	39.6	30.4	26.5	32.3
DLT	42.0	33.7	34.0	39.3
LS	37.8	28.5	26.2	30.8
MTN	42.5	32.3	33.2	37.3
NP	38.8	29.2	28.4	33.9
NTE	36.7	31.5	30.9	34.3
PAC	44.1	37.2	36.7	39.7
SE	43.3	35.6	34.8	39.5
SP	41.4	33.4	30.5	37.1

[38] In 1992 about 1/3 of farmers were surveyed, in 1997 it was 1/4 and in 2002 it was 1/5. For more on Ag Census Sampling methodology see: http://agcensus.mannlib.cornell.edu/AgCensus/censusParts.do?year=2002

[39] ERS published state productivity figures including inputs and output prices and standardized quantities by input type and commodity sold. The indices is only available for from 1960 through 2004.

The Lake States (LS) had a smaller exit rate on average, yet the Corn Belt's had notable decreases in exit rate between 1992 and 2002 rivals this. Systemically, all regions experienced sharp decreases in exit between 1992 and 1997, but this leveled off in 2002 and the 2007-2012 saw an increase. Since an increase in days worked off-farm can either be a precursor to exit or a means of subsidizing farm activities, we look at the sum of BFRs exiting and not workings off-farm. Table 3-3 shows that the number of farmers staying on farm to the number of farmers exiting peaks in the 2002-2007 period indicating that this period offers the strongest evidence of off-farm wages supporting on farm activities.

Table 3-3 BFR Exits and Farmers that Stay-on-Farm

CYEAR		AP	CB	DLT	LS	MTN	NP	NTE	PAC	SE	SP
1992	WrkOff=0	14.3	23.3	8.0	14.5	8.8	12.6	10.0	11.5	8.8	15.1
	EXIT=1	25.3	38.0	10.6	16.4	12.8	16.6	10.1	16.6	13.7	26.5
	W0/E1	0.56	0.61	0.75	0.89	0.69	0.76	0.99	0.70	0.64	0.57
1997	WrkOff=0	12.8	17.4	7.1	11.0	8.6	9.3	9.5	11.3	8.4	14.6
	EXIT=1	19.5	24.2	8.3	11.1	10.1	10.1	8.7	14.0	10.9	21.7
	W0/E1	0.66	0.72	0.85	0.99	0.85	0.92	1.10	0.81	0.76	0.67
2002	WrkOff=0	14.0	15.8	7.3	9.2	8.0	7.7	9.2	11.8	9.6	17.8
	EXIT=1	15.3	18.3	7.2	8.6	8.8	8.4	7.6	12.5	9.5	18.8
	W0/E1	0.91	0.87	1.02	1.07	0.91	0.92	1.22	0.95	1.00	0.95
2007	WrkOff=0	8.1	10.6	4.7	6.1	5.3	4.9	6.3	7.2	5.9	10.4
	EXIT=1	14.4	21.1	7.8	9.2	9.2	9.0	8.9	13.7	10.4	20.4
	W0/E1	0.56	0.51	0.60	0.67	0.58	0.55	0.70	0.52	0.57	0.51

Note: WrkOff=0 and Exit =1 are in thousands of farmers

Most years and regions dips below a WrkOff to EXIT ratio (WO/E) of less than 1 with a few notable exceptions, such as 1997 NTE and most regions in 2002. All regional 2002 WO/E are higher than the previous two years meaning that in 2002 BFRs as a whole both worked off-farm and exited less. Profitability is measured by comparing the value of output to expenses to the national agricultural output-input price ratio. Table 3-4 shows that there is a significant and positive association between BFRs that do not work off-farm and exiting, at least regionally, lending credibility to off-farm work subsiding on farm activities and/or the household.

Table 3-4 Exits and WrkOff0 Correlation

	wrkoff0	exit1
wrkoff0	1.000	.
exit1	0.856*	1

Note: (*) represents correlation significant at $\alpha = .05$

Table 3-5 lists description of the key explanatory variables. Individual observations are subsetted by beginning farmers earning >$2,000 in a given census year. We use gross return on assets *ROA* which is defined as the Total Value of Production (*TVP*) less production expenses (*EXP)* to make gross divided by total assets (*ASSETS*). *ASSETS* are defined as the sum of the value of land and buildings, (*VLAB)* and machines (*MACHVAL)*. We also take the natural log of assets (*lnASSETS*) in order to account for scale. Two sales class dummies are constructed, *Midsales* and *Highsales*, for $100,000<TVP≤ $500,000 and TVP>$500,000 respectively. *WrkOff* is a dummy variable that equals 1 if no days are worked off-farm. We use a set of 10 regional dummy variables to account for regional idiosyncrasies in addition to demographic variables like farmer age (*AGE*) and a dummy for race (*MINORITY*). *LIVESTOCK* is a dummy indicating if an operation’s sales is primarily livestock[40]. At the county-level we use STATEIO which is the defined as the input-output price ratio per state. AGSHARE is Agriculture’s share of GDP by state, UNEMPRATE is the State unemployment rate.[41]

Table 3-5 Description of Variables

Variable	**Description**
EXIT	Dummy: 1 if respondent exits farming
ROA	GROSSINC/ASSETS
GPAYINT	Government payment intensity
ASSETS	Sum of VLAB and MACHVAL ($1,000)
LnASSETS	Natural log of assets
LOWSALES	Dummy: 1 if TVP < $100K
MIDSALES	Dummy: 1 if $100K < TVP <= $250K
HIGHSALES	Dummy: 1 if > $250K
UNEMPRATE	County unemployment rate
NONAGSHARE	1- Agriculture’s share of State GDP
WRKOFF	Dummy: 1 if any days worked off-farm
OISTDEV	Output/Input price variation
xx_SP3	Seasonal rainfall index variation, where xx is the season
xx_HDD	Season total heating degree days, where xx is the season
xx_CDD	Season total cooling degree days, where xx is the season
AGE	Age of principal operator
LIVESTOCK	Dummy: 1 if operation's sales is primarily livestock
MINORITY	Dummy: 1 if operator is a minority
FAMILY	Dummy: 1 if operation is owned and operated by family
REGION	Production Region
CYEAR	Census Year of observation

[40] Using the 1992 SIC and NAICS post 1992 we classify enterprise type into 16 groups. See appendix for more details.

[41] Real GDP by state for Ag and NonAg is used from 1992-2012. It comes from BEA using the SICS 1992-1996 and NAICS 1997-2012. The documentation for 'when' GDP is calculated is not complete. We believe it is year end, because the documentation does not mention "fiscal", and changes are typically calculated from 7/1 to 6/30.”Either way State GDP is matched to the "closest" year-end to the Ag Census's Year end (12/31). Also the GDP in 1997-2012 is indexed to 2009, but the Real GDP from 1992-1996 is ambiguous in the documentation. Since we use Ag Share this ambiguity is irrelevant except for documentation.

Table 3-6 shows the means of key variables by *CYEAR*. Five-year Exit decreases over the series and are the lowest in the two periods beginning 1997 and 2002 at 47.0% and 34.8% respectively. This is contrasted with *ROA* which rose between 1997 and 2002, peaking at .146. Figure 3-3 plots *ROA* by region and *CYEAR*. Most regional ROAs peak in the 2002-2007 period with notable exceptions.

Table 3-6 Variable Means by CYEAR

Values	1992	1997	2002	2007	2012
EXIT	0.470	0.348	0.351	0.425	.
ROA	0.106	0.102	0.146	0.044	0.000
ASSETS	648	608	897	568	629
MIDSALES	0.138	0.106	0.103	0.101	0.115
HIGHSALES	0.024	0.026	0.032	0.040	0.046
UNEMPRATE	0.075	0.056	0.058	0.049	0.078
NONAGSHARE	0.973	0.986	0.987	0.987	0.985
WRKOFF	0.672	0.718	0.662	0.762	0.727
AGE	43.1	44.6	46.1	47.5	47.0
LIVESTOCK	0.523	0.544	0.524	0.495	0.460
FAMILY	0.825	0.846	0.869	0.837	0.841
MINORITY	.022	.028	.002	.001	.001
GPAYINT	0.187	0.137	0.162	0.155	0.159
AP	0.139	0.136	0.130	0.116	0.109
CB	0.209	0.187	0.179	0.182	0.183
DLT	0.055	0.058	0.058	0.058	0.052
LS	0.095	0.091	0.086	0.082	0.088
MTN	0.066	0.072	0.069	0.072	0.078
NTE	0.061	0.065	0.067	0.075	0.080
NP	0.093	0.082	0.078	0.074	0.088
PAC	0.082	0.086	0.091	0.102	0.094
SE	0.068	0.071	0.075	0.078	0.071
SP	0.132	0.152	0.167	0.162	0.157

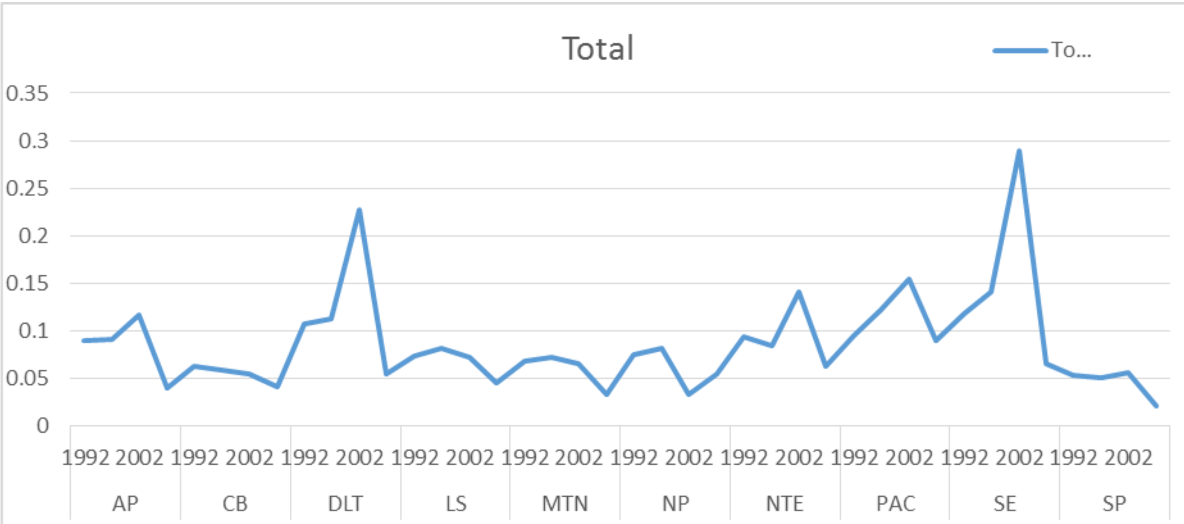

Figure 3-3 ROA by Region

The Corn Belt and Northern Plains actually saw a decrease in *ROA* during this period and the Mountain states had a nearly flat *ROA* from 1992 to 2007. GPAYINT is the greatest in the period beginning 1992 at .187 and only .155 by 2007 indicating that government payments are growing less than revenues in real terms. The average farmer age increases over the series from 43.1 to 47.0 years of age so BFRs are aging as a whole but are still younger compared to EFRs. The percent of family farms increases over the series from 82.5% to 84.1%. The percent of livestock enterprises decreased from 52.3% in 1992 to 46.0% in 2012. The proportion of both BFRs with Mid Sales (High Sales) rise from .138(.024) to .115(.046) respectively. The proportion of BFRs within certain regions change while others are remarkably stable. BFRs in *AP* actually decreases from 13.9% to 10.9%, *CB* falls from 20.9% to 18.3%, *DLT* around 5.8%, *LS* falls slightly from 9.5% to 8.9%, *MTN* increases slightly from 6.6% to 7.8%, *NTE* rises from 6.1% to 8.8%, *NP* slightly falls from 9.3% to 8.8%, *PAC* increases from 8.2% to 9.4%, *SE* slightly increases from 6.8% to 7.1%, and *SP* rises from 13.2% to 15.7%. The percent of non White BFRs hovers between .1% and 2.2% meaning that the BFR sample is racially homogenous which could be either a function of the $2,000 cut off or the actual composition of BFR startups.

The proportion of farmers working zero days off-farm does vary over the series from .328 to .273, so overall there are more BFRs working off-farm.

Climate Data. Table 3-7 shows sp3 variation by season and year.[42] In 2002 and 2007 we see that sp3 winter variation increases greatly in 2002 over previous years yet decreased in spring and the summer. SP3 is negative multiple seasons, indicating drought, especially winter, and that 2012 was also a dry summer. Table 3-8 shows the CDD and HDD totals by season and year. The first thing we notice is that HDD are miniscule in summer and CDD is miniscule in the winter, as the average temperature less often goes above 65˚F in the winter and below 65˚F in the summer. The heating and cooling degree days are pretty stable with a few exceptions. Spring and fall HDD decreases over time while spring and summer CDD increases.

Table 3-7 Seasonal Rainfall Variation (standard deviation)

Year	spring	summer	fall	winter
1992	1.067	1.063	0.822	0.879
1997	0.928	1.042	0.844	0.819
2002	0.901	0.913	1.097	0.996
2007	1.092	0.965	0.907	0.903
2012	1.065	1.026	0.968	0.968

[42] The original means, standard deviations, and variances were calculated for each division over the five years ending the census year which is the data used in the analysis. The climate summary statistics presented here are the means of the 5-year original statistics by county, thus are the original divisional statistics weighted by the number of counties in a given division.

Table 3-8 Seasonal Cooling and Heating Degree Days (total degrees)

	spring		summer		fall		winter	
Year	CDD	HDD	CDD	HDD	CDD	HDD	CDD	HDD
1992	133	1,145	826	78	178	1,055	12	2,720
1997	117	1,271	837	81	168	1,103	9	2,797
2002	158	1,160	912	69	209	961	13	2,575
2007	151	1,098	882	68	211	940	10	2,704
2012	166	1,088	949	72	188	995	10	2,780

3.5 Results

Table 3-9 presents regressions 1-5 where the first equation (1) excludes climate and risk, (2) adds only *OISTDEV*, (3) adds only climate, (4) adds only climate and removes CYEAR, and (5) adds everything excluding CYEAR, and removes outliers.[43] Interpreting probit coefficients is cumbersome because each coefficient is only valid for small movements at the variables mean. Therefore we calculate the marginal effects of the models' predictors in Table 3-10. *ROA* is only significant for (5) and has a coefficient of .007 meaning that a one unit increase in ROA decreases exit probability by .007 which is counterintuitive until one considers the weak significance level given the population size and absence of time adjustment. The weighted ROA in 2007 should definitely be looked as well as any other adjustments to asset values. *GPAYINT* is significant and positive in most specifications and yields a change of .016 and .025 in probability of exit. This is strange because other researchers such as Key and Roberts (2006) have documented government payments decreasing exit like while Kaukauskas (2013) show that

[43] Outliers are defined as having owned acres or gross operating Income at the 99th percentile or higher. Acres averaged 247 over the 5 Census periods.

reliance on government subsidies can increase disinvestment; neither one looked at the beginning farmer subset.

Table 3-9 Probit

	1	2	3	4	5
INTERCEPT	-0.258	-0.197	-1.38***	-3.472***	-3.381***
	(0.301)	(0.302)	(0.402)	(0.395)	(0.411)
ROA	0.009	0.009	0.008	0.004	0.029*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.017)
GPAYINT	0.065***	0.065***	0.063**	0.098***	0.097***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.027)
LNASSETS	-0.066	-0.066***	-0.067***	-0.082***	-0.08***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
MIDSALES	-0.076	-0.075***	-0.074***	-0.024**	-0.043***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
HIGHSALES	-0.206	-0.206***	-0.209***	-0.158***	-0.184***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)
UNEMRATE	0.016	0.015***	0.012***	0.036***	0.03***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
NONAGSHARE	-0.636**	-0.524*	-1.531***	-4.099***	-3.979***
	(0.308)	(0.311)	(0.389)	(0.379)	(0.393)
WRKOFF	0.003	0.003	0.002	-0.036***	-0.028***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
OISTDEV	.	-0.646***	.	.	2.685***
	.	(0.234)	.	.	(0.206)
AGE	0.005	0.005***	0.005***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LIVESTOCK	-0.044	-0.044***	-0.042***	-0.046***	-0.051***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
MINORITY	-0.135**	-0.14**	-0.149**	-0.065	-0.117*
	(0.065)	(0.066)	(0.066)	(0.066)	(0.069)
FAMILY	-0.213	-0.213***	-0.213***	-0.23***	-0.234***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Spring_sp3	.	.	0.041***	0.03**	0.034**
	.	.	(0.015)	(0.015)	0.015
Summer_sp3	.	.	-0.039***	0.063***	0.04***
	.	.	(0.014)	(0.014)	0.015
Fall_sp3	.	.	0.000	-0.010	-0.012
	.	.	(0.016)	(0.016)	0.016

Table 3-9 (continued) Probit

	1	2	3	4	5
Winter_sp3	.	.	-0.023	-0.063***	-0.056***
	.	.	(0.016)	(0.016)	0.017
Spring_cdd	.	.	0.000	-0.000	0.000
	.	.	(0.000)	(0.000)	(0.000)
Fall_cdd	.	.	-0.000**	-0.001***	-0.001***
	.	.	(0.000)	(0.000)	(0.000)
Winter_cdd	.	.	0.001**	0.002***	0.002***
	.	.	(0.000)	(0.000)	(0.000)
Spring_hdd	.	.	-0.000***	-0.001***	-0.000***
	.	.	(0.000)	(0.000)	(0.000)
Summer_hdd	.	.	0.000**	-0.000*	-0.000
	.	.	(0.000)	(0.000)	(0.000)
Fall_hdd	.	.	0.000	0.000***	0.000***
	.	.	(0.000)	(0.000)	(0.000)
REGION	YES	YES	YES	YES	YES
CYEAR	YES	YES	YES	NO	NO

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

Given the distribution of government payments to more established EFRs with historical program acreage, other factors such as BFR ownership of and cash-rents on program acres would provide useful insight. *LnASSETS* is significant and positive across all specifications and indicates that a small increase in *LnASSETS* results in a -.017 to -.021 change in EXIT. Marginal effects for *MIDSALES are -.006 to -.020* while those of *HIGHSALES are -.041 to -.054. UNEMRATE* is significant, varies in sign on the probit, but the marginal effects lead to between .003 and .009 increase in exit. A unit increase in *NONAGSHARE* yields between -.136 and -1.064 decrease in EXIT. *WRKOFF* is significant for (4) and (5) and leads to a -.007 to -.009 decrease in probability of exit which is an interesting in that it supports the narrative that off-farm work can be used to supplement farming or consumption. *OISTDEV* is significant but has conflicting marginal effects of -.167 and .699. Although time is not a factor in (5) there is still some evidence that risk increases BFR exit, especially when climate into taken into

Table 3-10 Marginal Effects

Variable	2	3	4	5
ROA	0.002	0.002	0.001	0.007
GPAYINT	0.017	0.016	0.025	0.025
LNASSETS	-0.017	-0.017	-0.021	-0.021
MIDSALES	-0.020	-0.019	-0.006	-0.011
HIGHSALES	-0.053	-0.054	-0.041	-0.048
UNEMRATE	0.004	0.003	0.009	0.008
NONAGSHARE	-0.136	-0.396	-1.064	-1.036
WRKOFF	0.001	0.001	-0.009	-0.007
OISTDEV	-0.167	.	.	0.699
Spring_sp3	.	0.011	0.008	0.009
Summer_sp3	.	-0.010	0.016	0.010
Fall_sp3	.	0.000	-0.003	-0.003
Winter_sp3	.	-0.006	-0.016	-0.015
Spring_cdd	.	0.000	0.000	0.000
Fall_cdd	.	0.000	0.000	0.000
Winter_cdd	.	0.000	0.001	0.001
Spring_hdd	.	0.000	0.000	0.000
Summer_hdd	.	0.000	0.000	0.000
Fall_hdd	.	0.000	0.000	0.000
AGE	0.001	0.001	0.001	0.001
LIVESTOCK	-0.011	-0.011	-0.012	-0.013
MINORITY	-0.036	-0.039	-0.017	-0.031
FAMILY	-0.055	-0.055	-0.060	-0.061
AP	-0.014	0.004	0.006	0.000
CB	-0.015	0.020	0.017	0.015
DLT	0.024	0.026	0.023	0.021
LS	-0.026	0.033	0.037	0.034
MTN	0.004	0.047	0.052	0.049
NTE	-0.002	0.055	0.070	0.071
NP	-0.009	0.026	0.011	0.014
PAC	0.015	0.046	0.044	0.045
SP	0.006	0.012	0.036	0.032
CYEAR	-0.038	-0.036	.	.
FAILMID	0.477	0.475	0.467	0.470
FAILLATE	0.304	0.303	0.290	0.293

consideration. Climate is significant in multiple specifications and the magnitudes of SP3_Stdev is non negligible for multiple seasons. Spring_sp3 was between .008 and .011 where as Summer_sp3 was between -.010 to .016. Winter_sp3 consistently decreases exit with a unit increase resulting in -.015 to -.016, but Fall_sp3 had no significant effect on exit. When looking at total cooling and heating degree days we find statistically significant but very small coefficients. *Spring_hdd* and *Summer_hdd* are significant but miniscule whereas *Fall_cdd* and *Winter_cdd* are significant yet analogously negligible. A one unit increase in *AGE* increases exit probability by only .001. The subset we are using is also younger on average than EFRs so care should be taken when interpreting any extrapolated effects of *AGE* outside of the 47 years on which the average BFR resides. *AGE* is significant and positive across most specification. *LIVESTOCK* has marginal effects of *-.011 to -.013.* , *MINORITY of -.017 to -.039*, and *FAMILY* of -.055 to -.061.

Goodness of Fit and Liability of Adolescence. Table 3-11 shows the goodness of fit with tests for the liability of adolescence hypothesis. *WRKOFF is* significantly different than zero in both specifications and is jointly significant along with LOA parameters. In regressions (2)-(5) the failure rate actually increases at decreasing rate over the interval. For example in (3) FAILMID is 1.83 while FAILLATE is -1.17 which means the local maximum exit rate occurs until 8 to 10 years of farming; the local maxima for (2), (4), and (5) may occur over a later interval.

Table 3-11 Liability of Adolescence and Goodness of Fit

	1	2	3	4	5
LOA:					
FAILMID	1.842	1.841***	1.837***	1.798***	1.807***
	(0.010)	(0.010)	(0.011)	(0.010)	0.011
MEMID	.	0.477	0.475	0.467	0.470
FAILLATE	1.174	-1.173***	1.17***	-1.117***	-1.124***
	(0.012)	(0.012)	(0.012)	(0.012)	0.012
MELATE	.	0.304	0.303	0.290	0.293
Goodness of Fit					
N	112957	112844	112802	112802	106430
Log Liklihood	-52387	-52327	-52256	-52673	-49697
LR	39961	39945	40045	39211	37041
LOA: FAILLATE = FAILMID , FAILLATE = FAILMID , FAILMID = 0					
ChiSq stat	32699	32602	32376	32163	30149
Pr > ChiSq	<.0001	<.0001	<.0001	<.0001	<.0001

3.6 Discussion

It appears that the Liability of Adolescence hypothesis only holds for BFRs when ignoring climate and profitability. There is strong evidence of a decreasing exit rate when BFRs go from 3-7 years in business to 8-10 years in business. But when we compare either interval with BFRs farming two years or less we see an increased probability of exit, although at a decreasing rate. Experienced farmers have a smaller exit rate compared to BFRs so we can infer that the hazard associated with intervals of 10 years or greater is even smaller. Other interesting findings were that size both in terms of assets and sales class does decrease BFR exit which agrees with other works. Yet intensity of government payments actually increases exit which may indicate that BFRs with greater dependence on government payments are especially at risk exit. We found that for BFRs working off-farms tends to supplement farming or the household consumption which adds to the literature on returns to farming and outside employment. We found that divisional climate information is useful, especially the sp3 rainfall index which show's that on average, exit decreases with spring rainfall variation and increases with winter variation, and is ambiguous in the summer. Net of time, the variance of output-input ratio decreases exit rate until climate is included and then increases, so there may be some unobserved correlation between the two. Future research should look at how crop diversification affects BFR exit especially given its role in mitigating climate related losses which are region and crop specific.

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Appendix A

Additional Information for Chapter 1

Appendix A-1

Chayanov household production and consumption

The "profit" maximizing conditions from figure 4. are still:

$P * \text{MP}_L = w$

Where P is the price of output, $\text{MPL} = \frac{\partial Y}{\partial L}$ and $w = \frac{\partial U / \partial l}{\partial U / Y} = \frac{\text{MU}_l}{\text{MU}_Y}$

= "subjective wage". It is through the subjective wage that subsistence households "self-exploit", i.e. lower their subjective wage as a response to a flattening of the household utility function.

Chayanov contends that consumer-to-worker ratio (*cw*) dictates the slope of the indifference curve; as the number of total consumers increase, the minimal level of consumption also increases, and the marginal utility of leisure i.e. non production, decreases. Figure () depicts household consumption constrained the household production function. Notice an increase in *cw* moves the household from $I_1 \rightarrow I_2$ and the point of tangency with the production function moves from $(L_1, Y_1) \rightarrow (L_2, Y_2)$, where $Y_2 > Y_1$.

In short, Chayanov shows how a change in family composition will change a household's production and consumption choices (Ellis, 1993).

Appendix A-2

Model for Safety Rationing in Detail

The utility function and production functions were:

(1) $U(Y_b, Y_g), = (\beta Y_b)^\delta + (\gamma Y_g)^\delta.$

The production technology is concave and represented by

(2) $Y_b = B(l)$, and

(3) $Y_g = G(l).$

Both consumption (utility) and production are subject to:

(4) $l_0(w) \geq l$,

(5) $Y_0(c) \leq Y_b + Y_g.$

The two endogenous arguments are subject to endowment and subsistence constraints as well as to two production constraints, therefore the system is over determined.

If the production technology is:

(6) $Y_b = B(l)$.

and,

(7) $Y_g = G(l).$

Then (2) and (3) are substituted into (1) giving:

(8) $U = [\beta \cdot B(l)]^\delta + [\gamma \cdot G(l)]^\delta,$

subject to:

(9) $l_0(w) \geq l$,

(10) $Y_0(c) \leq Y_b + Y_g$.

Here, l_0 is the maximum amount of labor available as a function of *w* workers in the household and Y_0 is the minimum amount of acceptable consumption as determined by *c* consumers in the household. The household then has a production possibilities frontier of:

(11) $\frac{\phi_b}{\phi_g} = -\frac{dY_g}{dY_b}$, where $\phi_i = \frac{\partial l}{\partial Y_i}$ for $i = \{b,g\}$.

If obtainable, the point of tangency between the production possibilities frontier and the household indifference curve will provides a point of maximal efficiency in consumption and production:

(12) $RPT = \frac{\phi_b}{\phi_g} = -\frac{dY_g}{dY_b} = \frac{\partial U}{\partial Y_b} / \frac{\partial U}{\partial Y_g}$ = MRS.

First evaluating first order necessary conditions and then substituting the labor and subsistence constraints from (5) and (6) into (8) yields:

(13) $\frac{\beta}{\gamma} \cdot (\frac{\gamma Y_g}{\beta Y_b})^{1-\delta} = \frac{\phi_b}{\phi_g}$,[44]

and,

(14) $(\frac{\beta}{\gamma})^{\delta} \cdot (\frac{Y_0(c)-B(l)}{B(l)})^{1-\delta} = \frac{\phi_b}{\phi_g}$.

An inspection of (8) shows that MRS is diminishing as required for convex preferences.

---

[44] Beattie, Taylor and Watts (2009) show that if ϕ_i can be solved explicitly for Y_b and Y_g, then $RPT = \frac{\phi_b}{\phi_g}$ reduces to $\frac{\partial Y_g}{\partial l} / \frac{\partial Y_b}{\partial l}$ which is just the inverse ratio of the marginal product of labor

Let S(*c*,*l*) $= \frac{Y_0(c)-B(l)}{B(l)}$, then (10) becomes:

(15) $\left(\frac{\beta}{\gamma}\right)^{\delta} \cdot S^{1-\delta} = \frac{\phi_b}{\phi_g}$.

Finally, operationalizing labor as a linear function of *w* and solving RPT for B^* and G^*:

(16) $R^* = G^*(c,w)/B^*(c,w)$,

Where R* is the optimal ratio of safe to unsafe consumption for a given household.

Appendix A-3

Population and Housing Characteristics for Ejura-Sekyedumase

Population

Population Characteristics (2000 Population and Housing Census figures)

10.	District Population (1984):	60,997
11.	District Population (2000):	81,115
12.	District Population (2010):	101,826 (projected)
13.	Population Growth Rate (2000):	1.8% per annum
14.	Males in 2000:	41,993 (51.77%)
15.	Females in 2000:	39,122 (48.23%)
16.	Children/Youthful Population in 2000:	50.5%
17.	Population Density in 2000:	60 persons per sq. km
18.	District's Share of Ashanti Region's Population (2000):	2.2%
19.	Urban Population (2000) (Mainly Ejura & Sekyedumase):	39,562 (48.8%)
20.	Rural Population (2000):	41,552 (51.2%)

21. Ethnicity

Akan, (the indigenous group), Kotokoli, Dagomba, Dagarti, Komkomba, Gonja, Ewe, Gruma, Fulani, etc thus earning the accolade "ECOWAS".

Appendix A-4

Table of Correlations and Significance

We looked at an additional ratio, *Net_cw_part* which defines *workers* as household members older than 9 and not in secondary school. One issue with incorporating school status in the definition of *worker* is that the child's school status and age are not mutually exclusive, especially in a developing country where students may start school late. For instance a preteen or adolescent still in primary school would be counted as a *worker* for *net_cw_part*, yet this definition may be highly correlated with the others. Correlation coefficients for the ratios are reported in the table at the bottom.. Since *net_cw_par*t is highly and significantly correlated with *cw_part* (r=.91), dropping this variable should yield more reliable standard error estimates without losing much information. *Cw* also has a statistically significant correlation with every other ratio, albeit less than one.

	Cw	*cw*_part	*net_cw*	*net_cw*_part
cw	1			
*cw*_part	0.6765 (0.000)	1		
net_cw	0.4115 (0.000)	0.1102 (0.205)	1	
*net_cw*_part	0.6812 (0.000)	0.9145 (0.000)	0.1788 (0.039)	1

Appendix A-5

Ramsey RESET test for functional form specification

H_0: model correctly specified

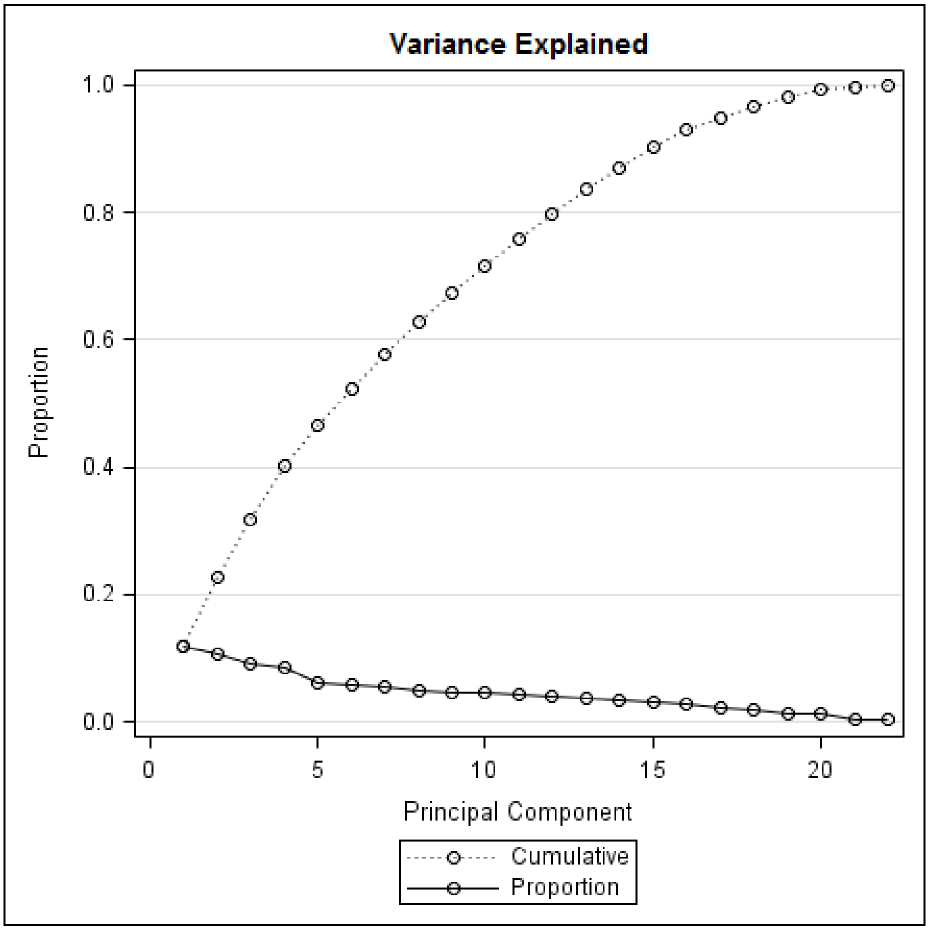
Dep. Variable	F	Prob > F
AFB1	1.60	0.196
Bilirubin	3.74	0.015
AST/ALT	1.18	0.324
Index	15.01	0.000

Appendix B

Additional Information for Chapter 2

Appendix B-1

Screen Plot of Principal Components of Predictors



Appendix B-2

BFR by Cluster

CLUSTER	ALL	1	2	3	Total BFRs
N	551	154	19	378	307,741
CONSTRAINED	0.060	0.030	0.000	0.074	
VPRODTOT	24844	25732	14927	25007	
NVPROD	23049	24806	14514	22826	
VPRODPA	578.127	536.774	1490.268	548.456	
NVPRODPA	567.780	531.707	1487.513	535.809	
lvprodtot	8.778	8.578	8.665	8.855	
lnvprod	8.753	8.594	8.824	8.807	
lvprodpa	4.721	4.987	5.865	4.576	
lNVPRODPA	4.696	5.003	6.060	4.531	
LTA	0.172	0.183	0.208	0.166	
WC2E	0.530	0.236	0.087	0.659	
LFNW	11.942	12.673	13.620	11.593	
WKSOFF	86.911	85.304	83.909	87.644	
ONFARM	1484	1298	1996	1527	
FTE	0.761	0.647	1.184	0.781	
TENURE	4.701	4.584	4.225	4.767	
AGE	45.772	45.900	55.017	45.272	
DEPENDENTS	1.001	0.997	0.801	1.012	
NUMLOANS	0.748	0.730	1.026	0.741	
HOMEVALUE	88870	187527	503997	32497	
NOCOLLEGE	0.056	0.007	0.000	0.077	
Single	0.172	0.175	0.000	0.179	
Midwest	0.273	0.245	0.198	0.287	
South	0.482	0.431	0.191	0.515	
West	0.179	0.298	0.553	0.118	
GrainOil	0.084	0.084	0.019	0.087	
DAIRY	0.022	0.014	0.000	0.026	
Hog	0.008	0.006	0.030	0.007	
Poultry	0.011	0.007	0.002	0.013	
Beef	0.376	0.352	0.338	0.387	
HHI	83969	84149	198390	78289	
FNW	305458	406577	1544698	207745	
ACRES	126	89.3	45.4	143.7	
OWNED	68.1	52.1	98.4	72.5	
FEMALE	0.140	0.161	0.057	0.136	

Appendix B-3

Forward Selection of Alternative Specifications

Step	Number In	Entered	Label				Partial R-Square	F Value	Pr > F	Wilks' Lambda	Pr < Lambda	Canonical Correlation	Pr > ASCC
1	1	DSHORT	Short term financial debt				0.021	11.62	0.0007	0.9790	0.0007	0.0210	0.0007
2	2	DEPENDENTS	Total members of household <18				0.016	8.8	0.0031	0.9634	<.0001	0.0366	<.0001
3	3	FROPMNUM	Numeratc	n (IN	FI-V22A-	V22E+EFIN	0.0156	8.57	0.0036	0.9484	<.0001	0.0516	<.0001
4	4	LHHI1					0.0096	5.21	0.0228	0.9393	<.0001	0.0607	<.0001
5	5	South					0.0106	5.79	0.0165	0.9293	<.0001	0.0707	<.0001
6	6	Single					0.0048	2.59	0.108	0.9249	<.0001	0.0751	<.0001
7	7	NOCOLLEGE	1 if Neithe	have	college	education	0.0066	3.55	0.0602	0.9188	<.0001	0.0812	<.0001
8	8	AGE	Age of survey respondent				0.004	2.13	0.1449	0.9152	<.0001	0.0848	<.0001
9	9	TENURE	Number of years operating a farm				0.0059	3.16	0.0761	0.9098	<.0001	0.0902	<.0001
10	10	DAIRY	Dairy - value of production				0.0041	2.2	0.1389	0.9061	<.0001	0.0939	<.0001
11	11	EVLABOR	Labor expense				0.0042	2.27	0.1324	0.9022	<.0001	0.0978	<.0001

Note: varlist = LHHI1 WC2E lFNW WKSOFF ONFARM FTE TENURE AGE DEPENDENTS NUMLOANS HOMEVALUE NOCOLLEGE SINGLE MidWest SOUTH WEST GrainOil Dairy Hog Poultry Beef ACPRPINS ACRES ACRESMLB ACTOT ANTOT APRINC ATOT DRINTP DRMAXPAY DSHORT EFINS EFINS_C EFINT EFRENT EFTAXES EFTOT ENBEN ENDEPR ETOT EVCWORK EVFEED EVFERTC EVFUELO EVLABOR EVLOTH EVLVPUR EVMAINR EVOTH EVSEEDP EVTOT EVUTIL FNW FRATDEN FRATNUM FRCRDEN FRCRNUM FRDADEN FRDANUM FRDCDEN FRDCNUM FRECODEN FRECONUM FROEDEN FROENUM FROPMDEN FROPMNUM FRROADEN FRROANUM FRROEDEN FRROENUM FRUIT FRWCDEN FRWCNUM FSALES ICROP IGFI IGOVT LCTOT LNNREALE LNREALE LNTOT MLBT NETW NFASST NFDEBT NFDEBT_D_V1 NFISOL2 NFNW OFFCAPGAIN OWNED P25 P26 P39 P518 P519 P528 P531 P884 R890 R1002 R1011 R1020 R1029 R1038 R1047 V74 V76_V1 V77_V1 V78_V1 V79_V1 V80_V1 V81A WAGERATE

EVLABOR EVLOTH EVLVPUR EVMAINR EVOTH EVSEEDP EVTOT EVUTIL FNW FRATDEN FRATNUM FRCRDEN FRCRNUM FRDADEN FRDANUM FRDCDEN

FRDCNUM FRECODEN FRECONUM FROEDEN FROENUM FROPMDEN FROPMNUM FRROADEN FRROANUM FRROEDEN FRROENUM FRUIT FRWCDEN FRWCNUM FSALES ICROP IGFI IGOVT LCTOT LNNREALE LNREALE LNTOT MLBT NETW NFASST NFDEBT NFDEBT_D_V1 NFISOL2 NFNW OFFCAPGAIN OWNED P25 P26 P39 P518 P519 P528 P531 P884 R890 R1002 R1011 R1020 R1029 R1038 R1047 V74 V76_V1 V77_V1 V78_V1 V79_V1 V80_V1 V81A VPRODCRP VPRODLIV VPRODLL VPRODTOT WAGERATE

Appendix B-4

Discriminant and Clustering

To briefly summarize the discriminant approach, say that $\mathbf{B^* = B_1, B_2, \ldots, B_p}$, where $\mathbf{B_j}$ is a nx1 vector of demeaned credit constraint determinants. If $\mathbf{B^*}$ is positive definite, it can be shown that $\mathbf{B}$ can be rewritten $\mathbf{E\Lambda E}$, where $\mathbf{E}$ where is a matrix of normalized Eigen vectors and Λ is diagonal vector of Eigen values (Johnson and Wichern, 2007). Additionally this approach allows for dimension reduction because variation in $\mathbf{B}$ can often be sufficiently captured by a subset of $\mathbf{B}$. The borrowing constraint $\mathbf{B^*}$ depends on observable characteristics such as assets, cash, age, education, experience, and expected profitability of the sector, etc.

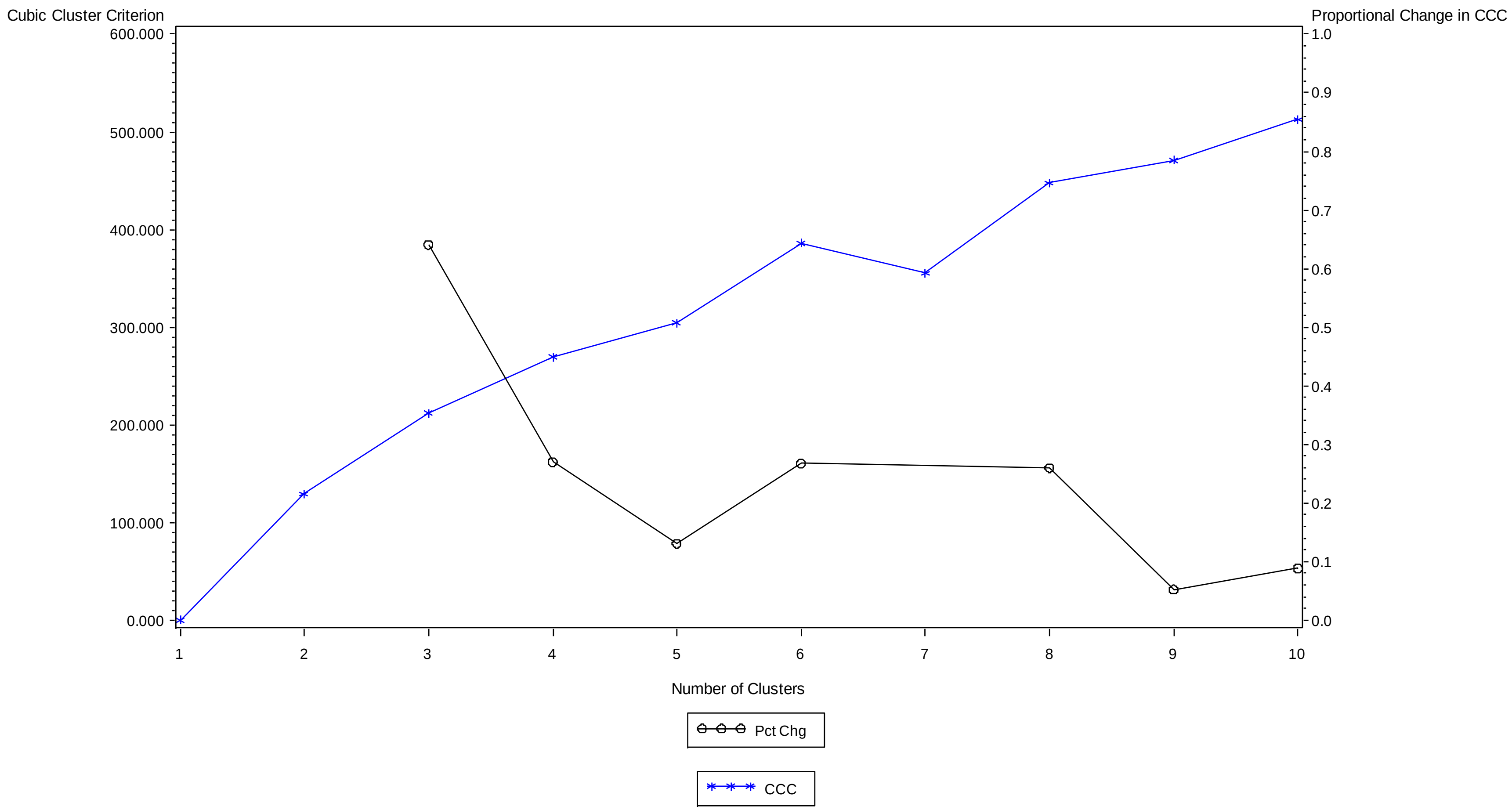
PCA and Clustering

Appendix B.1 depicts the scree plot from Principal Component Analysis (PCA). It takes 12 principal components to explain approximately 80% of the variation in the **X**. Dimension reduction is one of the benefits of using principal components, but seeing as no few components dominate the total variance of the system, reducing the number of predictors does not add much in the way of model prediction. A separate analysis was run on a reduced set of 12 principal components and results remained essentially unchanged. Both the logistic regression results and the matching results were essentially the same with the only a notable difference in the fit statistics i.e. percent concordant/discordant and error count estimates [sic] the model fit. As such, all 22 principal components are used in the final analysis. Next in Appendix B.5 we analyze the Cubic Clustering Criteria (CCC) for optimal cluster selection given 1-10 nonhierarchical groups, clustered on all 22 principal components. The benefit of this technique is that it utilizes local maxima in the changes of CCC. One drawback is that the nonhierarchical methods require the number of clusters to be predetermined. To get around this we chose a number that allows a diversity of clusters while still allowing for hypothesis testing within the constrained group. The figure below shows both CCC and percent change in CCC (PctCCC) plotted against number of clusters. CCC is monotonically increasing before and after 6 clusters but when looking at the percent change in CCC we find that PctCCC jumps at both 3 clusters and 6 clusters. Both of these as possible correct specifications so we run the analysis on both sets of clusters, selecting 3 in the end as the best fit for the data. We use clusters 2 and 3 as dummies for the probit regression since results are highly similar for allowing us to save on scarce degrees of freedom. We first used the k means approach via PROC FASTCLUS for 10 clusters and included cluster dummies into a logistic regression. Results of those matches are included in the Appendix B. We then reran the procedure 10 times, incrementally increasing the number of clusters, and used the change in Cubic Clustering Criteria to select 3 as the optimal number of clusters the table above shows BFR means by cluster. Note that cluster 2 does not have any credit constrained BFRs. Additionally the VPRODTOT of these 19 farmers is approximately $15,000, much lower than the clusters 1 and 3. The average age of 2 is also 55 compared to 1 and 3 being 45 years old. Both clusters 1 and 3 have VPRODTOTs > $25,000 but 3 has more than twice the percentage of constrained farmers, despite being a larger subsample than 1. The home value of 3 is $324,000 which almost doubles 1's HOMEVALUE at $187,525.

Theoretically credit constraints should be decreasing along HOMEVALUE as in the case of 2, but given the diversity of BFR financial structure and goals, it is difficult to draw a conclusion on the effect of HOMEVALUE without jointly accounting for other treatment determinants. Lastly, note the acres by group in Appendix B.2. Cluster 1 has substantially less acres than either 2 or 3. Despite their smaller holdings on average, this cluster is less likely constrained than 3 which may denote different preferences for expansion or inter-cluster variation.

Appendix B-5

Cubic Clustering Criteria



Appendix B-6

ARMS Credit Constraint Questions 2005-2007

Within the past 5 yrs have you encountered any of the following with regards to your credit or loan applications to lenders or creditors and:

1) R1120

- request for credit/loan application turned down or you were not given as much credit as you applied for

2) R1121

- INITIAL request for credit/loan turned down but later granted by reapplying to same institution or elsewhere

3) R1122

- Thought of applying for credit at a particular place but changed your mind because you thought you might be turned down

Appendix C

Additional Information for Chapter 3

Appendix C-1

Distribution of Farms by Size of Sales

Sales	**2012**	***2007***	***2002***	%chg
Less than $1,000	428,810	499,880	430,953	-0.5%
$1,000 to $2,499	236,501	270,712	307,368	-23.1%
$2,500 to $4,999	231,388	246,309	243,026	-4.8%
$5,000 to $9,999	248,616	254,834	246,624	0.8%
$10,000 to $24,999	271,511	274,274	272,333	-0.3%
$25,000 to $49,999	161,939	163,500	163,521	-1.0%
$50,000 to $99,999	133,988	129,124	142,532	-6.0%
$100,000 to $249,999	141,675	149,049	162,831	-13.0%
$250,000 to $499,999	95,653	96,251	85,909	11.3%
$500,000 to $999,999	77,562	63,567	44,348	74.9%
$1,000,000 to $2,499,999	58,203	41,863	21,460	171.2%
$2,500,000 to $4,999,999	14,892	9,845	4,719	215.6%
$5,000,000 or more	8,565	5,584	3,358	155.1%

Appendix C-2

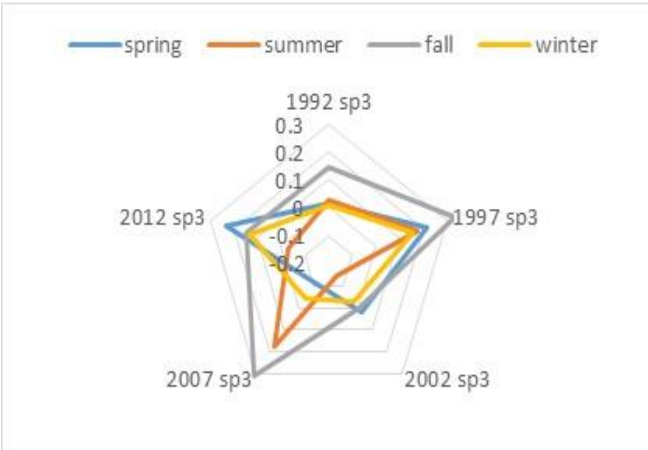
Other Climate Statistics

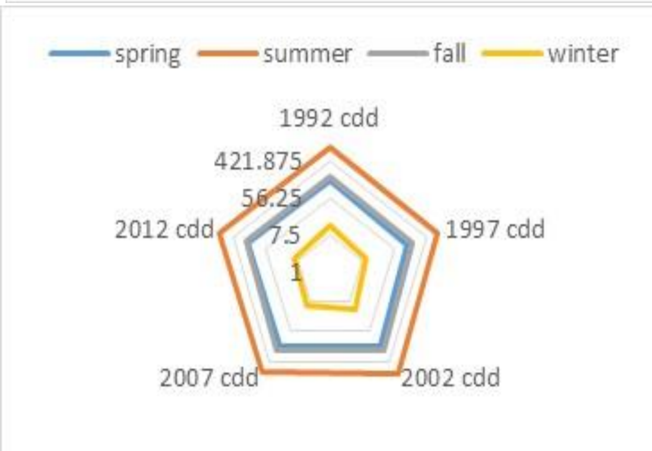
The figures below show both the central tendencies and the variation among the different years and seasons for SP3, CDD, and HDD. Reading clockwise from the top we see that 5 year average SP3 in the fall easily outstrips every other season excluding 2012 where fall SP3 indicated a dryness and spring rainfall approached a much wetter 0.3. We see more consistency in the range of sp3 for the summer whereas fall SP3 has a distorted range after 1997. Again the SP3 standard error and variance appeared to be more consistent in Summer, a little less in Spring, and inconsistent in the Winter and the Fall, going anywhere from the lower bound .75 to 1.35 in 2002. As expected Total CDD is on average highest in the hot months of Summer while HDD is highest in the cooler winter months. The range for CDD and HDD appear consistent but even minor dips in the regular pentagon can represent hundreds of degree days. Spring in 2007 appears to have a smaller CDD range and while the summer range increases. The range is HDD is much larger with Spring and Fall tightening in 1992 and 1997 and widening in 2002 and 2012. The Variance of CDD and are logged in order to represent the seasonal differences in magnitude. The variance in summer CDD by far outweighs that of the other seasons. The standard deviation of CDD and HDD also indicate that the largest variation in accumulated cooling days and heating days occur in during the Summer and Winter respectively. The variance is presented on a logarithmic scale (base 2.7) to adjust for extreme differences in the levels of heating and cooling degree days across the different seasons. Spring and Fall variances alternate between 1997 and 2002.

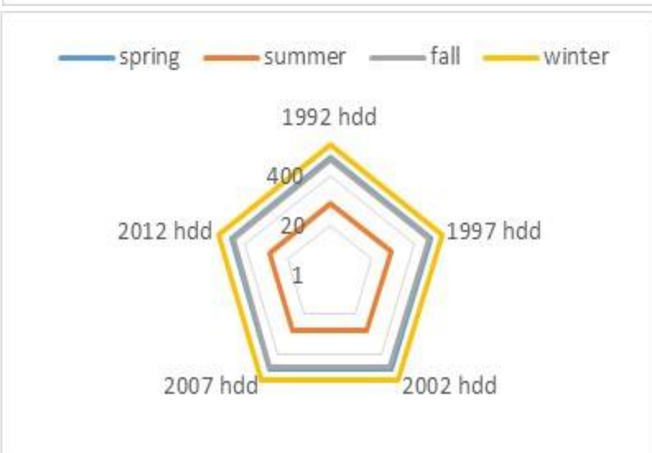
Appendix C-3

Climate Means and Ranges

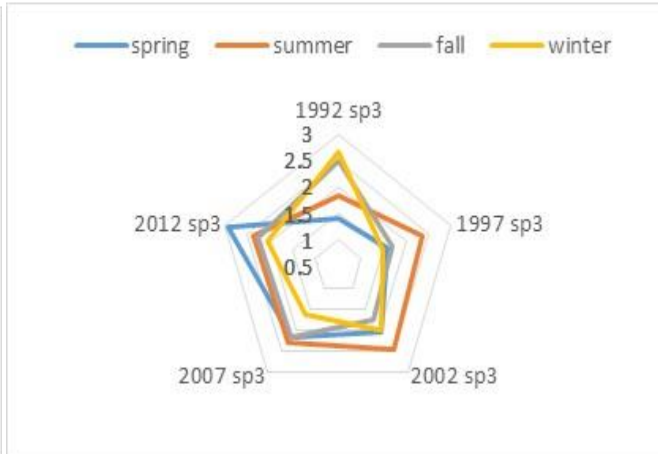
Mean

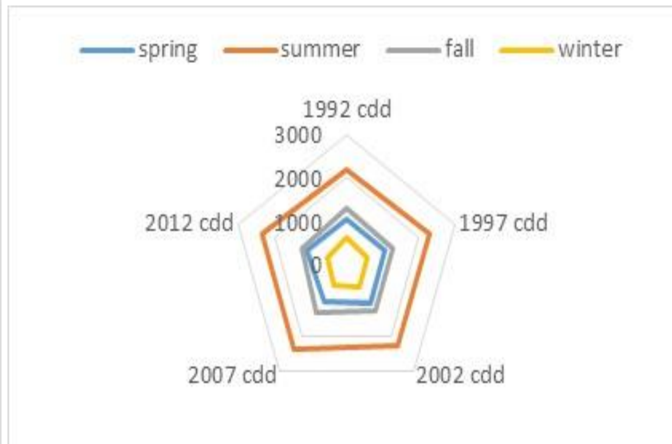


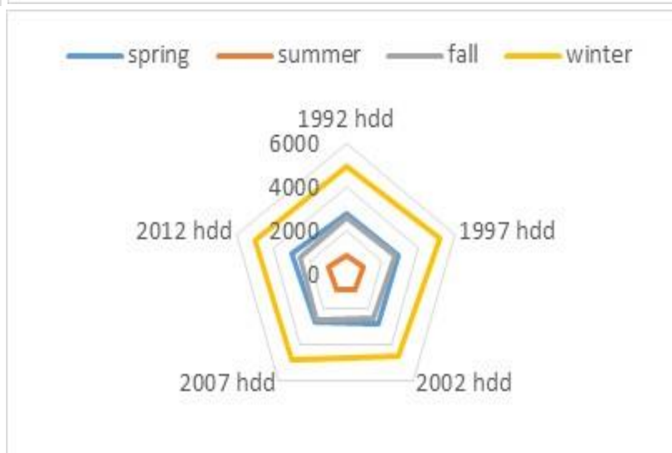




Range



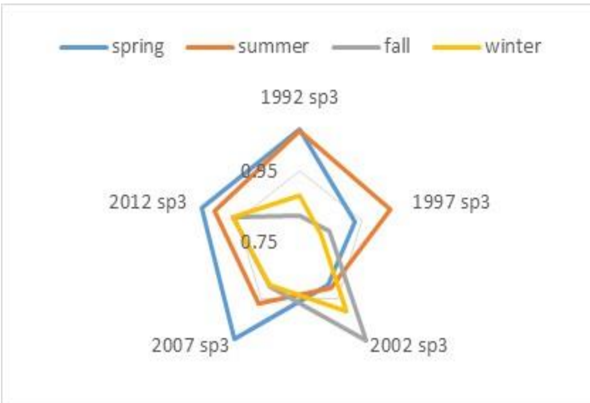


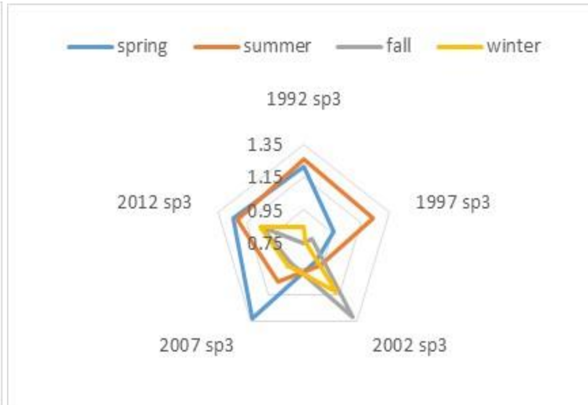


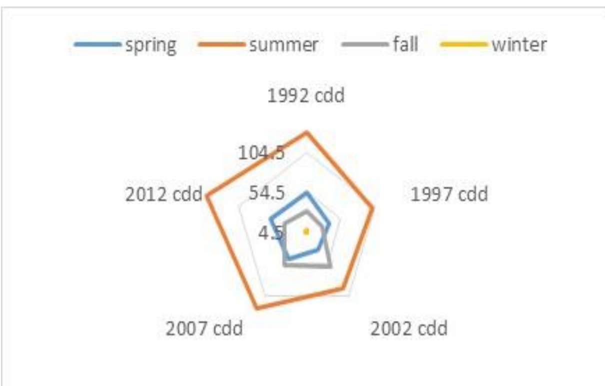
Appendix C-4

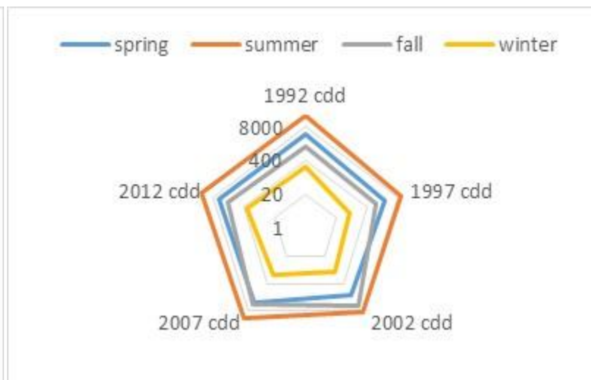
Climate Means and Ranges

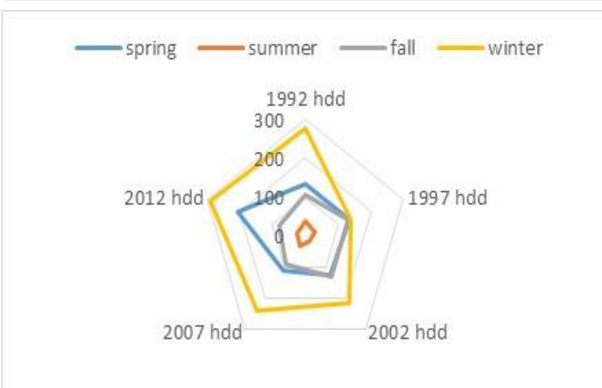
Standard Error **Variance**

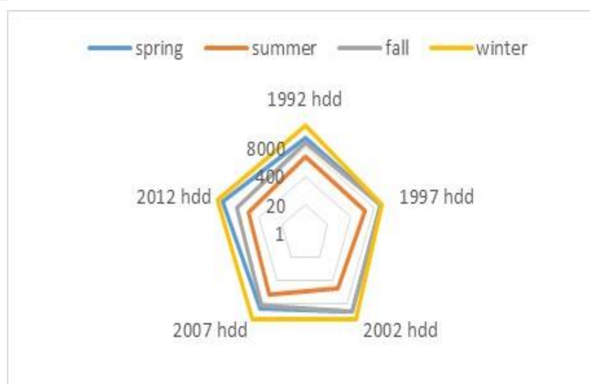












Appendix C-5

Data Notes LOA Derivation

Mahmood extends the works of Freeman et al. (1983), where t = time – t_0, α is the constant hazard rate, β is additional hazard caused by time-invariant covariates, and γ is how the covariates' effect on the hazard rate change over time (Freeman et al. 1983).

As the age of an institution approaches infinity, the hazard rate approaches a constant, or more formally:

7a. $\lim_{t \to 0} r_{jk}(t) = \alpha + \beta$, and

7b. $\lim_{t \to \infty} r_{jk}(t) = \alpha$

They estimate these hazard parameters simultaneously by assuming that they are covariant dependent:

8a. $\alpha_i = e^{A`X}$

8b. $\beta_i = e^{B`X}$

8c. $\gamma_i = CX$

Substitution equation (-) into (), we get:

9a. $r_{jk}(t) = e^{A`X} + e^{B`X} e^{C`Xt}$

Note that the limits above become:

9b. $\lim_{t \to 0} r_{jk} = e^{A`X} + e^{B`X}$, and

9c. $\lim_{t \to \infty} r_{jk}(t) = e^{A`X}$

Following the work of Mahmood (2000) and Freeman et al. (1983) we have,

β is a vector of parameters corresponding to variables that change the shape of the hazard rate r while the α parameters shift the hazard rate. We can test if (r) is different among t and whether it reaches rmax during adolescence. The result will be an indicator of BFR exit risk at different levels of firm experience. Identifying the individual parameters beyond the scope of this paper but the important lesson is that a local maximum/maxima exist beyond which the hazard associated with firm adolescence declines.

9d. $rjk(t) = \frac{b_{jk} a_{jk}{}^{b_{jk}} t^{bjk-1}}{1+(a_{jk}t)^{b_{jk}}}$, where

$a_{jk} = \exp(A^{jk}\alpha^{jk})$ and $b_{jk} = \exp(B^{jk}\beta^{jk})$.

r_{max} occurs at $r_{max} = a(b-1)^{1-1/b}$

and t_{max} occurs at $t_{max} = \frac{1}{a}(b-1)^{1/b}$