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Three essays on technology adoption and the roles of off-farm labor, human capital, and risk in contemporary US agriculture

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THREE ESSAYS ON TECHNOLOGY ADOPTION AND THE ROLES OF OFF-FARM LABOR, HUMAN CAPITAL, AND RISK IN CONTEMPORARY US AGRICULTURE

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ABSTRACT

Agriculture can be defined as the domestication and farming of plant and animal species to produce food and fiber products. Our society is fundamentally dependent on agriculture as it is the primary source of nutrients essential to human activities. Historically, the introduction of agriculture and technological development thereafter drastically changed the way human civilization has evolved into what it is today. New technologies allow farmers to produce more outputs with fewer inputs. Saved resources from agricultural production, such as land, labor and time, were used elsewhere to produce other goods and services that enrich the quality of our life.

The primary focus of my dissertation is how new agricultural technology is adopted by U.S. farmers in the face of risk and uncertainty surrounding today's agriculture. This dissertation contributes to the existing literature by reflecting the important recent trends in U.S. agriculture. In the first essay, I explore the implication of genetically modified crop varieties on farm households' income from off-farm sources, which explains approximately 90 percent of total farm household income in the United States. The second essay studies the relationship between farm operators' formal education and technology adoption. It reconsiders the conventional human capital theory and demonstrates that formal education can have a negative impact on technology adoption. The final essay focuses on the impact of farm producers' attitude toward risk on their use of various risk management strategies.

CHAPTER 1: INTRODUCTION

Agriculture can be defined as the domestication and farming of animal and plant species to produce food and fiber products. Our society is fundamentally dependent on agriculture as it is the primary source of the nutrients essential to human activities. Historically, the introduction of agriculture, and technological developments thereafter, drastically changed the evolution of human civilization into what it is today. New technologies allow farmers to produce more outputs with less input. Resources conserved from agricultural production, such as land, labor and time, were used elsewhere to produce other goods and services that enrich the quality of our lives.

1.1. Dissertation Overview

The primary focus of this dissertation is the adoption of technology in agriculture in the United States. Decisions to adopt new technologies are complex due to factors such as temperature and rainfall, which are mostly determined by the whims of nature. Dynamic social changes due to population and economic growth in the United States also play an important role. Such factors pose significant challenges to farmers in assessing the profitability and applicability of new technology to the specific environmental and economic conditions under which they operate. Therefore, an understanding of the factors associated with technology adoption is crucially important for policy-makers to secure sufficient supplies of food and fiber products while conserving natural resources. This understanding also has significant implications for the well-being of the consumers whose lives are profoundly dependent on affordable foods that are healthy and of good quality.

Technology adoption is one of the most widely studied topics in agricultural economics, dating back to the classic work by Griliches (1957) who studied the adoption of hybrid corn. In the simplest terms, technology adoption alters the production function, allowing farmers to produce more outputs with less input or lower costs. A great deal of empirical research has been devoted to this very topic to identify a wide range of factors that influence farmers' decisions to adopt a variety of technologies under diverse production, economic, and environmental conditions. Feder and Umali (1993), Feder, et al. (1985), and Sunding and Zilberman (2001), among others, provide a thorough review of significant contributions to this topic. The present dissertation contributes to the existing literature by reflecting upon recent trends in the US farm sector and their implications on technology adoption in agriculture.

The first essay studies the implications of genetically modified (GM) crop varieties, which were commercially introduced to US agriculture in 1996, involving off-farm labor participation by US farm households. Among the recent innovations in agriculture that are generally management intensive, GM crops are unique in that they significantly reduce labor requirements (Smith, 2002). Given the fact that an increasing number of farmers report income from off-farm sources,[1] the recent introduction of the time saving technology, and its widespread dissemination thereafter, is expected to have important implications for farm households' time allocation decisions.

The second essay builds on the first and focuses on the relationship between farm operators' human capital and technology adoption. It reconsiders the conventional human capital theory that highly educated farmers are more likely to adopt new technologies in a more modern empirical framework in which such farmers are also likely to find more lucrative employment opportunities off the farm. Considering the fact that farm operators now account for a much smaller share of the total work force than in the past,[2] while the number of college-educated farmers has been steadily increasing over the past five decades,[3] the chapter revisits and gives new insights into the relationship between farm operators' human capital and technology adoption in the contemporary U.S. farm sector.

In the final essay, we explore the impact of farm producers' attitudes toward risk on their use of various risk management strategies. Risk and uncertainty play a significant role in almost every aspect of our lives. Understanding individual attitudes towards risk is crucial for successful public policy

[1] In 2002, 93% of farm households reported off-farm income, up from 54% in 1970 (Dimitri et al., 2005). Mishra et al. (2002) reported that income from off-farm sources explained approximately 90% of total farm household income in 1999.

[2] Dimitri et al. (2005) provides a detailed account of the structural changes the US farm sector has experienced since the beginning of the 20th century. In 1900, farm labor explained 41% of the total U.S. workforce. The number continually declined over the course of the century: 21.5% in 1930, 4% in 1970, and 1.9% in 2002. The share of GDP contributed from the farm sector followed suit, accounting for 7.7% of total GDP in 1930, 2% in 1970, and 0.7% in 2002.

[3] Mishra et al. (2009) reported, from the 2004 Agricultural Resource Management Survey, that only 10 percent of farm operators had either attended or graduated from college in 1964 whereas the analogous figure rose to 48 percent in 2004.

interventions (Dohmen, et al., 2011, Weber, 2010). The central difficulty in risk research in agricultural economics is how to measure individual risk attitudes. A wide variety of methods have been proposed to measure farmers' risk attitudes, but often provide empirical results inconsistent with theoretical expectations (Fausti and Gillespie, 2006, Lagerkvist, 2005). Given the recent findings in economics and labor economics literature that a simple qualitative measure of risk attitudes can be the most versatile predictor of risky behaviors (Dohmen, et al., 2005, 2011), in this chapter, we will examine the validity of the same qualitative measure of risk attitudes used in these studies using data from a nationwide survey of farm households in the United States.

1.2. Theoretical Framework

The underlying theoretical framework in this dissertation is agricultural household models. The hallmark of agricultural household models is that the budget constraint is assumed endogenous unlike in the standard consumer model (Taylor and Adelman, 2003). According to Taylor and Adelman (2003), agricultural household models were first developed by Kuroda and Yotopoulos (1978) in an attempt to explain the absence of a positive effect of a commodity price increase on a market surplus of the commodity in rural Japan. This counterintuitive phenomenon is attributed to the profit effect (Singh, et al., 1986, Taylor and Adelman, 2003). In a neoclassical economic framework, where perfect information and zero transaction costs are assumed, an increase in a commodity price should unambiguously decrease demand for the commodity, assuming that it is a normal good. In the agricultural household model where a farm household plays the dual role of both consumer and producer, the price increase also invokes the profit effect as it enhances farm revenue and thus farm household income. This shifts the household's budget constraint outward and so does the demand curve for the commodity. Combined with the negative income and substitution effects, the net effect of the price increase on commodity demand becomes ambiguous in the presence of the profit effect. The own price elasticity of food demand can be positive when the profit effect outperforms the income and substitution effects, and if this is the case, it may decrease food supply in the market to the extent that the market is imperfect.

This example sheds light on the fundamental objective of agricultural household models. The raison d'etre of agricultural household models is to construct a theoretical framework to predict the effects of exogenous shocks to the farm sector (Singh, et al., 1986, Taylor and Adelman, 2003). Agricultural household models have been used as the building block of empirical research in the fields of agricultural economics. The models have been used in a wide range of applications including technology adoption, off-farm labor supply, migration, and income distribution (Taylor and Adelman, 2003). Chapters 2 and 3 discuss the applications of agricultural household models relevant to off-farm labor supply and farm operators' human capital, respectively, in the context of technology adoption.

1.3. Data

All the empirical analyses in this dissertation rely on data from the Agricultural Resource Management Survey (ARMS), a national survey conducted annually by the Economic Research Service (ERS) and the National Agricultural Statistics Service. The ARMS collects data to measure the financial conditions, operating characteristics of farm businesses, the cost of producing agricultural commodities, and the well-being of farm operator households. The ARMS also collects information on farm households, including detailed information on off-farm hours worked by farm operators and their spouses and the amount of income received from off-farm work.

The target population of the ARMS is operators associated with farm businesses representing agricultural production in the 48 contiguous states. A farm is defined as an establishment that sold or normally would have sold at least $1,000 of agricultural products during the year. Farms can be organized as sole proprietorships, partnerships, family corporations, non-family corporations, or cooperatives. Data is collected from one operator per farm, the senior farm operator. A senior farm operator is the operator who makes the majority of the day-to-day management decisions. Throughout this dissertation, operator households organized as nonfamily corporations or cooperatives and farms run by hired managers were excluded.

The ARMS has a complex stratified and multi-frame design and each observation in the ARMS represents a number of similar farms, the particular number being the survey expansion factor (or the inverse of the probability of the surveyed farm being selected for surveying). The complex survey design as well as the cross-sectional nature of the data requires an appropriate technique to estimate standard errors to account for potential heteroskedasticity. Although the delete-a-group jackknife procedure is the standard approach to obtain variance of estimated parameters, the obvious drawback is the small number of replication (Panel to Review USDA's Agricultural Resource Management Survey, 2007). Its validity is also in question when only a subset of the ARMS is used (Dubman, 2000, El-Osta, 2011, Goodwin, et al., 2003) as in all econometric analyses in this dissertation. El-Osta (2011) demonstrated that the jackknife estimation method tended to underestimate standard errors, relative to those obtained using the bootstrap method (Efron, 1982) or the robust Huber/White/sandwich estimator (Huber, 1967, White, 1980). This is of great concern especially when interpreting statistical results with borderline significance at the conventional levels (El-Osta, 2011).

Following the recent applications of the ARMS data in published studies (El-Osta, 2011, Mishra and El-Osta, 2008, Mishra, et al., 2010), all econometric analyses in this dissertation employ the robust Huber/White/sandwich estimator for standard errors estimation, unless otherwise noted. An exception is made in Chapter 4 when standard errors of the marginal effects in a double-hurdle model are calculated, for which the bootstrap method is recommended.

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CHAPTER 2: DOES "CONVENIENCE AGRICULTURE" AFFECT OFF-FARM LABOR ALLOCATION DECISIONS?

2.1. Introduction

The adoption of genetically modified (GM) crop varieties has increased rapidly since they were commercially introduced to US agriculture in 1996, due to higher expected yields, lower input costs, and fewer labor requirements (Fernandez-Cornejo and Caswell, 2006, Fernandez-Cornejo, et al., 2001). For example, in 2005, only 10 years after they were commercially introduced, herbicide-tolerant (HT) soybeans accounted for 85% of the total soybean acreage in the United States (Fernandez-Cornejo and Caswell, 2006). This rapid increase in the adoption of GM crops is a clear manifestation that perceived benefits from GM crops significantly outweigh additional costs incurred for a wide spectrum of potential adopters. The diffusion path that GM crops has taken so far in the United States stands in stark contrast to those taken by other technologies. While other recent innovations in agriculture, such as precision farming technologies, integrated pest management, and soil testing, often require more managerial time by farm operators, GM crops are management-saving (Smith, 2002). HT crop varieties, the most widely and rapidly adopted GM crops in the United States, significantly reduce labor requirements for weed control as they have been developed to survive the application of herbicides that previously would have damaged the crop as well as the targeted weeds (Fernandez-Cornejo and McBride, 2000). The simplicity and flexibility of GM crops relative to conventional crop varieties allow farmers to save labor and managerial time thereby improving efficiency of farming operation (Smith, 2002).

An important question arises as to how time savings made possible by the adoption of GM crops are allocated by farm households, especially by farm operators and their spouses. Theoretically, rational economic agents allocate their time across various activities so as to maximize their total utility. Thus, a natural consequence of adopting GM crops—a primary example of what Smith (2002) calls "convenience agriculture" technology—for farm operators and their spouses would be either (1) further expansion of the farm enterprise, (2) an increased off-farm labor supply, (3) increasing leisure time or (4) a combination of any or all of the above.

However, empirical evidence on the impact of the rapid increase in GM crop adoption on labor allocation decisions by farm households is scarce and inconsistent. While earlier studies found no evidence of correlations between GM crop adoption and off-farm labor supply (Fernandez-Cornejo, et al., 2001, Fernandez-Cornejo and McBride, 2000), more recently, Fernandez-Cornejo, et al. (2005) and Fernandez-Cornejo (2007) found a positive correlation between the adoption of HT crops and off-farm income, postulating that the increase in total income is due to greater off-farm labor supply.

In addition, most studies on this topic do not account for the joint nature of farm households' labor allocation decisions in estimating the impact of GM crop adoption. For example, Fernandez-Cornejo (2007) conjectured that the increase in off-farm income was a result of increased hours of off-farm work, but did not estimate off-farm labor supply by operators, their spouses or both. This is of great concern, considering the ample empirical evidence that off-farm labor allocation decisions between operators and their spouses were jointly determined (Gould and Saupe, 1989, Kimhi, 2004, Kimhi, 1994, Kwon, et al., 2003, Tokle and Huffman, 1991).

Herein lie the objectives of our analysis. First, we estimate the impact of GM crop adoption on off-farm labor supply by US farm households, allowing for the joint process through which operators and their spouses allocate their time between on- and off-farm work. In doing so, we expand the scope of existing studies and examine the degree to which the intensity of GM crop adoption, in terms of a share of GM crops acres (corn and soybeans) over total corn and soybean acres, influences off-farm labor supply as determined by farm operators and their spouses.

2.2. Conceptual Framework

Farm households' decisions about technology adoption and off-farm labor supply can be well represented in the context of the agricultural household model (Fernandez-Cornejo, et al., 2005, Huffman, 1991, Sumner, 1982) in which the farm household is assumed to maximize utility, $\boldsymbol{U}$, subject to three constraints: time, budget, and production. The objective function is given by

$$Max\ U = U(G, \boldsymbol{T_L}, \boldsymbol{H}, \boldsymbol{\Phi}), \tag{1}$$

where G is a composite good purchased by the farm household for direct or indirect consumption, $\boldsymbol{T_L}$ is a column vector[4] of leisure time for the operator and the spouse ($\boldsymbol{T_L} = (T_L^O, T_L^S)'$),[5] and $\boldsymbol{\Phi}$ represents a vector of other exogenous factors that influence the household's utility such as family characteristics.[6] The time constraint for the household is given as:

$$\boldsymbol{T} = \begin{pmatrix} T^O \\ T^S \end{pmatrix} = \begin{pmatrix} T_{on}^O + T_{off}^O + T_L^O \\ T_{on}^S + T_{off}^S + T_L^S \end{pmatrix} = \boldsymbol{T_{on}} + \boldsymbol{T_{off}} + \boldsymbol{T_L}, \tag{2}$$

where time endowment given to the farm household consists of those for the operator and the spouse, each of which can be distributed among three activities: on-farm work, off-farm work, and leisure. These three activities are denoted by subscripts, "on," "off," and "L." Assuming that all household income is going to be spent, the budget constraint is given by

$$P_g G = P_q Q - \boldsymbol{P_x'X} + \boldsymbol{W'T_{off}} + A, \tag{3}$$

where P_g, P_q and $\boldsymbol{P_x}$ are, respectively, prices of G, Q, and $\boldsymbol{X}$, Q is a composite farm output, and $\boldsymbol{X}$ is a vector of farm inputs, $\boldsymbol{W}$ is a vector of off-farm wage for the operator and the spouse ($\boldsymbol{W} = W^O, W^S)'$'), $\boldsymbol{T_{off}}$ is a vector of off-farm labor supply by the operator and the spouse ($\boldsymbol{T_{off}} = (T_{off}^O, T_{off}^S)$'), and A consists of all other sources of income such as interest and government transfers. To accommodate the assumption that all farm household income is spent, one can assume that the composite good, G, includes a variety of financial services including savings and investments. Note that $P_q G - \boldsymbol{P_x'X}$ represents the net farm household income and $\boldsymbol{W'T_{off}}$ is the total off-farm income for the household.[7]

The production technology constraint can be represented as

$$Q = Q[\boldsymbol{X}(\Gamma), \boldsymbol{T_{on}}(\Gamma), \boldsymbol{H}, \Gamma, \mathbf{R}], \quad \Gamma \geq 0, \tag{4}$$

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[4] All of the characters in bold font represent a column vector unless otherwise noted.
[5] Superscripts "O" and "S" denote "operators" and "spouses" respectively throughout this chapter. $(T_L^O\ T_L^S)'$ indicates that it is a 2×1 column vector.
[6] Following Hallberg et. al., (1991) we assume that farm household utility is determined by decisions and economic activities by the operator and the spouse. Any contribution to the household utility by any other members of the family belongs $\boldsymbol{\Phi}$.
[7] $\boldsymbol{W'T_{off}} = (W^O\ W^S)\begin{pmatrix} T_{off}^O \\ T_{off}^S \end{pmatrix} = W^O T_{off}^O + W^S T_{off}^S$.

where Γ is the intensity of technology adoption (i.e., the share of GM crops in this study), $\boldsymbol{H}$ is a vector of human capital for the operator and the spouse ($\boldsymbol{H} = H^O, H^S)'$, and $\mathbf{R}$ is a vector of exogenous factors pertinent to agricultural operation such as the site specific environmental factors and climatic conditions. Substituting the production technology constraint given by equation (4) into equation (3), we can obtain the technology constrained net household income due to Huffman (1991):

$$P_g G = P_q\{Q[\boldsymbol{X}(\Gamma), \boldsymbol{T_{on}}(\Gamma), \boldsymbol{H}, \Gamma, \mathrm{R}]\} - \boldsymbol{P}_x'\boldsymbol{X} + \boldsymbol{W}'\boldsymbol{T_{off}} + A. \tag{5}$$

The Kuhn-Tucker first order conditions are obtained by maximizing the Lagrangian function that incorporates the utility function, the budget constraint that accounts for the production function, and the time constraint given by equations (1), (5) and (2), respectively:

$$\begin{aligned} L = U(G, \boldsymbol{T_L}, \Phi) + \lambda\big(P_q\{Q[\boldsymbol{X}(\Gamma), \boldsymbol{T_{on}}(\Gamma), \boldsymbol{H}, \Gamma, \mathrm{R}]\} - \boldsymbol{P}_x'\boldsymbol{X} + \boldsymbol{W}'\boldsymbol{T_{off}} + A - P_g G\big) \\ +\boldsymbol{\gamma}'\big[T - \boldsymbol{T_{on}} - \boldsymbol{T_{off}} - \boldsymbol{T_L}\big] \end{aligned} \tag{6}$$

Some of the first order conditions are

$$\frac{\partial L}{\partial G} = \frac{\partial U}{\partial G} - \lambda P_q = 0 \tag{7}$$

$$\frac{\partial L}{\partial X} = \lambda\left(P_q \frac{\partial Q}{\partial \boldsymbol{X}} - \boldsymbol{P_x}\right) = 0 \tag{8}$$

$$\frac{\partial L}{\partial \Gamma} = \lambda\left\{P_q\left[\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right)'\left(\frac{\partial \boldsymbol{X}}{\partial \Gamma}\right) + \left(\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right)'\left(\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma}\right) + \frac{\partial Q}{\partial \Gamma}\right] - \boldsymbol{W}'\frac{\partial \boldsymbol{X}}{\partial \Gamma}\right\} - \boldsymbol{\gamma}'\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma} \leq 0 \tag{9}$$

$$\frac{\partial L}{\partial \boldsymbol{T_{on}}} = \lambda\left[P_q \frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right] - \boldsymbol{\gamma} \leq 0 \tag{10}$$

$$\frac{\partial L}{\partial \boldsymbol{T_{off}}} = \lambda \boldsymbol{W} - \boldsymbol{\gamma} \leq 0 \tag{11}$$

$$\frac{\partial L}{\partial \boldsymbol{T_L}} = \frac{\partial U}{\partial \boldsymbol{T_L}} - \boldsymbol{\gamma} = 0, \tag{12}$$

where λ and $\boldsymbol{\gamma}$ are the Lagrange multipliers. Note that $\boldsymbol{\gamma}$ is not a scalar but a 2×1 vector, with each element being the shadow price of time for the operator and the spouse. Equality in the first order condition indicates that we *a priori* expect an interior solution. For example, rearranging equation (10), we obtain the following:

$$\frac{\boldsymbol{\gamma}}{\lambda} \geq P_q \frac{\partial Q}{\partial \boldsymbol{T_{on}}} \tag{13}$$

The left hand side of equation (13) is the ratio of the shadow prices of time and the net farm household income, which represents the marginal rate of substitution between the two shadow prices for both operators and spouses. The right hand side of equation (13) is the marginal value product of on-farm labor, again for both operators and spouses. Within the range that $\boldsymbol{\gamma}$, λ and $P_q \frac{\partial Q}{\partial \boldsymbol{T_{on}}}$ are all positive, equality in equation (13) assures that the optimizing behavior takes place at a point where a positive amount of Q is produced and thus a positive amount of labor is supplied by both the operator and the spouse. Although past literature usually maintains equality in equation (10), we adopt inequality to account for the possibility that there may be some operators who do not work off the farm or spouses who do not work on the farm.

Following Fernandez-Cornejo, et al. (2005), the optimality condition for the intensity of technology adoption, Γ, can be obtained by rearranging equation (9):

$$P_q \left[\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right)' \left(\frac{\partial \boldsymbol{X}}{\partial \Gamma}\right) + \left(\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right)' \left(\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma}\right) + \frac{\partial Q}{\partial \Gamma} \right] - \boldsymbol{W}' \frac{\partial \boldsymbol{X}}{\partial \Gamma} - \frac{\boldsymbol{\gamma}'}{\lambda} \frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma} \leq 0$$

$$P_q \left[\frac{dQ}{d\Gamma}\right] - \boldsymbol{W}' \frac{\partial \boldsymbol{X}}{\partial \Gamma} - \frac{\boldsymbol{\gamma}'}{\lambda} \frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma} \leq 0, \tag{14}$$

where $\frac{dQ}{d\Gamma} = \left(\frac{\partial Q}{\partial \boldsymbol{X}}\right)' \left(\frac{\partial \boldsymbol{X}}{\partial \Gamma}\right) + \left(\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right)' \left(\frac{\partial \boldsymbol{T_{on}}}{\partial \Gamma}\right) + \frac{\partial Q}{\partial \Gamma}$. The first term on the left hand side in equation (14) is the value of marginal product due to an incremental change in the adoption intensity. The second and the third terms, respectively, represent the marginal input cost and the marginal cost of on-farm labor, both of which are due to the incremental change in the adoption intensity. When equality holds in equation (14), there is going to be a positive level of technology adoption at the equilibrium.

Given the optimal intensity of technology adoption, Γ^*, off-farm labor supply can be obtained by substituting in the optimal levels of on-farm labor and leisure into equation (2). That is,

$$\boldsymbol{T^*_{off}}(\Gamma) = \boldsymbol{T} - [\boldsymbol{T^*_{on}}(\Gamma^*) + \boldsymbol{T^*_L}]. \tag{15}$$

Equation (15) is the model of our interest, consisting of two-stage off-farm labor supply equations, with the first stage pertaining to the optimal intensity of technology adoption, Γ^*. Our empirical model, introduced in Section 2.4, will first estimate the optimal adoption intensity, Γ^*, so that its predicted value can be used as an instrument to estimate off-farm labor supply equations by both operators and their spouses.

2.3. Data

This study employs data from a nationwide Agricultural Resource Management Survey (ARMS) 2004-2006, developed by the Economic Research Service (ERS) and the National Agricultural Statistical Service (NASS). The ARMS survey is designed to link data on the resources used in agricultural production to data on use of technologies, including GM crops. The 2004-2006 ARMS queried farmers on all types of financial, production, and household activities, such as labor allocation and consumption expenditures. Specifically, it is used to gather information about the relationships among agricultural production, resources, and the environment. The ARMS is also used to determine production costs and returns of agricultural commodities and measures net farm income of farm businesses. Another aspect of ARMS's important contribution is the information it provides on the characteristics and financial conditions of farm households, including information on input and risk management strategies and off-farm income.

Operators associated with farm businesses representing agricultural production across the United States are the target population in the survey. USDA defines a farm as an establishment that sold or normally would have sold at least $1,000 of agricultural products during the year. Farms can be organized as sole proprietorships, partnerships, family corporations, nonfamily corporations, or cooperatives. Data are collected from one operator per farm, the senior farm operator, who makes most of the day-to-day management decisions. For the purpose of this study, operator households organized as nonfamily corporations or cooperatives and farms not growing cash grains were excluded. We selected farms that planted at least one acre of either corn or soybeans in the observation year. After deleting observations with missing values, a total of 4,394 observations are utilized in this study.[8]

Since the ARMS data has a complex survey design and is cross-sectional, it raises the possibility that the error terms in regression models are heteroscedastic. Although the delete-a-group Jackknife method is suitable for estimation of standard errors when the dataset has a complex survey design, its validity is in question when only a subset of the ARMS is used (Dubman, 2000) Accordingly, all standard errors were adjusted for heteroscedasticiy using the Huber-White sandwich robust variance estimator based on algorithms contained in STATA (Huber, 1967, White, 1980).

Table 2.1provides a list of variables and their definitions used in this study, and a comparison of means between adopters and non-adopters of GM crops. The second, third, and fourth column show means of each variable for the entire sample, adopters, and non-adopters, respectively. The last column provides a Z statistic (Chi-square statistic) from the test of equal mean between the adopters and non-adopters for continuous (discrete) variables. In our sample, the adoption rate of GM crops (either corn or soybeans) is 63%. Note that this figure is considerably lower than often published figures such as GM soybeans accounting for 85% of the total soybean acres in the United States in 2005 (Fernandez-Cornejo and Caswell, 2006), which we cited in the introduction. Figures such as this one are based on the total acreage and thus it is likely that the adoption rate of 85% is mostly explained by very large-scale operations. On the other hand, the figure in Table 2.1 is based on the number of operators who adopt GM crops; it simply claims that GM corn or soybeans is adopted by 63% of family farms that grew at least one acre of corn or soybeans in the observation year, which include farms of different sizes. Z and chi-square statistics in the last column are mostly significant at the 1% level, which validates the relevance of variables used in this study in explaining the adoption of GM crops. A simple comparison of

[8] For the purpose of the study, the sample consists of farm households with operators and their spouses. After deleting observations with missing values, we attempted to delete observations of farm households without a spouse, but all such observations had already been excluded from the sample. Consequently, no observations were deleted for not having a spouse. Readers should be warned that the target population in this study is farm households operated by a married couple and results may be subject to a sample selection effect of unknown degree in light of the entire farm population.

unconditional means between adopters and non-adopters demonstrates, for example, that, for farms adopting GM crops, operators and their spouses are less educated, older, and work longer hours off-farm.[9] For both categories, the spouses work much longer hours off-farm and the difference is more conspicuous for farms that do not adopt GM crops.

Table 2.1: Variable Definitions and Comparison of Summary Statistics by Adoption of GM Corn

Variable Definitions	Entire Sample	GM Crop Adoption: Yes	GM Crop Adoption: No	Z/Chi-2 Statistics	
GM Corn (=1 if adopted either GM corn or soybeans, 0 otherwise)	0.627	1	0		
Share of GM Corn Acres in Total Corn Acres	0.499	0.796	0		
Operator Characteristics					
Operator's Off-farm work hours (average per week)	7.238	8.809	6.306	5.293	***
Operator's Years of formal education	12.803	12.476	12.998	-9.885	***
Operator's Age	52.877	53.551	52.469	2.9386	***
Spouse Characteristics					
Spouse's Off-farm work hours (average per week)	17.620	16.598	18.217	-2.6858	***
Spouse's Years of formal education	13.120	12.814	13.303	-9.014	***
Spouse's Age	50.433	50.987	50.098	2.5834	***
Farm Characteristics					
Total operated acres (in 1,000 acres)	1.238	0.886	1.448	-7.7982	***
Entropy Index (continuous, 0 not diversified at all, 1 completely diversified)	0.280	0.271	0.285	-3.9735	***
Government payments (=1 if received, 0 otherwise)	0.891	0.814	0.938	162.3779	***
Debt to Asset Ratio = Total Liability/ Total Asset	0.183	0.158	0.198	-2.5802	***
Dairy (=1 if dairy is primary enterprise, 0 otherwise)	0.282	0.334	0.252	34.2763	***
Number of children 13 years old or younger	0.673	0.720	0.645	1.9323	***
Household net worth ($1,000)	1773.479	1615.277	1867.744	-3.3695	*
Regional Dummy Variables (=1 if farm is located in respective region, 0 otherwise)					
Heartland	0.296	0.266	0.314	11.5079	***
Northern Crescent	0.278	0.299	0.266	5.6638	**
Northern Great Plains	0.038	0.027	0.044	7.3717	***
Prairie Gateway	0.076	0.049	0.091	25.5669	***
Eastern Upland	0.073	0.092	0.063	12.4496	***
Southern Sea Board	0.105	0.113	0.099	2.1576	
Fruitful Rim	0.069	0.108	0.046	62.0403	***
Basin and Range	0.016	0.021	0.013	3.4582	*
Mississippi Portal	0.049	0.024	0.064	34.2661	***

[9] Note that, for both operators and spouses, the differences in age and education are statistically significant, but economically insignificant.

Table 2.1 cont'd

Variable Definition	Entire Sample	GM Crop Adoption Yes	No	Z/Chi-2 Statistics	
County Level Variables					
Unemployment Rate	5.246	5.360	5.178	3.3521	***
Metro (=1 if located in metro county, 0 otherwise)	0.359	0.403	0.332	22.8672	***
Soil Productivity Index	74.657	72.390	76.006	-8.6816	***
Average Rainfall	930.422	940.248	924.496	1.7545	*
Coefficient of Variation in Rainfall	0.041	0.051	0.035	6.3355	***
Amenity Index (ordinal, 1 = lowest, 7= highest)	3.047	3.174	2.971	6.9372	***
Observation Years					
2004	0.330	0.322	0.342	1.852	
2005	0. 356	0.335	0.390	13.789	***
2006	0.314	0.343	0.268	27.108	***
Number of Observations	4394	2755	1639		

[1]For continuous variables, Z-statistics from t-test is presented. For discrete variables, chi-square statistics is used.
***, **, and * indicate significance at 1%, 5% and 10%, respectively.

2.4. Empirical Framework

The empirical model consists of three equations: weekly off-farm work hours by operators and spouses and the adoption intensity of GM crops represented by the share of GM crop acres in the total crop acres. Based on the theoretical model above, we can express the intensity of GM crop adoption and labor allocation model as follows:

$$\begin{aligned} y_1 &= \alpha\, y_3 + \boldsymbol{\delta}'\boldsymbol{X_1} + \varepsilon_1 && \text{if } y_1^* > 0 \\ &= 0 && \text{if } y_1^* \leq 0 \end{aligned} \tag{16}$$

$$\begin{aligned} y_2 &= \beta\, y_3 + \boldsymbol{\eta}'\boldsymbol{X_2} + \varepsilon_2 && \text{if } y_2^* > 0 \\ &= 0 && \text{if } y_2^* \leq 0 \end{aligned} \tag{17}$$

$$\begin{aligned} y_3 &= (\gamma_1 \quad \gamma_2)\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} + \boldsymbol{\theta}'\boldsymbol{X_3} + \varepsilon_3 && \text{if } y_3^* > 0 \\ &= 0 && \text{if } y_3^* \leq 0 \end{aligned}, \tag{18}$$

where y_1 and y_2 are, respectively, weekly off-farm work hours by operators and their spouses and y_3 is the adoption intensity of GM crops while y_1^*, y_2^*, and y_3^* are the corresponding latent variables; α and β are coefficients of the adoption intensity of GM crops in respective labor supply equations for operators and their spouses; γ, $\boldsymbol{\delta}$, $\boldsymbol{\eta}$, and $\boldsymbol{\theta}$ are vectors of unknown parameters to be estimated; $\boldsymbol{X_1}$, $\boldsymbol{X_2}$, and $\boldsymbol{X_3}$ are vectors of exogenous variables. The error terms, $\varepsilon_1, \varepsilon_2$ and ε_3 are assumed to be normally distributed with zero means but ε_1 and ε_2 are assumed to be correlated at ρ.

To choose an appropriate econometric estimation procedure, the Smith-Blundell test of exogeneity (Smith and Blundell, 1986) is conducted to test the null hypothesis that the adoption intensity of GM crops (y_3) is exogenous to off-farm labor participation decisions (y_1 and y_2) in equations (16) and (17), using STATA command, *tobexog*, developed by Baum (1999). The test first estimates equation (18) without y_1 and y_2. $\boldsymbol{X_3}$ includes all the exogenous variables in $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ as well as four external exogenous variables that are not in $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$, serving as instruments. The four external instruments are soil productivity index, average rainfall, the coefficient of variation in rainfall, and the amenity index,[10] all of which are county-level aggregate variables.[11] The test then estimates equations (16) and (17) including the residuals from the first stage. If the residual term obtains a significant coefficient, it indicates that the adoption intensity of GM crops is endogenous to off-farm labor participation decisions. The test results indicate that the adoption intensity of GM crops is not endogenous to operators' off-farm labor supply, but it is to their spouses'.[12]

With this result, we employ the two-step estimation procedure described in Nelson and Olson (1978) that yields asymptotically consistent estimates of unknown parameters. First, we estimate the reduced form of equation (18) from which the endogenous variables, y_1 and $y_2$are absent and exogenous variables. Since the dependent variable, the share of GM crop acres in total crop acres, is censored from below at zero and above at one, we employ a double-censored Tobit estimation procedure to estimate the reduced form of equation (18). The second step involves estimation of equations (16) and (17) by a bivariate Tobit model. The linear prediction of the latent variable of the adoption intensity of GM crops from the first-stage Tobit model is used here to represent the intensity at which the farm household is

[10] The amenity index is developed by McGranahan (1999). It captures environmental attributes of farmland such as climate, topography, and water area that are highly correlated with farmland values. For more details, see McGranahan (1999).
[11] We expect these variables representing environmental conditions surrounding the farm to be correlated with the adoption of GM crops, but not with off-farm labor decisions.
[12] For operators' labor supply equation, F-statistic is 0.058 (p-value = 0.809). For their spouses', F-statistic is 8.476 (p-value = 0.004).

willing to and capable of adopting GM crops. The vectors of exogenous variables, $\mathbf{X_1}$ and $\mathbf{X_2}$, in equation (16) and (17) are two sets of variables influencing off-farm labor supply decisions for operators and spouses, respectively.[13] Operators and spouse characteristics include years of formal education, age, and age squared, with the expectation that younger or more educated farmers (both operators and spouses) are more likely to work more off-farm.

Farm characteristics include total operated acres, total operated acres squared, the entropy index of enterprise diversification, [14] a dummy variable for receiving government payments, and a dummy variable for farms whose primary enterprise is dairy. While we expect farms receiving government payments to work less off-farm, other farm characteristics may have negative impacts on off-farm labor supply; high labor requirements due to a large number of operated acres, diversification across enterprises and dairy farming can be an obstacle to seek off-farm employment. Debt to asset ratio and household net worth are included to control for the effect of the farm's financial well-being on off-farm labor participation. Although farms with high net worth are hypothesized to work less off-farm, the sign of debt to asset ratio is *a priori* ambiguous; higher financial leverage may induce farm operators to seek stable sources of income off-farm, while it may be a consequence of large investments into the farm operation, an indication of a commitment to farm business. Finally, we include the number of children 13 years old or younger to assess the relationship between the need for childcare and parents' work behaviors.

To capture regional characteristics that cannot be captured by all other variables, we include dummy variables representing the farm resource region defined by USDA (2010)[15] as well as county-level unemployment rate obtained from the Bureau of Labor Statistics (2011). We also include dummy variables representing observation years to control for any time-variant exogenous shocks to labor market conditions.

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[13] The only difference between the two vectors is that $\mathbf{X_1}$ contains age, education and off-farm working experience for operators while $\mathbf{X_2}$ contains those variables for spouses.

[14] The entropy index is a measure of diversification that ranges from 0 to 1, with 0 indicating a farm producing only one commodity and 1 indicating a completely diversified farm. See Jinkins (1992) and Harwood et al. (1999) for more details.

[15] See Figure 2.1 for a map of USDA Farm Resource Regions.

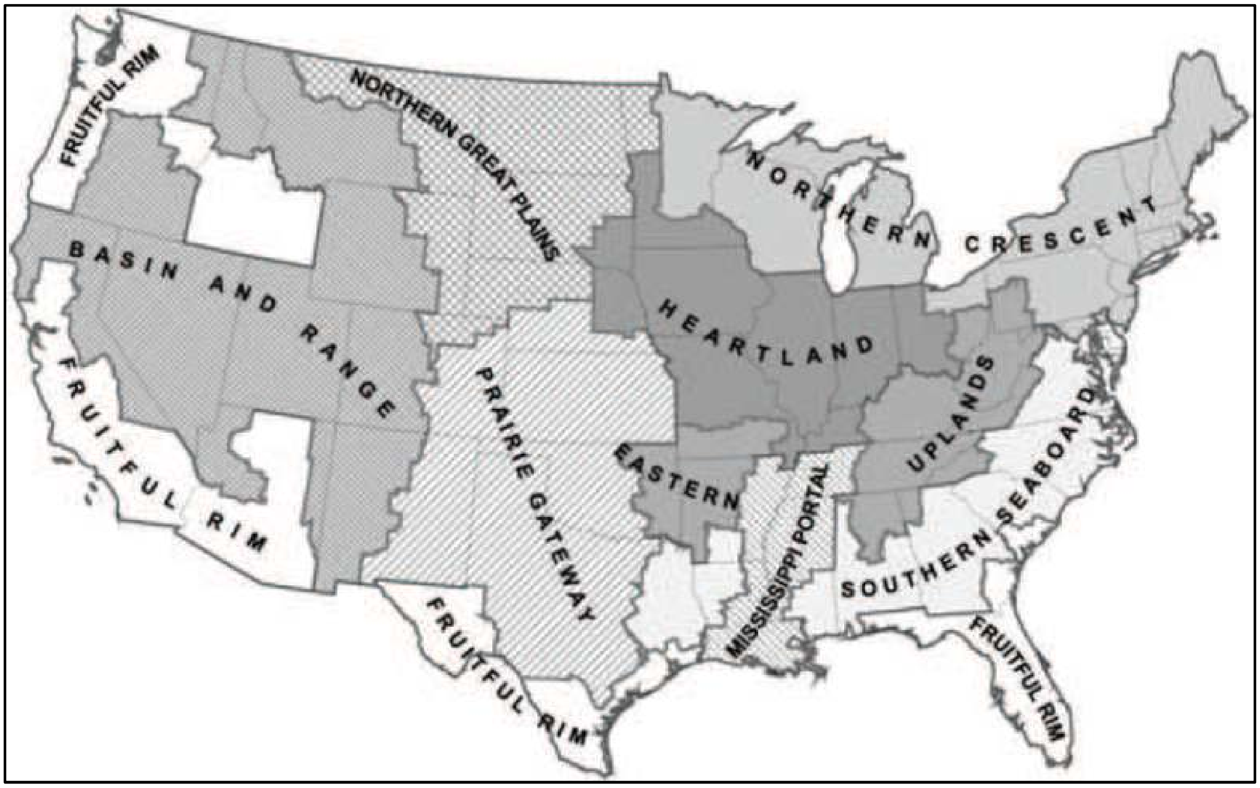

Figure 2.1: USDA Farm Resource Regions

2.5. Results

2.5.1. Double-censored Tobit Model

Econometric results for the first stage double-censored Tobit model of the adoption intensity of GM crops are presented in Table 2.2. We briefly review the results. Operator and spouse characteristics are largely insignificant, with the only exception being spouses' years of formal education. Most farm characteristics, in contrast, obtained a significant coefficient. The lack of significance of operator and spouse characteristics may be due to the ease of adoption GM crops, unlike other innovations that are more management-intensive (Smith, 2002). Relative to the base category of the Heartland region, five out of eight regional dummy variables obtained a significant coefficient, indicating the importance of regional characteristics in explaining GM crop adoption. Soil productivity index has a positive and significant coefficient; farms located in a county with high soil productivity are more likely to adopt GM crops. Average rainfall does not have an effect on GM crop adoption but its coefficient of variation does; farms in a county with variable rainfall patterns are less likely to adopt GM crops. Relative to the base year of

2006, GM crop adoption is less likely to occur in 2004 and 2005, which is consistent with the steadily increasing rate of GM crop adoption over the years.

2.5.2. Bivariate Tobit Model

Table 2.3 presents parameter estimates of the second-stage bivariate Tobit model of off-farm labor supply by farm operators and spouses, corresponding to equations (16) and (17), respectively. The estimated value of ρ is 0.171. The chi-square statistic of 0.171 (p-value < 0.00) from the likelihood ratio test of ρ = 0 indicates that the error terms in the two equations are correlated at a significant level. This validates use of the bivariate Tobit model instead of two separate Tobit models. The last column in Table 2.3 shows chi-square statistics from the test that compares equality of the coefficient estimates in the two equations. A significant chi-square statistics indicates that the explanatory variable has different impacts on off-farm labor supply by operators and their spouses. However, these factors appear to play distinctive roles in explaining off-farm labor supply by operators and their spouses, according to the significant chi-square statistics on personal and farm characteristics.

Coefficient estimates from Tobit models represent marginal effects of the latent variables (y_1^* and y_2^* in equations (16) and (17) in this study). But this quantity is not of our interest because the latent variables are not observable to the researchers (Greene, 2008). For variables with a significant coefficient estimate in the bivariate Tobit model, Table 2.4 provides two types of marginal effects, following the McDonald and Moffitt decomposition (McDonald and Moffitt, 1980).[16] The second and fourth columns represent the marginal effects of the explanatory variables on the probability of working off-farm by operators and their spouses, respectively. The third and fifth columns are, respectively, the marginal effects of the explanatory variables on the weekly off-farm work hours by the operators and their spouses who have positive off-farm work hours.

The primary interest in this study is how the adoption intensity of GM crops, represented by the share of GM crop acres, is related to off-farm labor supply measured by weekly off-farm work hours by

[16] Marginal effects are estimated at the means of the explanatory variables.

Table 2.2: Factors Affecting Adoption of GM Crop Varieties by Two-limit Tobit Model

Variables	Coefficient	Standard Errors
Operator Characteristics		
Operator's Years of Formal Education	0.012	(0.011)
Operator's Age	-0.011	(0.015)
Operator’s Age Squared	0.000	(0.000)
Spouse Characteristics		
Spouse's Years of Formal Education	0.026	(0.010)**
Spouse's Age	-0.003	(0.015)
Spouse’s Age Squared	0.000	(0.000)
Farm Characteristics		
Total Operated Acres	0.031	(0.000)***
Total Operated Acres Squared	-0.000	(0.000) **
Entropy Index	0.181	(0.128)
Government Payments (=1 if received, 0 otherwise)	0.503	(0.052) ***
Debt To Asset Ratio	0.085	(0.048) *
Dairy (=1 if Dairy is primary enterprise, 0 otherwise)	-0.243	(0.037) ***
Number of Children 13 Years Old or Younger	-0.039	(0.015) ***
Household Net Worth ($1,000)	0.000	(0.000)
Regional Dummy Variables (Heartland region is the base category.)		
Northern Crescent	-0.050	(0.048)
Northern Great Plains	0.068	(0.091)
Prairie Gateway	0.122	(0.065) *
Eastern Upland	-0.124	(0.068) *
Southern Sea Board	0.203	(0.072) ***
Fruitful Rim	-0.296	(0.099) ***
Basin and Range	-0.018	(0.164)
Mississippi Portal	0.401	(0.088) ***
County Level Variables		
Unemployment Rate	0.000	(0.010)
Metro	-0.015	(0.031)
Soil Productivity Index	0.005	(0.002) ***
Average Rainfall	0.000	(0.000)
Coefficient of Variation in Rainfall	-0.495	(0.286) *
Amenity Index (ordinal, 1 = lowest, 4 = highest)	-0.008	(0.023)
Observation Years		
2004	-0.135	(0.037) ***
2005	-0.103	(0.038) ***
Intercept	-0.045	(0.347)
Number of Observations = 4,395	Likelihood Ratio Chi-2(30) = 605.92	
Log pseudo likelihood = -4433.002	Prob > F =0.000	

***, **, and * indicate significance at 1%, 5% and 10%, respectively.

Table 2.3: Factors Affecting Off-farm Labor Supply by Bivariate Tobit Model

	Operators		Spouses		
Variables	Coefficient	Std. Err.	Coefficient	Std. Err.	Chi-2[1]
Share of GM Crop Acres in Total Crop Acres	2.370	(13.754)	24.789***	(8.886)	1.97
Personal Characteristics					
Years of formal education	1.797***	(0.646)	4.416***	(0.441)	11.49***
Age	2.351***	(0.591)	3.469***	(0.360)	2.89*
Age Squared	-0.028***	(0.005)	-0.043***	(0.003)	7.25***
Farm Characteristics					
Total operated acres	-10.780***	(0.002)	-3.031***	(0.001)	19.63***
Total operated acres squared	0.0001***	(0.000)	0.00002***	(0.000)	22.21***
Entropy Index	-9.269	(7.560)	7.509	(4.701)	3.98***
Government payments	-12.712*	(7.615)	-6.406	(4.954)	0.52***
Dairy	-36.369***	(3.968)	-8.510***	(2.613)	36.47***
Debt to Asset Ratio	-3.899	(3.757)	-4.680***	(1.748)	0.04***
Household net worth ($1,000)	-0.002**	(0.001)	-0.002***	(0.000)	0.29
Number of children	-0.570	(0.943)	-4.262***	(0.598)	11.59***
Regional Dummy Variables (Heartland region is the base category.)					
Northern Crescent	-0.138	(2.861)	4.022**	(1.818)	1.66
Northern Great Plains	-0.025	(5.015)	1.507	(2.815)	0.08
Prairie Gateway	0.926	(3.485)	-0.656	(2.074)	0.17
Eastern Upland	-0.632	(4.373)	3.123	(2.868)	0.58
Southern Sea Board	-10.828***	(2.986)	-3.086*	(1.848)	5.22**
Fruitful Rim	-11.442	(7.591)	7.187	(4.819)	4.66**
Basin and Range	-14.644	(9.803)	3.830	(4.949)	2.87*
Mississippi Portal	-18.095**	(7.440)	-16.856***	(4.599)	0.02
County Level Variables					
Unemployment Rate	-0.293	(0.601)	-1.086***	(0.352)	1.39
Metro	0.222	(1.721)	-1.205	(1.089)	0.56
2004	-1.096	(2.752)	5.116***	(1.718)	3.93**
2005	3.140	(2.630)	8.927***	(1.604)	3.93**
Intercept	-53.266***	(18.012)	-112.165***	(10.519)	
Number of Observations = 4,395					$\hat{\rho} = 0.171$
Log Likelihood = -18,781.181					Likelihood Ratio Test of $\rho = 0$
					Chi-2 (1)= 54.75***

[1] Chi-square statistics from the test that compares equality of coefficient estimates in the two equations.
***, **, and * indicate significance at 1%, 5% and 10%, respectively.

operators and their spouses. Results in Table 2.3 show that the coefficient of the adoption intensity of GM crops is insignificant for operators whereas it is positive and significant for their spouses.[17] The marginal effects estimates (Table 2.4) show that a unit increase in the adoption intensity of GM crops, i.e.,

[17] In order to check robustness of the results, we divided the sample into corn farmers and soybean farmers and applied the same model to the two subsamples. The results from the two models are quantitatively similar to the ones presented in Table 2.3.

Table 2.4: McDonald and Moffitt Decomposition of Tobit Coefficients

Variables	Operators $\frac{\partial F(\boldsymbol{X_1\delta}/\sigma_1)}{\partial x_{1i}}$ 1	$\frac{\partial E(y_1 \mid y_1>0)}{\partial x_{1i}}$ 2	Spouses $\frac{\partial F(\boldsymbol{X_2\eta}/\sigma_1)}{\partial x_{2i}}$	$\frac{\partial E(y_2 \mid y_2>0)}{\partial x_{2i}}$
Share of GM Crop Acres in Total Crop Acres			0.333	9.831
Personal Characteristics				
Years of formal education	0.014	0.407	0.059	1.751
Age	0.018	0.533	0.047	1.376
Age Squared	0.000	-0.006	-0.001	-0.017
Farm Characteristics				
Total operated acres	-0.082	-2.443	-0.041	-1.202
Total operated acres squared	0.000	0.00002	0.000	0.000
Entropy Index				
Government payments	-0.097	-2.880		
Dairy	-0.277	-8.241	-0.114	-3.375
Debt to Asset Ratio			-0.063	-1.856
Household net worth ($1,000)	-0.000	-0.000	-0.000	-0.001
Number of children			-0.057	-1.690
Regional Dummy Variables (Heartland region is the base category.)				
Northern Crescent			0.054	1.595
Northern Great Plains				
Prairie Gateway				
Eastern Upland				
Southern Sea Board	-0.082	-2.454	-0.041	-1.224
Fruitful Rim				
Basin and Range				
Mississippi Portal	-0.138	-4.100	-0.227	-6.685
County Level Variables				
Unemployment Rate			-0.015	-0.431
Metro				
2004			0.069	2.029
2005			0.120	3.541
Intercept	-0.405	-4.100	-1.508	-44.484

1. $\frac{\partial F(\boldsymbol{X_1\delta}/\sigma_1)}{\partial x_{1i}} = f(\boldsymbol{X_1\delta}/\sigma_1)\frac{\delta_i}{\sigma_1}$

2. $\left[\frac{\partial E(y_1 \mid y_1>0)}{\partial x_{1i}}\right] = \delta_i\left\{1-(\boldsymbol{X_1\delta}/\sigma_1)\frac{f(\boldsymbol{X_1\delta}/\sigma_1)}{F(\boldsymbol{X_1\delta}/\sigma_1)}-\left[\frac{f(\boldsymbol{X_1\delta}/\sigma_1)}{F(\boldsymbol{X_1\delta}/\sigma_1)}\right]^2\right\}$

growing no GM crops at all to growing GM crops only, leads to an 33% increase in the probability of working off-farm for spouses. The same change increases the average weekly off-farm hours by 9.8 hours for spouses.

These results are not fully consistent with *a priori* expectation that operators and spouses work longer off the farm due to the time savings made possible by the adoption of GM crops. The mixed results here may be attributed to the comparative advantages of operators and their spouses; operators are the primary decision-makers of the farming operation and are likely to have more farming responsibilities relative to their spouses. As the farm adopts a time saving technology at a higher intensity, the spouse, who may have spent some time working on the farm, assisting operators with record keeping, seeking contracts, etc., may decide to leave such farming duties to the operator and switch to full-time or increase the number of hours working off the farm. From an economic perspective, this is plausible as long as the spouse has a higher opportunity cost of working on the farm than the operator does.

For both operators and their spouses, personal characteristics obtained a significant coefficient with the expected sign (Table 2.3). For operators, however, the marginal effects of such variables are much smaller than those for their spouses. For example, an additional year of education leads to only a 1% increase in the probability of working off-farm and a 0.4 hours increase in the weekly off-farm working hours, while the analogous figures for their spouses are 6% and 1.8 hours (Table 2.4). The positive effect of education on off-farm labor supply is consistent with the human capital theory as well as empirical findings in literature (Goodwin and Mishra, 2004, Huffman, 1980, Huffman and Lange, 1989, Vergara, et al., 2004)

Getting older by one year increases the probability of working off-farm for operators (spouses) by 1.8% (4.6%) and the weekly off-farm working hours by 0.53 hours (1.32 hours). The positive impact of age, however, vanishes at around the age of 43 years old for operators and 40 years old for their spouses and becomes negative thereafter.[18] In summary, younger operators and their spouses are more likely to work off-farm and work longer hours on average, which is in accordance with Sumner (1982). The significant chi-square statistics on education, age, and age squared (Table 2.3) indicate that the impacts of these variables on off-farm labor supply are significantly different between operators and their spouses.

Large farms in terms of the total operated acres are less likely to work off-farm and work shorter hours. The coefficient estimates as well as the marginal effects for the total operated acres are all negative and significant at 1% level for both operators and their spouses. The negative relationship

[18] Calculated as $-\beta_{age}/(2 \times \beta_{age^2})$, by taking the partial derivative of the dependent variable with respect to age and setting it equal to zero, where β_{age} and β_{age^2} are the coefficient estimates in Table 2.3.

between farm size and off-farm labor supply are consistent with Fernandez-Cornejo (2007) and Nehring, et al. (2005). Unlike personal characteristics that exhibited stronger impacts on spouses' labor participation, the negative relationship is stronger for their operators than for spouses conceivably because extra labor requirements on the additional acres fall more on operators, the primary decision maker. For operators, an increase in total operated acres by 1,000 leads to an 8.2% decrease in the probability of working off-farm and a 2.4 hour decrease in the weekly off-farm work hours. The corresponding figures for their spouses are about one half at 4.1% and 1.2 hours.

Past studies (Howard and Swidinsky, 2000, Mishra and Goodwin, 1997) observed a negative relationship between receipt of government payments and off-farm labor participation. Our results support this relationship; for farms receiving government payments, operators are 9.7% less likely to work off-farm and, for those who do work off-farm, they work 2.88 fewer hours per week. We, however, do not observe a significant impact of government payments on their spouses' off-farm labor supply, unlike the recent findings by El-Osta, et al. (2008) who found a negative correlation between government payments and off-farm labor supply by both operators and their spouses.

Having a dairy enterprise is negatively correlated with off-farm labor supply in terms of both probability to work off-farm and off-farm work hours. This is consistent with the existing studies that labor intensive dairy operation and off-farm labor supply are negatively correlated (Fernandez-Cornejo, 2007, Lass, et al., 1991, Sumner, 1982). Dairy farm operators are 27% less likely to work off-farm and, when they do work off-farm, they work 2.8 fewer hours per week than operators from non-dairy farms do, whereas their spouses are 33.8% less likely to work off-farm and work 1.1 fewer hours per year relative to the non-dairy counterparts.

Financial leverage of the farm business measured by debt to asset ratio has a negative coefficient for both operators and spouses, but it is only significant for spouses. We mentioned earlier that the sign of this variable is *a priori* ambiguous. The negative impacts appear to support one of the alternative views presented earlier that higher debt-to-asset ratio may be an indication of a commitment to farming as a consequence of large investments into the farm business. Presumably, those who are committed to farm business, indicated by a high debt-to-asset ratio, prefer to manage risks on the farm rather than off the farm, and thus such farms are more likely to adopt GM crops that are yield increasing and cost reducing (Table 2.2). Household net worth has a negative and significant effect in both equations, but the impacts are economically insignificant. The presence of children under the age of 13 is found to have a negative and significant impact on off-farm labor supply of spouses. The results confirm the views that childcare negatively affects off-farm labor supply (Fernandez-Cornejo, et al., 2005, Kimhi and Lee, 1996). Because operators are predominantly male in the farm households, off-farm labor supply of spouses, most of whom are females, is more sensitive to the presence of young children in the family (El-Osta, et al., 2008, Fernandez-Cornejo, 2007, Furtan, et al., 1985, Huffman, 1980, Lass, et al., 1991). Our results confirm this view; the presence of an additional child younger than 13 years old in the household reduces the spouse's probability of working off-farm by 5.7% and off-farm working hours by 1.69 hours per week (Table 2.4).

Unlike the reduced form equation on the intensity of GM crop adoption (Table 2.2), regional dummy variables are mostly insignificant. What is instead significant is the county-level unemployment rate on spouses' off-farm labor supply. A 1% increase in the unemployment reduces the probability of working off-farm by 1.5% and average weekly work hours by 0.43. Finally, dummy variables for observations made in 2004 and 2005 are positive and significant for spouses. This is contrary to the increasing trend in off-farm labor supply in US farm sector, but the results should be interpreted with caution as they are based only on three-year observations.

2.6. Conclusion and Summary

The introduction of GM crop varieties in 1996 and the sharp increase in the adoption thereafter has dramatically changed the landscape of crop production in the United States. The convenient features of GM crops, including higher expected yields, lower pesticide costs, and fewer labor requirements, stand in stark contrast to other management and capital intensive technologies. An important question is how time savings made possible by the introduction of a convenient technology such as GM crops are reallocated by farm households. This study builds on the existing literature and expands the scope of analysis by measuring the adoption intensity of GM crops (corn and soybeans), and jointly estimating off-farm labor supply decisions by farm operators and their spouses due to changes in the adoption intensity of GM crops.

The econometric analysis demonstrated that the adoption intensity has no significant impact on off-farm labor supply by operators whereas it has a positive and significant impact on off-farm labor supply by their spouses. Since farm operators are, by definition, the primary decision-makers of the farm operation, they are likely to have comparative advantages in farming relative to their spouses, who tend to have less farming experience. Therefore, it is plausible that time savings made possible by the adoption of GM crops allow each member of the household to pursue an activity at which he/she has a comparative advantage, allowing operators to remain on farm and their spouses to work more off the farm. Marginal effects estimates showed that a unit increase in the adoption intensity of GM crops results in a 33% increase in the probability of working off-farm by their spouses. For spouses who do work off-farm, the same change in the adoption intensity of GM crops adds 9.89 hours per week to the off-farm labor supply.

The results also showed that the marginal effects of the explanatory variables have heterogeneous impacts on off-farm labor supply by operators and their spouses. While the variables related to farm operation influence operator's off-farm labor supply more prominently, off-farm labor supply by their spouses is more sensitive to changes in the personal and household characteristics. Similar observations were made by Benjamin, et al. (1996), who estimated a joint model of labor decisions for farm households in France. These results suggest that both operators and spouses play different but complimentary roles in maximizing household utility, further supporting the view that the farm household assigns different roles to the operator and the spouse based on their comparative advantages.

In concluding this chapter, we would like to note some of the limitations and caveats to this study. First, it is important to mention that diffusion of a new technology is a dynamic process (Rogers, 2003) and thus results from this study can only be applicable to the specific timeframe of the data analyzed. Studies using more recent data may provide a different picture of how farm households are adjusting their time allocation as they gain more experience with GM crop varieties. Secondly, different kinds of GM crops, i.e., herbicide tolerant, insect tolerant and stacked varieties, may have different implications on off-farm labor supply. Finally, it will be increasingly important to consider the prospect of crop failure as weeds and pests develop resistance to the herbicides and pesticides that are applied in greater frequency under GM crop production. It will be an exciting research topic for agricultural and labor economists to examine how the impact of a "convenient" technology on labor allocation decisions by farm households may change in a dynamic setting as the technology undergoes different stages of diffusion.

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CHAPTER 3: COULD EDUCATION BE A BARRIER TO TECHNOLOGY ADOPTION? EVIDENCE FROM A NATIONAL SURVEY

3.1. Introduction

Technology adoption is an extensively studied topic in agricultural economics. A plethora of empirical literature has identified a wide range of factors that influence technology adoption decisions by farmers. Education is one of the most frequently used variables in empirical models conceivably due to the human capital theory (Becker, 1994). Existing research mostly reveals that education is positively correlated with technology adoption. In agriculture, farmers with higher education have better access to information and knowledge that are beneficial to the farming operation. They also tend to possess a higher analytic capability to process the information and knowledge necessary to successfully implement new technologies and realize expected results. Hence, higher education allows farmers to make an efficient adoption decision (Rahm and Huffman, 1984) and be the early adopters who can take advantage of new technologies to extract maximum profit (Sunding and Zilberman, 2001). Highly educated farmers also tend to adopt new technologies with a greater intensity (Saha, et al., 1994).

The present study reconsiders this conventional belief. We hypothesize that the effect of education on technology adoption could be very heterogeneous and even be negative. Take the case of education and its impact on off-farm labor supply. Education increases farmers' human capital and gives them more lucrative employment opportunities off the farm, which in turn decreases managerial time on the farm to implement new technologies. This is particularly true for management-intensive technology.

Considering the facts that the number of college-educated farmers has been steadily increasing over the past five decades (Mishra, et al., 2009) and an increasing share of farm household income is derived from off-farm sources (Fernandez-Cornejo, 2007), it is of interest to accurately assess the effect of education on technology adoption in the context of farm households' labor allocation between on- and off-farm. In so doing, we estimate an econometric model of technology adoption that accounts for the endogeneity of off-farm labor participation using the propensity score matching method proposed by Mayen, et al. (2010). The primary interest is the potentially heterogeneous impacts of education on technology adoption contingent upon the farm household's dependence on off-farm income. Therefore, particular attention is given to the interaction between education and the dependence on off-farm income—calculated as a share of off-farm income, excluding unearned income, in total household income—and its impact on technology adoption. It has been theorized that operators of small farms are more likely to work off-farm (Fernandez-Cornejo, 2007) and less likely to adopt management-intensive technology (Saha, et al., 1994). This chapter examines the relationship between education, off-farm labor and two recent innovations in agriculture for a sample of crop producers in the United States, using data from the 2006 Agricultural Resource Management Survey (ARMS).

The two technologies considered in this study are precision farming and genetically modified (GM) crops. Precision farming is designed to optimize input use in agricultural production by exploiting information about within-field variability of soil and crops gathered through a suite of technologies (Paxton et al., 2011). Genetically modified crop varieties possess traits that are not possible through traditional plant breeding, such as herbicide tolerance and insecticide resistance, to allow for flexible weed and pest management practices (Fernandez-Cornejo and Caswell, 2006). These technologies share similar characteristics in that they both offer an alternative to crop production. They also became commercially available around the same time.[19] In contrast, precision farming requires a relatively large investment at the outset and is known for its management-intensive nature, while GM crops are easy to implement and considered management-saving (Smith, 2002). While GM crops became very popular shortly after their introduction (Fernandez-Cornejo and Caswell, 2006), the pace of adoption for precision farming has been modest (Banerjee, et al., 2008, McBride and Daberkow, 2003). The two contrasting technologies would allow us to improve the understanding about the relationship between education and technology adoption in contemporary US agriculture.

The rest of the chapter is organized as follows. Section 3.2 reviews existing literature on the relationship between education, technology adoption and off-farm labor supply in agriculture. Sections

[19] Precision farming became commercially available in the early 1990's (McBride and Daberkow, 2003) while GM crop varieties were commercially introduced in 1996 (Fernandez-Cornejo and Caswell, 2006).

3.3 and 3.4 provide a conceptual model and an empirical model, respectively. Section 3.5 describes data used in this study, followed by empirical results in Section 3.6. The final section offers concluding remarks.

3.2. Literature Review

In order to lay a comprehensive theoretical foundation about the effect of education on technology adoption, we attempt to unite findings from three different topics in the agricultural economics literature. We first review mixed empirical findings about the effect of education on technology adoption, followed by the effect of education on off-farm labor supply. Finally, we shed light on recent studies that account for these two effects within a single model to explain the decision making process through which farmers allocate their time between off-farm and on-farm activities, including technology adoption.

3.2.1. Education and Adoption

In agriculture, human capital of farm operators can be represented in a number of different ways, with formal education and farming experience being two of the most commonly adopted measures. Although farming experience can be the preferred measure in a static environment in which accumulated knowledge in farming operation or on-the-job training experiences do not depreciate or become obsolete (Huffman, 2001), formal education or schooling is widely considered to be the most important form of human capital (Becker, 1994). This is especially true in a dynamic political and economic environment where new technologies and information regularly become available (Huffman, 2001). In a more realistic setting, formal schooling will play a more prominent role than farming experience for farm operators to constantly update their knowledge and farming practices to stay competitive.

A number of empirical studies have shown the positive effect of education on the adoption of various types of technology in agriculture. For example, education is found to have a positive impact on the adoption of forward pricing methods (Goodwin and Schroeder, 1994), computer technologies (Huffman and Mercier, 1991, Putler and Zilberman, 1988) , the Internet (Mishra and Park, 2005, Mishra, et al., 2009), reduced tillage (Rahm and Huffman, 1984), recombinant bovine somatotropin (rbST) (Chang, et al., 2008), precision farming (Roberts, et al., 2004), genetically engineered corn (Fernandez-

Cornejo, et al., 2001), soil nitrogen testing (Fuglie and Bosch, 1995), conservation practices (Traore, et al., 1998) and the level of participation in government-supported conservation programs (Lambert, et al., 2007), among others.

On the other hand, there is some empirical evidence of an insignificant or even a negative effect of education on technology adoption. For instance, farmers' education was found to have an insignificant effect on the adoption of the variable rate technology (Khanna, 2001) and GPS guidance system for cotton farmers (Banerjee, et al., 2008). Nyaupane and Gillespie (2009) identified factors affecting the adoption of best management practices (BMP) for Louisiana crawfish producers, but education was found to be insignificant for the adoption of all but one BMP, of which education was found to be negatively correlated with the adoption.

Gould et al. (1989) studied factors affecting adoption of conservation tillage for Wisconsin farmers. They unexpectedly found that education is negatively correlated with adoption, holding constant other factors, such as the proportion of off-farm work time to on-farm work time, among others. This implies that highly educated farmers are less likely to adopt conservation tillage, given the same proportion of off and on farm work time. Because highly educated farmers are more likely to earn higher wages from off-farm work, they are expected to have a higher proportion of off-farm income to farm income given the same proportion of on and off farm work time, provided that the marginal value product of education is higher in off-farm work than on-farm. Therefore, it is plausible that highly educated farmers, who tend to be more reliant on off-farm income, have fewer incentives to spend time and effort on farming, including adoption of technologies such as conservation tillage.

As these examples show, the effect of education on technology adoption in empirical literature has yet to reach a consensus consistent with the economic theory. Although the mixed empirical evidence might to some extent be explained by factors such as types and diffusion stages of the technology (Sunding and Zilberman, 2001), few attempts have been made to explore the underlying reasons for such incoherent findings, perhaps because the underlying theory seems intuitively too appealing to refute.

3.2.2. Education and Off Farm Labor Supply

The inconsistent empirical results about the effect of education on technology adoption may also be attributed to the relationship between education and off-farm labor. The recent trend of increasing off-farm labor supply by US farm households can be explained by the relative increase in non-farm sector real wage and the decrease in demand for farm labor and family labor (housework) due to the development of labor-saving technologies (Huffman, 2001). In today's economic environment surrounding the US agricultural sector, highly educated farmers have higher incentives to work more off the farm, *ceteris paribus*. Farming becomes relatively less attractive as human capital accumulated and longer years of formal education becomes an advantage in finding more attractive off-farm employment opportunities.

Theoretically, however, the effect of education on off-farm labor supply is ambiguous; while higher education increases employment opportunities off the farm, farms with a highly educated operator may realize higher productivity in the farming operation and thus the reservation wage to work off-farm for such operators may be high (Huffman and Lange, 1989). The existing literature has mostly found that education is positively correlated with both off-farm labor participation and the intensity of off-farm work (Huffman, 1980, Huffman and Lange, 1989). Goodwin and Mishra (2004) found a strong and positive effect of education on off-farm labor participation. Huffman (1980) estimated the effect of education on the odds ratio of off-farm work participation and the number of days worked off-farm by farm operators. The study found a positive and significant effect of education on both the odds ratio and the number of days working off-farm by an operator.

From a theoretical standpoint, there are two contrasting effects of education on technology adoption. On one hand, higher education encourages technology adoption, but on the other hand, higher education increases off-farm labor supply, which inevitably affects on-farm labor supply and technology adoption. Although it is theoretically possible that increased off-farm labor income provides farmers with financial flexibility to implement a new technology, Wozniak (1993) concluded that the negative impact of reallocation of operators' time away from farming on technology adoption seems to be more significant than the financial flexibility due to off-farm income. The mixed findings about the effect of education on technology adoption in empirical literature can perhaps be attributed to the fact that the conventional technology adoption models do not always account for the positive impact of education on off-farm labor supply.

3.2.3. Technology Adoption and Labor Allocation

Although studies that have combined technology adoption and labor allocation into a single model had been largely nonexistent, recent exceptions are Fernandez-Cornejo, et al. (2005) and Fernandez-Cornejo (2007). The former explored the simultaneous process through which operators and spouses allocate their time between on and off farm work and its relation to adoption of herbicide tolerant (HT) soybean, a representative of a time-saving technology. The study found a positive correlation between education and off-farm work for operators but not for spouses. Also, the impact of education on adoption of HT soybeans was not statistically significant. The report by Fernandez-Cornejo (2007) employed a model similar to Fernandez-Cornejo, et al. (2005) but included adoption of yield monitors, which is required for precision agriculture, a representative of a management-intensive technology. The study confirmed a negative correlation between the adoption of yield monitor and off-farm income. However, the authors did not specifically discuss the role of education on the adoption of yield monitors.

3.3. Conceptual Framework

We employ the conventional agricultural household model (Fernandez-Cornejo, et al., 2005, Huffman and Lange, 1989, Huffman and Mercier, 1991, Lass, et al., 1989, Sumner, 1982) in which farm households are assumed to have a well-behaving utility function under three constraints: time, budget and production. The objective function to be maximized is given by

$$Max\ U = U(G, \boldsymbol{T_L}, \boldsymbol{\Phi}), \tag{1}$$

where G is a composite good the farm household purchases and consumes, $\boldsymbol{T_L}$ is a 2×1 vector where elements represent leisure time for the farm operator and the spouse, and $\boldsymbol{\Phi}$ is a vector of factors that influence farm household utility exogenously. The time constraint, $\boldsymbol{T}$, can be represented as

$$\boldsymbol{T} = \begin{pmatrix} \boldsymbol{T^O} \\ \boldsymbol{T^S} \end{pmatrix} = \begin{pmatrix} T^O_{on}[\boldsymbol{\Gamma}(\boldsymbol{H})] & T^O_{off}(H^O) & T^O_L \\ T^S_{on}[\boldsymbol{\Gamma}(\boldsymbol{H})] & T^S_{off}(H^S) & T^S_L \end{pmatrix} = \boldsymbol{T_{on}}[\boldsymbol{\Gamma}(\boldsymbol{H})] + \boldsymbol{T_{off}}(\boldsymbol{H}) + \boldsymbol{T_L}. \tag{2}$$

The matrix of the household time constraint, $\boldsymbol{T}$, consist of the operator's and the spouse's time constraints denoted as , $\boldsymbol{T^O}$ and $\boldsymbol{T^S}$, respectively. Both $\boldsymbol{T^O}$ and $\boldsymbol{T^S}$ are made up of three components: on-farm, off-farm, and leisure hours, denoted by subscripts, "on," "off," and "L," respectively. In light of the objective of this study, we explicitly specify that off-farm labor supply is a function of human capital, $\boldsymbol{H}$, and on-farm labor supply is a function of technology adoption, $\boldsymbol{\Gamma}$, which is also dependent on human capital. Note that $\boldsymbol{H}$ is a 2×1 vector that represents the human capital of the operator and the spouse for ith farm household and $\boldsymbol{\Gamma}$ is a 2×1 vector to account for the adoption of the two technologies considered in this study: precision farming and GM crops.

The budget constraint for the farm household is given by:

$$P_g G = P_q Q - \boldsymbol{P}'_{\boldsymbol{x}} \boldsymbol{X}[\boldsymbol{\Gamma}(\boldsymbol{H})] + \boldsymbol{W}'\boldsymbol{T_{off}}(\boldsymbol{H}) + A, \tag{3}$$

where P_g is the price of the composite good, P_q is the price of the farm output, Q is the quantity of the farm output produced, $\boldsymbol{P_x}$ is a $n \times 1$ vector of farm input prices, $\boldsymbol{X}$ is a $n \times 1$ vector of farm inputs, $\boldsymbol{W}$ is a 2×1 vector of off-farm wage for the operator and the spouse, and A represents all other sources of income including government subsidies and interest payments. Note that $P_q Q - \boldsymbol{P}'_{\boldsymbol{x}} \boldsymbol{X}[\boldsymbol{\Gamma}(\boldsymbol{H})]$ represents the net farm income and the vector of input decisions, $\boldsymbol{X}$, is dependent on the adoption of the two technologies. What is implicitly assumed in equation (3) is that all household income will be spent on G, which may include a variety of financial services such as savings and investments. The production constraint is given by:

$$Q = Q[\boldsymbol{X}(\boldsymbol{\Gamma}), \boldsymbol{T_{on}}[\boldsymbol{\Gamma}(\boldsymbol{H})], \boldsymbol{H}, \boldsymbol{\Gamma}(\boldsymbol{H}), \mathbf{R}], \;\; \Gamma \geq 0 \tag{4}$$

where $\boldsymbol{R}$ is a $m \times 1$ vector of exogenous variables relevant to agricultural production such as climatic and site-specific environmental conditions. Following Huffman (1991), the "farm technology – constrained measure of household net cash income" can be obtained by substituting equation (4) into equation (3):

$$P_g G = P_q \{Q[\boldsymbol{X}(\boldsymbol{\Gamma}), \boldsymbol{T_{on}}[\boldsymbol{\Gamma}(\boldsymbol{H})], \boldsymbol{H}, \boldsymbol{\Gamma}, \mathbf{R}]\} - \boldsymbol{P}'_{\boldsymbol{x}} \boldsymbol{X}[\boldsymbol{\Gamma}(\boldsymbol{H})] + \boldsymbol{W}'\boldsymbol{T_{off}}(\boldsymbol{H}) + A. \tag{5}$$

The Lagrangian function that incorporates the objective function and the constraints is given by

$$L = U(G, \boldsymbol{T_L}, \Phi) + \lambda(P_q Q\langle\{\boldsymbol{X}[\Gamma(H)], \boldsymbol{T_{on}}[\boldsymbol{\Gamma}(\boldsymbol{H})], \boldsymbol{H}, \boldsymbol{\Gamma}(\boldsymbol{H}), \mathbf{R}\}\rangle - \boldsymbol{P}_{\boldsymbol{x}}'\boldsymbol{X}[\boldsymbol{\Gamma}(\boldsymbol{H})]$$
$$+\boldsymbol{W}'\boldsymbol{T_{off}}(\boldsymbol{H}) + A - P_g G) + \boldsymbol{\gamma}'\{\boldsymbol{T} - \boldsymbol{T_{on}}[\boldsymbol{\Gamma}(\boldsymbol{H})] - \boldsymbol{T_{off}}(\boldsymbol{H}) - \boldsymbol{T_L}\}. \tag{6}$$

Some of the Kuhn-Tucker first order conditions are:

$$\frac{\partial L}{\partial G} = \frac{\partial U}{\partial G} - \lambda P_q = 0 \tag{7}$$

$$\frac{\partial L}{\partial \boldsymbol{X}} = \lambda\left[P_q\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right) - \boldsymbol{P_x}\right] = 0$$
$$P_q\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right) = \boldsymbol{P_x} \tag{8}$$

$$\frac{\partial L}{\partial \boldsymbol{\Gamma}} = \lambda\left\langle P_q\left\{\left[\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right)'\left(\frac{\partial \boldsymbol{X}}{\partial \boldsymbol{\Gamma}}\right)\right]' + \left[\left(\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right)'\left(\frac{\partial \boldsymbol{T_{on}}}{\partial \boldsymbol{\Gamma}}\right)\right]' + \frac{\partial Q}{\partial \boldsymbol{\Gamma}}\right\} - \left[\boldsymbol{P}_{\boldsymbol{x}}'\left(\frac{\partial \boldsymbol{X}}{\partial \boldsymbol{\Gamma}}\right)\right]'\right\rangle - \left[\boldsymbol{\gamma}'\left(\frac{\partial \boldsymbol{T_{on}}}{\partial \boldsymbol{\Gamma}}\right)\right]' \le 0$$
$$\frac{\partial L}{\partial \boldsymbol{\Gamma}} = \lambda P_q\left(\frac{\partial \boldsymbol{X}}{\partial \boldsymbol{\Gamma}}\right)'\left(\frac{\partial Q}{\partial \boldsymbol{X}}\right) + \lambda P_q\left(\frac{\partial \boldsymbol{T_{on}}}{\partial \boldsymbol{\Gamma}}\right)'\left(\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right) + \lambda P_q\left(\frac{\partial Q}{\partial \boldsymbol{\Gamma}}\right) - \lambda\left(\frac{\partial \boldsymbol{X}}{\partial \boldsymbol{\Gamma}}\right)'\boldsymbol{P_x} - \left(\frac{\partial \boldsymbol{T_{on}}}{\partial \boldsymbol{\Gamma}}\right)'\boldsymbol{\gamma} \le 0 \tag{9}$$

$$\frac{\partial L}{\partial \boldsymbol{T_{on}}} = \lambda\left[P_q\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right] - \boldsymbol{\gamma} \le 0$$
$$\left[P_q\frac{\partial Q}{\partial \boldsymbol{T_{on}}}\right] \le \frac{\boldsymbol{\gamma}}{\lambda} \tag{10}$$

$$\frac{\partial L}{\partial \boldsymbol{T_{off}}} = \lambda \boldsymbol{W} - \boldsymbol{\gamma} \le 0 \quad \text{and}$$
$$\boldsymbol{W} \le \frac{\boldsymbol{\gamma}}{\lambda} \tag{11}$$

$$\frac{\partial L}{\partial \boldsymbol{T_L}} = \frac{\partial U}{\partial \boldsymbol{T_L}} - \boldsymbol{\gamma} = 0$$
$$\frac{\partial U}{\partial \boldsymbol{T_L}} = \boldsymbol{\gamma} \tag{12}$$

Equations (10), (11), and (12) state the conditions for the optimal allocation of time among the three activities. Equation (12) shows that the marginal utility of leisure is equal to the Lagrange multiplier on the time constraint, which is the shadow price of time. Both equations (10) and (11) have the ratio of the two Lagrange multipliers—the marginal rate of substitution between the net farm income and time. At the equilibrium, both off-farm wages and the marginal value product of on-farm labor need to be less than or equal to the marginal rate of substitution between net farm income and time. The inequality is maintained in equations (10) and (11) to account for the possibility of corner solutions in which some operators and spouses may not work at all either on-farm or off-farm. On the other hand, equality is used in (12) because everyone is expected to have a positive amount of leisure time. Given these conditions, one can obtain the optimal level of off-farm labor supply, $\boldsymbol{T}^{*}_{\boldsymbol{off}}(\boldsymbol{H})$ by solving equation (2):

$$\boldsymbol{T}^{*}_{\boldsymbol{off}}(\mathbf{H}) = \boldsymbol{T}^{*} - \{\boldsymbol{T}_{\boldsymbol{on}}{}^{*}[\boldsymbol{\Gamma}(\boldsymbol{H})] + \boldsymbol{T}^{*}_{\boldsymbol{L}}\}. \tag{13}$$

Furthermore, the time-constrained intensity of technology adoption, $\boldsymbol{\Gamma}$, can be obtained by substituting equation (8) and equation (10) into equation (9):

$$\frac{\partial L}{\partial \boldsymbol{\Gamma}} = \lambda\left(\frac{\partial \boldsymbol{X}}{\partial \boldsymbol{\Gamma}}\right)' \boldsymbol{P_x} - \lambda\left(\frac{\partial \boldsymbol{X}}{\partial \boldsymbol{\Gamma}}\right)' \boldsymbol{P_x} + \lambda P_q\left(\frac{\partial Q}{\partial \boldsymbol{\Gamma}}\right) + \left(\frac{\partial \boldsymbol{T_{on}}}{\partial \boldsymbol{\Gamma}}\right)' \boldsymbol{\gamma} - \left(\frac{\partial \boldsymbol{T_{on}}}{\partial \boldsymbol{\Gamma}}\right) \boldsymbol{\gamma} \leq 0.$$

Further simplifying,

$$P_q\left[\frac{\partial Q}{\partial \boldsymbol{\Gamma}(\boldsymbol{H})}\right] \leq 0 \tag{14}$$

Equation (14) simply represents that, at the equilibrium, the marginal value product of technology adoption is zero if the technologies are adopted at a positive intensity and it is negative if the farm household opts not to adopt the technology at all.

Equations (13) and (14) represent the farm households' decisions with respect to technology adoption and off-farm labor supply. Note that on the left hand side of both equations is a 2×1 vector instead of a scalar; equation (13) shows the optimal level of on-farm labor supply by both the farm operator and the spouse; equation (14) is the optimal level of adopting GM crops and precision farming practices. Additionally, it is explicitly shown in equations (13) and (14) that decisions regarding off-farm labor supply and technology adoption are contingent upon human capital by the operator and the spouse.

3.4. Empirical Framework

3.4.1. Bivariate Probit Model

The econometric model we consider here consists of two equations: the adoption of precision farming and GM crops. Based on the general results in the previous section, we can express the technology adoption and labor allocation model as follows:

$$y_1 = \alpha\, y_3 + \boldsymbol{\delta}'\mathbf{X_1} + \varepsilon_1 \quad (15)$$

$$y_2 = \beta\, y_3 + \boldsymbol{\eta}'\mathbf{X_2} + \varepsilon_2 \quad (16)$$

where y_1 is a dummy variable that takes 1 if the farm adopts any type of precision farming technology and 0 otherwise, y_2 is also a dummy variable that takes 1 if the farm adopts any type of GM crops and 0 otherwise. y_3 is the farm households' labor allocation decision. α and β are unknown parameters and $\boldsymbol{\delta}$ and $\boldsymbol{\eta}$ are vectors of unknown parameters to be estimated. $\mathbf{X_1}$ and $\mathbf{X_2}$ are vectors of exogenous variables. The error terms, ε_1 and ε_2 are assumed to be normally distributed with zero means and correlated with each other at ρ. Equations (15) and (16) are estimated with a bivariate probit model.

3.4.2. Propensity Score Matching

An important econometric issue that arises in estimating a model such as the above is that of endogeneity. In the context of the model above, y_3, the farm household's labor allocation decision, could be endogenous. This chapter utilizes the propensity score matching approach proposed by Mayen, et al. (2010) to address the endogeneity issue. Although the propensity score matching method, originally developed by Rosenbaum and Rubin (1983), is designed to estimate a treatment effect on a dependent variable attributable to treatment status,[20] Mayen, et al. (2010) utilized the matching procedure as a sub-sampling technique to address sample selection.[21]

To implement the procedure, we categorize farms in the sample into two, full-time farms (treatment) and part-time farms (control). We define full-time farms as farms whose operator and spouse do not work off-farm, while part-time farms are defined as farms for which either operator or spouse (or

[20] Estimation of the "treatment effect" under non-experimental settings has recently become increasingly popular in social science research. There have been a number of reviews on theoretical background (Heckman et al., 1998; Imbens, 2004; Imbens and Wooldridge, 2009; Morgan and Harding, 2006; Nichols, 2007) and practical applications (Abadie et al., 2004; Baser, 2006; Becker and Caliendo, 2007; Becker and Ichino, 2002; Nannicini, 2007) as well as some empirical applications in agricultural economics (Liu and Lynch, 2007; Mayen et al., 2010; Tauer, 2009).

[21] In comparing technical efficiency of organic and conventional dairy farms in the United States, Mayen, et al. (2010) suspected and verified that acquisition of organic certification is endogenous. To rectify this, they estimated a probit model of propensity to be organic dairy farms and then utilized the predicted probability of being organic as a matching scheme to identify conventional dairy farms that share similar characteristics to organic dairy farms. See Mayen et al., (2010) for more details.

both) works off-farm. Rosenbaum and Rubin (1983) proposed the propensity score, which is a conditional probability of being in the treatment:

$$p(X) = Prob(T = 1|X = x) = E(T = 1|X = x), \tag{17}$$

where $p(X)$ in equation (17) can be obtained by a standard probit model. An important feature of the propensity score in equation (17) is that it summarizes information contained in k-dimentional vector, X, into a single-index variable (Becker and Ichino, 2002). A testable assumption that needs to be satisfied in specifying the probit model is the balancing property:

$$T \perp X|\, p(X) \tag{18}$$

When equation (18) is satisfied, assignment to treatment is random for observations with the same propensity score (Becker and Ichino, 2002). The predicted probability from the probit model is used as a propensity score to match full-time farms with part-time farms that share similar characteristics. We use the nearest neighbor matching with three matches.[22] The resulting sub-sample, to which we apply the bivariate probit model, will consists of all full-time farms and some part-time farms matched to full-time farms based on the propensity score.

As mentioned in Section 3.1, the primary interest in this study is the interaction between education and the farm households' dependence on off-farm income to evaluate the potentially heterogeneous impacts of education on technology adoption. We create two interaction terms: education and the dependence on off-farm income and education and the dependence on off-farm income squared. The latter is necessary to account for the potentially quadratic nature of the impact of education on technology adoption and the dependence on off-farm income.

3.5. Data

This study employs the 2006 Agricultural Resource Management Survey (ARMS) data, developed by the Economic Research Service (ERS) and the National Agricultural Statistical Service (NASS). The 2006 ARMS collected information on farm households, income received from and time spent on off-farm work,

[22] For every observation in the treatment, three observations with the closest propensity score in the control are matched.

net cash income from operating another farm/ranch, net cash income from operating another business, and net income from share renting. The target population of the survey is operators associated with farm businesses representing agricultural production in the 48 contiguous states. A farm is defined as an establishment that sold or normally would have sold at least $1,000 of agricultural products during the year. Farms can be organized as sole proprietorships, partnerships, family corporations, non-family corporations, or cooperatives. Data are collected from one operator per farm, the senior farm operator. A senior farm operator is the operator who makes the majority of the day-to-day management decisions. For the purpose of this study, operator households organized as nonfamily corporations or cooperatives and farms run by hired managers were excluded.

The ARMS has a complex stratified and multi-frame design and each observation in the ARMS represents a number of similar farms, the particular number being the survey expansion factor (or the inverse of the probability of the surveyed farm being selected for surveying). The complex survey design as well as the cross-sectional nature of the data requires an appropriate technique to estimate standard errors to account for potential heteroskedasticity. Following the recent applications of the ARMS data in published studies (El-Osta, 2011, Mishra and El-Osta, 2008, Mishra, et al., 2010), standard errors are estimated using the robust Huber/White/sandwich estimator (Huber, 1967, White, 1980).

Considering the nature of the two technologies tied to crop production, farms not reporting crop sales are also excluded from the sample. That leaves us with 2,986 observations, of which 44% (1,324 observations) is full-time farms. Table 3.1 provides the complete list of variables used in this study, their definitions and descriptive statistics. The second and third column in Table 3.1 presents the mean of the variables for full-time and part-time farms, respectively. The average share of off-farm income in total household income for full-time farms is very small but not exactly zero. This is because there are full-time farms whose operator and spouse do not work off-farm, but other members in the household do. Note that, for most variables, the means are significantly different for full-time and part-time farms, underscoring the need to address the endogeniety issue.

Table 3.1: Variable Definitions and Summary Statistics

Definitions of Variables Used in This Study	Full-time Farms	Part-time Farms	Matched Part-time Farms [1]
		Mean	
Full-time Farms (=1 if both operator and spouse do NOT work off-farm)	1.000	0.000	0.000
Share of Off-farm Income in Total Household Income [2]	0.023	0.580***	0.491***
Operator and Spouse Characteristics			
Operator's Years of formal education	13.341	13.894***	13.473
Operator's Age	58.922	52.240***	58.701
Spouse's Years of formal education	13.396	14.212***	13.386
Spouse's Age	56.504	49.727***	56.300
Farm Characteristics			
Log of Total Operated Acres	6.125	5.845***	6.118
Full Owners (=1 yes, 0 otherwise)	0.303	0.293	0.316
Full Tenant (=1 yes, 0 otherwise)	0.133	0.140	0.079***
Part Owner (=1 yes, 0 otherwise)	0.564	0.567	0.605**
Debt to Asset Ratio = Total Liability/ Total Asset	0.134	0.151**	0.132
Log of Household Net Worth	7.179	6.616***	7.195
Average Interest Rate for Loans	1.539	1.780***	1.538
Internet Access (=1 if yes, 0 otherwise)	0.738	0.833***	0.756
Dairy (=1 if dairy is primary enterprise, 0 otherwise)	0.075	0.045***	0.076
Number of Children Younger than 5 Years Old	0.145	0.184**	0.159
Number of Children between 6 and 13 Years Old	0.270	0.329**	0.301
Government Payments ($1,000)			
Direct Payments	28.661	19.549***	28.535
Indirect Payments	3.336	2.660	3.359
Conservation Reserve Program (CRP) Payments	0.892	0.967	0.995
Working Land Conservation Program (WLCP) Payments	1.661	0.963*	1.139
Regional Dummy Variables (=1 if farm is located in respective region, 0 otherwise)			
Heartland	0.124	0.185***	0.190***
Northern Crescent	0.168	0.164	0.177
Northern Great Plains	0.033	0.059***	0.037
Prairie Gateway	0.101	0.116	0.099
Eastern Upland	0.064	0.062	0.057
Southern Sea Board	0.145	0.131	0.129
Fruitful Rim	0.227	0.161***	0.184***
Basin and Range	0.037	0.056**	0.052*
Mississippi Portal	0.100	0.067***	0.075**

Table 3.1 cont'd

Definitions of Variables Used in This Study	Full-time Farms	Part-time Farms	Matched Part-time Farms
		Mean	
County Level Variables			
Unemployment Rate	5.195	4.838***	5.195
Population Interaction Zones in Agriculture 2000 (ordinal, 1= lowest interaction, 4 = highest)	1.737	1.614***	1.747
Amenity Index (ordinal, 1 = lowest, 7 = highest)	3.645	3.458***	3.526**
Soil Productivity Index	69.541	72.854***	72.321***
Coefficient of Variation in Rainfall	0.080	0.084	0.088
Average Rainfall	967.490	927.430***	936.300**
Number of Observations	1,324	1,652	1,014

[1] For every full-time farm, three part-time farms are matched based on the propensity score matching. Part-time farms can be matched multiple times.

[2] Calculated as total off-farm wage earned by operator, spouse, and all other family members divided by total household income. It is not necessarily zero for full-time farms if other family members earn off-farm income.

***, **, and * indicate a significant difference from the mean for full-time farms at 1%, 5% and 10%, respectively.

3.6. Results and Discussion

To formally examine the presence of endogeneity, we first conduct the Smith-Blundell test (Smith and Blundell, 1986) using STATA command *probexog*, developed by Baum (1999). The test examines if the residuals from the reduced form equation obtains a significant coefficient in the probit model, with the null hypothesis that the residuals have no explanatory power in the probit model. A rejection of the null hypothesis indicates endogeneity. We apply the test to equations (15) and (16) to examine the potential endogeneity of dependence on off-farm income using four external instruments: the number of children younger than five years old, the number of children between six and 13 years old, county-level average unemployment rates, and the Population Interaction Zones in Agriculture in 2000. These variables are assumed to have no impact on adoption of either precision farming or GM crops, but influence off-farm labor participation decisions by farm households. The chi-square statistics from Wald tests show that the dependence on off-farm income was endogenous to the adoption of GM crops, but not to the adoption of precision farming.[23] The rejection of the null hypothesis for the adoption of GM crops justifies the use of the propensity score matching to address the endogeneity.

3.6.1. Propensity Score Matching

Results from the probit model of the propensity to be a full-time farm are presented in Table 3.2. The list of variables used in the probit model satisfied the balancing property in equation (18). Several variables, mainly farm characteristics, obtained a significant coefficient. Highly educated spouses are less likely to work on farm. Farms with a lower average interest rate, higher debt to asset ratio, and higher household net worth are more likely to be full-time farms. Farm households with children younger than 13 years old are likely to work only on-farm, presumably due to the need for childcare. Farms receiving direct payments are less likely to work off-farm. A higher unemployment rate and population interactions at the county-level are discouraging factors for farm operators and spouses to work off-farm.

The predicted probability from the probit model is used as a propensity score to match full-time farms with part-time farms that share similar "propensity" to work full-time on farm. We employ the nearest neighbor matching with three matches.[24] That is, for every full-time farm, three part-time farms with the closest propensity score are identified and kept in the sample. Note that the same part-time farms can be matched to full-time farms more than once, but all of the matched part-time farms are weighted equally, regardless of the number of times they are matched to full-time farms. The resulting sample consists of 1,324 full-time farms and 1,014 matched part-time farms (Table 3.1). The last column in Table 3.1 shows means of the variables used in this study for the matched part-time farms. Some variables still exhibit a statistically significant difference in means between full-time and the matched part-time farms, such as full-tenant, part-owner, and the Heartland region. However, for most variables for which there is a significant difference in means between full-time and part-time farms (third column) the difference is now

[23] For precision farming, the chi-square statistic is 0.85 (p-value = 0.652). For GM crops, it is 7.711 (p-value =0.021).
[24] The choice of the number of matches requires a trade-off. When the number of matches is one, each treated observation is matched with one observation in the control group with the closest propensity score, however, any unmatched observations in the control cannot be utilized in subsequent econometric analyses. When the number of matches is larger, more observations can be utilized, but the quality of match may have to be compromised.

Table 3.2: Probit Estimates of Propensity to be Full-time Farmers

Variables	Coefficient	Robust Standard Errors
Operator and Spouse Characteristics		
Operator's Age	-0.054	0.034
Operator's Age Squared	0.001	0.000*
Operator's Formal Years of Education	-0.026	0.016
Spouse's Age	-0.022	0.033
Spouse 's Age Squared	0.001	0.000
Spouse 's Formal Years of Education	-0.133	0.017***
Farm Characteristics		
Log of Total Operated Acres	-0.001	0.018
Internet Access (=1 if yes, 0 otherwise)	-0.033	0.070
Average Interest Rate for Loans	-0.066	0.016***
Debt to Asset Ratio = Total Liability/ Total Asset	1.159	0.186***
Log of Household Net Worth	0.295	0.027***
Dairy	0.208	0.113*
Number of Children Younger than 5 Years Old	0.166	0.061***
Number of Children between 6 and 13 Years Old	0.134	0.041***
Government Payments ($1,000)		
Direct Payments	0.002	0.001***
Indirect Payments	-0.001	0.002
Conservation Reserve Program Payments	-0.004	0.005
Working Land Conservation Program Payments	0.005	0.003
County-level Variables		
Unemployment Rate	0.081	0.014***
Population Interaction Zones in Agriculture 2000	0.092	0.029***
Intercept	0.273	0.593
Number of Observations = 2,851	Likelihood Ratio Chi-2(20) = 662.04	
Log pseudo likelihood = -1622.224	Prob > F =0.000	

***, **, and * indicate significance at 1%, 5% and 10%, respectively.

insignificant. As a check, we conducted the Smith-Blundell test once again on this refined sample. The adoption of precision farming remains exogenous and the adoption of GM crops now becomes exogenous[25] as well, indicating that the sub-sampling approach using the propensity score matching successfully addressed the endogeneity.

3.6.2. Bivariate Probit Model on Technology Adoption

Table 3.3 presents results from the bivariate probit model on the adoption of precision farming and GM crops, corresponding to equations (15) and (16). The second and third (fourth and fifth) columns show coefficient and marginal effect estimates of factors explaining adoption of precision farming (GM crops).

[25] The chi-square statistic is 3.98 (p-value = 0.136) for precision farming and 2.183 (p-value =0.339) for GM crops.

Table 3.3: Factors Affecting Adoption of Precision Farming and GM Crops

	Bivariate Probit Model				
	Precision Farming		GM Crops		
Variables	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Chi-2 Statistics[1]
Operator Characteristics					
Education	0.050***	0.013	-0.053***	-0.018	17.05***
Education × Share of Off-farm Income	-0.059**	-0.015	0.099***	0.034	15.59***
Education × Share of Off-farm Income Squared	0.056*	0.014	-0.087***	-0.030	12.62***
Operator's Age	0.031	0.008	-0.032*	-0.011	5.50**
Operator's Age Squared	0.000	0.000	0.000	0.000	5.67**
Farm Characteristics					
Log of Total Operated Acres	0.049*	0.012	0.312***	0.105	36.27***
Full Owners	-0.184**	-0.046	-0.301***	-0.098	0.85
Full Tenant	0.233**	0.064	-0.320***	-0.100	14.21***
Debt to Asset Ratio	0.761***	0.195	-0.890***	-0.301	28.6***
Log of Household Net Worth	0.180***	0.046	-0.145***	-0.049	38.67***
Average Interest Rate	0.024	0.006	0.042**	0.014	0.47
Internet Access	0.273***	0.065	-0.097	-0.033	9.88
Dairy	-0.082	-0.020	0.759***	0.287	17.91***
Government Payments ($1,000)					
Direct Payments	0.000	0.000	0.002***	0.001	5.21**
Indirect Payments	-0.001	0.000	0.002	0.001	0.31
CRP Payments	0.008	0.002	-0.015**	-0.005	11.96
WLCP Payments	0.002	0.000	0.002	0.001	0.01
Regional Dummy Variables (=1 if farm is located in respective region, 0 otherwise)					
Northern Crescent	0.014	0.004	-0.555***	-0.165	12.02***
Northern Great Plains	-0.077	-0.019	-1.487***	-0.281	31.04***
Prairie Gateway	-0.001	0.000	-1.039***	-0.253	29.22***
Eastern Upland	0.066	0.017	-0.766***	-0.201	16.57***
Southern Sea Board	0.332**	0.094	-0.275*	-0.087	8.65***
Fruitful Rim	0.456***	0.131	-1.447***	-0.345	55.66***
Basin and Range	0.064	0.017	-1.361***	-0.274	15.68***
Mississippi Portal	-0.193	-0.045	-0.516***	-0.150	2.21
County Level Variables					
Amenity Index	-0.029	-0.007	-0.250***	-0.084	10.36***
Soil Productivity Index	0.006**	0.002	0.010***	0.004	1.07
Coefficient of Variation in Rainfall	-0.805**	-0.206	-0.465	-0.157	0.24
Average Rainfall	0.000	0.000	0.000	0.000	0.09
Intercept	-4.457***		1.280*		

Number of Observations = 2,338 $\hat{\rho} = 0.127$
Log Pseudo Likelihood = -2106.912 Likelihood Ratio Test of $\rho = 0$
Chi-2 (1)= 7.659***

[1] Compares coefficient estimates from two equations.
***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

The last column compares coefficient estimates across the two equations. A significant chi-square statistic indicates that the variable has different impacts on the adoption of the two technologies. The sample size of 2,338 represents all full-time farms and the matched part-time farms. The estimated correlation coefficient between the two error terms, $\hat{\rho}$, is statistically significant at 0.127 (p-value = 0.006), which validates the bivariate probit model instead of two separate probit models.

The primary interest of this study is the effect on technology adoption of education and the two interaction terms between education and the dependence on off-farm income. Coefficient estimates on the three variables are all statistically significant with expected signs, except that education has a negative coefficient in the GM crop equation. For the adoption of precision farming, education has a positive coefficient. This indicates that, for farms without off-farm income (so that both of the interaction terms become zero), education has a positive impact on the adoption of precision farming, which is consistent with the human capital theory and most empirical findings. For farms with no off-farm income, an additional year of education increases the probability of precision farming adoption by 0.013. On the other hand, education unexpectedly has a negative coefficient on the adoption of GM crops; an additional year of education decreases the probability of the adoption by 0.053. Several plausible explanations can be made for this unexpected result. First, highly educated farmers may be more aware of the controversy over GM crops, i.e., manipulation of gene structures in GM crops and its uncertain health effect, which may have discouraged them from adopting GM crops. Second, the rapid increase in the adoption of GM crops since 1996 may have induced educated farmers to seek a niche market by intentionally growing non-GM crop varieties, including organically grown crops. Third, due to the lower labor and human capital requirements, GM crops may have been well-accepted among relatively less educated farmers.

Once we take into account the two interaction terms, however, the impact of education on technology adoption shows a very different picture. Figure 3.1 depicts a profile of the marginal effect of education on the adoption of precision farming and GM crops at different levels of off-farm income dependence, based on the point estimates of the marginal effects in Table 3.3. For precision farming, the first interaction term is negative and significant while the second interaction term is positive and

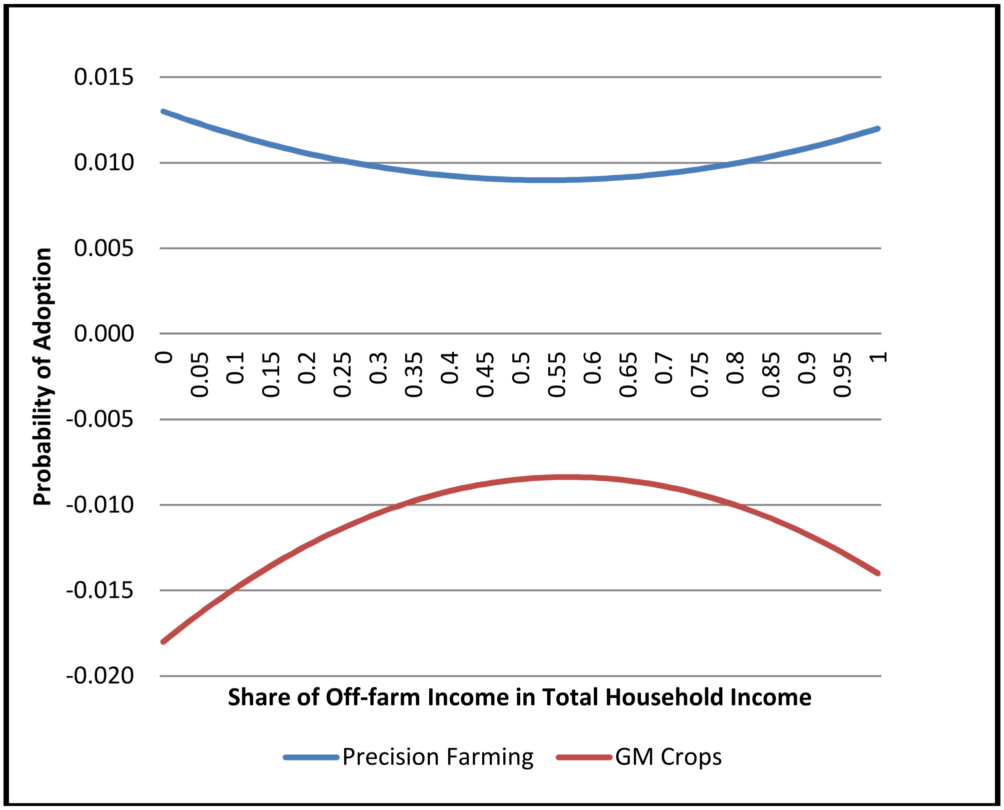

Figure 3.1: Marginal Effect of Education on Technology Adoption

significant (Table 3.3). As the dependence on off-farm income increases, the positive effect of education becomes smaller and smaller until the share of off-farm income in the total household income reaches around 53% after which the effect bounces back.[26] As expected, due to the management-intensive nature of precision farming, the effect of education on the adoption becomes smaller as part-time farms become increasingly dependent on off-farm income.

For GM crops, the effect of education is completely reversed; the first interaction term is positive and significant and the second interaction term is negative and significant. As part-time farms rely more on off-farm income, the negative effect of education mitigates, presumably because the time and management-saving nature of GM crops becomes more attractive for part-time farms that rely more on off-farm income, leaving less managerial time on-farm. Figure 3.1 shows that the marginal effect of education keeps increasing until the share of off-farm income reaches around 57%. Because the absolute

[26] Of course this could be an artifact of the restriction we impose on the model.

values of the marginal effects of the two interaction terms are larger for GM crops than for precision farming, the curvature of the marginal effect is steeper for GM crops than for precision farming (Figure 3.1).

In order to examine the robustness of the results, we estimated the same model with more parsimonious selections of explanatory variables. Results are summarized in Table 3.4. The first model (Model I) only includes the operator characteristics while the second model (Model II) also includes the farm characteristics. The third model (Model III) has the government-payment variables in addition to the operator and farm characteristics. In all of the three models, education and the two interaction terms are statistically significant and the sign of the coefficients in the two equations are exactly the same as in the full model presented in Table 3.3.[27] The quadratic relationship between the impact of education on the adoption of the two technologies and the dependence on off-farm income appears robust to model specifications.

Now we turn back to results in Table 3.3 to interpret the coefficients and the marginal effects of other explanatory variables. The farm characteristics are mostly significantly correlated with the adoption in both equations. The farm size in terms of the total operated acres has a positive impact on the adoption of both technologies, but its significance is more conspicuous for GM crops both statistically and economically. Full owners, farms who own all the acres they operate, are less likely to adopt both technologies while full tenants, farms who rent all the acres they operate, are more likely to adopt precision farming but less likely to adopt GM crops, relative to part owners who operate both owned and rented land. Out of the three variables representing the financial conditions of the farm business and household, farm debt to asset ratio and household net worth have a contrasting effect. Precision farming often requires a relatively large amount of initial investment and thus farms with a large household net worth (asset minus debts) and those farms that can take on a relatively large amount of farm debt are

[27] We also estimated several different versions of the model. For example we estimated a model in which spouse characteristics (education, age, and age squared) are included, in addition to all the variables in the full-model in Table 3.3. Results are essentially the same, although none of the spouse characteristics is significant.

Table 3.4: Alternative Specifications of Bivariate Probit Model

	Model I		Model II		Model III	
Variables	Precision Farming	GM Crops	Precision Farming	GM Crops	Precision Farming	GM Crops
Operator Characteristics						
Education	0.094***	-0.073***	0.050***	-0.078***	0.050***	-0.083***
Education × Share of Off-farm Income	-0.093***	0.116***	-0.055*	0.132***	-0.055*	0.143***
Education × Share of Off-farm Income Squared	0.081***	-0.113***	0.052*	-0.121***	0.051*	-0.130***
Operator's Age	0.043**	-0.013	0.030	-0.024	0.032	-0.028*
Operator's Age Squared	0.000***	0.000	0.000	0.000	0.000*	0.000
Farm Characteristics						
Log of Total Operated Acres			0.049**	0.278***	0.042	0.253
Full Owners			-0.196**	-0.393***	-0.203**	-0.363***
Full Tenant			0.222**	-0.373***	0.227**	-0.406***
Debt to Asset Ratio			0.785***	-0.671***	0.799***	-0.836***
Log of Net Household Worth			0.185***	-0.174***	0.188***	-0.186***
Average Interest Rate			0.019	0.022	0.018	0.029*
Internet Access			0.287***	-0.097	0.278***	-0.090
Dairy			-0.114	0.926***	-0.107	0.943
Government Payments ($1,000)						
Direct Payments					0.000	0.003***
Indirect Payments					-0.001	0.002
CRP Payments					0.007	-0.020***
WLCP Payments					0.001	0.000
Intercept	-2.906***	1.204**	-4.248***	1.081**	-4.250***	1.413***
$\hat{\rho}$	0.175***		0.109***		0.112***	
Number of Observations			2,338			

***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

favored to adopt precision farming.[28] In contrast, farms households with a smaller net worth and farm business with a lower debt to asset ratio are more likely to adopt GM crops. The convenient feature of GM crops such as lower input costs and higher expected yields may prove attractive for farm businesses and households under relatively unstable financial conditions. The average interest rate on loans, holding constant of debt to asset ratio and household net worth, can represent an objective measure of financial risk in the lending market (Goodwin and Mishra, 2000). Those farms borrowing at a higher interest rate are more likely to adopt GM crops, conceivably due to the ease of implementation, higher expected yields, and immediate returns. With the information intensive nature of precision farming, farms with Internet access are more likely to adopt precision farming, while labor-intensive dairy farms are more likely to adopt GM crops.

The positive and significant effect of direct payments on the adoption of GM crops suggests that agricultural subsidy is inducing technology adoption. A $10,000 increase in direct payments increases the probability of adopting GM crops by 2%. The significant marginal effect of government payments on GM crops can be attributed to the fact that farm program payments are tied to production of corn, soybean, cotton and other cash grain crops. Farm program payments may provide farmers with an additional source of income that can be used to purchase new technologies (Caswell, et al., 2001, Lambert, et al., 2006, Lambert, et al., 2007)

Literature indicates that technology adoption is affected by the geographical location of the farm (Mishra, et al., 2009). Table 3.3 shows that all regional dummy variables are statistically significant for GM crops; however, only two of them are significant for precision farming. In the case of precision farming, farmers in the Southern Sea Board and the Fruitful Rim regions have a higher probability of adopting precision farming compared to farmers in the Heartland region (the base category). Presumably, the lack of regional impacts on precision farming adoption is because we control for soil productivity index. For GM crops, farmers in the Heartland region have a higher probability of adopting GM crops

[28] Note that debt to asset ratio is a ratio of farm debt over farm asset while net worth is the difference between household asset minus household debt.

than those in any other region. Applicability of GM crops, especially insect-resistant crops, is dependent on the local environmental conditions (Fernandez-Cornejo and Caswell, 2006), and thus the regional dummy variables are more significantly correlated with the adoption of GM crops than precision farming.

3.7 Summary and Conclusions

While economic theory suggests that education has a positive effect on technology adoption by farmers, existing studies on technology adoption have yielded inconclusive results. We attribute this to the conventional technology adoption models that do not explicitly account for labor allocation decision between on- and off-farm, which is heavily influenced by human capital of farm operators and their spouses. The purpose of this study was to fill the gap between the economic theory and the mixed empirical findings in agricultural economics on the impact of education on technology adoption. We employed the propensity score matching method to refine the sample to address the endogeneity of off-farm labor participation. Using the two recent but contrasting innovations in agriculture, we estimated a bivariate probit model of technology adoption that allowed for interactions between education and the dependence on off-farm income.

The results confirm our expectation that the effect of education on technology adoption is significantly contingent upon the dependence on off-farm income. Findings from this study suggest that the effect of education on adoption of a management-intensive technology such as precision farming can be much smaller for part-time farms that are more reliant upon off-farm income. Highly educated farms have more lucrative off-farm employment opportunities, which increases the opportunity cost of farming. As the dependence on off-farm income increases, the marginal effect of education on technology adoption for part-time farms becomes smaller. Part-time farms are less likely to adopt new technologies relative to equally educated full-time farms. For the adoption of GM crops, a representative of a management-saving technology, the effect of education was found negative, contrary to *a priori* expectations, but the effect became less negative as the reliance on off-farm income increased.

Given the increasing federal spending on agri-environmental programs that encourage farmers to adopt environmentally benign practices over the last two decades (Cattaneo, et al., 2005), a precise assessment of the effect of education on technology adoption is necessary. Our findings suggest that simply targeting highly educated farmers to promote new technologies on the basis of the conventional theory is not sufficient to achieve an efficient policy outcome. Of particular importance is the nature of the technology, i.e., management and labor requirements, and the farm household's dependence on off-farm income. With the increasing trend in off-farm labor participation among farm households in the United States (Fernandez-Cornejo, 2007, Mishra, et al., 2009), the heterogeneous effects of education on technology adoption may become more prominent in the future.

Finally, some limitations this study has encountered are noted. First, the definition of precision farming in our data is more broadly defined than previous studies such as Banerjee, et al. (2008) and Roberts, et al. (2004). This may have obscured the relationship between off-farm labor supply and the adoption of precision farming. Second, our results showed that the marginal effect of education on the adoption of GM crops was negative. As mentioned earlier, this unexpected result could be attributed to the controversy over the genetically modified crops, especially for highly educated farmers, but further attention is warranted on this topic. Finally, it is necessary to apply the model used in this study to a different set of technologies to further confirm our proposition that the effect of education can be heterogeneous and even be negative, contingent upon the dependence on off-farm income. Future research will address these limitations to build on our early attempt to estimate the effect of education on technology adoption in the contemporary economic and social environment surrounding the US agricultural sector.

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CHAPTER 4: A CATEGORICAL DATA ANALYSIS ON INDIVIDUAL RISK PREFERENCES IN AGRICULTURE

4.1. Introduction

Risk and uncertainty have important implications to almost all economic decisions. It is essential that economists understand individual attitudes towards risk to accurately predict economic behaviors for successful public policy interventions (Dohmen, et al., 2005, Weber, 2010). Risk taking is often considered a distinctive characteristic among entrepreneurs (Block, et al., 2009, Caliendo, et al., 2009, Kamhon and Wei-Der, 2006). Since agricultural production is riskier than businesses in other sectors of the economy (Hardaker, et al., 2004), risk preferences should play a more pronounced role in explaining entrepreneurship and business decisions in the farm sector.

The riskiness of agriculture may be attributed to several factors that are beyond the control of producers. The biological processes of plant growth and climatic conditions inherent in agricultural production cause random production shocks, which cause price volatility due to inelastic demand for foods (Goodwin and Mishra, 2000, Holt and Chavas, 2002). A large volume of literature has been devoted to risk analysis in agricultural economics. The literature can be broadly classified into three categories: (1) how to measure farmers' risk perceptions, (2) normative analysis to provide a guideline for the optimal risk management strategies, and (3) how risk preferences, assuming that they are properly measured, influence farmers' actual decision-making (Holt and Chavas, 2002).

This chapter belongs to the third category, with three objectives. The overriding theme of the chapter is to examine the validity of the measure of risk preferences using data from a nationwide survey of farm operators. It attempts to examine the validity of one of the simplest, but frequently used, measures of risk preferences: farmers' own assessments of risk preferences measured on an 11-point Likert scale.[29] First, we identify the factors explaining farm operators' risk preferences represented by Likert scale risk attitude. Next, we estimate a multivariate probit model to compare Likert scale risk attitude against three discrete variables representing actual realization of risk preferencess, revealed through off-farm labor

[29] We call this variable "Likert scale risk attitude" hereafter.

participation, and use of contracts and crop insurance. Finally, we estimate a double-hurdle model to evaluate two different effects of risk preferences on adoption of a risk management strategy: whether or not a farmer adopts a risk management strategy and the intensity at which the farmer adopts the strategy.

4.2. Literature Review

Agricultural economists have relied on the expected utility framework as the basis of most empirical analysis of risk in agriculture (Holt and Chavas, 2002). The expected utility framework is a theoretical scheme derived based on the set of axioms developed by von Neumann and Morgenstern (1947). Because of its normative nature, the validity of the expected utility theory needs to be confirmed empirically (Hey, 1979). In fact, an increasing amount of empirical and experimental evidence has been accumulated to document the violations of the axioms in the expected utility theory (Machina, 1987, Starmer, 2000). Although the theoretical expectations of the expected utility theory often contradict the empirical evidence, it remains by far the most popular theoretical framework in agricultural economics due to its simplicity and the lack of better alternatives (Just and Peterson, 2010).

The central difficulty in these studies is how to measure individual risk preferences. A wide variety of methods have been proposed to measure farmers' risk preferences, but any proposed method is never free from contradiction with the empirical evidence, which are also subject to inconsistent findings within itself (Lagerkvist, 2005). For example, Fausti and Gillespie (2006) examined consistency across five risk-attitude measurement instruments. Not only did the authors find no consistency across different risk-attitude measurement instruments, they also found no significant relationship between levels of understanding of the survey questions by respondents and their consistency across risk-attitude measurement instruments. Their study suggests that the inconsistency cannot solely be attributed to the respondents' understanding of survey questions or lack thereof. Bard and Barry (2001) employed the "closing-in" method to elicit Illinois farmers' risk preferences. The "closing-in" method is an iterative procedure in which respondents are repeatedly asked to choose between gambles until their preferences converges to a narrow interval. The authors compared "closing-in" risk preferences against farmers' own assessments of risk preferences measured on an 11-point Likert scale; however, the authors found no correlation between them. The lack of consistency across risk-attitude measurement instruments is disturbing not only to economists who propose them, but also to those who need to rely on them for empirical analyses.

The measurement of risk preferences used in this study is qualitative and does not explicitly utilize the expected utility theory. Specifically, the respondents were asked to choose a number between 0 and 10 on a Likert scale to represent the level of risk at which they are comfortable in making decisions, with 0 being “avoid risks as much as possible” and 10 being “take risks as much as possible.” Economists are often skeptical about the validity of self-reported risk preferences such as this one for several reasons. First, this method, as well as any survey questions, is not incentive compatible. An incentive compatible measure of risk preferences obtained in an experimental setting is more suitable (Dohmen, et al., 2011). Second, the situational context of the question is broad and ambiguous. Therefore, responses may be based on a mix of factors, most notably risk preferences and risk perceptions, unobservable to researchers (Dohmen, et al., 2011). Responses may be obscured given that individuals often exhibit inconsistent risk preferences under alternative risky situations (Fausti and Gillespie, 2006).

In contrast, there are some advantages to using a self-reported risk preferences, including Likert scale risk attitude. Unlike an experimental method, Likert scale risk attitude can be obtained in a mail survey, which makes it possible to conduct a large scale-study at a relatively affordable cost (Dohmen, et al., 2011). Another important benefit is the ease of understanding the question. Fausti and Gillespie (2006, 2000) reported that a non-negligible share of the respondents demonstrated difficulty in understanding questions to elicit risk preferences in their survey. They also contended that respondents may not have paid sufficient attention while answering the questions. Using a very simple question format, as in Likert scale risk attitude, is recommended to the extent that these concerns are relevant (Fausti and Gillespie, 2006).

There is an absence of empirical evidence in agricultural economics that Likert scale risk attitude can obtain theoretically consistent findings. However, the same is not the case in other branches of economics. Dohmen, et al. (2011) conducted a field experiment with 450 randomly selected adults in

Germany and confirmed that Likert scale risk attitude was a good predictor of actual risk-taking behavior. Although risk preferences measurements catering to a specific situational context always outperformed other measures in that context, Likert scale risk attitude was the best all-round predictor of risk behaviors in all contexts (traffic offenses, portfolio choice, smoking, and occupational choice) than other measures constructed from lottery questions (Dohmen, et al., 2011). The findings in this study have significant implications for risk research in agricultural economics in which researchers often rely on lottery questions to ask respondents to choose between a given monetary award for certain and a chance to win a larger monetary award with a given probability less than one. Dohmen, et al. (2011) demonstrated that such questions will be a good predictor of risky behaviors under circumstances such as gambling, but not necessarily of others. Likert scale risk attitude is found to be the most consistent predictor of risky behaviors under various circumstances and can be used as a global assessment of individual risk preferences (Dohmen, et al., 2011).

The findings in Dohmen, et al. (2011) are supported by several other empirical studies. For example, in a study to estimate individuals' migration propensity in Germany, Jaeger, et al. (2010) used the same 11-point Likert scale risk attitude and found that risk-loving individuals are more likely to migrate. Caliendo, et al. (2009) also utilized the 11-point Likert scale risk attitude and observed that self-employed persons are more risk-loving than others when they became self-employed out of unemployment in Germany[30]. Block, et al. (2009), using a 7-point Likert scale risk attitude, showed that entrepreneurs who started their ventures with identified business opportunities are more tolerant to risk than those entrepreneurs who started ventures out of necessity to earn a living.

To summarize the discussion so far, there is ample evidence in labor economics and entrepreneurship literature to confirm the validity of Likert scale risk attitude, while no such evidence exists in agricultural economics. Although this study does not directly compare Likert scale risk attitude with other risk preferences measurements as in Bard and Barry (2001) and Fausti and Gillespie (2006),

[30] The geographical scope of these studies is Germany because they all rely on the German version of the census data that contains questions to elicit respondents' risk attitude on a 11-point Likert scale.

we estimate three econometric models and attempt to empirically examine if Likert scale risk attitude obtains coefficients with theoretically expected signs.

4.3. Econometric Framework

4.3.1. Ordered Logit Model

With an ordinal structure of Likert scale risk attitude, we estimate an ordered logit model to identify the factors associated with risk preferences. The ordered logit model (also known as cumulative logit models for ordinal responses) takes a natural log of cumulative odds of the dependent variable that has an ordinal structure. That is,

$$\log\left[\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right] = \log\left[\frac{\sum_{j=1}^{j} \pi_j}{\sum_{j=j+1}^{J} \pi_j}\right], j = 1, \cdots, J, \tag{1}$$

where Y is an ordinal dependent variable with J categories, π_j is the probability that Y_i is categorized in the jth category (Agresti, 2007). In this study, $J = 11$, as farmers' risk preferences is measured on an 11-point Likert scale. The first category is used as a base category and all of the interpretations that follow are relative to the base category. Equation (1) represents the log of odds: the ratio of the probability that, Y_i, ith farmer's risk attitude, is classified into jth or lower categories to the probability that Y_i is classified into $j + 1$st or higher categories. This log of odds is regressed against a set of explanatory variables, that is,

$$\log\left[\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right] = \boldsymbol{Z}'\boldsymbol{\gamma} + \varepsilon, \tag{2}$$

where $\boldsymbol{Z}$ is a vector of explanatory variables and $\boldsymbol{\gamma}$ is a vector of unknown parameters to be estimated.

An important econometric issue that arises in estimating the model using Likert scale risk attitude as a dependent variable is that of endogeneity. In many cases, it may be more reasonable to assume that risk attitude is exogenous to farm business decisions. Therefore, drawing causal interpretation based on the results from the ordered logit model may be inadvisable (Dohmen, et al., 2011) and readers should be warned that the results only helps us to understand the association between Likert risk preferences and the explanatory variables.

4.3.2. Multivariate Probit Model

To estimate the impact of risk preferences on actual realization of risk preferences revealed through use of contracts and crop insurance and off-farm labor participation, we estimate a multivariate probit model. This approach is superior to individually estimating three probit models whenever the error terms in the respective models are correlated to each other. This is a legitimate concern in this study as there exists many risk management strategies in agriculture and some tools may be complements to or substitutes for others. The multivariate probit model allows us to test if the error terms in the three equations are significantly correlated with each other. Likert scale risk attitude serves as an exogenous variable in each of the three equations.

We assume that a farmer adopts a risk management tool if it increases his/her utility. Following notations in Walton, et al. (2008), we can express the farmer's risk management problem as:

$$U_i^* = U_i^{AD} - U_i^{NA} \tag{3}$$

$$U_i^* = \boldsymbol{X}_i'\boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_i, \qquad \forall\, i = 1, \cdots, 5, \tag{4}$$

where U_i^* is the net utility from adopting ith risk management tool, U_i^{AD} is utility from adopting ith risk management tool, U_i^{NA} is utility from not adopting ith risk management tool, $\boldsymbol{X}_i$ is the vector of the exogenous variables that influences U_i^*, $\boldsymbol{\beta}_i$ is the vector of unknown parameters to be estimated, and $\boldsymbol{\varepsilon}_i$ is the error term assumed to be normally distributed with zero mean. $\boldsymbol{\varepsilon}_i$ and $\boldsymbol{\varepsilon}_j$ are assumed to be correlated with $\rho_{ij}\ \ \forall\, i \neq j$. Note that U_i^* is a latent variable that is unobservable to the researcher; what is observable instead is a discrete decision of whether the farmer adopts a risk management strategy or not, expressed as:

$$y_i = \begin{cases} 1 \text{ if } U_i^* > 0 \\ 0 \text{ otherwise} \end{cases} \quad \forall\, i = 1, \cdots, 5. \tag{5}$$

Since we have three dependent variables with two outcomes, there are $2^3 = 8$ possible states of the world. For example, the probability that the farmer adopts all of the three risk management strategies or $\sum y_i = 3$ can be obtained by repeatedly applying the conditional probability theorem (Amemiya, 1994):

$$\Pr[y_1 = 1, y_2 = 1, y_3 = 1,] = \Pr[y_1 = 1 |\ y_2 = 1, y_3 = 1] \times \Pr\ [y_2 = 1, y_3 = 1] \tag{6}$$

where the second term on the right hand side of equation (6) can be further rearranged as

$$\Pr[y_2 = 1, y_3 = 1,] = \Pr[y_2 = 1 |\ \ y_3 = 1] \times \Pr\ [y_3 = 1], \tag{7}$$

and so on to eventually obtain

$$\begin{gathered}\Pr[y_1 = 1, y_2 = 1, y_3 = 1\ ] \\ = Pr[y_1 = 1 |\ y_2 = 1, y_3 = 1] \times \Pr[y_2 = 1 |\ \ y_3 = 1] \times \Pr\ [y_3 = 1]\end{gathered} \tag{8}$$

Substituting equations (4) and (5) into equation (8), we obtain

$$\begin{gathered}\Pr[y_1 = 1, y_2 = 1, y_3 = 1\ ] \\ = \Pr\ [\boldsymbol{X}_1'\boldsymbol{\beta}_1 < \varepsilon_1 |\ \boldsymbol{X}_2'\boldsymbol{\beta}_2 < \varepsilon_2, \boldsymbol{X}_3'\boldsymbol{\beta}_3 < \varepsilon_3,] \times \Pr\ [\boldsymbol{X}_2'\boldsymbol{\beta}_2 < \varepsilon_2 |\ \boldsymbol{X}_3'\boldsymbol{\beta}_3] \times \Pr[\ \boldsymbol{X}_3'\boldsymbol{\beta}_3 < \varepsilon_3].\end{gathered} \tag{9}$$

Similarly one can obtain the other seven states of the world. As apparent in equation (9), estimation of the multivariate probit model requires intensive calculation of multivariate standard normal distribution. The standard method is simulation-based approaches instead of algorithms based on standard linear numerical approximation (Cappellari and Jenkins, 2003). The Geweke Hajivassiliou Keane (GHK) smooth recursive conditioning simulator is the most popular simulator as it possesses a number of desirable properties, such as unbiasedness of the simulated probabilities, and the simulator is continuous and differentiable in the parameters of interest (Cappellari and Jenkins, 2003). Although these desirable properties are asymptotic, finite sample bias can be reduced to negligible levels when the number of draw is set close to the square root of the sample size (Cappellari and Jenkins, 2003).

4.3.3. Double-hurdle Model

Although it is a common approach, the drawback of probit models is the loss of information. In particular, a binary variable does not capture the intensity at which a farmer adopts the risk management strategies after he/she decides to adopt it. To address this issue, we construct a variable representing the share of farm income under contracts in total value of production as a proxy for the intensity at which farmers use contracts. Of the three dependent variables used in the multivariate probit model, use of contracts was chosen to create an intensity measure based on data availability. The choice of the dependent variable here bodes well, as the literature suggests that factors affecting whether or not to adopt contracts are different from those affecting the quantity and frequency of contract use (Katchova and Miranda, 2004). A classic approach to incorporating the intensity measure would be a Tobit model due to James Tobin (1958). The Tobit model, however, assumes that the same underlying process determines both the probability that the dependent variable is censored and the conditional expectation of the dependent variable given that it is not censored (Burke, 2009). In the context of this study, The Tobit model assumes that the same underlying process determines whether a farmer uses contracts or not and the intensity at which the farmer uses them given that he/she decides to adopt it. As a consequence, the marginal effect of a regressor on these two outcomes always obtain the same sign (Wooldridge, 2001). This simplifying assumption is of concern in the current context in which we would like to allow for two different effects of risk preferences on whether a farmer adopts agricultural contracts or not and the intensity at which the farmer adopts the contracts. Cragg (1971) proposed a more flexible double-hurdle model in which these two outcomes are determined by separate processes. The double-hurdle model is also more flexible than Heckman's two stage model (Heckman, 1979) as it allows for possibility of zero observations in both of the two outcomes (Cameron and Trivedi, 2005, Wooldridge, 2001).

Since the double-hurdle model employs two separate processes to determine two outcomes, the model has two latent variables. Following notations in Mishra, et al. (2009) and Blundell and Meghir (1987) and suppressing subscript for individual observations,

$$y_1{}^* = \boldsymbol{X_1\beta_1} + \varepsilon_1 \tag{9}$$

$$y_2{}^* = \boldsymbol{X_2\beta_2} + \varepsilon_2, \tag{10}$$

where $y_1{}^*$ is the latent variable representing the decision of whether or not to use agricultural contracts (Tier 1), $y_2{}^*$ is the other latent variable representing the intensity at which agricultural contracts are used (Tier 2). $\boldsymbol{X}$ and $\boldsymbol{\beta}$ are, respectively, the vectors of independent variables and parameters to be estimated and ε_1 and ε_2 are the error term. Note that subscripts, 1 and 2, for $\boldsymbol{X}$ and $\boldsymbol{\beta}$ indicate that the two latent variables can be specified by different sets of independent variables and error terms. The double-hurdle model obtains consistent estimates of $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ by maximizing the following likelihood function:

$$f(y_1, y_2|\boldsymbol{X_1}, \boldsymbol{X_2}) = [1 - \Phi(\boldsymbol{X_1\beta_1})]^{(1-y_1)} \left\{ \frac{\Phi(\boldsymbol{X_1\beta_1})(2\pi)^{-\frac{1}{2}}\sigma^{-1}\exp[-(y_2 - \boldsymbol{X_2\beta_2})^2]}{\Phi\left(\frac{\boldsymbol{X_2\beta_2}}{\sigma}\right)} \right\}^{y_1}, \tag{11}$$

where y_1 is a dummy variable that takes a value of one when ${y_1}^* > 0$ and Φ is the standard normal cumulative density function (Burke, 2009). We also estimate two marginal effects. One is the impact of a unit change in an explanatory variable on the probability that y_2 is observed, or in the context of this model, the probability that the farmer uses contracts:

$$\frac{\partial \Pr\,(y_2 > 0|\boldsymbol{X_1})}{\partial x_j} = \beta_{1j}\varphi(\boldsymbol{X_1\beta_1}). \tag{12}$$

The other is the impact of a unit change in an explanatory variable on the dependent variable given that it is not censored, or, in the given context, the marginal effect on the intensity at which contracts are used for those who use contracts:

$$\frac{\partial \mathrm{E}\,(y_2|y_2 > 0; \boldsymbol{X_2})}{\partial x_j} = \beta_{2j}\left\{1 - \lambda\left(\frac{\boldsymbol{X_2\beta}}{\sigma}\right)\left[\frac{\boldsymbol{X_2\beta}}{\sigma} + \lambda\left(\frac{\boldsymbol{X_2\beta}}{\sigma}\right)\right]\right\}. \tag{13}$$

The standard errors for the two marginal effects are estimated following the bootstrap procedures with 2,000 replications as recommended by Burke (2009).

4.4. Data

This study uses data from the 2001 Agricultural Resource Management Survey (ARMS) conducted by the National Agricultural Statistics Service (NASS) and the Economic Research Service (ERS). An important feature of the 2001 ARMS, particularly relevant to this study, is that it contains a question that queries the respondents' risk preferences that is very similar to the one used by Dohmen, et al. (2011). Specifically, the respondents were asked to choose a number between 0 and 10 on a Likert scale to represent the level of risk at which they are comfortable in making decisions, with 0 being "avoid risks as much as possible" and 10 being "take risks as much as possible." In this study, we compare this variable, which can be seen as perceptions about their own risk preferences, against variables representing actual realization of their risk preferences revealed by decisions they make in farming operation, which are also obtained from 2001 ARMS data. Figure 4.1 presents the histogram of Likert Risk preferences measured on a 11-point Likert scale. A huge spike in the middle of distribution (Figure 4.1) shows that the majority of respondents chose 5 at the center of the Likert scale, indicating that most farmers consider themselves as neither risk taking or risk averse. However, this does not necessarily mean that those who chose 5 are risk neutral in terms of curvature of utility function, as there is no theoretical connection between this question and respondents' utility function.

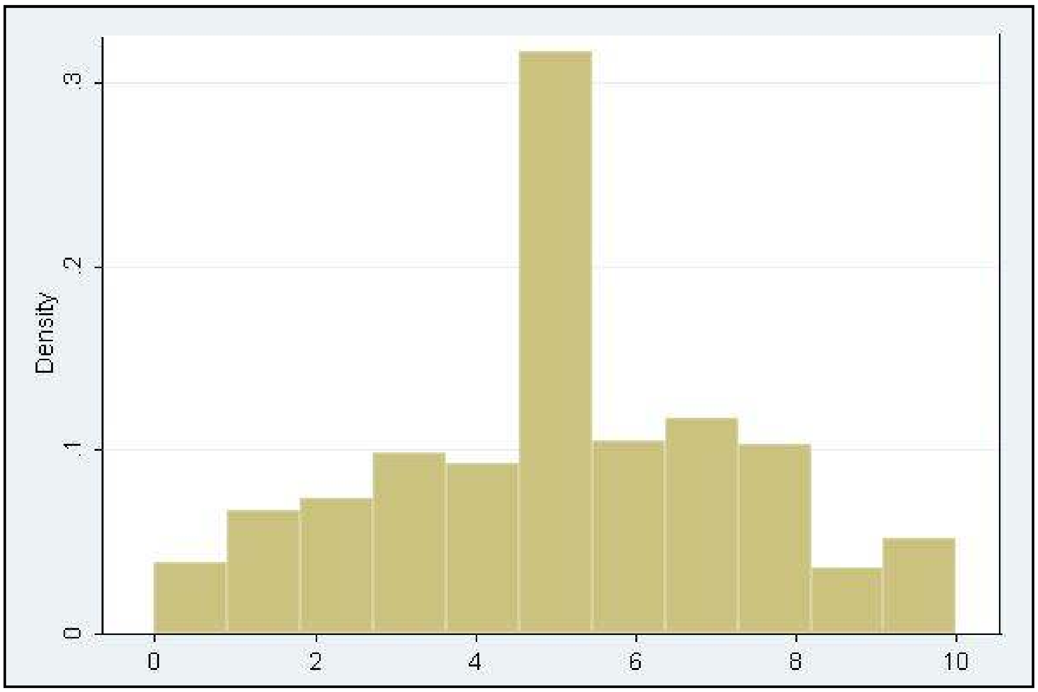

Figure 4.1: Risk Attitude Measured on an 11-point Likert Scale

The ARMS provides information about the relationships between agricultural production, resources, and the environment as well as about the characteristics and financial conditions of farm households, management strategies and off-farm income. Operators associated with farm businesses representing agricultural production in the 48 contiguous states make up the target population of the survey. Data are collected from the senior farm operator, who makes most of the day-to-day management decisions. For statistical purposes, USDA currently defines a farm as an establishment that sold or normally would have sold at least $1,000 of agricultural products during the year (USDA 2005). For the purpose of this study, our sample only includes farms that are classified as family farms that are organized as sole proprietorships, partnerships, or family corporations because they are closely controlled by their operators and the operator's household (USDA 2005). Any operator households organized as nonfamily corporations or cooperatives and farms run by hired managers are excluded from this study because we are interested in farm business decisions made by individual farmers and his/her families not by hired managers. Also, any observations with missing values are deleted, which leaves us with 5,162 observations.

Definitions of variables used in this chapter and their summary statistics are provided in Table 4.1. It presents conditional means for observations with Likert scale risk attitude less than five, equal to five, and greater than five. A significant F-statistic for one-way ANOVA or Pearson chi-square statistics in the last column indicates that the conditional means for the three groups are different from each other. Most variables, except for most regional dummy variables, have a significant F or chi-square statistic, indicating some correlation between Likert scale risk attitude and independent variables, although it does not control for any confounding factors. Notably, a higher proportion of farmers who chose less than five on Likert scale risk attitude are part-time farmers (work off-farm as a primary occupation), less likely to be raised on farm, less educated, younger, and female. Those who chose more than five tend to operate a farm with more acres with diversified crop mix, measured by the entropy index. Such farmers are also more likely to have expanded acreage, participated in more farm programs, and accumulated more debts during the five years previous to the survey year of 2001. Calculating rate of return and preparing income and net worth statements also appear to be positively correlated with Likert scale risk attitude.

4.5. Results and Discussion

4.5.1. Ordered Logit Model

Factors associated with individual risk preferences are identified by the ordered logit models. Table 4.2 presents odds ratio and standard error estimates. Following Dohmen, et al. (2011), three versions of the ordered logit models are estimated. The first version consists of only operator characteristics, while the second version includes both operator and farm characteristics. The third model is added to assess the

Table 4.1: Variable Definitions and Comparison of Summary Statistics by Risk Categories

Variable Definition	Likert Risk Attitude < 5	Likert Risk Attitude = 5	Likert Risk Attitude > 5	F/chi statistics[1]	
Risk Attitude (Measured on 11-point Likert scale)	2.380	5.000	7.549		
Contracts (=1 if used either marketing or production contracts, 0 otherwise)	0.231	0.302	0.395	116.623	***
Farm Income Under Contracts/ Total Value of Production	0.169	0.214	0.268	32.540	***
Operator Characteristics					
Primary Occupation (=1 if off-farm, 0 if farm)	0.414	0.300	0.227	151.959	***
Raised on Farm (=1 if Yes, 0 No)	0.799	0.829	0.836	9.553	***
Years of formal education	13.212	13.342	13.723	27.820	***
Age	56.530	54.661	51.089	88.090	***
Race (=1 if Non-White race, 0 if otherwise)	0.070	0.058	0.062	1.998	
Gender (=1 if female, 0 if male)	0.082	0.047	0.033	46.788	***
Number of children (13 years old or younger)	0.378	0.446	0.578	20.590	***
Farm Characteristics					
Total operated acres (in 1,000)	1.002	1.355	1.820	8.540	***
Certified organic farm (=1 if yes, 0 otherwise)	0.010	0.011	0.015	2.341	
Debt to Asset Ratio	0.114	0.218	0.208	4.430	**
Entropy Index (continuous, 0 not diversified at all, 1 completely diversified)	0.015	0.021	0.026	23.450	***
Soil Productivity Index (County-level Mean)	71.636	71.736	72.093	0.560	
Full owner (=1 if full owner, 0 otherwise)	0.500	0.375	0.302	151.845	***
Tenant (=1 if tenant, 0 otherwise)	0.094	0.128	0.146	23.358	***
Part owner (=1 if part owner, 0 otherwise)	0.406	0.498	0.552	78.227	***
High Value Crop Farms (=1 if yes, 0 otherwise)	0.089	0.110	0.128	14.325	***
Livestock Farms (excluding Dairy) (=1 if yes, 0 otherwise)	0.503	0.429	0.383	53.897	***
Operate More Acres than in 1996 (=1 if yes, 0 otherwise)	0.239	0.311	0.415	122.789	***
Participate Farm Programs more than in 1996 (if yes, 0 otherwise)	0.135	0.159	0.221	47.114	***
Have More Debt than in 1996 (if yes, 0 otherwise)	0.213	0.289	0.438	207.197	***
Rate of Return (=1 if calculated, 0 otherwise)	0.245	0.338	0.460	197.722	***
Statement (=1 if Farm keeps income and net worth statement, 0 otherwise)	0.338	0.472	0.593	237.991	***

Table 4.1 cont'd

Variable Definition	Likert Risk Attitude < 5	= 5	< 5	F/chi statistics[1] = 5	
Regional Dummy Variables (=1 if farm is located in respective region, 0 otherwise)					
Heartland	0.127	0.132	0.139	1.254	
Northern Crescent	0.129	0.127	0.127	0.020	
Northern Great Plains	0.054	0.058	0.085	16.297	***
Prairie Gateway	0.115	0.130	0.111	3.042	
Eastern Upland	0.173	0.120	0.100	44.707	***
Southern Sea Board	0.137	0.139	0.137	0.029	
Fruitful Rim	0.131	0.154	0.156	5.220	*
Basin and Range	0.045	0.043	0.052	1.827	
Mississippi Portal	0.089	0.097	0.092	0.520	
Number of Observations	1,735	1,489	1,938		

*** and ** indicate significance at 1% and 5% levels, respectively.

[1]For continuous variables, ANOVA F-statistics is presented. For discrete variables, Pearson chi-square statistics is used.

effect of geographical locations of farms.[31] Comparison of the results across the three versions highlights the importance of operator characteristics in explaining individual risk preferences. The only exception is age, which is significant in the second and third models, but not in the first. Gender effects are significant. Not only are female operators more risk averse, the presence of children younger than 13 years old in the household makes female operators even more risk averse, while no such effect exists for male operators. Farm characteristics also have very consistent results in the second and third models. Farmers who operate more acres are more likely to take risks, and those operators who farmed more acres in 2001 than in 1996 are also associated with risk taking. Although causal interpretations are not advisable, having taken more debt in the previous five years is positively correlated with risk taking. Two variables representing business management activities also have odds ratios greater than one. In both the second and third models, farm operators who calculates rate of return to the farm business and prepares income and net worth statements are associated with a higher score on the Likert risk question. Along with the

[31] An important assumption in the ordered logit model is that of the parallel regression assumption, which is frequently violated (Long and Freese, 2006). The Brant test rejects the parallel regression assumption. Therefore, we also estimated the same models using interval regression and ordered probit models as in Dohmen et al. (2011). Statistical and economic significance of the results are very similar to those in the ordered logit models.

Table 4.2: Factors Explaining Individual Risk Preferences

Variables	Ordered Logit Model on Likert Scale Risk Attitude					
	Model 1		Model 2		Model 3	
Operator Characteristics	Odds Ratio (Std. Err)					
Primary Occupation	1.963***	(0.111)	1.495***	(0.096)	1.480***	(0.095)
Raised on Farm	1.096	(0.077)	1.054	(0.079)	1.055	(0.079)
Years of formal education	1.079***	(0.013)	1.040***	(0.013)	1.038***	(0.013)
Age	1.021	(0.014)	1.032**	(0.016)	1.031*	(0.016)
Age Squared	1.000***	(0.000)	1.000***	(0.000)	1.000***	(0.000)
Race	1.043	(0.116)	1.050	(0.122)	1.032	(0.121)
Gender	0.638***	(0.079)	0.735***	(0.095)	0.731**	(0.095)
Number of children	0.997	(0.029)	0.981	(0.031)	0.982	(0.031)
Number of children × Gender	0.603***	(0.075)	0.642***	(0.119)	0.646**	(0.119)
Farm Characteristics						
Total operated acres			1.036***	(0.012)	1.037***	(0.013)
Total operated acres squared			1.000	(0.000)	1.000	(0.000)
Certified organic farm			1.360	(0.367)	1.356	(0.366)
Operate More Acres than in 1996			1.166**	(0.070)	1.166**	(0.070)
Participate Farm Programs more than in 1996			1.026	(0.073)	1.026	(0.073)
Have More Debt than in 1996			1.547***	(0.094)	1.559***	(0.095)
Rate of Return			1.116***	(0.027)	1.115***	(0.027)
Statement			1.437***	(0.085)	1.445***	(0.087)
High Value Crop Farms			1.373***	(0.122)	1.333***	(0.129)
Livestock Farms (excluding Dairy)			0.976	(0.055)	0.952	(0.056)
Regional Dummy Variables						
Northern Crescent					0.981	(0.092)
Northern Great Plains					1.036	(0.118)
Prairie Gateway					1.009	(0.099)
Eastern Upland					1.035	(0.108)
Southern Sea Board					1.202*	(0.119)
Fruitful Rim					1.108	(0.110)
Basin and Range					1.063	(0.156)
Mississippi Portal					1.017	(0.108)
Number of Observations	5,162		4,861		4,861	

***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

positive relationship between operator's years of formal education and risk preferences, the results here speak to the important relationship between risk preferences and information. It is plausible that farmers who are more willing and capable of collecting information are able to make more informed decisions, possibly allowing them to take on riskier business enterprises. The results here, however, shed light on a potential drawback of using Likert scale risk attitude. Ideally, risk preference should be measured where respondents share the same perception about a risky event. Because the Likert risk question in the 2001 ARMS lacks a specific situational context, it cannot control for potentially heterogeneous risk perceptions in assessing risk preferences. The fact that variables representing individual ability and willingness to acquire information have a positive influence on risk preferences shows that Likert scale risk attitude cannot isolate the effect of risk perception from risk preferences. High value crop farms and risk taking are positively correlated, while no regional dummy variables has any significant association with individual risk preferences, with the only exception being the Southern Seaboard Region, which has a positive association with risk preferences at 10% significance level.

Dohmen, et al. (2011) estimated a similar model but only included personal characteristics as their sample consists of the general population in Germany. The unique dataset from the 2001 ARMS allowed us to identify not only individual characteristics of farm operators, but also farm business characteristics that explain the global measure of risk preferences for US farm households. That there is no impact of the regional dummy variables on individual risk preferences is not unexpected, but offers a new addition to our understanding about farmers' individual risk preferences.

4.5.2. Multivariate Probit Model

Table 4.3 presents coefficient estimates from the multivariate probit model, consisting of three equations: use of contracts and crop insurance and off-farm labor participation. We conduct the likelihood ratio test that examines the null hypothesis that the error terms in all three equations are not correlated with each other. The chi-square statistic for the test has degrees of freedom equals to 3, because there are a total of three combinations of two error terms out of three[32]. The chi-square statistic of 109.619 (p-value < 0.00) is clear evidence against the null hypothesis, which justifies the use of multivariate probit model instead of three individual probit models.

[32] $C_2^3 = \frac{3!}{(3-2)!2!} = 3$

The primary interest in the multivariate probit model is the coefficient estimate of Likert scale risk attitude. Likert scale risk attitude has a positive and significant coefficient in contracts and crop insurance equations. Contrary to *a priori* expectation, risk prone farmers are more likely to use contracts and crop insurance, two representative risk management strategies in agriculture. In contrast, Likert scale risk attitude has a negative and significant coefficient in off-farm labor equation. Note that the dependent variable in off-farm labor equation takes a value of one for farm operators whose primary occupation is off-farm work. Thus, risk-loving farmers are less likely to work off-farm, which is consistent with the widely held view that off-farm work is often considered a less risky occupational choice than farming. An important question remains as to why using contracts and crop insurance are positively correlated with risk-loving attitudes. We offer a few alternative explanations to this unexpected result. First, risk preferences in general may have two opposing effects on farmers' decisions to use risk management strategies. For one, risk averseness may impose a negative impact on doing something new, including risk management strategies. Risk-loving farmers may be more willing to initiate risk management strategies, which, at the outset, may be perceived risky due to contractual and legal complexities involved. On the other hand, risk-averse farmers may initially be reluctant to adopt a new risk management strategy, but gradually become more willing to adopt it at a greater intensity if it is suitable for reducing and diversifying risks. Because all of the dependent variables in the multivariate probit models are binary and discrete, our model is unable to capture the possible effect of risk preferences on the adoption intensity of risk management strategies, if any. This is the primary motivation to estimate the double-hurdle model on contract use, results for which we discuss later in this section.

Alternatively, as indicated by its inconsistent performance in Bard and Barry (2001) and Fausti and Gillespie (2006), Likert scale risk attitude may not represent the true risk preference of individuals as accurately as researchers would hope for, despite its simplicity of the question in the elicitation procedure. Operator and farm characteristics and regional dummy variables are included to control for factors relevant to use of contracts and crop insurance and off-farm labor participation. These variables obtained

Table 4.3: Factors Affecting Adoption of Risk Management Strategies

Variables	Multivariate Probit Model					
	Contracts		Crop Insurance		Primary Occupation	
Likert Scale Risk Attitude	0.019**	(0.009)	0.025**	(0.010)	-0.041***	(0.009)
Operator Characteristics						
Primary Occupation	-1.800	(0.094)	-1.063***	(0.153)		
Raised on Farm	0.060	(0.058)	0.218***	(0.067)	-0.351***	(0.053)
Years of formal education	0.019**	(0.010)	0.035	(0.011)	0.063**	(0.010)
Age	0.034***	(0.011)	0.018	(0.012)	0.026***	(0.011)
Age Squared	-0.000***	(0.000)	-0.000*	(0.000)	-0.000***	(0.000)
Race	-0.092	(0.083)	-0.156*	(0.092)	0.208***	(0.080)
Gender	0.043	(0.096)	-0.198*	(0.116)	0.227***	(0.084)
Farm Characteristics						
Total operated acres	-0.011	(0.007)	0.024***	(0.008)	-0.071***	(0.010)
Total operated acres squared	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Certified organic farm	0.218	(0.170)	0.041	(0.181)	-0.138	(0.197)
Debt to Asset Ratio	0.017	(0.015)	0.013	(0.021)	0.012***	(0.015)
Entropy Index	3.127***	(0.473)	-0.693	(0.480)	-8.899	(0.665)
Soil Productivity Index	-0.008***	(0.002)	0.005**	(0.002)	-0.003***	(0.002)
Full owner	0.187***	(0.051)	-0.586***	(0.062)	0.518	(0.046)
Tenant	-0.048	(0.061)	0.038	(0.065)	-0.105***	(0.072)
Rate of Return	0.007	(0.019)	0.029	(0.020)	-0.054***	(0.021)
Statement	0.026	(0.048)	0.204***	(0.053)	-0.450***	(0.047)
High Value Crop Farms	-0.263***	(0.070)	-0.006	(0.074)	-0.259***	(0.081)
Livestock Farms (excluding Dairy)	-0.116**	(0.049)	-0.986***	(0.057)	0.388***	(0.046)
Regional Dummy Variables						
Northern Crescent	-0.151	(0.081)	-0.874	(0.088)	-0.231	(0.085)
Northern Great Plains	-0.475***	(0.096)	0.233**	(0.104)	-0.422	(0.107)
Prairie Gateway	-0.529***	(0.089)	-0.047	(0.088)	-0.114***	(0.085)
Eastern Upland	0.026	(0.084)	-0.624***	(0.096)	0.075	(0.081)
Southern Sea Board	0.463***	(0.090)	-0.460***	(0.099)	-0.344*	(0.091)
Fruitful Rim	0.044	(0.085)	-0.720***	(0.093)	-0.140**	(0.091)
Basin and Range	-0.408***	(0.115)	-0.801***	(0.124)	-0.200**	(0.112)
Mississippi Portal	0.156*	(0.082)	-0.307***	(0.089)	-0.205***	(0.090)
Intercept	-0.329	(0.360)	-0.779**	(0.393)	-0.927***	(0.360)
Number of Observations = 5,162			LR test of $\rho_{ij} = 0 \; \forall \; i, j = 1, \cdots, 3, i \neq j$			
Log Likelihood = -7,330.317			chi2(3) = 109.619***			

Presented figures are coefficient estimates. Figures in brackets are standard error estimates.

*** and ** indicate significance at 1% and 5% levels, respectively.

obtained mostly expected results. We briefly review some interesting results. Age and age squared, respectively, have a positive and negative coefficient in all the equations, representing the conventional quadratic profile that the effect of age on the dependent variables is increasing at a decreasing rate. Non-white or female farmers are less likely to purchase crop insurance and instead more likely to work off-farm. County-level soil productivity index has mixed impacts. Farms located in a county with more productive soil are less likely to use contracts but more likely to purchase crop insurance. Farm operators in such counties are also less likely to work off-farm, presumably because of a higher opportunity cost of farming. Calculating rate of return to farm business and preparing income and net worth statements both have a negative impact in off-farm labor equation. A majority of farm type and regional dummy variables have significant coefficients in all three equations. A more geographically specific and regionalized modeling approach may prove beneficial to obtain further insights into factors affecting the three dependent variables. Nonetheless, the model presented here accomplishes the primary objective to assess the impact of Likert scale risk attitude on use of risk management strategies, using a large scale representative sample of farmers.

4.5.3. Double-hurdle model

The unexpected result that risk-loving farmers are more likely to use contracts and crop insurance leads us a more flexible modeling approach to delineate the relationship between risk preferences and use of risk management strategy. We construct a variable representing the intensity of contract use represented by a share of farm income under contracts in the total value of production.[33]

Agricultural contracts are important risk management strategies for farmers as they can stabilize

[33] According to MacDonald, et al. (2004), agricultural contracts are arrangement "for the transfer of agricultural products from farms to downstream users such as processors, elevators, integrators, retailers, or other farms." Production and marketing contracts are the two of the most major forms of agricultural contracts. While production contracts are agreements on production inputs and practices between farmers and contractors, marketing contracts specify a pricing scheme and sales outlets for the commodity prior to harvest (MacDonald and Korb, 2011). Production contracts are more popular in livestock production while marketing contracts are more widely used in crop production (MacDonald and Korb, 2011). Agricultural contracts explain an increasing share of agricultural sales. In 2008, production and marketing contracts accounted for 38 percent of the total value of agricultural production in the United States (MacDonald and Korb, 2011), up from 36 percent in 2004, and 28 percent in 1991(MacDonald, et al., 2004).

farm income by substantially reducing risks associated with input prices, production, and output prices inherent in agriculture. In general, farmers can retain a greater degree of autonomy in marketing contracts than in production contracts. Although some agricultural contracts are not designed to reduce risks, the risk management aspect of agricultural contracts provides important benefits to farmers (MacDonald, et al., 2004). While we are aware that different contracts address various types of risks in agriculture, i.e., production risk, price risk, etc, to varying degrees, the underlying assumptions in estimating the double-hurdle model, therefore, are that any contract is risk reducing than without it and that risk reduction is the major motivation for famers to use agricultural contracts.

The objective of the double-hurdle model is to decompose the relationship between risk preferences and contract use into two components: whether or not a farmer use contracts and the intensity at which the farmer use them. Our expectation, based on the unexpected results in the multivariate probit model, is that risk-loving has a positive impact on the former and risk averseness has a positive impact on the latter. Table 4.4 summarizes coefficient and marginal effect estimates from the double-hurdle model. Marginal effects are estimated at the means of the explanatory variables. Also presented are standard error estimates of the marginal effects, calculated by the bootstrap method described in Burke (2009). In Table 4.4, Tier 1 refers to whether or not contracts are used represented by equation (9) and Tier 2 represents equation (10), corresponding to the intensity of contract use.

Likert scale risk attitude has a positive and significant effect in Tier 1, but no such effect is found in Tier 2. The results here confirm our expectation that risk averseness can be a deterrent to doing something new, even if its purpose is to manage risks. More risk-loving famers are more likely to use contracts, as it was the case in the multivariate probit model. The marginal effect estimate of 0.010 indicates that an increase in Likert scale risk attitude by one on the 11-point scale increases the probability that a famer uses contracts by 1%. Since the standard deviation of Likert scale risk attitude is 2.44, a one standard deviation increase in Likert scale risk attitude increases the same probability by 2.4%.

Table 4.4: Factors Affecting Use and Intensity of Use of Contracts

Variables	Double-Hurdle Model					
	Tier 1 (Contract Use)			Tier 2 (Intensity of Contract Use)		
	Coefficient	Marginal Effect		Coefficient	Marginal Effect	
Likert Scale Risk Attitude	0.035***	0.010***	(0.002)	0.004	0.004	(0.003)
Operator Characteristics						
Primary Occupation	-0.875***	-0.244***	(0.015)	0.002	0.002	(0.020)
Raised on Farm	0.194***	0.054***	(0.017)	-0.017	-0.016	(0.019)
Years of formal education	0.001	0.000	(0.003)	-0.004	-0.004	(0.004)
Age	0.031**	0.009***	(0.003)	-0.011***	-0.010***	(0.004)
Age Squared	0.000***	-0.000***	(0.000)	0.000***	0.000***	(0.000)
Race	-0.163*	-0.045*	(0.025)	0.025	0.023	(0.028)
Gender	-0.058	-0.016	(0.030)	0.024	0.022	(0.031)
Farm Characteristics						
Total operated acres	0.002	0.000	(0.005)	-0.031***	-0.029**	(0.012)
Total operated acres squared	0.000	0.000	(0.000)	0.000***	0.000	(0.001)
Certified organic farm	0.281*	0.078*	(0.046)	-0.038	-0.034	(0.060)
Debt to Asset Ratio	0.015	0.004	(0.039)	0.104***	0.095***	(0.025)
Entropy Index	4.813***	1.343***	(0.165)	0.243*	0.221*	(0.129)
Soil Productivity Index	-0.008***	-0.002***	(0.001)	-0.003***	-0.003***	(0.001)
Full owner	0.009	0.002	(0.014)	0.081***	0.073***	(0.016)
Tenant	-0.029	-0.008	(0.019)	-0.084***	-0.076***	(0.025)
Rate of Return	0.026	0.007	(0.005)	-0.003	0.007	(0.005)
Statement	0.186***	0.052***	(0.013)	-0.001	-0.001	(0.016)
High Value Crop Farms	-0.193**	-0.054**	(0.021)	0.039	0.035	(0.028)
Livestock Farms (excluding	-0.243***	-0.068***	(0.013)	0.207***	0.189***	(0.020)
Regional Dummy Variables						
Northern Crescent	-0.110	-0.031	(0.024)	0.320***	0.291***	(0.036)
Northern Great Plains	-0.390***	-0.109***	(0.027)	0.135**	0.123**	(0.051)
Prairie Gateway	-0.557***	-0.155***	(0.025)	0.219***	0.199***	(0.048)
Eastern Upland	-0.005	-0.001	(0.024)	0.286***	0.260***	(0.036)
Southern Sea Board	0.601***	0.168***	(0.024)	0.297***	0.271***	(0.034)
Fruitful Rim	0.078	0.022	(0.025)	0.367***	0.335***	(0.039)
Basin and Range	-0.388***	-0.108***	(0.032)	0.221***	0.201***	(0.057)
Mississippi Portal	0.227***	0.063***	(0.023)	0.248***	0.226***	(0.036)
Intercept	-0.638			0.885***		
Number of Observations	5, 162					

Figures in brackets are standard error estimates of marginal effects calculated by bootstrap method with 1, 000 replications.
*** and ** indicate significance at 1% and 5% levels, respectively.

In contrast, risk preferences have no significant impact on the intensity at which contracts are used.[34]

A brief comparison of operator and farm characteristics across the two tiers gives us an interesting insight. More operator characteristics are significant in Tier 1 than in Tier 2, while more farm characteristics exhibit significance in Tier 2 than in Tier 1. It can be surmised that operators' personal characteristics, including risk preferences, play more pronounced roles when it comes to decisions at a more fundamental level, such as the one-time decision of whether or not to use contracts. In contrast, farm business characteristics may have more significant effects for decisions that have to be made on a relatively more frequent basis, such as adjusting the intensity of contract use.

Primary occupation has a very significant effect on contract use (Tier 1) both statistically and economically; farmers who works off-farm as a primary occupation is 24% less likely to engage in contracts. Farmers raised on farm are 5% more likely to use contracts. Age has a positive impact on whether or not to use contracts (Tier 1) but the quadratic relationship holds again, indicated by the negative and significant coefficient on age squared. Interestingly, when it comes to the intensity of contract use (Tier 2), age has a negative impact, but the impact is mitigated at higher ages due to the positive and significant effect of age squared. Racial minority farmers are 4.5% less likely to use contracts.

Total operated acres have a negative and significant impact on the intensity of contract use; a 1,000-acre increase in total operated acres leads to a 3% decrease in the intensity of contract use, measured by the share of farm income under contracts in the total value of production. Highly leveraged farms in terms of debt to asset ratio tend to use contracts at a higher intensity; a unit increase in debt-to-asset ratio increases the intensity of contract use by 9.5%. The entropy index is one of the few farm characteristics that have a significant impact in both Tiers 1 and 2. Note that this is a continuous variable ranging from 0 to 1, with 0 being no diversification at all and 1 being completely diversified. Enterprise diversification can be a risk management strategy by itself, but it has a positive correlation with contract use. A one standard deviation (0.048) increase in the entropy index leads to a 6.43% increase in the

[34] We estimated the same double-model separately for marketing contracts and production contracts. Likert scale risk attitude obtained essentially the same results in both models: a positive and significant effect in Tier 1 but no significant effect in Tier 2.

probability of contract use and 1.06% increase in the share of farm income under contracts. As it was the case in the multivariate probit model (Table 4.3), the soil productivity index has a negative impact on contract use and the negative effect holds true for the intensity of contract use. The probability of contract use and the intensity of contract use decrease by 2.76% and 4.15%, respectively, due to a one standard deviation (13.835) increase in the soil productivity index. Relative to part owners, who operate both owned and rented acres, a full-owner, on average, makes use of contracts at a higher intensity by 7.3% whereas a full-tenant does so at a lower intensity by 7.6%.

Farm types and the regional dummy variables are mostly significant in both Tiers 1 and 2. Interestingly, the regional dummy variables have mixed signs in Tier 1, however, in Tier 2, all of them have a positive and significant effect, relative to the excluded group of the Heartland region. Although the primary interest in this chapter is the relationship between Likert scale risk attitude and actual realization of risk preferences revealed through farm business decisions, for a more thorough understanding of the factors affecting contract use, a modeling approach specific to regions and farm types may be warranted.

4.6. Conclusion

Risk analysis in agricultural economics requires an accurate measurement of individual risk preferences. Agricultural economists often rely on the expected utility framework to quantify risk preferences, but any proposed measurement of risk preferences is never free from contradiction with the empirical evidence (Lagerkvist, 2005). The existing studies in agricultural economics documented inconsistency across different measures of risk preferences (Bard and Barry, 2001, Fausti and Gillespie, 2006). The focus of this chapter was risk preferences measured on a Likert scale. Although there has been no clear evidence of the validity for this variable in agricultural economics, in other branches of economics, risk preferences measured on a Likert scale was found a better predictor of actual risky behaviors under various circumstances (Dohmen, et al., 2011). A number of empirical studies utilized Likert scale risk attitude and obtained theoretically consistent results (Block, et al., 2009, Caliendo, et al., 2009, Jaeger, et al., 2010).

The overriding theme of the chapter was to examine the validity of Likert scale risk attitude using data from a nationwide survey of farm operators. We first estimated the ordered logit models and observed the importance of operators' personal characteristics such as primary occupation, education, age and gender. Their effects are robust to different model specifications. We then estimated the multivariate probit model to compare Likert scale risk attitude against three discrete variables representing actual realization of risk preferences revealed through off-farm labor participation and use of contracts and crop insurance. We unexpectedly found that risk-loving operators were more likely to use contracts and crop insurance, for which we posited an alternative explanation. That is, risk averseness may impose a negative impact on doing something new, even if it is to diversify and reduce risks, while risk averseness may be positively correlated with the intensity at which farmers are willing to use risk management strategies that are proven to be successful for the existing operation.

In order to empirically test this hypothesis, we examined the two potentially conflicting impacts of risk preferences on the adoption of agricultural contracts by a double-hurdle model. The results partially confirmed our expectation. Risk-loving farmers are more likely to use agricultural contracts, but it has no impact on the intensity at which these contracts are adopted. The finding in this study is consistent with the hypothesis in the sense that risk averse farmers are less likely to *begin to* use agricultural contracts, which may pose a considerable amount of risk to those who have never used it before.

The absence of a significant effect of Likert scale risk attitude on the intensity of contract use in the double-hurdle model may be attributed to the lack of situational context in Likert scale risk attitude. Dohmen, et al. (2011) report that, although Likert scale risk attitude is the most versatile predictor of risky behaviors under numerous settings, a measurement of risk preferences catered to a specific context always outperformed Likert scale risk attitude. Since data on the intensity of contract use in the double-hurdle model were available for only those who have adopted contracts, a measurement of risk preferences more specific to the contracting decisions may be necessary to better understand the relationship between risk preferences and the intensity of contract use.

As mentioned earlier, farm types and the regional dummy variables mostly obtained significant coefficients in both the multivariate probit model and double-hurdle model. Although it is beyond the scope of this study, a modeling approach specific to regions and farm types is recommended for a more detailed analysis of the factors affecting use of contracts and crop insurance. Nonetheless, this chapter fulfills the primary objective of empirically assessing the validity of Likert scale risk attitude, using a large scale representative sample of farmers. This chapter also provides important findings about factors explaining individual risk preferences for US farmers and the effect of risk preferences on use of risk management strategies.

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CHAPTER 5: SUMMARY AND CONCLUSIONS

The overriding theme of this dissertation was technology adoption in US agriculture. Although technology adoption is one of the most widely studied topics in agricultural economics, the present dissertation reflected upon the recent social and economic changes surrounding US farm sector and analyzed their implications on technology adoption.

The focus of the second chapter was the introduction of GM crops in US agriculture and its impact on off-farm labor allocation decisions by farm households. GM crops possess traits that are not possible through traditional plant breeding, such as herbicide tolerance and insecticide resistance, to allow for flexible weed and pest management practices (Fernandez-Cornejo and Caswell, 2006). Among the recent innovations in agriculture, GM crops are unique in that they are easy to implement and significantly reduce labor requirements. Despite the rapid increase in the adoption of GM crops immediately after the introduction in 1996, few studies have explored the impact of the time savings made possible by GM crops on farm households' time allocation decisions. To the best of the author's knowledge, this is the first study to examine the impact of GM crop adoption on off-farm labor participation by both farm operators and their spouses. Another feature of this study was that we quantified the intensity of GM crop adoption instead of using a binary dummy variable. The adoption intensity was calculated as the share of GM crop acres, soybeans and corn combined, in the total corn and soybeans acres. We utilized data from the 2004 – 2006 ARMS and estimated the bivariate Tobit model of off-farm labor supply by farm operators and their spouses.

The results from the econometric analysis partially confirmed *a priori* expectation that the adoption of the time saving technology, i.e., GM crops, leads to increased off-farm labor supply. We demonstrated that the adoption intensity has no significant impact on off-farm labor supply by farm operators whereas it has a positive and significant impact on off-farm labor supply by their spouses. Since farm operators are, by definition, are the primary decision-makers of farm operation, they are likely to have a comparative advantage in farming operation to their spouses, who tend to have less farming experience. Therefore, it is plausible that time savings made possible by the adoption of GM crops allow each member of the household to pursue an activity at which he/she has a comparative advantage, allowing operators to remain on farm and their spouses to work more off the farm. Marginal effects estimates showed that a unit increase in the adoption intensity of GM crops, i.e., growing no GM crops at all to growing GM crops only, results in a 33% increase in the probability of working off-farm by farm operators' spouses. For the spouses who do work off-farm, the same change in the adoption intensity of GM crops adds 9.89 hours per week to off-farm labor supply. The econometric analysis in this chapter also demonstrated that different sets of variables explained off-farm labor participation decisions by farm operators and their spouses. While the variables related to farm operation influence the operators' off-farm labor supply more prominently, off-farm labor supply by their spouses is more sensitive to the personal and household characteristics such as age, education, and the presence of young children. These results suggest that farm operators and their spouses play different but complimentary roles in maximizing household utility, further supporting the view that the farm household assigns different roles to the operator and the spouse based on their comparative advantages. The chapter provided important findings about the impact of the time saving technology in US agriculture and its implication on farm households' time allocation decisions.

The third chapter builds on the second chapter and considered the adoption of two technologies: GM crops as a representative of an easy-to-implement and management-saving technology and precision farming as a representative of a capital- and management-intensive technology. Given these two recent but contrasting innovations in US agriculture, the primary focus of the chapter was the relationship between farm operators' human capital, represented by years of formal schooling, and the adoption of these two technologies. In agriculture, farmers with higher education generally have better access to information and knowledge that are beneficial to farming operation. They also tend to possess a higher analytic capability to process the information and knowledge necessary to successfully implement new technologies and realize expected results. Hence, higher education allows farmers to make an efficient adoption decision (Rahm and Huffman, 1984) and be the early adopters who can take advantage of new technologies to extract maximum profit (Sunding and Zilberman, 2001). This chapter reconsidered this conventional belief. We hypothesized that the effect of education on technology adoption could be heterogeneous and even be negative. For example, education increases farmers' human capital and gives them more lucrative employment opportunities off the farm, which in turn decreases managerial time on-farm to implement new technology. Education, therefore, is expected to have a much smaller impact for those farmers who work off-farm than those who do not. Considering the facts that the number of farmers with college education has been steadily increasing over the past five decades (Mishra, et al., 2009) and an increasing share of farm household income is derived from off-farm sources (Fernandez-Cornejo, 2007), it is crucial to accurately assess the effect of education on technology adoption.

Using data from the 2006 ARMS, we estimated the bivariate probit model to examine the factors associated with the adoption of GM crops and precision farming. In doing so, we employed the propensity score matching method proposed by Mayen, et al. (2010) to address the endogeneity issue. The technology adoption model featured interactions between education and the dependence on off-farm income, with the expectation that the dependence on off-farm income influences the effect of education on technology adoption. The results confirmed *a priori* expectation and demonstrated very contrasting impacts of education on the adoption of the two technologies. The effect of education on the adoption of precision farming was positive for full-time farms, but much smaller for part-time farms that are more reliant upon off-farm income. When it comes to the adoption of GM crops, the effect of education was found negative for full-time farms, contrary to our expectation, but less negative for farms that are more reliant on off-farm income. Given the increasing federal spending on agri-environmental programs that encourage farmers to adopt environmentally benign practices over the last two decades (Cattaneo, et al., 2005), a precise assessment of the effect of education on technology adoption is necessary. Our findings suggest that simply targeting highly educated farmers to promote new technologies on the basis of the conventional theory is not sufficient to achieve an efficient policy outcome. Of particular importance is the nature of the technology, i.e., management and labor requirements, and the farm household's dependence on off-farm income. With the increasing trend in off-farm labor participation among farm households in the United States (Fernandez-Cornejo, 2007, Mishra, et al., 2009), the heterogeneous impacts of education on technology adoption may become more prominent in the future.

As a caveat to the second and third chapters, it is important to note that diffusion of technology is a dynamic process (Rogers, 2003) and thus results from these chapters may only be applicable to the specific timeframe of the data analyzed. Studies using more recent data may provide a different picture of how education and time allocation decisions influence the adoption of GM crops and precision farming, which deserves further academic attention.

The conceptual framework in the second and third chapters was based on the agricultural household model introduced in the first chapter. While the model proved useful for the objectives in these chapters, a caveat was the assumption of risk neutrality among farm households. The fourth chapter, therefore, sheds light on the role of individual farmers' risk preferences in technology adoption. The central difficulty in risk research in agricultural economics is how to measure individual risk preferences. A wide variety of methods have been proposed to measure farmers' risk preferences, but any proposed method is never free from contradiction with the empirical evidence (Lagerkvist, 2005). The measurement of risk preferences used in this chapter was of qualitative nature. Specifically, the respondents were asked to choose a number between 0 and 10 on a Likert scale to represent the level of risk at which they are comfortable in making decisions, with 0 being "avoid risks as much as possible" and 10 being "take risks as much as possible." Although the validity of self-reported risk attitudes such as this one is in questions for several reasons discussed in Chapter 4, a recent study by Dohmen, et al. (2011) demonstrated that risk preferences measured on a Likert scale is the best all-round predictor of risky behaviors.

Using this qualitative measure of risk attitudes measured on an 11-point Likert scale found in the 2001 ARMS, we estimated three econometric models to identify the factors explaining individual farmers' risk attitudes and the effect of the risk preferences on the adoption of risk management strategies. We first estimated the ordered logit models and observed the importance of the operators' personal characteristics such as primary occupation, education, age and gender. We then estimated the multivariate probit model to compare Likert scale risk attitude against three discrete variables representing actual realization of risk preferences revealed through off-farm labor participation and use of contracts and crop insurance. The results unexpectedly showed that risk loving operators were more likely to adopt contracts and crop insurance. The plausible explanation we proposed for this surprising results was that risk averseness may impose a negative impact on doing something new, even if its purpose is to diversify and reduce risks, while risk averseness may be positively correlated with the intensity at which farmers are willing to use risk management strategies that are proven to be successful for the existing operation. The third model, a double hurdle model, was estimated to empirically assess the hypothesis that there are two potentially conflicting impacts of risk preferences on the adoption of risk management strategies, using agricultural contracts as an example. The results partially confirmed our expectation. Risk loving farmers are more likely to use agricultural contracts, but it has no impact on the intensity at which these contracts are adopted. The finding in this study is consistent with the hypothesis in the sense that risk averse farmers are less likely to *begin to* use agricultural contracts, which may pose a considerable amount of risk to those who have never used it before. As suggested by Dohmen, et al. (2011), a more context-specific measure of risk preferences may be more appropriate to explain the intensity of contract use. In addition, the fact that Likert scale risk attitudes obtained significant coefficients in all of the three models estimated in this chapter attests to its potential as a valid measure of risk preferences for risk research not only in labor economics and entrepreneurship literature but also in agricultural economics. Although the results were only partially consistent with our expectation, this chapter fulfilled the primary objective of empirically assessing the validity of Likert scale risk attitudes, using a large scale representative sample of farmers.

Finally, the contributions of the empirical findings provided in this dissertation are summarized. As mentioned in the first chapter, our society is fundamentally dependent on agriculture as it is the primary source of the nutrients essential to human activities. Adoption of new technologies alters production function, enhances productivity, and allows farmers to produce more output with less input. As a consequence, more wealth is produced and conserved resources from farm production can be used elsewhere to produce other goods and services, which would contribute to enrich the quality of our lives. In order to secure sufficient supplies of food and fiber products, policy-makers are required to have a good understanding of the factors associated with technology adoption. The understanding is also indispensable for the well-being of the consumers whose lives are profoundly dependent on affordable foods that are healthy and of good quality.

Although the geographical focus of the empirical analyses presented in this dissertation is limited to the United States, their implications are not. Poverty reduction, the first of the Millennium Development Goals put forth by the United Nations in 2000 (United Nations, 2012), is arguably the most imminent global issue the current generation faces. Given the fact that a vast majority of the poor in developing countries are heavily dependent on agriculture for their livelihoods, improving production efficiency in agriculture is the key to reducing poverty in these countries. Consequently, it is extremely important to understand the factors affecting technology adoption in agriculture. Technologies such as genetically modified crop varieties and precision farming considered in this dissertation are already widespread in US farm sector, but yet to be fully accepted in many other countries. The practical benefits of the simple and qualitative measure of risk attitude considered in the forth chapter may be more pertinent to risk research in developing countries. Findings from this dissertation may prove beneficial for policy makers in countries that are introducing or will introduce these technologies to forecast their potential impacts on the agricultural sector and the rest of the society. It is with my sincere hope that this dissertation makes humble contributions to improve the well-being of those involved in agriculture, both producers and consumers, not only in the United States, but elsewhere in the world.

5.1. References

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