FACTORS AFFECTING COTTON PRODUCERS' CHOICE OF MARKETING OUTLET

A Thesis

by

JASON DEAN PACE

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Approved by:

Chair of Committee,	John R.C. Robinson
Committee Members,	Dmitry Vedenov
	Calvin Parnell
Head of Department,	Parr Rosson

December 2012

Major Subject: Agricultural Economics

ABSTRACT

In recent years, changes in government policies, supply and demand fundamentals and price patterns in the cotton market have led to several shifts in how producers market their cotton. This thesis examined producer cash marketing choices, including direct and indirect hedging, in four different periods since 2001. Special emphasis was placed on the 2010 season—a season characterized by historically high prices and volatility. Producer marketing behavior was modeled as a discrete choice between four different cash market outlets: forward contracting with a merchant, post-harvest cash contracting, contracting with a merchant pool and contracting with a cooperative pool. Hedging was characterized as a tool that was used in conjunction with one of the four discrete choices. This thesis employed multinomial logit estimation to determine the influence of factors on producers' choice of primary cash marketing decisions. Data were collected from a mail survey of the population of cotton growers in Texas, Oklahoma and Kansas. The most important determinants of cotton cash marketing choices were 1) prior participation in cooperative pools, beliefs about the value of pre-harvest pricing, beliefs about the performance of merchant pools, willingness to accept lower prices to reduce risk, and several socio-economic variables.

DEDICATION

To my parents, Ricky and Terresa Pace

ACKNOWLEDGMENTS

I would like to thank my committee chair, Dr. Robinson, for going above and beyond the call of duty in guiding me through my studies and the research process. I would not have been able to complete this daunting endeavor without his patience and positive attitude. Thanks to my committee members, Drs. Vedenov and Parnell, for their flexibility and willingness to serve. Thanks to Caroline Gleaton for her tireless support in all phases of this project.

Thanks to my graduate student colleagues and faculty in the Department of Agricultural Economics for making this experience enriching and challenging.

I would also like to thank Cotton Incorporated for their generous funding of this project.

TABLE OF CONTENTS

	Page
ABSTRACT …………………………………………………………………..	ii
DEDICATION ………………………………………………………………….	iii
ACKNOWLEDGMENTS …………………………………………………….	iv
TABLE OF CONTENTS …………………………………………………………….	v
LIST OF FIGURES ………………………………………………………………….	vii
CHAPTER I INTRODUCTION …………………………………………………….	1
CHAPTER II BACKGROUND …………………………………………………….	4
Adoption Studies	4
Adoption Studies Employing Multinomial Logistic Regression …..	5
Hedging Studies ……………………………………………………………..	8
Marketing Studies …………………………………………………………...	12
Non-cotton and General Commodity Marketing Studies ………….	12
Cotton Marketing Studies …………………………………………….	13
CHAPTER III DATA AND METHODOLOGY ………………………………	17
Survey Instrument Development ………………………………………	17
Data Development …………………………………………………………..	19
Development of Explanatory Variables ……………………………	23
Operator and Operation Characteristics ……………………….	24
Risk Attitude and Risk Perception Variables ………………….	25
Other Risk-Reducing Activities ……………………………….	29
Model Specification ..………………………………………………….	31
CHAPTER IV RESULTS ……………………………………………………..	33
Diagnostics ………………………………………………………………….	33
Summary Statistics ………………………………………………………….	35
Regression Results ………………………………………………………….	37
Log-likelihood Coefficients………………………………………..	38
Marginal Effects Coefficients………………………………………	41

CHAPTER V CONCLUSIONS AND FUTURE RESEARCH ………………. 44

Implications for the Cotton Industry ………………………………….. 44
Implications for Public Policy ………………………………………… 47
Future Research ……………………………………………………….. 48
Logit Analysis of Insurance Choices ……………………………… 48
Hedging Revisited …………………………………………………. 48
Demand Systems Approach to Modeling Producer Marketing Decisions…………………………………………………………… 49

REFERENCES ………………………………………………………………… 51

APPENDIX A ………………………………………………………………….. 54

APPENDIX B ………………………………………………………………….. 57

APPENDIX C ………………………………………………………………….. 59

LIST OF FIGURES

Page

Figure 1 U.S. Domestic Mill Use and Exports Since 1985…………………… 3

Figure 2 Texas Counties Represented in Survey……………………………… 19

Figure 3 Nearby Futures in Cents/Lb Since July 2001………………………... 21

CHAPTER I

INTRODUCTION

Cotton production has supported local economies throughout the Southern United States for two hundred years. Advances in bioengineering have led to the development of more pest-resistant and less water-intensive varieties that have allowed cotton to expand to cooler, drier climates, thus increasing the possible acreage devoted to cotton and domestic cotton production. More recently, trade liberalization, growing population and industrialization of large Asian countries such as China, India and Pakistan have led to a rapidly increasing demand for textiles (Meyer et al 2007).

Cotton is the fifth most produced field crop in the United States and the most prevalent row crop in Texas, which contains the most agricultural land of any U.S. state (NASS, 2007). Yet, since many of the oldest land-grant universities and applied economics programs in the United States are in primarily corn-producing regions, cotton is historically understudied by agricultural economists. Nevertheless, cotton is an important crop for several reasons:

1. Cotton's production and use lie on the forefront of global demographic transition of the Asian countries listed previously, as well as other growing economies such as Indonesia, and industrialized economies such as Egypt.
2. The United States has significant political interests in many of the foreign countries heavily producing or milling cotton.

3. The United States' cotton market has transitioned from a primarily domestic market to an export market beginning in the 1990s (See figure 1). This shift has changed the landscape of marketing outlets. Large cooperative pools now contract directly with mills worldwide which has served to expand cooperatives' influence and opportunities. Cotton prices have become more affected by exchange rates, which diversifies export markets and enables U.S. producers to not be dependent on a weak dollar and low interest rates for bullish prices. Additionally, globalization of the cotton market has led to an increase in volatility. The U.S. cotton market must now incorporate information about supply and demand shifters (e.g. weather events, economic policy in foreign countries, etc.) on a global scale, rather than a national one.
4. Cotton comprises a significant portion of commodity index funds, which have become popular among investors given the strength of commodities relative to equity markets since the recession of 2007-08 (Power and Robinson 2008).
5. Cotton price patterns have undergone dramatic changes since the last cotton-specific marketing studies were conducted.
6. Changes in federal crop insurance programs, premiums and coverage levels have had a profound effect on cotton, the majority of which is produced in the Southwest, a region characterized by high yield variability.
7. The cotton market exhibits characteristics that are somewhat unique among major commodities, such as the prevalence of large marketing pools and the trading of individual bales which can be traced back to a specific producer.

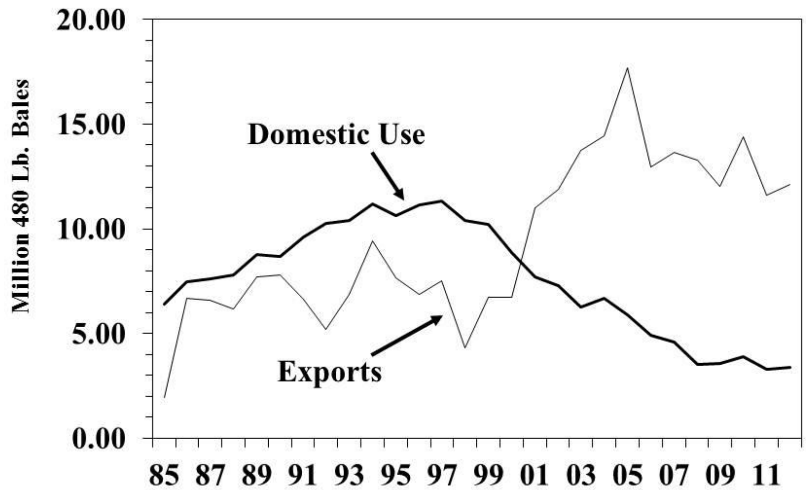

Figure 1. U.S. Domestic Mill Use and Exports Since 1985

These factors necessitate two things this thesis hopes to accomplish: (1) further extension of the agricultural economics literature on optimal hedging and producer marketing choices to cotton, and (2) an updating and expansion of recent previous studies on cotton marketing.

CHAPTER II

BACKGROUND

The agricultural economics literature is replete with studies of marketing, insurance, and hedging. These include both theoretical work, e.g., optimal hedge ratios, as well as empirical studies of the levels and determinants of either hedging or insurance. These strands of literature have their parallels with research on technology adoption because of the influences of information, uncertainty, and socio-economic determinants.

Adoption Studies

Feder (1980) modeled producers' willingness to adopt fertilizer as an innovation of production technology. Adoption was viewed not as a discrete choice, but a choice of optimal allocation between traditional (non-fertilized) and modern (fertilized) acres among a producer's total available land, subject to the constraint of available cash reserves. Feder posited that, due to the uncertainty faced by producers considering adopting a new production technology, the overall yield risk caused by adoption increases as the relative share of land devoted to the modern mode of production increases.

Wozniak (1984) applied principles of adoption literature to the decision of cattle producers to use feed additives. Wozniak used a logit model to demonstrate that the probability of adoption of an innovation increases as uncertainty decreases. Differences in uncertainty among producers faced with an adoption decision can be attributed to differences in "human capital," such as age, experience and education. Stated another way, the most important fixed cost of adoption in Wozniak's study was information. Producers with more information—which comes at a cost—about an innovation have a greater incentive to adopt. Additionally, the probability of adoption increases with economies of size. Larger operations have a greater opportunity cost of not adopting. Human capital has a diminishing effect on the probability of adoption, where size of operations has a more constant effect. Size of operations can overtake education and experience as the driving factor of adoption at a particular value.

Adoption Studies Employing Multinomial Logistic Regression

This paper will model the factors that influence several qualitative choices (cash marketing outlets) among cotton producers. The objective of qualitative choice modeling is to determine each explanatory variable's contribution to the marginal probability of adoption of one choice (dependent variable) over another. When the dependent variable choices are non-ordinal, Ordinary Least Squares (OLS) Regression cannot be used (Pindyck and Rubenfeld 1991). Instead, a Maximum Likelihood Estimator must be employed. Maximum likelihood estimators express regression coefficients on a 0-1 interval. The most basic MLE is the Linear Probability Model (LPM). The dependent variable in LPM must be binary. LPM is sufficient to use when the explanatory variable values (x's) have a mostly linear relationship with the probability of adoption and are not clustered around the extreme low or high end of their respective distributions. If observed x-values for any explanatory variable in a LPM are skewed towards either tail of their distributions, LPM can yield coefficients less than zero or greater than one, which cannot be interpreted in terms of marginal probability.

The most basic LPM that fits values of *y* to a distribution is the Probit model. The Probit model is a binary model where the values of *y* are a function, G, of explanatory variables,

$$P(y = 1|X) = G(\beta_0 + X\beta) \tag{1}$$

G is the Cumulative Distribution Function (CDF),

$$G(z) = \Phi(z) \equiv \int_{-\infty}^{z} \phi(z)dz \tag{2}$$

and $\phi(z)$ is the standard normal probability density function (Woolridge 2002):

$$\phi(z) = (2\pi)^{-\frac{1}{2}}\left(e^{\frac{-z^2}{2}}\right) \tag{3}$$

Logistic regression is an extension of Probit that fits values of *y* directly to a strictly increasing logistic function in the form:

$$G(z) = \frac{e^z}{(1 + e^z)} \tag{4}$$

This method is employed when the dependent variable can take on more than two non-ordinal values, hence the name “Multinomial Logistic Regression.” Its simplicity allows MLE to be performed for each possible value of *y* as the odds of being observed over each other possible value of *y*. In the applied economics literature, MNL adoption studies refer to the values *y* can take on as choices of adoption of an “innovation.” An innovation can be defined as some proposed technique, concept or strategy that an agent deems as being “new” (Mercer, 2004). Here, let *J* represent the number of alternative choices in a model, *j* represent any particular choice, and *k* represent any choice among *J* other than *j*. A general form of MNL estimation, then, is:

$$P(Y=j) = \frac{e^{Z_j}}{\sum_{k=0}^{j} e^{Z_k}} \tag{5}$$

Where:

$$Z_j = \beta'_j X_i, Z_k = \beta'_k X_i \tag{6}$$

The arithmetic of Equation 5 allows *J* logarithmic odds ratios to be computed. These ratios elicit the natural logarithm of the odds of a subject (observation), selected at random, choosing each *j* over each *k* (Isengildina and Hudson 2001a):

$$\ln\left(\frac{P_{ij}}{P_{ik}}\right) = \alpha + \sum X'_i\left(\beta_j - \beta_k\right) + E_i \tag{7}$$

Once the regression coefficients have been estimated with MLE, it is necessary to calculate the marginal effects on the probability of adoption of a one-unit change in each explanatory variable. This is accomplished by taking the first-order derivative of the log-likelihood function with respect to X_i (Equation 7) and evaluating it at the means of the explanatory variables (Isengildina and Hudson 2001a):

$$\gamma_j = \frac{\partial P_j}{\partial X_i} = P_j\left[P_j - \sum_{k=0}^{j} P_k \beta_k\right] = P_j\left[\beta_j - \bar{\beta}\right] \tag{8}$$

Where Υ_j can be interpreted as the marginal probability that the "average" producer will adopt choice *j* over choice *k*.

Skaggs (2001) employed logistic regression to determine the factors leading to the adoption of drip irrigation systems for New Mexico chile producers. They also expanded their analysis to include the question of whether or not their respondents were likely to adopt in the near future. As in Wozniak and Feder, age and farm size were shown to be significant in determining whether or not a producer was a "low-technology" (traditional irrigation) or "high-technology" (sub-surface irrigation) irrigator. Producers who maintained a significant operation in crops other than chiles were less likely to adopt high-tech irrigation, supporting the hypothesis that diversification of enterprises is a risk-reducing activity that can substitute for other risk-management tools, in the same manner as off-farm income.

Amudavi et al (2008) used logistic regression to model Kenyan grain farmers' propensity to adopt *Push-pull Technology* (PPT) to manage cereal stem-borers and an endemic weed species known as *Striga* as a result of field workshops. Participation in the workshops was influenced by producers' geographic region, education, soil fertility and intensity of pest infestation. Regression results showed the probability of adoption increased significantly when a producer attended a workshop.

Hedging Studies

Adoption decisions can similarly apply to marketing and risk management. For example, Shapiro and Brorsen (1987) used a survey of Indiana corn and soybean producers to estimate a system that captured both the probability of the discrete choice of whether or not to hedge, and the continuous level of hedging if hedging is adopted. Shapiro and Brorsen employed a tobit model on their data—gleaned from an in-person survey of 41 producers at a workshop—to characterize producer futures market use. A censored regression model was necessary because several observations exhibited a level of hedging of zero if the producer did not adopt hedging. In addition to human capital and farm size, subjective risk assessment, producer self-characterization of management ability, leverage, income stability and perceptions of changes in income due to adoption were influential in producers' decisions whether to hedge and at what.. The probability of adoption and level of hedging was directly related to leverage. Interestingly, Shapiro and Brorsen found experience and formal education have an inverse relationship to the decision to hedge. Possible reasons for the counterintuitive result were sampling bias inherent in the survey respondents and the idea that education fosters the ability to use other tools to reduce risk.

Pennings and Leuthold (2000) elicited the probability of hedging depending on several producer attitude and perception variables. Their study was distinguished from much of the adoption literature in that it disaggregated observations from the population of producers into segments. Segments within the population were segregated by operation size and geographic region. Pennings and Leuthold posited that unobservable latent variables can be accounted for in a model by pinning them to observable operator/operation characteristics through confirmatory factor analysis. Their system simultaneously estimated links between latent variables and observations, and the relationships between the observable characteristics. Testing for heterogeneity among the population, the authors found that disaggregating into two segments based on market-outlet choice (either selling to a cooperative or selling to a merchant) was statistically significant. Among producers selling to cooperatives, risk attitude and risk perception were found to be the leading determinates of hedging behavior. Among producers selling to merchants, market orientation and the valuing of the ability to exercise entrepreneurial freedom were found to be the driving factors of hedging behavior. As a possible explanation for a lack of relationship between education and actual hedging, Pennings and Leuthold found that the role of understanding the futures market was insignificant when their population was broken out into two segments. All in all, cooperative producers were more apt to consider the financial structure of their farms and preserving their operation itself in deciding whether to hedge, and merchant-affiliated producers were more apt to consider their ability to follow the markets and exercise "entrepreneurial freedom" in deciding whether to hedge.

Lapan and Moschini (1994) improved upon traditional mean-variance derivation of the optimal hedge ratios with a system that takes into account agent risk-aversion. The mean-variance hedge in this study was taken to be the optimal hedge ratio absent of production risk. The obvious presence of production risk in agriculture meant that the optimal hedge ratio faced by producers was actually less than that predicted by the mean-variance method. Production risk was assumed to be jointly distributed (lognormal) with price risk and basis risk. Constant Absolute Risk Aversion (CARA) coefficients were derived for representative soybean farms in Iowa (compiled at the county level), and retrofitted to the period from 1974-1990 in order to compute exact solutions for optimal hedge ratios. Due to the amount of yield variability and the negative correlation between prices and yield in agricultural commodities, the study concluded that taking into account production risk as a random variable is imperative to computing optimal hedge ratios. It was also asserted that the model using CARA functions was useful when different distributions and utility functions were assumed.

Coble (2000) used representative farms to compute optimal hedge ratios given stochastic yield, price and basis risk. Yield was assumed to be normally distributed and expected future cash price was presumed to be log-normally distributed. They initially found that producers' optimal hedge ratios decreased as yield risk increased. This was consistent with the idea that greater uncertainty of yield leads the producer to have a larger exposed hedge position, thus reducing the demand for hedging. Coble also found that the optimal hedge ratio was inversely related to price-yield correlation. This is due to the fact that yield-price correlation provides a "natural hedge," reducing the demand for hedging. Coble then applied four insurance designs to each of the four farms in the model: (1) MPCI, (2) MVP, (3) RI and (4) CRC. Generally, there was no effect on the optimal hedge ratios for coverage levels below the minimum requirements for commodity program participation. It was found that yield insurance designs are complementary to the demand for hedging. MVP led to a slightly higher hedge ratio than MPCI. The revenue insurance products had different effects. RI was shown to have a non-linear relationship with the optimal hedge ratio. RI was complementary to hedge ratios in lower- to mid-level levels of coverage, and exhibited a substitution effect at higher coverage levels. CRC was found to be more complementary to hedging since its upside price component is analogous to a call option. CRC was found to be substitutionary to put options since a put option payoff is inversely related to price.

Riley and Anderson (2009a) compared the cost of hedging with other variable input costs. Commodity Costs and Returns Data from the USDA-ERS were compared with historical futures and cash contract prices for corn, soybeans, cotton and wheat. An unhedged position was used as the baseline scenario, with three hedging strategies compared: (1) a 100% hedge prior to planting, (2) a 1/3 hedge at planting time and (3) a 1/3 hedge half way through the season. It was determined that the cost of hedging related to other variable costs had increased slightly for corn and soybeans. This is due to the fact that both corn and soybeans have emerged as a renewable fuel source, which has increased volatility in these markets, hence, option premiums and margin calls have increased. Cotton and wheat hedging costs (as of 2009) had not significantly changed relative to the increase in other variable input costs.

Marketing Studies

Non-cotton and General Commodity Marketing Studies

Brorsen and Anderson (2001) applied the concept of behavioral finance to producer marketing choices. They deduced from previous studies that markets are only inefficient for brief periods of time, therefore, producers should view markets as efficient when selecting a marketing strategy. Behavioral finance offers some explanations of why producers make biased marketing decisions. Five types of bias-inducing behaviors were identified: (1) Anchoring, (2) Myopic Loss Aversion and Regret, (3) Fallacy of Small Numbers, (4) Overconfidence and (5) Hindsight Bias. The authors stated that the best way for producers to prevent mistakes is to use the same marketing strategy year after year; therefore, extension education programs should be focused on reinforcing the efficient market hypothesis and encouraging producers to remain disciplined in their marketing strategies.

Brorsen and Anderson (2005) tested the hypothesis that “most farmers receive a below-average price for their crop,” a statement that is often mentioned in some form in the popular press. Daily prices paid data were collected from three Oklahoma wheat elevators. Behavioral finance theory states that producers will exhibit patterns based on psychological responses to events. Granger causality was used to determine if there was a consistent pattern of wheat producers selling in the bottom third of the market, relative to seasonal average prices. It was determined that a majority of wheat producers do not sell in the bottom one-third of the market. There was some evidence, however, that producers wait beyond the end of the calendar year for higher prices, which is not a reasonable expectation.

Riley and Anderson (2009b) compared the subjective probabilities of corn, cotton and soybean growers’ price expectations with implied volatility using the Black-Scholes Model. They found that producers tend to significantly underestimate volatility and expect significantly higher contract settlement prices.

Cotton Marketing Studies

Although relatively understudied, cotton has seen some similar research of risk management choices. This includes analysis of optimal hedge ratios by Berck (1981) and Coble et al (2000). The two main empirical efforts date from the post-1996 farm bill era of price volatility. Isengildina and Hudson used logit analysis (2001a) and a systems approach (2001b) to analyze grower survey data measuring the primary choice of marketing outlet: (1) cash sales, (2) forward pricing (either through pools or merchants) and (3) direct hedging through the futures market. As with previous adoption and marketing studies, independent variables in the model were divided into operator and farm characteristics, use of other available risk management tools and non-economic variables. Operator and farm characteristics included farm size, education, market-specific training and age. Other risk management tools included crop insurance, government payments and off-farm income. Non-economic variables included attitude questions that captured producers' posture towards direct hedging, and evaluation of their own marketing performance versus that of pools.

Isengildina and Hudson showed that the probability of choosing forward pricing over cash sales increased with farm size and decreases with off-farm income and income from government payments. The attitude that pool usage can net producers a higher price than they could net marketing on their own was directly related to indirect hedging. Producers who purchased coverage levels above the government-mandated minimum were 11 percent more likely to choose cash sales as a marketing outlet. Predictably, risk aversion was found to be directly related with direct hedging, which confirmed the idea that growers view forward pricing as a risk-reduction tool. Financial leverage was not statistically significant in predicting choice of marketing outlet.

Vergara et al (2004) implemented a mail survey of Mississippi and Texas cotton growers to elicit data and test hypotheses similar to those of Isengildina and Hudson. Vergara et al classified "forward pricing" as either with a merchant or with a pool. Thus, marketing outlet choices included cash sales, merchant forward contracting, pool contracting and futures market contracting (i.e., direct hedging). In addition to typical instrumental variables (examples: insurance choices, formal education, farm size), producer perceptions of yield and price variability were included. They hypothesized that yield and price variability were important in eliciting producers' risk aversion because of these factors' influence on the optimal hedge ratio (as distinguished from the minimum-variance hedge ratio). Producer knowledge level of marketing outlets and money spent on market advisory services was included. Other producer perceptions such as orientation to marketing strategies in terms of returns and perception of market efficiency were included. Interestingly, price and yield variability were not statistically significant in the model. Size of operation was directly related to pool pricing and inversely related to cash sales. Producers more willing to accept a lower price (less risk-averse for returns to marketing) were less likely to adopt pool pricing. Money spent on market advisory services was directly related to forward pricing, pool pricing and futures pricing. Age was inversely related to futures market usage because, according to the authors, the opportunity cost of education about the futures market increases with age. Crop insurance purchase was directly related to futures pricing and forward pricing, which confirmed prior theoretical predictions that forward pricing is complementary to crop insurance coverage (Coble et al 2000).

Since the Isengildina and Vergara studies, the U.S. cotton market has experienced restructuring from globalization, the influence of ethanol and competing crops, and the alleged financialization of agricultural markets. Although this last influence is not supported by available research (Power and Robinson 2008; Janzen et al

2012), the last five years have seen several periods of historically high and volatile prices (Carter and Janzen 2009). The anecdotal result of high cotton prices is grower shifting back and forth among traditional outlets like cooperative pools or merchant contracts. In addition, the last decade has seen cotton merchants begin organizing and managing their own marketing pools in competition with the large cooperatives.

The aforementioned changes in the cotton market suggest the need for an updated picture of cotton marketing decision making. This paper represents an econometric analysis of a recent survey effort of growers in the southwestern region, i.e., Kansas, Oklahoma, and primarily Texas.

CHAPTER III

DATA AND METHODOLOGY

As with the previous empirical studies of cotton, this research involved a survey of cotton growers to obtain current information about cotton marketing outlet choices. Anecdotal evidence suggests that roughly half of Texas growers market their cotton through cooperative seasonal pools, with the balance sold through merchant contracts (both forward and spot) and merchant controlled pools. Another goal of the survey process was to obtain selling price performance data for the 2010 cotton crop, as well as respondent socio-economic and demographic information.

Survey Instrument Development

Elements of the survey instruments used by previous researchers (Isengildina and Hudson 2001; Vergara et al 2004) were adapted to the present task to include newer marketing outlets (i.e., merchant pools), current crop and revenue insurance products, and current issues. The survey solicited the percentage shares of 2010 cotton production that were allocated among four different marketing outlets. Many of the same risk management attitude and belief questions used by previous research were applied in 5-point Likert scale format. Following development and IRB approval of the survey instrument, the survey was implemented as a two round mailing with a postcard reminder. Surveys were mailed to the current listing of the Cotton Board mailing list for Kansas, Oklahoma, and Texas. The Cotton Board is a quasi-government organization charged by USDA for "…the oversight and administrative arm of the Cotton Research

& Promotion Program, representing U.S. Upland cotton… To fund the Program, the Cotton Board collects a per-bale assessment of all Upland cotton harvested and ginned in the U.S., as well as an importer assessment for all Upland cotton products imported into the U.S. (Cotton Board 2012)." In essence, this mailing list represented the whole population sample of those in Kansas, Oklahoma, and Texas who sold cotton in 2010-11.

For the first survey implementation, 6,627 questionnaires were mailed out on March 1, 2012, with a reminder postcard sent to the entire population ten days later. The second mailing to non-respondents was April 15, 2012. The two weeks between the initial mailing and the postcard reminder, and the four weeks between the postcard reminder and the second mailing, was inspired by Dillman. Dillman recommended the second mailing follow the postcard reminder by fifteen business days (Dillman 1978). I opted to wait an additional week to ensure that as many of the first survey respondents as possible could be removed from the second mailing list. Of the total mailings, 100 were returned to sender as undeliverable. A total of 314 surveys were returned, of which 51 had unusable/incomplete responses. Figure 2 is a map of Texas counties represented in the survey.

[1] This includes all cotton farmers who sold upland cotton as well as landlords with share rent contracts. Share rent landlords vary in their marketing involvement, hence this likely contributed to non-response to the marketing survey questionnaire.

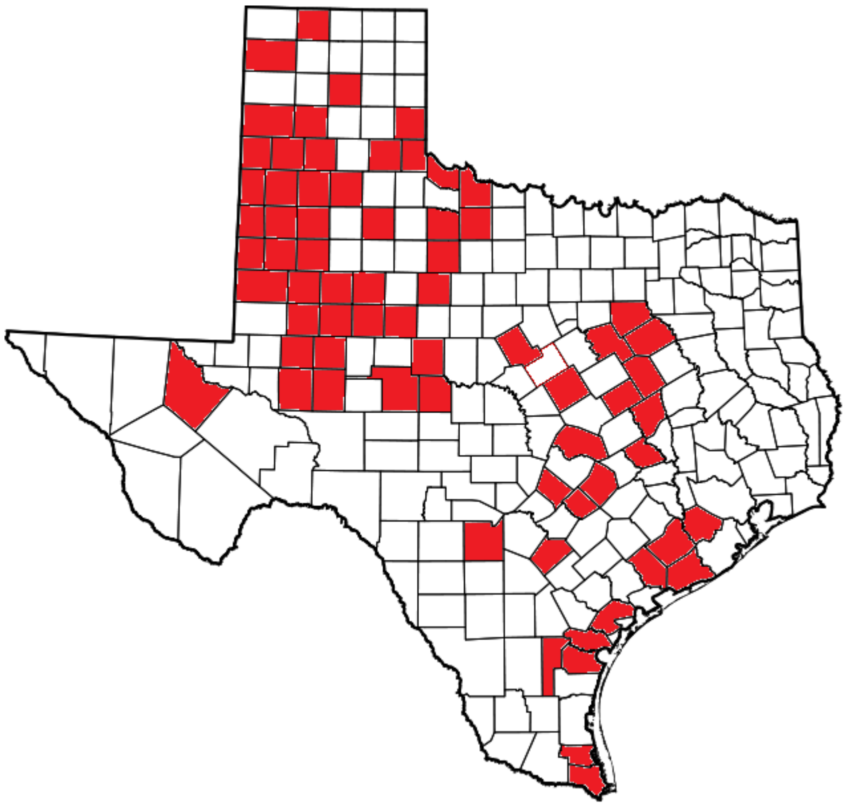

Figure 2. Texas Counties Represented in Survey

Data Development

The survey elicited shares of cotton sold through various cash marketing outlets in various time periods. The four cash marketing outlet choices were (1) forward contracts with a merchant, (2) post-harvest spot contracts with a merchant, (3) contracts with a merchant pool and (4) contracts with a cooperative pool. Survey respondents were also given the option of a fifth marketing outlet choice, denoted as "other," which they were then asked to describe. Since most of the respondents who marketed a majority of their cotton through the "other" outlet described their choice as selling on the post-harvest open cash market, these responses were collapsed into the "post-harvest spot contract with a merchant" category, reducing the model to four dependent variables. In order to perform the logit analysis, each respondent's highest reported share of marketing outlet was designated as their primary choice. Their primary choice of outlet was recorded, with the cooperative pool outlet being designated as the base value. This was possible because most respondents indicated a clear percentage-wise primary choice. The eight observations with an even allocation among two or more marketing outlets were excluded from the analysis, leaving 263 usable responses. Of these, twelve were from Oklahoma or Kansas, which matches the roughly 94% Texas share of cotton production in the three state region (NASS 2007).

List of Dependent Variables and Abbreviations:

1) FORWARD — Direct forward contract with a merchant
2) CASH — Post-harvest spot contract with a merchant
3) MPOOL — Contract with a merchant pool
4) COOP — Contract with a cooperative pool

The four time periods represented in the survey were (1) 2001-2006, (2) 2007-2009, (3) 2010 and (4) 2011. The cotton market in each of these time periods is thought to exhibit different price behavior. The 2001-2006 period was marked by relatively low prices with the exception of the price spike of late 2003 and early 2004 (Robinson 2012). Weaker foreign demand and the relative strength of the U.S. Dollar may have been factors. The 2007-2009 period was characterized by dramatic price increases in cotton, followed by a sharp decline that was coincident with global recession (Power and Robinson 2008). The increase in prices and volatility during this time may be attributed to soaring global demand in emerging countries such as China and India and an overall increase in commodity prices due to increased demand for biofuels. Figure 3 outlays the recent price history of cotton leading up to the survey.

Figure 3. Nearby Futures in Cents/Lb Since July 2001

2010 primary choices were used as the dependent variable in this paper because of the historic increase in price and volatility. Since cotton producers might exhibit behavioral finance patterns such as "hindsight bias" and "myopic loss aversion and regret," it is likely the events of 2010 could have induced the most pronounced reordering of marketing preferences (Brorsen and Anderson 2001). Respondents' open-ended comments, as provided for at the end of the survey, indicated many producers were suspicious of contract non-delivery fraud on the part of some of their peers. These comments bolster anecdotal evidence that marketing preferences were being reexamined even prior to the ending of the 2010 harvest.

While only shares allocated in the 2010 season were used as the dependent variable in the logit analysis, a consistent primary choice of cooperative marketing in both the 2001-2006 and 2007-2009 time periods was developed into a 0/1 independent variable indicating a history of cooperative participation. This was accomplished by determining the primary choice for each respondent in each of time periods 1 and 2. If the primary marketing choice in both time periods for the i^{th} respondent was cooperative pool, the variable CHIST (coop history) was assigned a value of 1; 0 if otherwise. CHIST was hypothesized to be negatively related to the likelihood of choosing any other marketing outlet over cooperative pools.

Marketing choices in 2011 were elicited in the survey to help bolster evidence of shifting preferences as a result of the 2010 price spike. This proved to be unhelpful due to widespread abandonment caused by the 2011 Texas drought. For 2010 and 2011 marketing shares, respondents were given options to report their "intended" shares (if no crop was harvested), "expected" shares (if a crop was harvested, or expected to be harvested, and had not been contracted yet), or "actual" shares (if a crop had been harvested and already contracted). It was hoped giving the respondents the opportunity to report "intended" shares for 2011 would elicit the marketing choices for producers who abandoned crops, but most respondents did not utilize this reporting option. Thus, 2011 marketing choices are included in the summary statistics for description only.

Development of Explanatory Variables

Factors believed to influence marketing decisions can be divided into three groups: (1) operator and operation characteristics, (2) risk attitude and perception variables and (3) usage of alternative risk management strategies. See table 1 below for a list of all independent variable names and abbreviations that will be used heretofore.

Table 1. List of Independent Variables and Abbreviations

Abbreviation	Description	Type
CHIST	History of cooperative marketing	0/1 indicator variable
CDIV	Influence of cooperative pool dividends on participation	5-point Likert scale
HEDGED	Incidence of hedging	0/1 indicator variable
MPCI	Participation in MPCI program	0/1 indicator variable
RI	Participation in RA or CRC programs	0/1 indicator variable
PHPBLF	Effectiveness of pre-harvest marketing strategies	5-point Likert scale
WILLING	Willingness to settle for a lower price to reduce risk	5-point Likert scale
AVGPR	Agreement with statement "Co-op seasonal pools tend to give an average price."	5-point Likert scale
MPBLF	Agreement with statement "Merchant pools will probably get a higher price than co-op pools."	5-point Likert scale

Table 1 (Continued).

PRRISK	Potential for crop price variability to affect farm income	5-point Likert scale
ATTITUDE	Producer self-characterization of risk-aversion relative to other farmers	5-point Likert scale
OFFINC	Off-farm income	Continuous—percentage
ASSETS	Total assets in operation	Categorical
LEVERAGE	Percentage of borrowed assets	Continuous—percentage
EDUC	Respondent highest completed formal education level	Categorical
ACRES	Size of operation in acres	Continuous
IRR	Percentage of operation irrigated	Continuous—percentage

Operator and Operation Characteristics

Operator characteristics measured in this study are years of formal education and age. Operation characteristics include net worth (assets), size of operation (in acres), percentage of operation that is irrigated, and leverage. Net worth was elicited by asking the respondent to characterize the dollar amount of assets in their operation by one of six discrete categories. Size of operation was included in the analysis because of several previous studies that indicated size of operations reduces the risk and cost of information of seeking alternative marketing strategies (Wozniak 1984). Irrigated acres were measured because irrigation reduces yield risk and thus provides for a wider range of marketing alternatives available to the producer such as direct bale forward contracts with merchants. Theoretically, there would be a direct relationship between the likelihood of adoption of FORWARD or MPOOL over COOP and irrigated acres.

Leverage is historically considered to increase the overall risk in an investment (Collins 1985) and has been studied extensively in agriculture. Isengildina and Hudson (2001a) did not find leverage to be statistically significant in their study, but it was included in this analysis because of the historical precedent. Leverage was elicited in the survey by asking the producer to record the percentage of his/her assets in the operation that were borrowed.

The statement "Co-op marketing dividends and/or revolvement of past book credits, retains, etc., are very influential in my decision to participate in cooperative seasonal pools," was scored on a 5-point Likert scale, with "1" indicating strong disagreement and "5" indicating strong agreement. This question was included to measure the contribution of attitude towards cooperative pool dividends to the probability of adopting cooperative pooling over other alternatives. It was hypothesized that respondents indicating agreement with this statement would be more likely to contract with cooperatives; however, the possibility exists that producers view dividends as a "bonus" rather than a tool to maximize returns to marketing.

Risk Attitude and Risk Perception Variables

There is an extensive history in economics literature of using five-point Likert scale questions to elicit risk attitudes, risk perception, and the comfort level of usage of certain risk management tools (Pennings and Leuthold 2000; Isengildina and Hudson 2001; Vergara et al 2004; Franken et al 2008). This paper has employed similar techniques for survey questions of cotton producers.

In the first group of risk attitude questions, respondents were asked to rate their level of agreement (on a five-point scale with “1” indicating strong disagreement, “3” indicated indifference and “5” indicating strong agreement) with various statements regarding risk management tools. The four risk management tool questions assessed for this paper are as follows:

1) “Pre-harvest marketing strategies will, on average, result in a higher price than selling at harvest.”
2) “I am willing to take a lower price to reduce price risk.”
3) “Co-op seasonal pools tend to give an average price.”
4) “Merchant pools will probably get a higher price than co-op pools.”

The first statement, “Pre-harvest marketing strategies will, on average, result in a higher price than selling at harvest,” is typically thought to be directly related to the likelihood of both direct and indirect hedging, as was the case in Isengildina and Hudson (2001a) and Vergara and Coble (2004). Isengildina and Hudson viewed forward contracting with a merchant as a form of indirect hedging. Thus, this question was included in the analysis. Another alternative hypothesis for this question was that agreement with the effectiveness of pre-harvest pricing would be inversely related to the likelihood of adopting post-harvest cash marketing over cooperative marketing.

The second statement, “I am willing to take a lower price to reduce price risk,” was included in the analysis to measure the relationship between a respondent’s willingness to “settle” for an average price and their likelihood of adopting cash marketing or direct forward contracting over cooperative pools. The theoretical objective of pooling is to sell equal parts of the pooled commodity in regular intervals throughout the year to obtain an annual average price (Vergara et al 2004). Intuitively, this is a risk-reducing activity that requires a producer to forego an opportunity to earn higher returns to marketing by selling on his/her own.

The third statement, "Co-op seasonal pools tend to give an average price," measures the respondent's belief that cooperative pools actually do pay out average prices. This question was included in the analysis because anecdotal evidence suggests some skepticism on the part of producers that cooperative pools operate according to the premise of average pricing, as discussed in the previous paragraph. In addition, growers who prefer merchant marketing channels might agree with this statement as an acknowledgement of what they believe is the main disadvantage of co-op performance.

The fourth statement, "Merchant pools will probably get a higher price than co-op pools," was included in the analysis to measure if the recent emergence of merchant pools as players in cotton marketing has been brought about by a change in producer attitudes, or if merchant pools have been successful in developing the perception that they pay better than cooperative pools. Clearly, one would expect agreement with this statement to be directly related to the probability of adopting merchant pools over cooperative pools.

A question was included asking respondents to rank the potential for a risk source to effect farm income, on a five-point scale with "1" indicating a low potential to effect farm income, and "5" indicating a high potential to effect farm income. The risk source measured here is "crop price variability." Crop yield variability was omitted from the analysis because it was not a statistically significant predictor of hedging decisions in Vergara et al (2004) and, moreover, producer perceptions of yield variability are reflected in insurance choices. Crop price variability was included in this analysis to measure the degree to which producer perceptions of price variability cause producers to market more or less cautiously. Different possible relationships between PRRISK and marketing might exist. On the one hand, producers who view price risk as the main source of revenue risk might be inclined to adopt cooperative marketing, assuming they view the objective of coops is to pay an average price (as in the variable CPBLF). On the other hand, producers with a high level of agreement on PRRISK might prefer to lock in a forward price by contracting directly with a merchant. The latter case is intuitive because producers who view yield risk to be a greater source of revenue risk than price risk would be inclined to not contract with a merchant because of the possibility of non-delivery due to abandonment or low yield. This study adopted the latter hypothesis: that the sign on CPBLF for MPOOL and FORWARD is positive.

Finally, in keeping with precedent from previous literature, producers' self-characterization of risk-aversion in relation to other producers was measured on a five-point scale, with "1" indicating the respondent is much less willing to accept risk than their peers, and "5" indicating the respondent is much more willing to accept risk than their peers. It was hypothesized that producers more willing to accept risk than their peers would be more likely to "market on their own," or, in other words, choose cash marketing or direct forward contracting over cooperative pooling. This is due to a commonly expressed belief among producers that the purpose of pool marketing is to "outsource" marketing decisions, which is supported in the open-ended respondent comments in the survey.

Other Risk-Reducing Activities

Risk-reducing activities by producers other than marketing methods include crop insurance, participating in government commodity programs, maintaining cash and credit reserves, off-farm income, and hedging with futures and options. Two different types of crop insurance coverage, off-farm income and instance of hedging were included in the analysis for this paper.

Crop insurance coverage can typically be grouped into two types: yield insurance and revenue insurance. The program names and coverage levels have changed considerably over the years. Since the econometric model for this paper was based on 2010 data, Multiple Peril Crop Insurance was used as the standard yield insurance product. Revenue coverage could be purchased in 2010 under two different program types: Revenue Assurance (RA) and Crop Revenue Coverage (CRC). RA and CRC both insure a percentage of gross revenue and trigger indemnity payments if gross revenue falls below the coverage level. The key difference between CRC and RA is that CRC revalues gross revenue at harvest time if the harvest cash price is higher than the futures price at planting. Thus, RA is analogous to having a combination of yield insurance and a put option. CRC is analogous to having yield insurance, a put option and a call option. CRC AND RA can both be substitutionary for forward pricing in the presence of yield risk and low harvest time price expectations. Alternatively, they can both complement forward pricing at higher harvest time price expectations. Since CRC and RA have similar relationships to forward pricing in terms of price and yield expectations, they were collapsed into a single 0/1 indicator variable for this thesis. Yield insurance was hypothesized to be directly related to the probability of choosing direct forward contracting over cooperative pooling, since it was assumed that contract non-delivery due to abandonment or low yield is the largest risk faced by producers who have direct bales contracts with merchants.

Off-farm income was included in the regression (OFFINC). Off-farm income generates cash reserves from other sources that can be used to offset losses to farm income due to yield loss or adverse price movement. Essentially, off-farm income can be used for self-insurnace. Thus, off-farm income is viewed as a risk-reducing activity outside of marketing alternatives and can substitute for forward pricing of some kind. Respondents were asked to indicate the percentage of their 2010 crop that was hedged using futures and options, broken down into two categories: (1) matched (cotton hedged that was also contracted with a pool or merchant) and (2) unmatched (expected or actual production that was hedged using futures and/or options and was not contracted through another marketing outlet as in (1)). The variable was developed into a dummy variable with any instance of hedging on the part of a respondent set equal to 1; 0 if otherwise. Producer hedging behavior is studied frequently over the last twenty years and has been considered both complimentary and substitutionary to various types of marketing choices and risk management activities. Isengildina and Hudson (2001a) collapsed futures hedging with forward contracting (which they deemed a form of "indirect hedging") into a single dependent variable in their model, viewing the decision to hedge as a marketing outlet in and of itself. This thesis sought to treat futures hedging separate from forward contracting because of the ability to hedge an open commodity, a strategy that typically consists of options contracts, which have only fixed transaction costs upfront and no margin calls. More importantly, this thesis included futures hedging on the right-hand side of the econometric model since it can function as an alternative risk management strategy, in the same manner as government commodity programs and insurance.

Model Specification

In following Vergara et al (2004), a simple model depicting the i^{th} producer's discrete choice of adoption of the j^{th} marketing outlet is as follows:

$$\Gamma_{ij} = g(X_i\beta) + \varepsilon_i \tag{9}$$

Where X_i is the set of explanatory variables defined in the previous section, β is a vector of parameters and ε_i is a normally distributed error term with a mean of zero. Using the Multinomial Logit estimation procedure discussed in Chapter 2, with cooperative pool marketing (COOP) designated as the base value (intercept) in the regression specification, the log-likelihood ratios are designated as follows:

$$\Gamma_{i1} = \ln\left[\frac{P_{i,FORWARD}}{P_{i,COOP}}\right] \tag{10}$$

$$\Gamma_{i2} = \ln\left[\frac{P_{i,CASH}}{P_{i,COOP}}\right] \tag{11}$$

$$\Gamma_{i3} = \ln\left[\frac{P_{i,MPOOL}}{P_{i,COOP}}\right] \tag{12}$$

The regression coefficients are listed in Appendix B and can be interpreted as the vectors of $(\beta_j - \beta_k)$ from Equation 7 for each Γ_{ij}. Also listed in Appendix B are the marginal effects on the probability of adoption of each marketing choice for each independent variable at its mean, as described in Equation 8.

Stata was used for the regression estimation and diagnostics. Survey data were initially recorded in Excel. After data entry and development, the dataset was imported into Stata for N = 263 observations. The Multinomial Logistic Regression command "mlogit" was executed for the independent variables listed in table 1 with the four marketing choices as dependent variables. The dependent variables were assigned numbers in the dataset (1 = FORWARD, 2 = CASH, 3 = MPOOL and 4 = COOP), and choice number 4 (COOP) was designated as the base value. Stata automatically drops collinear variables in Multinomial Logistic Regression unless the option "Keep Collinear Variables" is checked. Stata was not commanded to keep collinear variables and no variables were dropped as collinear. The variance-covariance matrix of independent variables was ran for diagnostics using the "correlate" command.

CHAPTER IV

RESULTS

Diagnostics

As previously mentioned, no independent variables were dropped from the model in Stata due to collinearity. This is supported by reviewing the variance/covariance matrix (See appendix C). The largest correlation coefficient in absolute value is on RI, MPCI (-.4429). This is an expected result due to the presumed substitutionary relationship between revenue and yield insurance. Since it's reasonable for a producer with certain characteristics (e.g., mixture between irrigated and non-irrigated land or use of partial option hedges) to use revenue and yield insurance products jointly, both variables were kept in the analysis. One other noteworthy correlation coefficient was on ACRES, IRR (.4269). It is not intuitive to believe that percent of acreage irrigated would increase with farm size, since larger farms exhibit economies of scale and thus diffuse production risk more than small farms, thus the relationship between these two variables was assumed random. Predictably, ASSETS, ACRES (.3889) exhibited some correlation, but both variables were included in the analysis to allow for the possibility that smaller operations with strong cash positions can own more expensive production technology such as pickers or high-yield irrigation systems. AGE, LEVERAGE showed a predictable negative relationship (-.353). It is reasonable to believe younger producers have younger tenures of operation and are therefore more likely to be in repayment of land and capital expenditure loans than older producers. CDIV, CHIST were directly related. Common sense supports that producers reporting a history of cooperative marketing would view cooperative dividends as influential in their choice of marketing outlet. Both variables were included because it was discovered that, among producers who reported cooperative pooling as their primary marketing choice, a significant portion of them reported being "indifferent" towards the influence of dividends in their choosing of cooperatives. The average score for the question "Co-op marketing dividends and/or revolvement of past book credits, retains, etc., are very influential in my decision to participate in cooperative seasonal pools," among cooperative pool participants was 3.59 with a standard deviation of 1.11. Since the dependent variable values in multinomial logistic regression are already fitted to a distribution, heteroskedasticity is not a concern. There was a relationship between the question "Co-op seasonal pools tend to give an average price," and the variables CDIV (.3058) and CHIST (.3012). This is an interesting observation in that it indicates there is at least some perception among legacy cooperative pool participants that seasonal pools actually do pay an average price.

A geographic dummy variable, GEOG, indicating whether or not a respondent was from a region in Texas (Gaines and Dawson counties) known for marketing and ginning independently, was dropped from the analysis. The standard error for GEOG on CASH was too large to warrant meaningful analysis. The anomaly was likely due to not enough responses in the Gaines/Dawson county area. CHIST also had a relatively large standard error for CASH (1020.76) and MPOOL (1281.83), but was kept in the analysis because of the statistically significant and intuitive result on FORWARD, which will be discussed in the section on regression results.

Summary Statistics

Appendix A provides a listing of key variable names, descriptions, and summary statistics of variables used in the subsequent regression analysis. Of the four primary market outlet choices in 2010, 64% of respondents primarily sold through seasonal cooperative pools, while 16%, 11%, and 7% primarily sold through merchant forward contracting, merchant spot contracts after harvest, or merchant pools, respectively. That such a large share of the crop was committed early in the 2010 growing season is not surprising given the relatively good price level during the first half of 2010. As it turned out, the 11% of growers who sold after harvest probably received the higher prices given the unexpected and unprecedented price rally in late 2010.

The mean of the CHIST variable indicates that 55% of the respondents had a history of selling through the cooperative seasonal pool. This fits anecdotal evidence of half of Texas growers marketing this way. It also conforms to the slightly above neutral rating of CDIV, the statement that cooperative dividends and book credits are an incentive to pool participation. On average, the respondents were slightly more inclined to agree that pre-harvest pricing results in a higher price, and slightly less inclined to agree that merchant pools tend to give higher prices than cooperative pools. These results could reflect slightly more pool supporters/believers in the data set. However, there is the possibility of lingering negative bias on the part of 2010 merchant pool participants[2]. Similarly, the above neutral agreement with cooperative pools giving an average price could reflect a mixture of pool supporters (who accept getting an average price) and those who prefer alternatives to the cooperative pool.

Risk attitudes were slightly above neutral for the relevant variables WILLING (i.e., to accept lower prices for less risk) and ATTITUDE (self-assessment of willingness to accept risk relative to other growers). Price risk, PRRISK, was seen as fairly influential in overall net revenue risk with a mean of 4.338 on a 1 to 5 scale.

Only 5.7% of the respondents indicated any level of hedging with futures or options for the 2010 crop. This low level of hedging conforms with prior research studies.

Given the survey response rate, some discussion about how well the data represent the population of cotton growers in the region using the summary statistics. According the 2007 Census of Agriculture, the average size of a cotton farm in Texas is 647 acres. The mean of ACRES in this study was 1,032. Such a result is indicative of possible sampling bias. Yet, if the theories on the cost of information about marketing as discussed in Chapter 2 are true, it stands to reason that larger operations may have more information about their marketing practices at their disposal and thus be more inclined to participate in a survey. Larger operations may also exhibit more diversity in marketing choices to diffuse risk, which may lead to a respondent being more likely to participate in a survey about marketing than a respondent who views a marketing outlet

[2] It is essential to point out, however, that negative bias towards seasonal pooling or any kind of preharvest pricing could have affected the results of many variables in this survey, given the price movements in late 2010/early 2011. This effect may not be unique to attitude questions regarding pooling.

as a means to reduce time spent on marketing activities. This discrepancy is supported in Vergara et al (2004) where the mean farm size was 1,002 acres.

The percentage of reported acres that were irrigated from the survey was roughly 32%, which is sufficiently close to the 2007 figure of 34%. The average survey respondent age in the study was 57.8, which conforms to the 58.9 average age of principal farm operator from the 2007 Census of Agriculture. Producers' former education level was not elicited in the 2007 census, but the mean of EDUC in this study was 2.4 which was very close to Isengildina and Hudson's (2001) result of 2.71 (both indicated the average respondent had slightly more than a high school education). The mean percentage of off-farm income in this study was 16%, which was comparable to Isengilidina and Hudson's (2001) result of 20%. The summary statistics for all demographic variables and operation characteristics in this study match either generally accepted population data or data from previous cotton marketing studies.

Regression Results

The model was estimated with 262 observations, giving a pseudo R^2 value of .6067, which indicates the overall model is a good fit. Generally speaking, R^2 is interpreted as the proportion of variation in the dependent variable that is explained by the set of independent variables. This explanation is less sufficient for logit models, however, since the variation in the dependent variable is contained in a 0-1 interval. For logit models, pseudo R2 is used, which elicits the proportion of variation explained in the full model (with all independent variables) to a model with an intercept term only (no independent variables). Procedurally, this is performed by dividing the log-likelihood ratio of the full model by that of a model with all independent variables restricted out:

$$Pseudo\ R^2 = \frac{LLR_{unrestricted}}{LLR_{restricted}} \tag{13}$$

Using seasonal cooperative pools as the base, the multinomial logit parameter estimates and marginal effects coefficients are shown in appendix B.

Log-likelihood Coefficients

The strongest predictor of cooperative pool usage was historical usage. Producers whose primary choice from 2004-2009 was cooperative pools were highly unlikely to adopt forward contracting in 2010. Historical co-op usage was not significant in predicting cash market or merchant pool usage over co-op usage in 2010. This is not surprising given the similarities between seasonal co-op and merchant pools. Another interesting result was that producers' self-characterization of co-op dividend importance in their marketing decisions was not significant when historical co-op usage was included in the regression. This lines up with anecdotal evidence that dividends are less influential after the price spike of 2010-11. A handful of respondents wrote in the "comments" section of the survey that they perceived mismanagement of both co-op and merchant pools in 2010.

PHPBLF was directly related to choosing forward contracting over co-ops and significant at the alpha = .05 level. This is somewhat contrary to Isengildina and Hudson's (2001) result in which producers stated that a marketing pool could get them a higher price than they could get marketing on their own. The result is interesting because it demonstrates a possible change in attitude towards the co-ops ability to maximize welfare. Presumably, producers were more apt to market their own cotton after the price spike of 2010-11. Three other possible reasons are: (1) the sign could represent a long-standing “defeatist” attitude by co-op customers that pre-harvest pricing isn’t truly possible or effective; or (2) producers who have a history of contracting with a merchant have simply done well enough times to reflect a higher PHPBLF value; or (3) co-op customers do believe in the effectiveness of forward pricing of some kind, but simply believe that co-op pooling is best way to capitalize on opportunities.

WILLING was a significant predictor of choosing merchant spot cash sales over co-op marketing. It was inversely related to marketing through co-op pools. Producers willing to accept a lower price to reduce price risk would be less likely to sell on the harvest-time cash market (β = -1.21, z = -2.50). Along the same lines, producers who consider themselves more willing to accept risk than their peers are significantly more likely to choose post-harvest cash sales over co-ops. Both of these results confirmed Isengildina and Hudson’s (2001) findings. In their study, producers who believed that pools netted them a higher price than “marketing on their own” were less likely to adopt cash sales as a marketing choice, and more likely to adopt cash sales if they were more willing to accept risk related to other producers. Interestingly, WILLING elicited a result contrary to the conclusion drawn by Vergara et al (2004). Their study revealed that, at the time, less risk-averse producers were more likely to adopt co-op marketing. The change in relationship between risk aversion and preference for co-op marketing may be due to the change in expectations of co-op pool performance in light of the more recent high prices and high volatility. It might also be the case that, since this study was heavily focused on Texas, more risk-averse producers are less prone to adopting forward contracting with merchants because of higher yield variability when compared to other regions of the country such as the Southeast.

Yield variability was not a significant predictor of any specific marketing technique in the Vergara et al (2004) study. This thesis includes the variable IRR in its analysis which is, theoretically, inversely related to yield variability. A higher percentage of total acreage dedicated to irrigated production would lead to lower yield variability. The coefficient on IRR for choosing forward contracting over co-op marketing is negative and statistically significant at the $\alpha = .05$ level ($\beta = -0.002$, $z = -2.50$). This is a somewhat puzzling result because it was hypothesized that greater yield variability would have an inverse relationship with the probability of adopting merchant forward contracting over cooperative pooling. One possibility is that the full effect of yield risk on the landscape of marketing alternatives was not felt until the record drought of the 2011 season. Anecdotal evidence suggests that acreage contracts were readily available prior to 2011, but were ceased to be offered in Texas almost entirely in 2012, with the merchants opting instead for direct bales basis contracts (Bynum 2012).

Finally, producers who preferred forward contracting to co-op marketing believed that merchant pools give a higher price than co-ops (MPBLF). The regression coefficient of MPBLF on Γ_1 was 1.17 with a z-score of 2.18. Why this variable was significant in choosing forward contracting and not in choosing merchant pools over co-op pools is an interesting result. One possible explanation lies in how respondents reported which merchant or merchant pool they contracted with. There are many merchants that offer both direct forward contracts and pooling. In some cases, respondents reported contracting with a specific merchant pool, but indicated their primary 2010 choice was direct forward contracting. This indicates there was likely some confusion as to how respondents' general marketing choice and relationship with a specific merchant were to be reported. A second possible explanation involves the relatively small number of producers reporting merchant pools as their primary choice (19 out of 263 responses). In addition to MPBLF, EDUC and OFFINC were uniquely significant predictors of merchant pool contracting. This suggests that some coefficients on MPOOL could be biased. A possibly remedy would be to collapse MPOOL into other types of forward pricing. MPOOL could be collapsed into COOP, per the similarities between co-op pools and merchant pools. Alternatively, MPOOL could be collapsed into FORWARD for two different justifications: (1) many merchants offer both forward contracting and pooling, and (2) merchant customers in general might tend to believe merchant pools are better than cooperative pools per their affiliation with merchants, even though they forward contract. Further research may be warranted to explore the possible complementary or substitutionary relationships between similar types of forward pricing.

Marginal Effects Coefficients

In terms of the marginal probability of adoption at the independent variable means (as derived from the log-likelihood functions in Equation 8), some interesting results are revealed. While the log-likelihood regression coefficient on CDIV for CASH was not significant, producers believing that co-op dividends were not influential in their choice of marketing arrangement were 6.41% more likely to choose cash sales over co-op marketing. The marginal effect carried a z-score of -3.94. Confirming the log-likelihood coefficient for WILLING on CASH, producers were 5.28% less likely to choose cash selling over co-ops if they were willing to accept a lower price to reduce risk (z = -2.86). Producers who viewed price risk as a source of revenue risk were 6.8% (z = -2.89) less likely to adopt cash sales over co-op pooling. Producers who said they were more willing to accept risk than other farmers were 5.87% (z = 3.03) more likely to adopt cash sales over co-op pooling. Another economically intuitive result was that producers who believed pre-harvest pricing led to higher prices received relative to other methods (PHPBLF) were 6.3% (z = 2.52) more likely to adopt forward contracting over co-op pooling. In terms of insurance choices, respondents were 7.77% more likely to adopt CASH over COOP at the mean value of MPCI (z = 2.06).

While the marginal effects coefficients are more conducive to interpretation than the log-likelihood coefficients, they are open to problems. Mainly, the coefficients only represent the variable's contribution to the marginal probability of adoption at their means. As a variable value moves away from the mean and towards the endpoint, the marginal effect on the probability of adoption at that point may be greater or lesser than at the mean. For example, at very high levels of ACRES, additional acres may have very little effect on the probability of adopting FORWARD over COOP, whereas at the mean of ACRES, a larger farm might be significantly more likely to forward contract.

Another important interpretation consideration with the marginal effects is the scale of the independent variables. Returning to the same ACRES example, the marginal effect of ACRES on MPOOL (the probability of adopting MPOOL over COOP) at the mean is only 0.003%, but the coefficient is statistically significant at the $\alpha = .05$ level. Such a result may seem trivial, but it is necessary to consider the scale: the increase in farm size of one acre at the mean leads to an increase in the marginal probability of adopting MPOOL over COOP of 0.003%. Given that the mean of ACRES is 1,032 with a standard deviation of 1,122, a minimum of 16 and a maximum of 9,000, this result should not be ignored.

CHAPTER V

CONCLUSIONS AND FUTURE RESEARCH

The findings presented in this thesis have various implications for producers, merchants, pool managers, policy makers and academia. The remainder of this thesis will be devoted to discussing these implications and providing a launching point for future research endeavors.

Implications for the Cotton Industry

Cotton industry professionals on both sides of the marketing apparatus may find the results presented in this thesis interesting. Every season, producers are faced with the question of how to maximize welfare by choosing the marketing outlet—or combination of outlets—with the best risk-balancing capability. Producers want to minimize risk but are also concerned with the ever-present question of which marketing arrangement will net them the highest price. As presented in the summary statistics, producers who cash contracted in 2010 wound up receiving the highest average price for their crop, but it is necessary to reinforce the idea that prices vary randomly—especially considering that successive price increases happened throughout the Southwestern harvest and shortly thereafter, which is normally a point in the season where prices are low due to the acute increase in supply after harvest. This thesis lines up with previous literature on producer marketing in that it finds no evidence contradictory to the efficient market hypothesis. The fact that a shifting of marketing preferences has occurred between the cotton marketing studies of the early 2000s and 2010—and likely occurred between 2010 and 2011—speaks to the idea that markets cannot be timed. Producers, then, are best advised to continue to diversify marketing arrangements to diffuse risk, and to use the marketing outlets and hedging tools that work best with their respective crop insurance choices (program types and coverage levels), yield history, cash reserves and financial risk. Producers should consider the complimentary and substitutionary relationships between insurance, loan programs, cash marketing outlets and hedging mentioned in this thesis to minimize overlap between risk-management strategies and redundant costs.

On the other side of the marketing apparatus, pool managers and merchants may find a few particular results from this thesis helpful in understanding the producers they buy from. One of these noteworthy results lies in the apparent change in attitude among producers towards cooperative pool pricing objectives since the Vergara et al (2004) study. Their findings suggested that the typical co-op pool customer at the time was less-risk averse compared to other producers, presumably because a seasonal pool does not offer the same price guarantee as a forward contract with a merchant. This thesis found the opposite result. Such a finding lines up with anecdotal evidence that suggests that cooperative pools have come to be viewed as the "status quo," whereas other marketing alternatives are perceived as being more aggressive. This is not entirely surprising given the producer cognizance of seasonal pools failing to capture the upside price movement in late 2010. In light of this, pool managers may need to reassess their own selling and pricing strategies and ensure that the resulting changes to their strategies are being effectively communicated to producers in order to instill confidence that the pools are truly working to maximize producer welfare. Moreover, it appears that dividends and book credits are not as influential as one would think; thus, public relations efforts toward producers should be aimed more at improving the perception of actual pool performance—especially over long periods of time—instead of the benefits of co-op ownership.

The marginal effects coefficients enumerated on p. 40 have a unique application for pool managers. Pool managers may want to target producers with characteristics that are directly related to adoption of the pools the managers represent, such as the effect of PRRISK on COOP. Conversely, pool managers may not find it worth their efforts to market their services to producers with characteristics that are inversely related to the adoption of merchant or cooperative pools, such as the effect of ATTITUDE on COOP.

Merchants may find value in the result that indicates a significant, direct relationship between the opinion that merchant pools pay a higher price than co-op pools and the probability of adopting both forward contracting and merchant pool contracting over co-op pools. While somewhat obvious, this result is important in that there was agreement across the board on this question among all merchant customers regardless of whether they were in a pool or had a direct contract. It may be prudent for merchants to develop new pools, pool together with other merchants or increase their efforts to induce producers into existing pools. This would capitalize on the attitude among merchant customers that merchant pooling is superior while reducing the yield risk exposure inherent in direct forward contracting.

Implications for Public Policy

Facing the prospect of direct payments and counter-cyclical payments being phased out of the cotton program entirely in the 2012 farm bill, it is imperative to come to a better understanding of the various market-based risk-management strategies and how they interact with one another. Since no coefficients on the 0/1 indicator variables for insurance were statistically significant, it is difficult to ascertain producer knowledge level of these interactions. The agricultural economics literature documents evidence of redundance in the marketing and hedging strategies of producers and their insurance choices, and this thesis produced no results that indicate producers have a better understanding of these interactions. More education at extension workshops on the complimentary or substitutionary effects between insurance and hedging may be warranted.

An alternative policy consideration is to shift subsidies from insurance programs to helping producers with the cost of direct hedging. Subsidies could be used to help producers post margin on futures contracts or pay option premiums. In such a program, market price movements would trigger smaller payments throughout the year, rather than a large volume of indemnities being paid out at harvest. Analysis may be needed to determine if these smaller payments would accomplish similar results as insurance for a lower cost to society.

Future Research

Logit Analysis of Insurance Choices

Tying in with the previous paragraph, further analysis on insurance choices may be warranted given the changing policy environment. An initial analysis could be conducted with the data set used for this thesis. Logistic regression could be used to model the factors leading to the insurance choices of producers in this study. A binary logit estimation could be performed with the two variables RI and MPCI. Alternatively, multinomial logit or tobit could be employed to allow for the possibility of no insurance purchase. Such a study might help shed light on producers' use of insurance in conjunction with their cash marketing choices, hedging decisions, operator and operation characteristics and risk attitudes.

Hedging Revisited

As mentioned in Chapter 3, hedging was included as an explanatory variable in this analysis because of its function as a substitute for insurance and government commodity programs and its ability to be used independently of other marketing arrangements. Estimation of a hedging model with hedging as a dependent variable may be warranted. This is necessary both for the cause of updating the literature on hedging given the new market conditions mentioned in this thesis, and for new explanations and considerations of hedging behavior. In addition to merely modeling the decision of whether or not to hedge, a possible interesting analysis would be to elicit the factors determining whether or not a producer who hedged matched his/her futures or options contracts with other forward pricing methods. Hedging may be viewed not just to reduce risk, but to maximize returns to marketing.

Demand Systems Approach to Modeling Producer Marketing Decisions

The multinomial logit framework allowed for comparison with prior studies. However, since the survey measured shares of production allocated to alternative marketing outlets, more information can be brought to bear. This suggests the possibility of a demand system framework such as the seemingly unrelated regression approach employed by Isengildina and Hudson (2001b). Such a model could be built on the classical assumption that demand for a good (in this case, a marketing outlet, which would be seen as a service available to a grower they can use to maximize returns to marketing) is a function of its own price, the price of substitutes and compliments and income. The cost of information about a marketing outlet X could be likened to own-price. The transaction costs associated with and cost of information about alternative risk management strategies (insurance, hedging, etc) could be likened to cross-prices. Producers' availability of human capital and access to cash and credit reserves could be likened to income. A possible functional form is as follows:

$$Demand_{Outlet\ J} = F(Cost\ of\ Information_J, Transaction\ Costs_K, Human\ Capital)$$

Where transaction costs include commission on futures and options trades, the opportunity cost of funds posted for margin calls, options premiums and crop insurance premiums.

The results from a demand system specification might differ from the results of the primary choice model employed in this thesis. Some producers in the data set indicated marketing a significant portion of their crop through secondary and, in some cases, tertiary outlets. Diversification of marketing outlets might have a risk-balancing effect that makes it harder to distinguish between producers with different risk attitude and perception characteristics. Different marketing outlets might also prove to be complimentary to one another in some cases. For example, pool pricing may be complimentary to forward contracting for a producer attempting to balance the risk inherent in average pricing with the certainty of pre-harvest pricing. In contrast, certain independent variables might exhibit more explanatory power if information about secondary marketing choices is preserved. An example of this effect would be a producer who markets their crop through two related outlets, such as forward contracting and pool contracting with the same merchant due to their affiliation with the merchant and desire to compliment pre-harvest pricing with average pricing. Survey questions that were not included in the logit specification such as, “my local merchant representative is more important to me than the parent company in deciding which merchant I will contract with,” may prove influential in predicting a producer’s marketing strategy.

REFERENCES

Amudavi, David, Zeyaur R. Khan, Japhether M. Wanyama, Charles A. O. Midega, Jimmy Pittchar, Ahmed Hassanali, and John A. Pickett. 2008. "Evaluation of Farmers' Field Days as a Dissemination Tool for Push-Pull Technology in Western Kenya." *Crop Protection* 2009 (28): 225-235.

Brorsen, B. Wade and Kim B. Anderson. 2001. "Implications of Behavioral Finance for Farmer Marketing Strategy Recommendation." St. Louis, MO, NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, April 2001.

Bynum, Timothy R. 2012. United Cotton Growers Cooperative. Personal Communication.

Carter, Colin A. and Joseph P. Janzen. 2009. "The 2008 Cotton Price Spike and Extraordinary Hedging Costs." *Agricultural and Resource Economics Update* 13 (2): 9-11.

Coble, Keith H., Richard Heifner, and Manuel Zuniga. 2000. "Implications of Crop Yield and Revenue Insurance for Producer Hedging." *The Journal of Agricultural and Resource Economics* 25 (2): 432-452.

Coble, Keith H., J. Corey Miller, Manuel Zuniga, and Richard Heifner. 2004. "The Joint Effect of Government Crop Insurance and Loan Programmes on the Demand for Futures Hedging." *European Review of Agricultural Economics* 31 (3): 309-330.

Collins, Robert A. 1985. "Expected Utility, Debt-Equity Structure, and Risk Balancing." *American Journal of Agricultural Economics* 67 (3): 627-629.

"The Cotton Board." Accessed May 31, 2012, www.cottonboard.org.

Dillman, Don. 1978. *Mail and Telephone Surveys: The Total Design Method.* John Wiley & Sons. New York. 180-188.

Feder, Gershon. 1980. "Farm Size, Risk Aversion and the Adoption of New Technology Under Uncertainty." *Oxford Economic Papers* 32 (2): 263-283.

Franken, Jason R. V., Joost M. E. Pennings, and Philip Garcia. 2008. "Do Transaction Costs and Risk Preferences Influence Marketing Arrangements in the Illinois Hog Industry?" St. Louis, MO, NCCC-134 Conference on AppliedCommodity Price Analysis, Forecasting, and Market Risk Management, 2008.

Isengildina, Olga and Darren M. Hudson. 2001a. "Factors Affecting Hedging Decisions Using Evidence from the Cotton Industry." St. Louis, MO, NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, April 23-24, 2001.

Isengildina, Olga and Darren M. Hudson. 2001b. "Cotton Producers' Use of Selected Marketing Strategies." *The Journal of Cotton Science* 5 (2001): 206.

Janzen, Joseph P., Aaron D. Smith, and Colin A. Carter. 2012. "Commodity Price Comovement: The Case of Cotton." St. Louis, MO, NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, April 2012.

Lapan, Harvey and Giancarlo Moschini. 1994. "Futures Hedging Under Price, Basis, and Production Risk." *American Journal of Agricultural Economics* 76 (3): 465-477.

Mercer, D. E. 2004. "Adoption of Agroforestry Innovations in the Tropics: A Review." *Agroforestry Systems* 61 (1): 311-328.

Meyer, Leslie, Stephen MacDonald, and Linda Foreman. 2007. *Cotton Backgrounder (Economic Report from the Economic Research Service)*. USDA Economic Research Service.

"National Agricultural Statistical Service, 2007 Census of Agriculture." United States Department of Agriculture, accessed July 2012, http://www.agcensus.usda.gov/Publications/2007/Full_Report/Volume_1,_Chapter_1_State_Level/Texas/st48_1_032_032.pdf.

Pennings, Joost M. E. and Raymond M. Leuthold. 2000. "The Role of Farmers' Behavioral Attitudes and Heterogeneity in Futures Contracts Usage." *American Journal of Agricultural Economics* 82 (4): 908-919.

Pindyck, Robert and Daniel L. Rubinfeld. 1991. *Econometric Models & Economic Forecasts*. Third ed. McGraw-Hill, Inc. New York. 248-286.

Power, Gabriel J. and John R. C. Robinson. 2009. "Cotton Futures Dynamics: Structural Change, Index Traders and the Returns to Storage." St. Louis, MO, NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2009.

Riley, John Michael and John D. Anderson. 2009a. "Comparison of Hedging Cost with Other Variable Input Costs." St. Louis, MO, NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2009.

Riley, John Michael and John D. Anderson. 2009b. "Producer Perceptions of Corn, Soybean and Cotton Price Risk." Atlanta, GA, Southern Agricultural Economics Association Annual Meeting, January 31-February 3, 2009.

Shapiro, B. I. and B. Wade Brorsen. 1987. "Factors Influencing Farmers' Decisions of Whether Or Not to Hedge." Chicago, IL, NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 1987.

Skaggs, R. K. 2001. "Predicting Drip Irrigation use and Adoption in a Desert Region." *Agricultural Water Management* 51: 125-142.

Vergara, Oscar, Keith H. Coble, Thomas O. Knight, George F. Patrick, and Alan E. Baquet. 2004. "Cotton Producers' Choice of Marketing Techniques." *Agribusiness* 20 (4): 465-479.

Wooldridge, Jeffrey M. 2003. *Introductory Econometrics: A Modern Approach*. Second ed. Thomson South-Western.

Wozniak, Gregory D. 1987. "Human Capital, Information, and the Early Adoption of New Technology." *The Journal of Human Resources* 22 (1): 101-112.

APPENDIX A

Summary Statistics of 2012 Survey of Southwestern Cotton Marketing Choices[3]

Variable	Description	Mean	STDDEV	Minimum	Maximum
COOP	0/1 indicator of primary co-op pool choice	0.639	0.481	0	1
FORWARD	0/1 indicator of primary merchant forward contracting choice	0.156	0.363	0	1
CASH	0/1 indicator of primary merchant spot market choice	0.113	0.340	0	1
MPOOL	0/1 indicator of primary merchant pool choice	0.072	0.259	0	1
CHIST	0/1 indicator of historical marketing with co-op pool	0.55	0.498	0	1
CDIV	5-pt scale of influence of co-op dividends and book credits (5=more influential)	3.247	1.147	1	5
HEDGED	0/1 indicator of 2010 hedging	0.057	0.232	0	1
MPCI	0/1 indicator of 2010 purchase of multi-peril crop insurance	0.414	0.494	0	1
RI	0/1 indicator of 2010 purchase of revenue insurance	0.525	0.515	0	1
PHPBLF	5-pt scale belief about pre-harvest pricing and higher prices (5=strongly agree)	3.414	0.833	1	5

[3] See table 1 in the text for a list of variable names and definitions.

WILLING	5-pt scale of willingness to take a lower price to reduce price risk (5=more willing)	3.095	0.888	1	5
CPBLF	5-pt scale belief that co-op pool marketing gives average prices (5=strongly agree)	3.650	0.886	1	5
MPBLF	5-pt scale belief that merchant pools give higher price than co-op (5=strongly agree)	2.795	0.769	1	5
PRRISK	5-pt scale view of price risk as source of revenue risk (5=high potential effect)	4.338	0.707	2	5
ATTITUDE	5-pt scale comparison to other farmers' willingness to accept risk (5=much more willing)	3.243	0.857	1	5
OFFINC	Percent of household income from off-farm sources	16.0%	23.9%	0%	100%
ASSETS	Total market value of assets in farming operation (1=<$100K, 2=$100K--$499K, 3=$500K--$999K, 4=$1M--$1.99M, 5=$2M-$4.99M, 6=>$5M)	2.592	1.300	0	5
LEVERAGE	Percent of total dollars invested in operation that are borrowed	35.4%	32.6%	0%	100%
AGE	Respondent age in years	57.802	13.671	25	98
EDU	Respondent education level (0=<HS, 1=HS or GED, 2=some college, 3=4-yr degree, 4=grad school	2.430	0.993	0	4
ACRES	Size variable (2010 total cotton acres planted)	1,032	1,132	16	9,000

IRR	Total 2010 planted cotton acres that were irrigated	332.4	528.3	0	4,000

APPENDIX B

Log-likelihood Coefficients and Marginal Effects

	FORWARD		CASH		MPOOL	
	Log	Marginal	Log	Marginal	Log	Marginal
CHIST	**-6.46***	0.5424	-20.789	-0.704	-20.708	-0.507
	-4.93	*0.01*	*-0.02*	*-0.01*	*-0.02*	*-0.01*
CDIV	-0.529	0.0198	**-1.610***	**-0.064***	-0.766	-0.001
	-1.49	*1.05*	*-3.63*	*-3.94*	*-1.73*	*-0.09*
HEDGED	-0.511	0.5170	**-2.812****	0.113	-20.213	-0.852
	-0.49	*0.01*	*-1.76*	*0*	*-0.01*	*-0.01*
MPCI	-0.388	-0.0333	1.029	**0.078***	-0.946	-0.046
	-0.45	*-0.71*	*1.11*	*2.06*	*-0.87*	*-1.26*
RI	-0.621	-0.0437	0.686	0.064	-0.883	-0.033
	-0.76	*-0.97*	*0.79*	*1.79*	*-0.91*	*-1.01*
PHPBLF	**0.967***	**0.0632***	0.181	-0.018	0.225	-0.015
	2.13	*2.52*	*0.4*	*-0.95*	*0.4*	*-0.77*
WILLING	-0.358	0.0109	**-1.209***	**-0.053***	-0.286	0.011
	-0.91	*0.52*	*-2.5*	*-2.86*	*-0.56*	*0.64*
CPBLF	**-0.804****	-0.0373	-0.517	-0.002	-0.425	0.007
	-1.78	*-1.64*	*-1.09*	*-0.12*	*-0.79*	*0.39*

MPBLF	**1.18***	**0.0545****	0.000	**-0.049****	**1.457***	0.037
	2.18	*1.89*	*0*	*-1.76*	*2.04*	*1.53*
PRRISK	0.661	0.0379	-0.658	**-0.068***	1.221	**0.047***
	1.19	*1.29*	*-1.09*	*-2.89*	*1.71*	*1.96*
ATTITUDE	0.485	-0.0080	**1.396***	**0.059***	0.364	-0.013
	1.07	*-0.34*	*2.68*	*3.03*	*0.63*	*-0.67*
OFFINC	0.024	0.0014	-0.023	**-0.002***	0.044	0.002*
	1.51	*1.61*	*-1.19*	*-3.24*	*2.1*	*2.51*
ASSETS	-0.033	0.0133	-0.229	-0.006	-0.414	-0.015
	-0.12	*0.85*	*-0.72*	*-0.5*	*-1.09*	*-1.14*
LEVERAGE	0.009	0.0009	-0.012	-0.001	0.006	0.000
	0.73	*1.31*	*-0.83*	*-1.66*	*0.38*	*0.37*
AGE	0.022	0.0005	-0.014	-0.002	0.067	**0.003****
	0.87	*0.29*	*-0.44*	*-1.5*	*1.9*	*1.92*
EDUC	-0.25	0.0172	-0.526	-0.010	**-0.95****	-0.029
	-0.61	*0.82*	*-1.12*	*-0.53*	*-1.9*	*-1.93*
ACRES	0.0004	0.0000	-0.0005	**0.000***	**0.001***	**0.00003***
	1.20	*1.5*	*-1.23*	*-2.84*	*2.09*	*2.93*
IRR	**-0.002***	**-0.0002***	-0.0002	0.000	0.000	**0.00005****
	-2.50	*-3.06*	*-0.18*	*1.22*	*-0.05*	*1.79*

*Denotes coefficient that is statistically significant at the alpha = .05 level , while ** implies significance at alpha = .10 level. (z-statistics are in italics)

APPENDIX C

Variance-Covariance Matrix of Independent Variables

	CHIST	CDIV	HEDGED	MPCI	RI	PHPBLF	WILLING	CPGLF	MPBLF	PRRISK	ATTITUDE	OFFINC	ASSETS	LEVERAGE	AGE	EDUC	ACRES	IRR
CHIST	1																	
CDIV	0.3475	1																
HEDGED	-0.078	-0.0964	1															
MPCI	0.0508	0.064	-0.0413	1														
RI	-0.0215	0.0379	0.0013	-0.4429	1													
PHPBLF	0.0722	0.0707	0.1148	-0.111	0.1996	1												
WILLING	0.0739	0.0838	0.028	-0.0246	0.1257	0.2811	1											
CPGLF	0.3012	0.3058	0.0039	-0.0625	0.0684	0.07	0.078	1										
MPBLF	-0.229	-0.2167	0.0447	-0.0054	-0.0795	0.1089	0.0581	-0.2509	1									
PRRISK	-0.0065	-0.0487	0.0675	0.0436	0.1117	0.1773	0.0315	0.0483	-0.0397	1								
ATTITUDE	-0.0638	0.1009	0.0651	-0.201	0.0905	0.1556	-0.0013	-0.0006	0.0985	0.0038	1							
OFFINC	-0.0017	-0.1157	0.0352	0.0777	-0.007	0.0201	0.0021	-0.0218	-0.0048	-0.0084	-0.1	1						
ASSETS	0.0215	0.0126	0.0016	-0.1163	0.1171	0.1382	-0.0411	0.0161	0.0342	0.0722	0.2087	-0.2589	1					
LEVERAGE	-0.1137	0.0372	0.0411	-0.0505	0.0867	0.0735	0.141	-0.0336	0.0372	0.1326	0.0693	0.092	-0.0945	1				
AGE	0.1709	0.07	-0.1519	0.0702	-0.1739	-0.0991	-0.1035	0.0775	-0.0442	-0.0898	-0.0333	-0.0566	-0.0294	-0.353	1			
EDUC	-0.0241	0.0338	0.0906	0.017	0.149	0.0822	-0.0062	-0.0266	-0.0369	0.0932	-0.0302	0.1871	0.0958	-0.1034	-0.1366	1		
ACRES	-0.098	-0.0086	-0.0203	-0.0897	0.167	0.0231	0.0608	0.0151	-0.0749	0.0658	0.0833	-0.1872	0.3889	0.0434	-0.1463	0.0414	1	
IRR	0.0633	-0.0184	0	-0.0208	0.0801	-0.0215	-0.0395	0.0396	0.0283	0.0578	0.0594	-0.2022	0.2925	0.0934	-0.0193	0.0114	0.4269	1