ABSTRACT

KOTSIRI, SOFIA. Three Essays on the Economics of Precision Agriculture Technologies. (Under the direction of Roderick M. Rejesus.)

This study consists of three essays focused on economic issues related to cotton precision farming (PF) technologies in the Southeastern region of the United States. Precision farming technologies are typically delineated as either site specific information gathering (SSIG) technologies or as variable rate technologies (VRT). The first essay investigates the effect of farmers' perceived spatial yield variability on precision technology adoption. We extend the theoretical model developed by Isik and Khanna (2002) and find empirical evidence that farmers who perceive their yields as variable will more likely adopt at least one of the precision farming components. In addition, farmers who use computer in their farm management, believe that the technology will be profitable and important in the future, acquire precision farming information through university publications, as well as younger ones who plan on being in the industry for more years, will more likely adopt at least one of the technology's components.

The second essay explores factors that differentiate environmentally motivated farmers (i.e., those who rank environmental benefits higher than profit, based on a Likert style ranking) from farmers who make decisions based solely on financial criteria. To achieve this objective, we apply a proportional odds model that accounts for the ordered nature of the dependent variable. Our results indicate that participation in agricultural easement programs, perceived importance of precision farming (PF) in the future, as well as the perceived improvement in environmental quality following the precision technologies'

use, all positively influence the decision to adopt for environmental reasons. In contrast, educational attainment and use of University Publications to acquire information about precision agriculture have a positive impact on adoption based on profit motives. A second issue that we study is examining the factors that affect farmers' perceptions about perceived improvements in environmental quality following the precision technology adoption.

The third essay examines the factors affecting the duration of duration of use of soil sampling and yield monitor technologies. A duration analysis that accounts for selectivity bias is used to investigate the impact of different variables on the speed of abandonment. The estimated Weibull model for soil sampling suggests that farm size is the most important determinant in using soil sampling. Farmers with larger farm sizes tend to use soil sampling for a shorter period of time. On the other hand more experienced farmers with longer planning horizons, whose income comes mainly from farming sources, will likely use soil sampling longer. Regarding yield monitors, more experienced cotton farmers, those who believe that PF will be important in the future, those that have higher levels of educational attainment, and farmers whose income is not solely dependent on farming, will more likely utilize the technology longer.

Three Essays on the Economics of Precision Agriculture Technologies

by
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DEDICATION

To my *husband Ioannis*,

without whom this thesis wouldn't have started and, needless to say, been completed

to my *son Andreas*,

without whom this thesis would have been completed a year earlier

and to my *parents Andreas and Liana*,

without whom there would have been no me.

BIOGRAPHY

Sofia Kotsiri was born in 1984 in Patras, Greece. She was the first child of Andreas Kotsiris and Liana Terzi. In 2001 she was named a scholar of the National Scholarship Foundation of Greece for her admission ranking in the University of Patras (1st among 150 students). She received her undergraduate and masters' degrees in Economics from the University of Patras in 2005 and 2007, respectively. Along with her academic studies, she worked for the National Telecommunications Organization of Greece (OTE). In August of 2007 she came to the United States to pursue her PhD in Economics at North Carolina State University. Her doctorate was funded by scholarships from the Foundation of George and Victoria Karelias, and from A. Mentzelopoulos' bequest. As a graduate student, she taught undergraduate courses in Economics, worked for the Graduate School, and had internships at the North Carolina Solar Center (NCSC) and the Institute for Emerging Issues (IEI).

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CHAPTER 1

INTRODUCTION

Precision agriculture consists of site specific information gathering technologies (SSIG), such as yield monitors, soil sampling, aerial imagery etc., as well as variable rate input application technology (VRT). These technologies allow farmers to identify the spatially heterogeneous parts of their fields, and apply their inputs at a variable rate based on location-specific needs rather than uniformly based on average conditions. In particular, SSIG equipment uses information about soil, climate factors, landscape and through software they design a digital map that depicts the variation in different parts of the field. The farmer can afterwards collect and analyze these spatial data and implement the appropriate management response based on the information. The use of VRT requires the adoption of at least one SSIG technology. As a consequence, farmers can minimize the over or under application of their inputs, which implies potential increase in profits - given the high price of fertilizers, they now use inputs more efficiently - and improvement in environmental quality, due to less chemical runoff. Site specific technology has been utilized in the production of major commodity crops (i.e., wheat, soybeans, corn, peanuts), but in our study we focus only on cotton production in the Southeastern region of the United States.

The first essay examines the effect of perceived spatial yield variability on precision technology adoption. Using a two step multinomial probit/logit model, and a sequential Heckman correction model, we find that farmers who believe that their within-field spatial yield variability is high are the ones more likely to utilize precision farming information

technologies and/or apply their inputs at a variable rate. On the other hand, farmers who perceive their yields as more spatially homogeneous would tend not to adopt any of the precision technologies bundle. The multinomial probit model accounts for decisions made at one time, since currently many producers hire VRT service providers to do the grid soil sampling, data analysis, and input recommendations. On the other hand, the two step Heckman correction model considers the possibility of evaluating the effectiveness of SSIG first before adopting VRT at a second time. The importance of our study lies in the fact that it examines the effect of perceptions about a variable that affects profitability of the technology and not perceptions about attributes of technology as it is the case with most technology adoption studies. Also, in reality what really matters is the farmers' prior perception about within-field spatial variability rather than the actual spatial variability.

My second essay has two objectives. The first examines what differentiates environmentally motivated farmers (i.e., those who rank environmental benefits higher than profit, based on a Likert style ranking) from farmers who make decisions based solely on profit maximization criteria. Knowing the characteristics of precision technology users that adopt for environmental reasons and are more in tune with the environmental benefits of the technology would allow for more targeted educational and information dissemination programs that focus on the environmental advantages of the technology. A proportional odds model (POM) is proposed to estimate the factors affecting the degree of social responsibility on the technology adoption. The marginal effects indicate that the participation in agricultural easement programs, the perceived importance of precision farming (PF) in the future, as well as the perceived improvement in environmental quality following the

precision technologies' use, all positively influence the decision to adopt for environmental reasons. In contrast, educational attainment and use of University Publications to acquire information about precision agriculture have a positive impact on adoption based on profit motives. These results suggest that there may be a need for further technical advice and information from Extension focusing on environmental benefits of precision agriculture. The second objective explores the characteristics of producers who observed these improvements following precision technology adoption. Based on logistic regressions, the probability that a farmer observed any improvements in environmental quality (through the adoption of technology) was higher if the farmer used manure in his/her fields, was less dependent on income coming only from farming sources, and perceived that PF will be profitable in the future.

The third essay identifies factors that determine the duration of use of soil sampling and yield monitors. Previous studies have focused on the factors affecting the abandonment of the soil sampling technology, but none have investigated factors affecting the duration of use of site-specific information gathering technologies. This analysis will give some insights as to what factors make the adoption of the specific technologies more sustainable. We can only observe the actual length of use for those who adopted and abandoned the technology prior to the survey date. For the farmers who have not discontinued its use at the time of the survey, we have the problem of censoring, because they might quit in the future, but this is not an observable action. For these individuals, the statistical process is to right censor the duration at the end of the observation period. In this case, we assume that the farmer will eventually abandon the technology. We estimate a sample selection Weibull model

(Boehmke et al., 2006), and compare it with the simple parametric (Weibull) and semi-parametric (Cox) specifications of the hazard function in this analysis. The estimated Weibull model for soil sampling suggests that cotton producers with larger farms tend to use soil sampling technologies for a shorter period of time. On the other hand, farmers with longer planning horizons, and more experience will more likely use soil sampling for a longer duration. We also find that the length of use of yield monitors tend to be longer for farmers who believe that precision farming will be important in the future, are more educated and more experienced, and whose income comes mainly from farming.

CHAPTER 2

FARMERS' PERCEPTIONS ABOUT SPATIAL YIELD VARIABILITY AND PRECISION TECHNOLOGY ADOPTION

2.1 Introduction

Large agricultural fields consist of numerous sites (or sub-locations) that typically differ from one another with respect to the factors that affect crop yields (i.e., different soil characteristics for different locations). Variable rate technologies (VRT) aim to take advantage of the heterogeneity within fields by allowing farmers to vary input applications depending on location-specific needs. By contrast, conventional farm management practices apply inputs at a single rate uniformly across the entire field (typically based on its average conditions). If the responsiveness of yields to input varies substantially across a field, this average uniform application strategy (URT) can result in over-application of inputs on some parts of the field and under-application on other parts. Thus, variable rate application can potentially improve efficiency of input use (Torbet et al., 2007) and may lead to increased profitability and higher environmental benefits, especially in fields that are spatially heterogeneous. Moreover, it gives greater flexibility to farmers in choosing employees, since the electronic monitoring (guidance systems) does most of the steering and the detailed work (Griffin et al., 2004).

A prerequisite for successful implementation of VRT is the use of site-specific information gathering (SSIG) technologies that enable one to determine the degree of spatial

heterogeneity in fields. These SSIG technologies range from yield monitors to grid soil sampling and provide information about the variation in the physical and chemical properties of the soil across a field. Using spatially-referenced data from these site-specific technologies (e.g., nutrient content, soil quality, site-specific yields) allows one to apply varying input rates to match the within field variability. Hence, variable rate technology (VRT) adoption necessarily requires the adoption of at least one SSIG technology. However, the use of VRT in cotton production has historically been low relatively to other major crops. Reasons could be the high fixed cost of investment, software incompatibility (Griffin et al., 2004), and possibly lack of information and sufficient networks that would diffuse the feasibility and benefits of precision technology.

Previous studies based on farm survey data and discrete choice modeling techniques have investigated factors influencing the adoption of variable rate technologies (Fernandez-Cornejo, Daberkow, and McBride (2001); Khanna, Epouhe, and Hornbaker (1999); Khanna (2001); Roberts et al. (2004)). All of these studies aimed to determine farm (or farmer) characteristics (e.g., farm size, age, education, etc.) that significantly influence the decision to use VRT. Khanna (2001) and Roberts et al. (2004) assessed the impact of these farm characteristics within a framework that allows for sequential adoption of SSIG and VRT. Note that none of these studies specifically explored the role of farmers' perceptions about within-field variability in the decision to adopt the so-called VRT bundle (at least one SSIG technology along with VRT).

The objective of this paper is to determine whether farmers' perceptions about their spatial yield variability significantly influence the decision to adopt precision farming

technology. Previous literature has shown that the profitability of VRT critically depends on the degree of spatial heterogeneity in farmers' fields (Roberts, English, and Mahajanashetti, 2000; Isik and Khanna, 2002). Higher yield variability typically results in higher economic returns from variable rate applications, under the assumption of certainty and risk neutrality. But in reality what really matters is the farmers' prior perception about within-field spatial variability rather than the actual spatial variability. For example, a farmer who has not used any SSIG technology may believe that the spatial variability of the field is low (i.e., believes that the field is more spatially homogenous) based solely on prior experience of farming (See Rejesus et al., 2010 for evidence of this behavior). Hence, this particular farmer may decide not to utilize the VRT bundle because he believes that the potential economic returns from this investment may not be worth it due to the perceived lack of spatial heterogeneity (even if the field is, in reality, spatially heterogeneous).

Examining whether spatial yield variability perception affects VRT adoption behavior is consistent with recent literature that advocates the use of subjective perceptions in empirical models explaining economic behavior (Nyarko and Schotter, 2002; Manski, 2004; Bellemare, 2009). As Delavande, Gine, and McKenzie (2009) have shown, there are a number of studies in the agricultural economics literature that demonstrate how subjective perceptions influence decision-making in agriculture. For example, Hill (2007) found that subjective expectations about future coffee prices influence the allocation of labor used in coffee production. Gine, Townsend and Vickery (2008) reveal that farmers' perceptions about the start of the monsoon season affect their planting decisions even after controlling for a wide-range of farmer characteristics. The role of perceptions has also been examined in a

number of technology adoption studies as well (Gould, et al., 1989; Adesina and Zinnah, 1993; Adesina and Baidu-Forson, 1995; Sall et al., 2000; Abadi Ghadim, Panell, and Burton, 2005). Adrian et al. (2005) looks into three types of perceptions regarding precision technology adoption: the perceived usefulness, perceived net benefits and perceived ease of use. But note that most of these technology adoption studies investigate the influence of perceptions about the attributes of the technology itself and not the effects of perceptions about a spatially explicit factor that determines the profitability of the technology (i.e., field heterogeneity). Most recent studies (Larson and Roberts, 2004, Marra and Rejesus, 2010) studied how the use of SSIG technologies and specifically yield monitors influence the perceived within field spatial yield variation. To the best of our knowledge, no study has yet investigated the impact of perceptions about a spatially explicit variable in the adoption of agricultural technologies and this paper contributes to the literature in this regard.

2.2 Model

2.2.1 Conceptual Framework

We consider a constant returns production function $Y_i = f(x_i^j, z_i)$, where x_i is the applied input (e.g., fertilizer) per acre and z_i is the level of soil attribute (e.g., nutrient content) per acre at site i (Isik and Khanna, 2002). Under a uniform rate of input application, we would expect that $z_i = \bar{z}$ (i.e., from the producer's perspective, soil attribute is fixed at the perceived average based on information from prior experience farming). However, we assume that producers who choose to use only SSIG technologies recognize variability in *z* across the *i*

different sites and there is some uncertainty with the information from SSIG (i.e., information from SSIG is not perfect). In this case, our production function is represented as $Y_i = f(x^U, z_i)$ and the situation in which the farmer does not use any SSIG technologies is represented as $Y_i = f(x^U, \bar{z})$. Let *S* be a binary indicator of whether a farmer has utilized at least one SSIG technology, and *V* be a binary indicator that reflects the variable rate input application after the evaluation of the information obtained from the SSIG technologies. Both SSIG and VRT adoption can be observed, so we can distinguish between the following scenarios:

Scenario 1: S=0 and V=0 [No SSIG use and hence no VRT adoption]

Scenario 2: S=1 and V=0 [SSIG use but no positive evaluation, hence no VRT adoption]

Scenario 3: S=1 and V=1 [SSIG use and positive evaluation, hence VRT adoption]

The farmer's problem is to choose the optimal input level *x* after s/he has decided on whether s/he will use the conventional practices (scenario 1), use at least one SSIG technology but apply inputs uniformly (scenario 2), or purchase the whole package (scenario 3). Thus, the farmer will maximize the following expected utility:

(1) $$\max_{x_i, x} E\{U\} = E\{(1-S)EU_1 + S(1-V)EU_2 + (SV)EU_3\},$$

where EU_n (*n*=1, 2, and 3) are the expected utilities under each of the three scenarios.

Incorporating the partial adoption of precision technology (scenario 2) in equation (1) and building on the specification used in Isik and Khanna (2002; p. 252), equation (1) can be rewritten as:

(2) $$\max_{x_i, x} E\{U\} = E\{(1-S)(W_0 + A\pi^U) + S(1-V)(W_0 + A\pi^U - K^S) + (SV)(W_0 + A\pi^V - K^V)\}$$

or as

(3) $$\max_{x_i, x} E\{U\} = E\{W_0 + A\pi^U - SK^S + SV(A\Delta\pi - \Delta K)\},$$

where W_0 reflects the initial wealth, π^U is the quasi-rent (revenue minus fertilizer/input costs) using conventional uniform rate technology (URT), π^V is the quasi-rent under VRT, with $\Delta\pi = \pi^V - \pi^U$, A denotes the fixed land such that for N homogeneous sites of size A_i, it holds that $\sum_{i \in N} A_i = A$, and K^S, K^V are the fixed cost for SSIG and VRT practices, respectively, with $K^s < K^V$, and $\Delta K = K^V - K^s$.

The utility-maximizing adoption decision is obtained through a two-stage decision process. The farmer first obtains the utility-maximizing level of input use for each of the three adoption scenarios above. Assuming an internal solution, the first-order condition (FOC) to determine input use under scenario 1 is:

(4) $$\frac{\partial U}{\partial x^U} = E[U_W(Pf_x(x^U, \bar{z}) - w)] = 0,$$

where $\bar{z}$ is the average value of the soil attribute. Equation (4) reduces to the profit-maximizing condition: $Pf_x(x^U, \bar{z}) = w$. On the other hand, the optimal input levels for scenario 2 (SSIG only), and scenario 3 (VRT adoption) are determined using the FOC:

(5) $$\frac{\partial U}{\partial x_i^j} = E[U_W(Pf_x(x_i^j, z_i + z_i\varepsilon_i) - w)] = 0,$$

where j represent scenarios 2 and 3 ($j = U, V$) , and ε_i is the soil attribute uncertainty that arises from the imperfect information provided by the SSIG technology error, which is

assumed to vary proportionally with the level of the soil attribute. The second-order condition $\frac{\partial^2 U}{\partial x_i^{j2}} = H < 0$ is satisfied under risk aversion and a quasi-concave production function.

2.2.2 Comparative Statics: Technology Adoption and Perceived Spatial Variation

Given the optimal input levels from the FOCs in (4) and (5), the farmer decides to adopt SSIG technologies only (scenario 2) if the following conditions hold:

(6) $$EU[W_0 + A\pi^U - K^S] > EU[W_0 + A\pi^U]\text{, and}$$

(7) $$EU[W_0 + A\pi^U - K^S] > EU[W_0 + A\pi^V - K^V].$$

Similarly, the farmer will decide to purchase the VRT bundle (scenario 3) only if the following conditions hold:

(8) $$EU[W_0 + A\pi^V - K^V] > EU[W_0 + A\pi^U]$$

(9) $$EU[W_0 + A\pi^V - K^V] > EU[W_0 + A\pi^U - K^S].$$

It is necessary to add more structure to the decision rules (i.e., add more detailed specifications) in equation (6) to (7) to ascertain the effect of perceived spatial variation on the precision technology adoption decision. First, we assume an exponential utility function $U = -e^{-\varphi W}$ where the Arrow-Pratt measure of risk aversion is defined as: $\varphi = {-\bar{U}_{ww}}/{\bar{U}_w}$. Second, the variability of returns associated with precision technology scenarios 2 (i.e., SSIG

adoption only) and 3 (i.e., SSIG and VRT adoption) are represented by σ_U^2 and σ_V^2, respectively. Given these additional assumptions and using a second-order Taylor series approximation of expected utility, a risk-averse decision-maker would choose scenario 2 (SSIG only) if the following conditions hold:

(10) $$U[W_0 + A\pi^U - K^S] - U[W_0 + A\pi^U] - U_W[W_0 + A\pi^U - K^S]\sigma_U^2\varphi > 0 \text{, and}$$

(11) $$U[W_0 + A\pi^U - K^S] - U[W_0 + A\pi^V - K^V] - U_W[W_0 + A\pi^U - K^S]\sigma_U^2\varphi > 0 .$$

Similarly, a risk-averse producer would choose scenario 3 (SSIG and VRT) if the following conditions hold:

(12) $$U[W_0 + A\pi^V - K^V] - U[W_0 + A\pi^U] - U_W[W_0 + A\pi^V - K^V]\sigma_V^2\varphi > 0 \text{, and}$$

(13) $$U[W_0 + A\pi^V - K^V] - U[W_0 + A\pi^U - K^S] - U_W[W_0 + A\pi^V - K^V]\sigma_V^2\varphi > 0 .$$

The first two terms in the above equations indicate that incentives to adopt precision technologies, either SSIG only (scenario 2) or the VRT bundle (scenario 3), increases as the expected utility following adoption increases, whereas the third term shows that incentives to adopt decrease as the variability of precision technology returns (σ_U^2, σ_U^2) and the degree of risk aversion (φ) increase.

Explicitly utilizing the exponential utility specification and to be more consistent with the decision rules in the earlier equations (6) to (9), the risk-averse farmer will choose scenario 2 (SSIG only) if:

(14) $$E[-e^{-\varphi(W_0 + A\pi^U - K^S)}] \geq E[-e^{-\varphi(W_0 + A\pi^U)}] > 0 \text{, and}$$

(15) $$E[-e^{-\varphi(W_0 + A\pi^U - K^S)}] \geq E[-e^{-\varphi(W_0 + A\pi^V - K^V)}] > 0 .$$

Similarly, the risk-averse farmer will choose scenario 3 (SSIG and VRT) if:

(16) $$E[-e^{-\varphi(W_0+A\pi^V-K^V)}] \geq E[-e^{-\varphi(W_0+A\pi^U)}] > 0 \text{, and}$$

(17) $$E[-e^{-\phi(W_0+A\pi^V-K^V)}] \geq E[-e^{-\phi(W_0+A\pi^U)}] > 0 .$$

Hence, given the same monotonic utility functions for all scenarios, it is clear from (15) to (17) that risk averse farmers will adopt precision technologies (scenarios 2 or 3) if the quasi-rent differential between the adoption and non-adoption of precision technologies is positive. This quasi-rent differential using the assumption above is derived in detail in Appendix A and can be expressed as:

(18) $$\Delta\pi = -\frac{P}{2f_{xx}}[\sigma_z^2(f_{xz})^2 - \frac{(f_x)^2}{A}\sum_{i\in N} A_i(\frac{F_i^2}{(1-F_i)^2})].$$

The quasi-rent differential expression in (18) can then be used to evaluate the effect of spatial yield variability perceptions on incentives to adopt precision technology because of the presence of the σ_z^2 variable on the right-hand side of the equation. This represents the within field spatial variability of the soil attribute. But note that this is not perfectly known and, as argued in the introduction, the perceived within field spatial yield variability is a typically used proxy in order to actually make ex ante adoption decisions. Hence, we can represent the perceived within field yield variability as $\hat{\sigma}_z^2$.

Using equation (18) and a moment generating function approach (See Yassour et al. 1981; Isik and Khanna, 2002), it can be shown that the necessary condition for the farmer to choose scenario 2 (SSIG only) is:

(19) $$-\frac{AP}{2f_{xx}}[\hat{\sigma}_z^2(f_{xz})^2-\frac{(f_x)^2}{A}\sum_{i\in N}A_i(\frac{F_i^2}{(1-F_i)^2})]-K^S-\frac{\varphi}{2}\sigma_U^2>0\ ,$$

and the necessary condition for the farmer to choose scenario 3 (SSIG and VRT) is:

(20) $$-\frac{AP}{2f_{xx}}[\hat{\sigma}_z^2(f_{xz})^2-\frac{(f_x)^2}{A}\sum_{i\in N}A_i(\frac{F_i^2}{(1-F_i)^2})]-K^V-\frac{\varphi}{2}\sigma_V^2>0.$$

Given the positive sign of conditions (19) and (20), precision technology adoption occurs if the quasi-rent differential is greater than the fixed cost plus the risk premium ($\frac{\varphi}{2}\sigma_V^2$). Therefore, incentives for adoption of precision technology adoption increase with increases in expected returns from the technologies due to higher perceived within field spatial yield variability. In other words, the theoretical decision rules in (18) and (19) suggest that a higher perceived within field spatial yield variability increases returns to adoption of precision technologies and, consequently, increases incentives to adopt these precision technologies. The positive relationship between perceived within field spatial variability and adoption incentives shown in this theoretical model is what we want to empirically test below.

2.3 Estimation

The technology adoption decision is demonstrated as a discrete choice, which takes the following values:

(21) $$Y_i=\begin{cases}1 & if\ \ U^*_{PF_1}>U^*_{PF_2} \quad \text{and } U^*_{PF_1}>U^*_{PF_3}\\ 2 & if\ \ U^*_{PF_2}>U^*_{PF_1} \quad \text{and } U^*_{PF_2}>U^*_{PF_3}\\ 3 & if\ \ U^*_{PF_3}>U^*_{PF_1} \quad \text{and } U^*_{PF_3}>U^*_{PF_2}\end{cases}\ .$$

We approached this problem both from the perspective of: (1) a simultaneous decision (Multinomial Logit/Probit Model), where farmers decide simultaneously whether they will utilize SSIG technologies and/or VRT, and (2) a sequential adoption decision (three-step Heckman Correction Model), where cotton producers first decide on the SSIG technology they will use, and then on the appropriate management response, i.e., VRT or URT implementation. The motivation behind the Multinomial Logit/Probit was that nowadays many farmers hire VRT service providers to do all the work, i.e., grid soil sampling, data analysis, input recommendation and variable rate input application (Surjandari and Batte, 2003). Thus a farmer does not necessarily need to adopt SSIG technology first and then on second time decide on the input application. With this approach we also account for the fact that farmers may adopt specific components of the technology (e.g., SSIG only) rather than the whole bundle.

Given that we have survey data with a relatively low response rate (see data description in Section 2.3 below) and possible over-representation of larger farms (>500 acres), we implemented a weighted estimation based on the 2002 Ag. Census. More specifically, we estimated post stratified survey weights in a weighted multinomial logit/probit regression. This would adjust for potential under or over representation of survey respondents within strata. Farmers were classified into h=1 to 72 strata depending on farm location (by state) and cotton acreage (12 states × 6 acreage classes [1–99, 100–249, 250–499, 500–999, 1000– 1999, or 2000+ acres]). Weights were then estimated using a ranking procedure suggested by Brackstone and Rao (1976).

2.3.1 Two Step Approach: Multinomial Logit/Probit

From the above model, the empirical equations to be estimated are specified as follows:

(22) $$Y_1 = \beta_1' Z + \varepsilon_1$$

(23) $$Y_2 = \beta_2' Z + \varepsilon_2$$

(24) $$Y_3 = \beta_3' Z + \varepsilon_3.$$

We first estimate a multinomial logit (MNL) model where the dependent variable (i.e., the precision farming technology choice Y_i) is discrete and takes the values of 1, 2, and 3, respectively. MNL is an extension of the binary logistic regression and allows for more than two discrete outcomes for the dependent variable. Producers in our specification are considered consumers of agricultural technologies that are choosing among these alternatives.

The probabilities associated with the choices in (22)-(24) take the form:

(25) $$\text{Prob}(Y_i = j) = P_{i,j}.$$

Thus, the log likelihood for a multinomial logit model with independent observations becomes:

(26) $$\text{Log } L = \sum_i \sum_j Y_{ij} \log P_{i,j}.$$

Since we cannot identify separate βs for all of the choices, we set the coefficients for one of the outcomes (i.e., the reference or base alternative) equal to one (Jones, 2000). Hence, the probability of farmer *i* choosing alternative *j* is given by:

(27) $$P_{i,j} = P(Y_i = j) = \frac{\exp(x_i\beta_j)}{1+\sum_{j=1}^{3}\exp(x_i\beta_j)}, \quad j = 2,3,$$

and the choice probability for the base is:

(28) $$P_{i,j} = P(Y_i = 1) = \frac{1}{1+\sum_{j=1}^{3}\exp(x_i\beta_j)},$$

where x_i is the vector of independent variables associated with farmer *i*, and β_j is the vector of parameters associated with the alternative *j*.

In our case, the non adoption of both SSIG and VRT (scenario 1) may be treated as the baseline category. The multinomial logit model, which accounts for the simultaneity of choices, would then identify the probability of using SSIG and applying inputs at a uniform rate (relative to the non adoption alternative) and the probability of using SSIG and applying inputs at a variable rate (relative to the non adoption choice). The estimated parameters of a multinomial logit tend to be difficult to interpret directly as compared to a bivariate choice model. To capture the effect of the explanatory variables on the farm management decisions, we examine the derivative of the probabilities with respect to the explanatory variables. These derivatives are defined as (Greene 1990):

(29) $$\frac{\partial \text{Prob}(Y_i = j)}{\partial x_{ik}} = P_j[\beta_{jk} - \sum_{j=1}^{3}\text{Prob}(Y_i = j)\beta_{jk}], \; j=1, 2, 3; \; k=1,\ldots, K.$$

The above relationship demonstrates the marginal effect of x_{ik} on the probability of adopting one of alternatives 1, 2, and 3.

We calculate both the average marginal effects *AME* (i.e., calculating the marginal effects for each observation and then taking the average of it), as well as the marginal effects at the average, *MEA* (i.e., marginal effects calculated at the means of each independent variable). Studies have shown though, that evaluating the derivatives at their sample means leads to biased predictions (Akay and Tsakas, 2008), and, thus, AME may be preferred over MEA, which is why we only report AME in the tables.

The MNL method is computationally simpler than other multi-choice regression approaches (e.g., multinomial probit), but it relies on the restrictive assumption of Independence of Irrelevant Alternatives (IIA). This property states that the probability of choosing among two alternatives is not affected by the presence of additional alternatives, i.e., the error terms of the choice equations are independent and homoscedastic (Greene, 2003). If the IIA assumption is violated, then the MNL approach may not be appropriate and other multi-choice models that do not rely on this assumption would be preferred, such as the multinomial probit (MNP) model.

The MNP model is a natural alternative to the MNL approach in that it relaxes the IIA assumption inherent in the MNL model, and allows a more flexible pattern of error correlation (Cameron and Trivedi, 2005). The structural equations of the MNP model are (Greene, 2003):

(30) $$U_{i,j} = x_j \beta_{i,j} + \varepsilon_{i,j}, \text{ where } j = 1, 2, 3 \text{ and } \varepsilon_j \sim N(0,\Sigma)$$

Therefore, the probability associated with alternative *j* equals:

(31) $$P_{i,j} = \text{Prob}(Y_i = j) = \text{Prob}\{\varepsilon_{i,k} - \varepsilon_{i,j} \leq (x_{i,j} - x_{i,k})' \beta\} \text{ for all } k$$

The computation is time consuming (for dimensionality higher than 2), because the distribution of ε is such that (30) does not have a closed form solution. Moreover, Σ has to be positive definite. To facilitate the estimation of MNP, one often makes the assumption that the alternative errors are independent standard normal so that Σ=I. In this case, (30) reduces to a one dimensional integral, that can be approximated by quadrature methods (Cameron and Trivedi, 2005)[1].

In this study, we estimate both the MNL and MNP models. But we also perform a Hausman test (Hausman and McFadden, 1984) to determine whether the IIA assumption is violated in our data (and in essence determine whether MNL or MNP is more appropriate). The basic idea of the Hausman test is to estimate the model with all of the alternatives and then to re-estimate it, dropping one of the alternatives. If IIA holds, then omitting alternatives in the estimation should not change the parameter estimates systematically. Statistically significant differences in the parameter estimates suggest that the IIA assumption is violated and the results from the MNP may be preferred.

2.3.2 Endogeneity of Spatial Yield Variability Perceptions

The explanatory variable of main interest in this study is a measure of farmer's spatial yield variability perceptions (denoted as $SYCV_i$ and is part of the vector x_i). We want to determine whether spatial variability perceptions affect the precision technology choice. A potential problem with this variable is endogeneity, since it is likely that there are unobserved

[1] Since we use only 3 choices, identification should not be a problem, and restrictions on standard deviations and correlations are not required (Greene, 2003).

variables (e.g., unobserved management ability, motivation) that influence both the spatial variability perceptions and the choice of precision technologies to adopt. Hence, we utilize an instrumental variable (IV) approach to control for this endogeneity, where the first stage is estimating the equation below by ordinary least squares (OLS) regression:

(32) $$SYCV_i = \boldsymbol{\alpha}_1 \mathbf{W}_i + e_i,$$

where $\mathbf{W}_i$ is a vector of control covariates (that include instrumental variables) and e_i is an error term.

The predicted value of $SYCV_i$ in (32) is then utilized in the MNL/MNP instead of the actual $SYCV_i$ value. The use of an IV approach in the estimation requires good instruments in $\mathbf{W}_i$ that are correlated with $SYCV_i$, but likely uncorrelated with the unobservables that affect precision farming adoption decisions (embodied in the error term). Without any strong instruments, the inferences from our estimation must be interpreted with caution. The use of the predicted values of $SYCV_i$ in the MNL/MNP necessitates the use of bootstrapped standard errors, since the conventional standard errors would be incorrect. We followed a bootstrapping technique based on replicate weights for complex survey data. We resample with replacement in stratum *h*, since problems arise either when the units are sampled without replacement or when the number of sampled clusters per stratum is small (Shao, 1996).

2.3.3. Three Step Approach: Heckman Correction Model

An alternative approach to estimate the effect of spatial yield variability perceptions on the adoption of variable rate technologies is with a binary choice model (i.e., probit or logit):

(33) $$VRT_{i,n}^{*} = \beta_1 SYCV_{i,n} + \beta_2 X_{i,n} + \varepsilon_n \text{ , } n\text{=0, 1,}$$

where $VRT_{i,n} = 1$ if $VRT_{i,n}^{*} > 0$ (i.e., producer *i* adopted the VRT bundle) and $VRT_{i,n} = 0$ otherwise. As above, $SYCV_{i,n}$ is a measure of the within-field spatial variability perceptions, $\mathbf{X}_i$ is a vector of observable covariates, β_1 is the effect of spatial variability perceptions to be estimated, $\boldsymbol{\beta}_2$ is vector of parameters to be estimated, and ε_n is an error term, where $\varepsilon_n \sim N(0,\Omega)$. We can view the decision model in (33) as part of a sequential decision process where the first step is a decision to adopt SSIG technology and the second step is a decision to adopt VRT technology (given that one adopts SSIG). This is plausible because the adoption of VRT technologies necessarily requires adoption of a SSIG technology. Only SSIG adopters have the choice of applying the VR technology. Therefore, within a sequential decision process, one can estimate (33) using only the subsample of SSIG technology adopters.

A concern with the approach of including only the SSIG subsample is non-random sample selection (i.e., farmers may self-select into the SSIG adopter pool). To account for this selection issue, one can use Heckman's (1979) procedure of appending an inverse mills ratio to equation (33). A SSIG adoption equation as specified below can first be estimated using a binary choice model (i.e., probit or logit):

(34) $$SSIG_{i,m}{}^{*} = \boldsymbol{\gamma}\mathbf{Z}_{i,m} + v_m,\ m=0,\ 1,$$

where $SSIG_{i,m} = 1$ if $SSIG_{i,m}{}^{*} > 0$ (i.e., producer i adopted SSIG technologies) and $SSIG_{i,m} = 0$ otherwise, $\mathbf{Z}_{i,m}$ is a vector of observable covariates, $\boldsymbol{\gamma}$ is a vector of parameters to be estimated, and v_m is an error term. Note that estimating (34) requires the "full" sample of cotton producers that includes both the adopters of SSIG and the non-adopters of SSIG. From the parameter estimates in (34), the inverse mills ratio for the sub-sample $SSIG_{i,m} = 1$ is computed as follows:

(35) $$\hat{\lambda}_i = \frac{\phi(\mathbf{Z}_{i,m}\hat{\boldsymbol{\gamma}})}{\Phi(\mathbf{Z}_{i,m}\hat{\boldsymbol{\gamma}})},$$

where ϕ and Φ are standard normal probability density function (pdf) and cumulative density function (cdf), respectively. The inverse mills ratio in (35) is then appended to equation (33) as an extra explanatory variable to account for potential non-random sample selection. The performance of the Heckman model depends on the collinearity between the inverse Mills ratio and the explanatory variables in the outcome equation (33) (Jones, 2001). The fact that we did not exclude any of the regressors used in first stage regression, from the outcome equation, along with the high degree of non-response, might increase the risk of high collinearity[2].

As with the MNL model above, endogeneity of the spatial variability perceptions variable is still a problem in the estimation of equation (33). An instrumental variable

[2] The VIFs (Variance Inflation Factors) diagnostics are all below 1.6 for all independent variables, which suggests that none of them could be considered as a linear combination of other regressors. Hence, multicollinearity is not a problem for our specification

approach using predicted values of $SYCV_i$ is also used in the three-step Heckman correction model here.

2.4 Data

Data for this study were collected from a survey of cotton producers in 12 states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas and Virginia. This survey was developed to query cotton producers about their attitudes toward and use of precision farming technologies (i.e., SSIG and VRT). Following Dillman's (1978) general mail survey procedures, the questionnaire, a postage-paid return envelope, and a cover letter explaining the purpose of the survey were sent to each producer. The initial mailing of the questionnaire was on February 20, 2009, and a reminder post card was sent two weeks later on March 5, 2009. A follow-up mailing to producers not responding to previous inquiries was conducted three weeks later on March 27, 2009. The second mailing included a letter indicating the importance of the survey, the questionnaire, and a postage paid return envelope. A mailing list of 14,089 potential cotton producers for the 2007-2008 marketing year was furnished by the Cotton Board in Memphis, Tennessee. Among responses received, 1981 were counted as valid, and thus used in our study.

Our survey consisted of three main sections: 1. precision agriculture technology (i.e., sources of information about technology, ways of applying inputs, expectations, etc.), 2. farm and production data (i.e., farm location, acres of owned and/or rented land, yields per acre

etc.), and 3. socioeconomic characteristics (i.e., age, experience with farming, education level, income etc). Only 35% of the valid responses indicated use of at least one SSIG technologies (some producers made use of more than one technology), and around 19% applied their inputs at a variable rate. The most popular SSIG technologies were grid and zone soil sampling, followed by yield monitors with GPS. The most used variable rate management applications were for fertility or lime, then followed by growth regulators. Less than half of respondents are high school graduates and almost 25% has a bachelor's degree. Most of the farmers' income ranges from $50,000 to $99,000 annually, whereas as 10% of cotton producers in our survey have income above $500,000.

2.5 Variable Construction & Empirical Specification

2.5.1 Dependent Variables

Based on the estimation strategies described above, we construct the necessary dependent and independent variables using responses from the survey questionnaire. To construct the dependent $VRT_{i,n}$ variable, we utilized the survey question that asked farmers to indicate the acres on which five information gathering technologies (i.e., yield monitoring with GPS, aerial satellite, handheld GPS units, green seeker and electrical conductivity) were used in order to make the variable rate decision (i.e., drainage, lime, seeding, growth regulator, fungicide, herbicide, irrigation etc). Moreover, VRT application includes map-based and sensor-based methods. Thus, we checked whether the farmers who reported number of acres on which they applied VRT, also indicated how they generate their input application map.

(See Figure 1, questions 17, 26 and 28). Any producer who provided an answer for these questions[3] is a VRT adopter ($VRT_{i,n} = 1$). For the MNL/MNP approach, this variable coincides with scenario 3 (i.e., Y_i=3: SSIG and VRT adoption).

To construct the Site-Specific Information Gathering Technology (*SSIG*) variable, we used the answers of farmers who checked one of the following in question 16 of the survey questionnaire: cotton yield monitors, grid sampling, soil maps, satellite imagery, aerial photography or COTMAN technologies (See Figure 2). This sample consists of all SSIG adopters (that also adopted either URT or VRT approach). For the MNL/MNP model, we used the same question to depict SSIG users, but we excluded the farmers who utilize VRT (i.e., Y_i=2: SSIG and URT adoption). The remaining producers that did not adopt both SSIG and VRT correspond to the first (non-adopter) category in the MNL/MNP approach (i.e. Y_i=1: no adoption of SSIG and VRT).

The $SYCV_i$ variable, on the other hand, is calculated based on the answers about the least productive, average productive and most productive sections of the farmer's field (See Figure 3). We first utilize the spatial variability formula used in Larson and Roberts (2004) to calculate the perceived Spatial Yield Variability (*SYVAR*) variable:

$$SYVAR = 0.33*(Y_{LOW} - Y_{AVG})^2 + 0.33*(Y_{MID} - Y_{AVG})^2 + 0.33*(Y_{HIGH} - Y_{AVG})^2, \quad (36)$$

where Y_{LOW} is the estimate for the yield of the least productive portion of field, Y_{AVG} is the estimated average yield for the typical field, Y_{HIGH} is the estimated yield for the most

[3] There was a small fraction of farmers who answered "don't know". We included them in the adopters' category in the sense that they might have not been aware of the exact number of acres where they utilized VR practices.

productive portion, and Y_{MID}=3* Y_{AVG} - Y_{LOW} – Y_{HIGH}. We, then, used the *SYVAR* and Y_{AVG}, in order to create the coefficient of spatial yield variability ($SYCV_i$) statistic based on the following formula:

$$SYCV_i = \frac{SYVAR_i^{0.5}}{Y_{avg}} * 100, \tag{37}$$

where $SYVAR_i^{0.5}$ is the standard deviation of spatial yield variability estimated using (36).

2.5.2 Explanatory Variables

From our review of the existing literature, we identified the potential explanatory variables affecting precision farming adoption decisions and created proxy variables when needed (based on the availability of data). The same set of explanatory variables is used in the MNL/MNP model and the Heckman model[4]. Farmer and farm characteristics, that are hypothesized to affect technology decisions (based on the literature) were education, age, use of computer in farm management, experience in farming, percentage of taxable income from farming, perceptions about future importance and profitability of precision farming, manure application, information about precision agriculture through university publications, average yields, plan of farming, participation in agricultural easement programs, and location dummies.

[4] In addition, we utilized the same set of explanatory variables in both stages of the 2-step Heckman approach (with the only difference that the VRT probit regression includes the region dummies). In practice, it is very difficult to find plausible identification restrictions, in which case the Heckman model is estimated with the same set of regressors in each equation. Then, identification relies on the non-linearity of inverse mills ratio (Jones 2001, Cameron and Trivedi, 2005).

We would expect that producers with a bachelors or a graduate degree are most likely to adopt precision technology (*EDUC*), because of the human capital and the technical skills that they have acquired through their education. Younger farmers (*AGE*) are expected to be more familiar with the new technologies, thus more likely to adopt precision farming. Nonetheless, they are also less experienced, which implies that they might not be aware of their field variability, thus not eager to adopt new technologies. Hence, the sign cannot be determined a priori. The sign indeterminacy is similar regarding the years of farming (*EXPERIENCE*). The use of computer (*COMPUTER*) is hypothesized to have a positive effect on precision farming, since this means that farmers may be more comfortable with new technologies and this variable can also be considered as a proxy for innovativeness (Surjandari and Batte, 2003). To capture the effect of income in technology adoption, we used a proxy variable that accounted for the percentage of the 2007 taxable household income coming only from farming (*INCOME*), which is different from categories of pretax total household income from both farm and nonfarm sources (as used in Banerjee et al., 2008). We would expect that the higher this percentage, the higher the probability of adopting precision technology, in the sense that farmers who make a living mostly by farming will probably invest more on practices improving their yields and profitability. Similarly, information resulting from university publications (INFO) will likely affect farmers in favor of precision technology. Last, farmers who participated in agricultural easement programs (AG EASE) are more concerned about the environment, thus more likely to adopt environmentally-friendly practices, such as precision technologies.

Moreover, we incorporated farmers' perceptions about the potential profitability and importance of precision farming in the near future (i.e., 5 years from the time the survey was conducted). We would expect that farmers who perceive that precision farming will be important (*IMPORTANCE*), as well as those who believe that its use will be more profitable in 5 years (*PROFIT*), are more likely to adopt SSIG and VRT technologies. We added variables for manure use (*MANURE*), past average yields (*YIELDS*), , farmer's future plan about farming (PLAN), as well as 12 state dummies (AL, AR, FL, GA, LA, MS, MO, NC, SC, TN, TX and VA) that capture the effect of farm location on VRT adoption[5]. We would expect that higher average cotton lint yields in the past (*YIELDS*) may imply positive effect on the probability of adopting VRT. The effect of manure on VRT is expected to be negative. Farmers who use manure might less likely adopt VRT, since manure is not as responsive to site-specific information technologies compared to inorganic fertilizers (Khanna, 2001). On the other hand, the more years somebody plans to work at his farm (PLAN), the higher the probability of utilizing precision technologies.

Regarding the variable of interest ($SYC\hat{V}$), we expect that farmers who perceive their yields as more variable, would be more likely to utilize information gathering technologies, in order to better see their true within field variability. In addition, there is a higher likelihood that farmers who have higher spatial yield variability perceptions will also apply their inputs at a variable rate. Farmers, who perceive their yields as more homogeneous than what they are in reality, will more likely not utilize the technology.

[5]We omitted the TX dummy during the estimation.

2.5.3 Instruments for Spatial Yield Variability Perceptions

For the vector $\mathbf{W}_i$, we included two instrumental variables -- the 10-year county average yields and the sum of dryland and irrigated cotton acres (own and rented). We used the 2007 acres as a reference and the 2008 acreage if there is no information based on the 2007 acres. The 10-year county average (*PINDEX*) may be a good instrument since it is publicly available information that gives a benchmark to individual producers as to where their field may stand in comparison to the county (NASS, USDA). Hence, we posit that it influences perceptions about spatial variability but is not correlated with farm-level unobservable variables. The expected sign of *PINDEX* is ambiguous and depends on how farmers see their fields in high or low yielding areas. Regarding the total acreage (*FARM SIZE*), previous studies (Isik and Khana, 2002) have indicated a positive relationship between the farm-size and the spatial within field yield variability. Therefore, we would expect that producers who operate large farms would believe that their yields are more variable.

2.6 Results & Discussion

2.6.1. Multinomial Logit/Probit Estimation

The first stage perceived spatial yield variability regression indicate significant coefficients and sensible signs. Farmers in high yielding areas perceive that their yields are more homogenous, whereas farmers with large acreage believe that their yields are more variable (Table 2).

In Table 3, we present the parameter estimates from both the MNL and MNP models. As noted above, we use the "non-adoption" category *(alternative 1*) as the reference point or the base category for the second-stage estimation of the multinomial logit/probit model. Results of the Hausman test to determine the appropriateness of IIA indicate that the null hypothesis of IIA validity is rejected (i.e., differences in coefficients are systematic). The chi-squared statistic when omitting alternative 2: ((SSIG & URT) and comparing it with the full model with all alternatives is 11.19 (p-value<0.001). On the other hand, the chi-squared statistic when omitting alternative 3: ((SSIG & VRT) and comparing it with the full model with all alternatives is 5.28 (p-value=0.0053). These results suggest that IIA may be violated and the MNP model may be preferred in this case. The parameter estimates from the MNL or MNP model are simply the values that maximize the likelihood function and typically do not have direct interpretation. Hence, marginal effects need to be calculated to properly assess the effects of the explanatory variables on precision technology choice.

Based on Table 5, the conditional probability of adopting at least one SSIG technology with uniform rate input applications (i.e. choosing *alternative 2*) was significantly related with the predicted spatial yield variability perceptions ($SYC\hat{V}$), the educational level of the producer (*EDUC*), the information received from university publication about precision technology (*INFO*), the expectations about the potential profitability of precision farming in 5 years (*PROFIT*), the perceptions about its future importance (*IMPORTANCE*), and the years somebody plans on being into farming (*PLAN*). Producers, who perceive that their yields are more variable ($SYC\hat{V}$ **)**, will more likely adopt SSIG technologies (by 0.01%). More educated farmers (*EDUC*), producers who believe that information gathering

technologies will be important in five years (*IMPORTANCE*), and those who plan on farming more years (*PLAN*), will more likely utilize these technologies (by 0.2, 13.6, and 1.6 percentage points, respectively). Similarly survey participants who acquired information about precision agriculture through university publications have 4.3% higher probability of adopting SSIG technologies than the other two alternatives, all else held constant.

On the other hand, the perceptions about future profitability (*PROFIT*) seem to inversely affect the use of information gathering technologies and the uniform rate input application. Farmers who believe that the new technology will be less profitable in the future are likely to use SSIG technologies but apply their inputs at a uniform rate (11.2%). Although, these farmers may access their true yield variability through SSIG, they are reluctant to purchase VRT if they consider precision farming potentially non profitable. Among the regional dummies, AL, AR, LA, MS, NC, SC, TN, and VA all positively affect the probability that farmers, whose fields are located in one of the above states, will adopt SSIG technologies compared to a farm in TX, which is considered as the benchmark category due to the high number of farms.

With respect to farmers choosing the third alternative (i.e., adoption of at least one SSIG technology and then application of VRT), we found that higher perceived spatial yield variability ($SYC\hat{V}$) increases the probability of adoption by 0.007%. Farmers with more years of formal education (*EDUC*), who use computer (*COMPUTER*), university publications to access precision farming information (*INFO*), have less experience in farming (*EXPERIENCE*), as well as those who believe that precision agriculture will be profitable in the future (*PROFIT*) will more likely use the VRT bundle (by 1.3%, 8.3%, 10.5%, 0.2% and

13.9%[6], respectively). The positive and significant coefficient of the *PROFIT* variable is indicative of the importance of the profit maximizing decision in farmer's behavior. The probability of using a new technology is higher for those who believe that this technology would bring profits in the near future (i.e., 5 years from now). Last, all state dummies except from Florida (FL) have a positive impact on the probability of VRT adoption, all held constant.

Our marginal effects are consistent with Roberts et al. (2004) and Khanna (2001) for the majority of the explanatory variables. However, we should not ignore the fact that our variables are constructed using survey questions, thus differences in the signs might result from the differences between the data and the variable construction.

2.6.2. Heckman Correction Model

The estimation in the first stage of the Heckman approach includes both the farmers who used URT as well as the VRT adopters (Table 6). Second stage results are presented in Table 7. The effect of perceived spatial yield variability ($SYC\hat{V}$ **)** on the probability of adopting VRT (conditional on the adoption of SSIG) is positive and its AME is statistically significant at the 1% level. It suggests that farmers, who tend to the think that their within-field spatial yield variability is higher, are the ones more likely to adopt VRT (0.007%). Likewise, those who reported higher expectations for future profitability (*PROFIT*) will more likely adopt the VRT bundle (14% increase in probability of adoption). The p-value of the inverse mills ratio

[6] The interpretation of marginal effects is as follows: a 1 unit increase in log(INCOME) which represents a 100% increase in INCOME, will increase the probability of adoption P[Y=3] by 0.001. That is a 100% increase in INCOME increases the probability by 0.1 percentage points.

(*IMR*) indicates that sample selection is not a potential problem in our model specification. The rest of our explanatory variables are statistically insignificant.

2.7 Conclusions

Applying econometric models (MNL/MNP and Heckman) that account for simultaneous and sequential adoption, we examine the role of perceived spatial yield variability as it relates to the precision farming adoption decision. Higher likelihood of adopting precision technologies is associated with spatial yield variability perceptions, age, information, plans about farming, use of computer, and perceptions about expected profitability and importance of precision technologies. Our results suggest that farmers who perceive their yields as more spatially variable are the ones most likely to adopt site-specific technologies, and/or apply their inputs at a variable rate. Those who view their yields as less heterogeneous (i.e., lower spatial yield variability) will probably not utilize any of the site specific technologies. This is consistent with the theoretical insight in Isik and Khanna (2002) who found that higher spatial variability increase the incentives to adopt precision technologies. Our estimates are robust under the two regression model specifications investigated. Furthermore, by giving different weights to farms of different sizes, we alleviate the problem of over-representation that may come from larger cotton farms (i.e., non-representative sample due to a low response rate).

Our results have important implications for policy makers, agribusiness firms and technology suppliers. Since the perceived yield variability of SSIG adopters leads to higher

conditional probability of VRT adoption, VRT dealers have incentives to offer discounted or free initial spatial maps of farmer fields so that producers can better see their true within field variability and potentially adopt the SSIG/VRT technology. The impact of perceptions on precision farming makes the role of mass media, extension, and social networks more critical in providing information and training about the benefits of precision agriculture. More informed producers will likely have more accurate perceptions about their spatial yield variability. Economic characteristics, risk factors, and past outcomes play a systematic role in the formation of expectations (Delavande et al., 2009). If we neglect to account for the factors affecting the subjective beliefs, then estimated perceptions may be inaccurate and the decision to adopt precision technologies may be affected.

The use of subjective perceptions in our study expands the range of demographic variables that have been used throughout the adoption literature. However, there are current limitations that need to be further addressed. First, our regressions were based on farmers' estimates about their spatial yield variability. Aside from the limitation of using instruments that we had to deal with, the spatial variability estimates provided by farmers also do not necessarily reflect accurate predictions. Studies have showed that, when people are asked about their expectations (i.e., average field productivity), only 23% is closest to the true mean, whereas the majority gives the median and/or mode (Delavande et al., 2009). Furthermore, we do not have estimates about input prices and we did not incorporate VRT equipment costs that could influence farmers' economic incentives by choosing VRT versus URT. Another limitation is the cross sectional nature of our dataset. The input application decisions affected by perceived yield variability cannot be extended over a longer time

horizon, in order to compare perceptions of the individual farmer, before and after the adoption.

Future research could involve more extensive data from previous surveys (2001 and 2005). The respondents might be different but we can possibly still shed more light on the effect of farmers' perceptions on technology adoption over this longer nine-year period. Moreover, we could include the third and fourth moments (i.e., skewness and kurtosis of the reported yields for different proportions of the field) and see their impact on technology adoption. Another study could also measure the intensity of perceived yield variability. For example, farmers were asked to indicate by how much more/less were their average yields more/less variable (i.e., by 5%, 10%, 20%, 30%, 40%, 50% or above) after using yield monitors. This information was not examined in the current study because of the small number of respondents who answered this question. In addition, we could investigate how the evaluation of different sources of information about precision technology affect the perceptions about yield variability (e.g., do farmers who receive information from farm dealers report higher yield estimates than those who rely more on university extension or crop consultants).

Table 2.1 Summary of dependent and independent variables used in the Multinomial Logit Model & Heckman Model

Variable Name	Description	Obs	Mean
SYCV	Perceived Spatial Yield Variability (lbs. lint/acre)	1054	47.51
PINDEX	Soil productivity index using 10-year county yields as a proxy (US Dept. of Agriculture, National Agricultural Statistics Service, 2010)	1981	5470
FARM SIZE	Total acreage of dry land (sum of rented and owned acres) for the 2007 crop season	1499	653.8
SSIG **(**for MNL/MNP)	Farmer used at least one site-specific information gathering technology (yes=2; no=0) but not VRT	321	2
SSIG (for Heckman)	Farmer used at least one site-specific information gathering technology and/or VRT (yes=1; no=0)	694	1
VRT	Farmer applied her inputs at a variable rate (yes=1; no=0)	1495	0.249
EDUC	Years of Formal Education Excluding Kindergarten	1592	14.16
AGE	Age of the farm operator (as of the 2009 survey year)	1660	56.09
EXPERIENCE	Number of Years farming	1644	31.63
IMPORTANCE	Farmer perceived that precision farming would be important in five years from now (yes=1; no=0)	1631	0.846
PROFIT	Farmer perceived that precision farming would be profitable to use in the future (yes=1; no=0)	1599	0.534
INCOME	Percentage of 2007 taxable household income coming only from farming sources	1611	72.24
COMPUTER	Farmer uses computer for farm management (yes=1; no=0)	1664	0.537
YIELDS	Estimate of average yield per acre for 2007 crop season	1970	837.2
MANURE	Farmer applied manure on his/her fields (yes=1; no=0)	1699	0.181
INFO	Farmer used University publications to obtain precision farming information (yes=1; no=0)	1634	0.348
PLAN	Years to plan farming in the future	1642	3.749
AG EASE	Farmer participated in agricultural easement programs (yes=1; no=0)	1648	0.085

Table 2.1 continued

	Location Dummies			
AL	Farm located in Alabama	(yes=1; no=0)	1981	0.063
AR	Farm located in Arkansas	(yes=1; no=0)	1981	0.041
FL	Farm located in Florida	(yes=1; no=0)	1981	0.016
GA	Farm located in Georgia	(yes=1; no=0)	1981	0.099
LA	Farm located in Louisiana	(yes=1; no=0)	1981	0.044
MS	Farm located in Mississippi	(yes=1; no=0)	1981	0.072
MO	Farm located in Missouri	(yes=1; no=0)	1981	0.022
NC	Farm located in North Carolina	(yes=1; no=0)	1981	0.095
SC	Farm located in South Carolina	(yes=1; no=0)	1981	0.030
TN	Farm located in Tennessee	(yes=1; no=0)	1981	0.056
TX	Farm located in Texas	(yes=1; no=0)	1981	0.445
VA	Farm located in Virginia	(yes=1; no=0)	1981	0.011

Table 2.2 OLS regression of SYCV

Variable	Coefficient (Std.err)	P-value
PINDEX *	-0.095 (0.052)	0.070
FARMSIZE **	0.200 (0.088)	0.024
INTERCEPT ***	3668.9 (333.9)	<0.001
No. of Obs. 750		
F(2, 747) = 4.61		

*, **, *** denote significance levels at a 10%, 5% and 1% respectively

Table 2.3 Weighted Multinomial Logit and Probit Parameter Estimates (N=770)

Variable	Multinomial Logit Coefficient	Multinomial Logit P-value	Multinomial Probit Coefficient	Multinomial Probit P-value
Scenario 2: SSIG-URT Adoption (Y_i=2)				
INTERCEPT	-7.246 ** (1.316)	0.002	-5.917 ** (1.234)	0.002
$SYC\hat{V}$	0.001 (0.0007)	0.112	0.001 (0.0006)	0.102
EDUC	0.075 * (0.035)	0.075	0.054 * (0.023)	0.053
AGE	-0.064 (0.051)	0.251	-0.048 (0.035)	0.215
YIELDS	0.00004 (0.0003)	0.896	0.00006 (0.0002)	0.813
INFO	0.732 *** (0.128)	<0.001	0.564 *** (0.099)	0.001
IMPORTANCE	1.299 ** (0.486)	0.037	0.950 ** (0.314)	0.019
PROFIT	-0.564 ** (0.110)	0.002	-0.399 ** (0.082)	0.002
INCOME	0.001 (0.002)	0.487	0.001 (0.002)	0.511
COMPUTER	0.394 ** (0.107)	0.010	0.378 ** (0.076)	0.002
EXPERIENCE	0.032 (0.034)	0.383	0.026 (0.026)	0.350
MANURE	-0.080 (0.120)	0.528	-0.050 (0.101)	0.631

Table 2.3 continued

PLAN	0.137 ** (0.048)	0.030	0.101 ** (0.039)	0.038
AG EASE	-0.002 (0.134)	0.984	-0.056 (0.090)	0.550

Scenario 3: SSIG-VRT Adoption (Y_i=3)

INTERCEPT	-10.86 ** (2.029)	0.002	-8.922 ** (2.121)	0.004
$SYC\hat{V}$	0.0009 ** (0.0002)	0.005	0.0009 ** (0.0002)	0.014
EDUC	0.144 (0.079)	0.118	0.113 (0.064)	0.122
AGE	-0.002 (0.016)	0.885	-0.001 (0.010)	0.923
YIELDS	0.0002 (0.0002)	0.301	0.0002 (0.0001)	0.312
INFO	1.176 *** (0.118)	<0.001	0.913 *** (0.082)	<0.001
IMPORTANCE	0.635 ** (0.196)	0.018	0.437 ** (0.134)	0.014
PROFIT	1.084 ** (0.223)	0.003	0.774 *** (0.142)	0.001
INCOME	0.012 (0.009)	0.226	0.008 (0.006)	0.242
COMPUTER	0.914 * (0.379)	0.052	0.696 ** (0.248)	0.026

Table 2.3 continued

EXPERIENCE	-0.008 (0.014)	0.585	-0.005 (0.009)	0.616
MANURE	-0.198 (0.207)	0.376	-0.165 (0.169)	0.362
PLAN	0.0001 (0.080)	0.998	0.005 (0.053)	0.917
AG EASE	0.187 (0.174)	0.324	0.099 (0.140)	0.501

Table 2.4 Weighted Marginal Effects* from the Multinomial Logit Model (N=770)

	Scenario 1=No Adoption ($Y_i=1$)		Scenario 2=SSIG-URT Adoption ($Y_i=2$)		Scenario 3=SSIG-VRT Adoption ($Y_i=3$)	
Variable	Marginal Effect	P-value	Marginal Effect	P-value	Marginal Effect	P-value
$SYC\hat{V}$	-0.0001 ** (<0.001)	0.002	0.0001 * (<0.001)	0.092	0.00005 * (<0.001)	0.078
EDUC	-0.016 ** (0.007)	0.024	0.003 ** (0.001)	0.030	0.012 ** (0.006)	0.038
AGE	0.005 (0.004)	0.211	-0.008 (0.005)	0.156	0.002 (0.002)	0.258
YIELDS	-0.00002 (<0.001)	0.619	-5.38e-06 (<0.001)	0.880	0.00003 (<0.001)	0.121
INFO	-0.146 *** (0.019)	<0.001	0.046 ** (0.017)	0.007	0.100 *** (0.005)	<0.001
IMPORTANCE	-0.157 *** (0.038)	<0.001	0.139 ** (0.052)	0.008	0.018 (0.024)	0.455
PROFIT	-0.027 ** (0.010)	0.008	-0.114 *** (0.017)	<0.001	0.141 *** (0.018)	<0.001
INCOME	-0.001 (0.0007)	0.166	-0.0002 (0.0002)	0.207	0.001 (0.0008)	0.108
COMPUTER	-0.098 *** (0.018)	<0.001	0.013 (0.020)	0.509	0.084 ** (0.032)	0.008
EXPERIENCE	-0.002 (0.003)	0.537	0.004 (0.003)	0.234	-0.002 * (0.001)	0.085
MANURE	0.021 * (0.011)	0.064	-0.002 (0.020)	0.908	-0.018 (0.024)	0.447
PLAN	-0.012 (0.010)	0.247	0.017 *** (0.004)	<0.001	-0.005 (0.006)	0.394

Table 2.4 continued

AL	-0.262 *** (0.023)	<0.001	0.060 *** (0.018)	0.001	0.202 *** (0.030)	<0.001
AR	-0.290 *** (0.053)	<0.001	0.128 ** (0.043)	0.003	0.161 ** (0.077)	0.038
FL	-0.032 (0.053)	0.551	-0.091 (0.098)	0.355	0.123 (0.105)	0.243
GA	-0.265 *** (0.024)	<0.001	0.046 (0.053)	0.383	0.219 *** (0.035)	<0.001
LA	-0.393 *** (0.021)	<0.001	0.212 *** (0.018)	<0.001	0.181 *** (0.018)	<0.001
MS	-0.278 *** (0.086)	<0.001	0.131 *** (0.025)	<0.001	0.147 ** (0.070)	0.037
MO	-0.125 * (0.066)	0.061	0.021 (0.042)	0.606	0.103 *** (0.027)	<0.001
NC	-0.319 *** (0.040)	<0.001	0.155 *** (0.018)	<0.001	0.163 *** (0.040)	<0.001
SC	-0.403 *** (0.047)	<0.001	0.207 *** (0.025)	<0.001	0.196 *** (0.048)	<0.001
TN	-0.317 *** (0.067)	<0.001	0.132 *** (0.033)	<0.001	0.184 *** (0.050)	<0.001
VA	-0.402 *** (0.069)	<0.001	0.211 ** (0.091)	0.021	0.191 *** (0.036)	<0.001

*__Note:__ Reported Values are the Average Marginal Effects (AME) and the P-Values based on **Bootstrapped Robust Standard Errors**

Table 2.5 Weighted Marginal Effects* from the Multinomial Probit Model (N=770)

	Scenario 1=No Adoption ($Y_i=1$)		Scenario 2=SSIG-URT Adoption ($Y_i=2$)		Scenario 3=SSIG-VRT Adoption ($Y_i=3$)	
Variable	Marginal Effect	P-value	Marginal Effect	P-value	Marginal Effect	P-value
$SYC\hat{V}$	-0.0002 ** (<0.001)	0.006	0.0001 * (<0.001)	0.081	0.00007 (<0.001)	<0.001
EDUC	-0.016 ** (0.007)	0.026	0.002 ** (0.001)	0.030	0.013 * (0.007)	0.054
AGE	0.005 (0.004)	0.183	-0.008 (0.005)	0.120	0.002 (0.001)	0.165
YIELDS	-0.00002 (<0.001)	0.577	-1.15e-06 (<0.001)	0.973	0.00002 (<0.001)	0.144
INFO	-0.149 *** (0.019)	<0.001	0.043 ** (0.017)	0.016	0.105 *** (0.004)	<0.001
IMPORTANCE	-0.148 *** (0.029)	<0.001	0.136 ** (0.045)	0.003	0.011 (0.026)	0.662
PROFIT	-0.027 ** (0.011)	0.011	-0.112 *** (0.018)	<0.001	0.139 *** (0.016)	<0.001
INCOME	-0.001 (0.0008)	0.215	-0.0002 (0.0001)	0.202	0.001 (0.0008)	0.123
COMPUTER	-0.108 *** (0.018)	<0.001	0.024 (0.016)	0.143	0.083 ** (0.027)	0.002
EXPERIENCE	-0.002 (0.003)	0.484	0.004 (0.003)	0.202	-0.002 ** (0.001)	0.036
MANURE	0.021 (0.013)	0.103	0.0008 (0.023)	0.971	-0.022 (0.027)	0.418
PLAN	-0.011 (0.010)	0.233	0.016 *** (0.004)	0.001	-0.004 (0.005)	0.357

Table 2.5 continued

AL	-0.262 *** (0.023)	<0.001	0.069 *** (0.014)	<0.001	0.193 *** (0.028)	<0.001
AR	-0.295 *** (0.065)	<0.001	0.133 ** (0.043)	0.002	0.161 * (0.083)	0.054
FL	-0.048 (0.053)	0.365	-0.070 (0.066)	0.294	0.118 (0.089)	0.186
GA	-0.272 *** (0.025)	<0.001	0.050 (0.050)	0.316	0.221 *** (0.033)	<0.001
LA	-0.400 *** (0.023)	<0.001	0.222 *** (0.026)	<0.001	0.178 *** (0.027)	<0.001
MS	-0.281 ** (0.090)	0.002	0.134 *** (0.028)	<0.001	0.147 ** (0.071)	0.039
MO	-0.126 * (0.067)	0.061	0.038 (0.039)	0.332	0.087 ** (0.030)	0.004
NC	-0.330 *** (0.037)	<0.001	0.164 *** (0.020)	<0.001	0.165 *** (0.039)	<0.001
SC	-0.389 *** (0.062)	<0.001	0.204 *** (0.018)	<0.001	0.184 *** (0.056)	0.001
TN	-0.320 *** (0.062)	<0.001	0.138 *** (0.030)	<0.001	0.182 *** (0.048)	<0.001
VA	-0.402 *** (0.071)	<0.001	0.213 ** (0.091)	0.019	0.188 *** (0.033)	<0.001

*__Note:__ Reported Values are the Average Marginal Effects (AME) and the P-Values based on Bootstrapped Robust Standard Errors

Table 2.6 Weighted 1st Step Probit Model of SSIG Adoption

Variable	Coefficient	P-value	Marginal Effect	P-value
INTERCEPT	-1.733 ** (0.665)	0.009	---	---
EDUC	0.059 ** (0.028)	0.037	0.018 ** (0.008)	0.034
AGE	-0.024 ** (0.009)	0.012	-0.007 ** (0.002)	0.012
YIELDS	0.00006 (<0.001)	0.452	0.00002 (0.00002)	0.450
INFO	0.683 *** (0.129)	<0.001	0.206 *** (0.035)	<0.001
IMPORTANCE	0.571 ** (0.198)	0.004	0.172 ** (0.059)	0.004
PROFIT	0.133 (0.144)	0.358	0.040 (0.043)	0.357
INCOME	0.003 (0.002)	0.117	0.001 (0.0007)	0.110
COMPUTER	0.298 ** (0.133)	0.025	0.090 ** (0.039)	0.022
EXPERIENCE	0.013 (0.008)	0.110	0.004 (0.002)	0.110
MANURE	0.112 (0.182)	0.537	0.034 (0.055)	0.538
PLAN	0.034 (0.040)	0.396	0.010 (0.012)	0.395

Wald chi2(12) = 105.80

Pseudo R-squared = 0.1826

N= 770

Table 2.7 Weighted* 2nd Step Probit Model of VRT Adoption

Variable	Coefficient	P-value	Marginal Effect	P-value
INTERCEPT	-5.584 (4.256)	0.231	---	---
$SYC\hat{V}$	0.0003 ** (0.0001)	0.030	0.00007 ** (<0.001)	0.026
IMR	-0.041 (4.729)	0.993	-0.008 (0.963)	0.993
EDUC	0.071 (0.083)	0.419	0.014 (0.015)	0.351
AGE	0.012 (0.020)	0.575	0.002 (0.004)	0.566
YIELDS	0.0001 (<0.001)	0.255	0.00002 (<0.001)	0.214
INFO	0.528 (0.647)	0.441	0.107 (0.123)	0.385
IMPORTANCE	0.112 (0.487)	0.824	0.022 (0.097)	0.814
PROFIT	0.689 ** (0.199)	0.011	0.140 *** (0.031)	<0.001
INCOME	0.007 (0.007)	0.356	0.001 (0.001)	0.277
COMPUTER	0.462 (0.406)	0.293	0.094 (0.074)	0.205
EXPERIENCE	-0.009 (0.012)	0.476	-0.001 (0.002)	0.467
MANURE	-0.080 (0.115)	0.507	-0.016 (0.023)	0.484
PLAN	-0.018 (0.027)	0.533	-0.003 (0.005)	0.497
AG EASE	0.020 (0.069)	0.776	0.004 (0.014)	0.765
AL	1.011 *** (0.186)	0.001	0.206 *** (0.029)	<0.001
AR	0.805 ** (0.323)	0.042	0.164 ** (0.081)	0.044
FL	0.648 * (0.320)	0.083	0.132 * (0.076)	0.083
GA	1.173 *** (0.068)	<0.001	0.239 *** (0.035)	<0.001
LA	0.904 ** (0.185)	0.002	0.184 *** (0.021)	<0.001
MS	0.788 ** (0.267)	0.022	0.160 ** (0.069)	0.020

Table 2.7 continued

MO	0.516 ** (0.104)	0.002	0.105 *** (0.029)	<0.001
NC	0.874 *** (0.112)	<0.001	0.178 *** (0.039)	<0.001
SC	0.907 *** (0.180)	0.001	0.184 *** (0.049)	<0.001
TN	0.981 ** (0.204)	0.002	0.199 *** (0.060)	0.001
VA	0.974 ** (0.215)	0.003	0.198 *** (0.060)	0.001
N= 727				

*__Note:__ Reported Values are the Average Marginal Effects (AME) and the P-Values based on **Bootstrapped Robust Standard Errors**

17. For each variable rate cotton management decision in the left column of the table below, indicate the acres on which the five information gathering technologies were used to make the variable rate decision. Leave blanks where the technology was not used. (Provide your best estimate.)

Variable Rate Decision	1. Yield Monitoring with GPS	2. Aerial/Satellite Infrared Imagery	3. Handheld GPS Units	4. Green Seeker	5. Electrical Conductivity (for example, Veris, Soil Doctor)
Drainage					
Fertility or Lime					
Seeding					
Growth Regulator					
Harvest Aids					
Fungicide					
Herbicide					
Insecticide					
Irrigation					

Figure 2.1A

Variable rate input application includes map-based and sensor-based methods. Map-based uses a computer to generate an input application map. The map is entered into a data card and placed in a variable rate controller on the implement or tractor. Sensor-based uses sensors to measure desired properties and the information is used immediately to control a variable rate applicator on-the-go.

26. Have you used a map-based method to apply inputs? (Circle one) Yes No **(If No, go to Question 28)**

28. Have you used a sensor-based method to apply inputs? (Circle one) Yes No

Figure 2.1B

Figure 2.1: Variable Rate Technology (VRT) Construction (2.1A and 2.1B)

16. How do you assess the yield variability *within* a typical cotton field on your farm? (Check all that apply)
Cotton yield monitor _____ Grid sampling _____ Year-to-year field records _____
Soil maps _____ Consultants' estimates _____ Satellite imagery _____
Aerial photography _____ COTMAN _____ Other (specify) _____

Figure 2.2: Site Specific Information Gathering Technologies (SSIG) Construction

15. Yields vary within a field. Give your best estimate for *cotton yields* (lbs. lint/acre) for the following portions of your **typical field**:

For Dryland: Least productive 1/3 _____ Average productive 1/3 _____ Most productive 1/3 _____

For Irrigated: Least productive 1/3 _____ Average productive 1/3 _____ Most productive 1/3 _____

Figure 2.3: Perceived Spatial Yield Variability (SYCV) Construction

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CHAPTER 3

PRECISION FARMING TECHNOLOGIES, ENVIRONMENTALLY MOTIVATED FARMERS, AND PERCEIVED IMPROVEMENTS IN ENVIRONMENTAL QUALITY

3.1 Introduction

This essay is part of the precision farming literature that focuses on non-financial factors affecting farmers' decisions about precision technology adoption. Farmers who adopt precision agriculture technologies typically expect that they can decrease the use of fertilizers and chemicals, thereby improving profits and environmental quality due to the lower likelihood of fertilizer/chemical runoff (Auernhammer, 2001). The concept of environmental quality is multi-dimensional and it is linked to a number of interrelated factors, i.e., soil management practices, soil type, topography, organic matter content, crop, weather effects, and prior management (Hatfield, 2000). Although the reduction of input use through precision farming (PF) can logically translate into potential improvements in environmental quality, these positive environmental externalities from precision farming technologies have not yet been fully understood over a longer duration of time.

Regarding farmers' attitudes towards the environment, the literature shows that their environmental interests are not clear and they seem to affect the speed of entry rather than the probability of adoption (Wynn et al., 2001). Farmers may realize the importance of environmental benefits, but they might not be willing to adopt new practices with large fixed

cost for equipment and uncertain profits, that would potentially risk the socio-economic viability of the farm enterprise (Napier and Brown, 1993). For example, Van Kooten et al. (1990) found that farmers are unwilling to sacrifice as little as 5% reductions in net returns in favor of improved soil quality, although some soil quality improvement due to precision farming may contribute to an additional 7.2% in revenue (Swinton and Lowerberg-DeBoer, 1998). Other studies found that a regulation to adopt environmentally-friendly practices is more effective than education in inducing adoption (Bosch et al., 1995).

However, there have also been studies that demonstrate farmers' willingness to be "environmentally motivated" and attenuate an amount of their profits in order to meet their social goals. A large percentage (80%) of farmers in a survey conducted in rural areas of Mississippi agreed that precision technology can be used to achieve a cleaner environment and that they would be willing to pay in order to protect the environment for human health reasons (Hite et al., 2002). Another study found that farmers were willing to forgo higher yields by reducing input use in order to avoid the risk of a moderate environmental damage (Lohr et al., 1999). A farmer may, however, adopt environmentally-friendly technologies in order to decrease the possibility of future environmental regulations imposed by the government rather than to be environmentally motivated (Mudalige and Weersink, 2004).

To consider the joint role of financial viability and environmental responsibility, Morris and Potter (1995) classified farmers in the following four groups: i) *active participants* who voluntary adopt agri-environmental measures (AEM) for both environmental protection as well as financial reasons (Wilson and Hart (2001), ii) *passive adopters*, who practice AEM mostly for financial reasons, iii) *conditional non adopters* who

would participate only under certain circumstances (e.g., if there is payment/subsidy for adopting), and iv) *resistant non adopters* who are against the adoption of agri-environmental measures. In a similar framework, Lynne and Casey (1998) added the assumption of "other interest" in addition to the primary "self interest" (i.e., profit maximizing). The challenge to the scientific community at large would be to better understand the different types of farmers listed above and provide financially rewarding technologies/practices that also promote sustainable environmentally-friendly farming.

This study consists of two objectives related to the environmental aspects of precision agriculture technologies. First, we investigate the characteristics of farmers adopting precision technology due to factors other than the profit motivations (i.e., environmental goals). Second, we examine variables – including the relative importance of various reasons for adopting precision farming – that are correlated with perceived improvements in environmental quality following adoption of precision farming technology. Whether or not the farmer characteristics are found to be correlated with adoption motives is important as previous studies of precision farming adoption decisions are assumed solely based on the profit motive following microeconomic theory.

Our first objective extends the work of Pandit et al. (2011) by looking more carefully at factors influencing the adoption of precision technologies based primarily on environmental motives.[7] What are the characteristics of farmers who adopt precision

[7] Pandit et al. (2011) more generally investigated the different factors that affect the three different motives for adopting precision agriculture –profit, environmental reasons, and being at the forefront of technology – using a simultaneous equations framework. Our study is more focused in the sense that we examine those individuals who rank potential environment benefits higher than potential profit advantage as their main reason for adopting precision technologies (i.e., an environmentally motivated farmer). The Pandit et al. (2011) study does not make

technologies mainly for its environmental benefits? We distinguish between the profit maximizing farmers (i.e., those who rank profits strictly higher than the environmental benefits) and the more environmentally motivated farmers (i.e., those who prioritize potential environmental improvements over profits as the reason for adopting the technology). The definition of an environmentally motivated farmer was based on a Likert-style ranking of the importance of three reasons for adopting precision technologies: (1) profit, (2) environmental benefits, and (3) being at the forefront of technology. For our first objective, we analyze farm and/or farmer characteristics associated with those who explicitly state that they adopt precision technologies mostly for their environmental benefits rather than for the potentially higher profits.

Our second objective is to determine what factors affect any perceived improvements in environmental quality that precision cotton farmers experience during the eight year period where surveys were conducted (i.e., we will use data from three cross section surveys in 2001, 2005 and 2009; see data discussion below). Larkin et al. (2005) identified factors affecting perceived improvement in environmental quality due to precision technologies using the 2001 survey, and found that about 36% of precision technology adopters in 2001 perceived some environmental quality improvement after the adoption. Our study extends Larkin et al.'s (2005) work and provides more evidence on whether relationships found in 2001 are consistent over time, and/or whether different factors have become more dominant with the gradual diffusion of precision technology over time. Note that we do not have a

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this more specific delineation in their analysis (i.e., they used the actual reported ranking of each motive as the dependent variable regardless of whether the environmental motive is ranked higher or lower than the profit motive).

quantifiable measure of environmental quality, i.e., actual measures of improvements in soil properties. We only observe farmers' reported perceptions of whether they experienced improvement in environmental quality following the adoption of precision farming (PF). Having knowledge of farmers' characteristics who adopt precision technologies for environmental reasons and/or who perceive environmental benefits from these technologies would help identify where to initiate educational and regulatory efforts designed to increase the use of environmentally-friendly production practices like precision farming. Knowing the characteristics of precision technology users that adopt for environmental reasons and are more in tune with the environmental benefits of the technology would allow for more targeted educational and information dissemination programs that focus on the environmental advantages of the technology. Agribusiness providers and extension educators would be able to know which type of precision farmers are more informed about the environmental contributions of precision technologies and the consequent interventions needed to increase awareness. Results from this study would also be useful in developing more targeted educational programs promoting "green" production practices, such as organic farming or integrated pest management (IPM).

Knowler et al. (2007) tried to synthesize the factors affecting adoption of environmentally-friendly conservation practices coming from 31 studies, and they found that there are no universally significant independent variables. Larkin et al. (2005) and Pandit et al. (2011) also demonstrated that there are several farmer characteristics (e.g., farm size, yield levels, farmer age, and experience) that systematically influence environmental motives for adoption and perceived environmental improvements from precision farming based on

single cross-section data. We build on these existing studies to further explore whether these relationships hold over time (i.e., especially for the factors influencing perceived environmental improvements) and whether there are other important elements that affect environmental motives/perceived environmental improvements.

3.2 Empirical Approaches

3.2.1 Empirical Approach for Objective 1: Adoption due to Environmental Reasons

3.2.1.1 Conceptual Framework: Adoption due to Environmental Reasons

Technology adoption is usually modeled as a choice between two alternatives: the traditional technology and the new one (i.e., in our case, the precision technology). Farmers choose the alternative that maximizes their expected utility (Fernandez et al., 2004). A farmer *i* is likely to adopt precision technologies if the utility of adopting, $U_{i,PF}$ is larger than the utility of not adopting, $U_{i,NO}$, that is $U_i^* = U_{i,PF} - U_{i,NO} > 0$. Since the actual utilities are not observable, we define $U^*_{i,j} = V_{i,j} + \varepsilon_j$, where V is the systematic component of U related to the expected utility of adopting ($j=PF$), and of not adopting ($j=NO$), and define a random disturbance (ε) that accounts for errors in perception and measurement, as well as unobserved attributes and preferences (Payne et al., 2003).

The potential environmental benefits (*EB*) and profit benefits (*PB*) of precision technologies are two main factors that determine the utility derived from adoption and these two variables are typically included in V (i.e., $V_{i,j} = f(EB, PB)$). Assume there exists a latent

variable or index (Y^*) that measures the degree of importance of *EB* relative to *PB* in determining the utility derived from adoption of precision technologies. Hence, higher values of Y^* indicate that the relative weight given to *EB* is more than to *PB*, and the expected utility derived from precision technologies is determined more by environmental reasons rather than potential profit improvements. Lower values of Y^* imply the reverse (i.e., more weight to *PB* than *EB*). There is also a value of Y^* where the relative weights of *EB* and *PB* in determining utility are equal (i.e., indifference between *EB* and *PB*).

Given the existence of Y^* for each farmer *i*, we are interested in determining the factors and/or characteristics that affect Y^* such that:

(1) $$Y_i^* = X_i'\beta + \varepsilon_i,$$

where Y_i^* is the unobserved latent variable (as defined above) that depends linearly on X, β are parameters to be estimated, and ε is the standard normal distributed random error (Greene, 1997). The problem with the specification in (1) is that Y_i^* is unobserved. However, in the precision agriculture survey for 2009, farmer respondents were asked to rank the importance (i.e., 1 to 5 scale, 5 being very important) of the following reasons for adopting precision farming technologies: environmental benefits, profits, and being at the forefront of agricultural technology. If the ranking for environmental benefits is *strictly lower* than the profit motive, then we can assume that the unobserved Y_i^* is below some minimum threshold μ_1. If the ranking of environmental benefits as a reason for adopting precision technologies is *strictly higher* than the profit motive, then we can know that the unobserved Y_i^* is above a maximum threshold μ_2. Lastly, if the ranking of environmental benefits as a reason for

adopting precision technologies is *equal to* the profit motive, then the unobserved Y_i^* is in between the minimum (μ_1) and maximum (μ_2) thresholds.

With the observed ranking structure above, one can represent the unobserved index that represent the importance of environmental benefits as follows:

(2)
$$Y_i = 1 \quad \text{if} \quad Y_i^* < \mu_1$$
$$Y_i = 2 \quad \text{if} \quad \mu_1 < Y_i^* < \mu_2$$
$$Y_i = 3 \quad \text{if} \quad \mu_2 < Y_i^*.$$

Given the ordinal nature of the observed variable in (2), a proportional odds model (or what is more commonly known as an ordered logit model) can be used to empirically examine the factors that influence environmental motives as a reason for adopting precision technologies.

3.2.1.2. Estimation Methods: Proportional Odds Model POM (Ordered Logit)

The proportional-odds (or cumulative) logit model is a common model for an ordinal response variable based on the assumption that the slope of coefficients does not vary over different alternatives except after passing the cut-off points (McCullagh and Nelder, 1989, Peterson and Harrell, 1990). The structure of the ordinal dependent variable in (2) indicates that we can categorize the farmer respondents as follows: "profit oriented" if $Y_i = 1$, "indifferent" if $Y_i = 2$, and "environmentally motivated" if $Y_i = 3$. In order to estimate (1) given the ordinal dependent variable in (2), some of the threshold values need to be fixed, thus the lowest value is set at minus infinity $\mu_1=-\infty$, and the highest value is set at plus infinity $\mu_2=+\infty$. Then,

(3)
$$\Pr[Y_i = j] = \Pr[\mu_{j-1} < Y_i^* \leq \mu_j] = \Pr[\mu_{j-1} < X_i'\beta + \varepsilon_i \leq \mu_j]$$

$$= \Pr[\mu_{j-1} - X_i^{'}\beta < \varepsilon_i \leq \mu_j - X_i^{'}\beta]$$

$$= F(\mu_j - X_i^{'}\beta) - F(\mu_{j-1} - X_i^{'}\beta),$$

where F is the cdf of ε_i.

The marginal effects in the probabilities are computed as (Cameron and Trivedi, 2005):

(4) $$\frac{\partial \Pr[Y_i = j]}{\partial X_i} = \{F'(\mu_{j-1} - X_i^{'}\beta) - F'(\mu_j - X_j^{'}\beta)\}\beta,$$

where F' denotes the derivative of F. For the ordered logit model, ε is logistically distributed with $F(z) = e^z / (1+e^{-z})$. Assuming a linear utility function and choice probabilities that depend only on observed individual-specific characteristics (Judge et al., 1985), the proportional-odds model is defined as:

(5) $$\log_{it}[\Pr(Y_i > j)] = \log_e \frac{\Pr[Y_i > j]}{\Pr[Y \leq j]} = -\mu_j + \beta X_i,$$

where the odds ratio $\frac{\Pr[Y_i > j]}{\Pr[Y \leq j]}$ denotes the ratio of the probability of adopting PF to the probability of not adopting PF, conditional on the vector X of explanatory variables. In this study, we have specified 3 ordinal choices (j=1, 2, and 3). Thus the cumulative logit model can be represented with 2 intercepts (μ_1 and μ_2), instead of one intercept, as would be the case for the binary choice model.

3.2.1.3. Robustness Checks

The POM described above is very restrictive because it assumes that all variables meet the proportional odds/parallel lines assumption (Williams, 2006). This implies that all

coefficients (except the intercepts) would be the same except for sampling variability (Williams, 2006). To deal with this problem, the following solutions have been suggested: a) implement a less parsimonious non-ordinal alternative, such as multinomial logit, b) apply a generalized ordered logit model, that relaxes the parallel lines assumption for *all* variables, or c) try a more flexible approach: the partial proportional odds model, that relaxes the constraint of proportional odds *only for those variables where it is violated* (see Robustness Checks section below).

Following the Peterson and Harrell (1990), we assume a gamma parameterization of partial proportional odds model with a logit function, shown as:

$$P(Y_i > j) = g(X_i'\beta_j) = \frac{\exp[\mu_j - (X_i'\beta_j + T_i'\gamma_j)]}{1 + \exp[\mu_j - (X_i'\beta_j + T_i'\gamma_j)]}, \tag{6}$$

where T_i is a $q \times 1$ vector, $q \leq m$, containing the values of degree of social responsibility on the subset of m explanatory variables for which the proportional odds assumption does not hold, and γ_j is a $q \times 1$ vector of regression coefficients associated only with the jth cumulative logit, and representing the deviations from the proportionality.

Another way to estimate the model is via a dichotomous choice method, where the farmer is either more likely to adopt based on profit, or more likely to adopt based on environmental criteria (i.e., we do not consider the "indifferent" scenario). Due to the very small number of environmentally motivated farmers (only 3%), a standard logistic regression can underestimate the probability of rare events. Thus, we address this issue by following a *rare events logit* model as presented in King and Zeng's (2000) study. We define an indicator variable Y_i that takes on the value of one if the farmer values environmental benefits higher

than profit, or zero if the farmer values profit higher than environmental benefits. The unobserved variable Y_i^* is distributed according to a logistic density with mean m_i, such that

(7) $$P(Y^*) = \frac{e^{-(Y_i^* - m_i)}}{(1+e^{-(Y_i^* - m_i)})^2},$$

and for the observed variable Y_i, the model becomes:

(8) $$\Pr(Y_i = 1 \mid \beta) = \pi_\iota = \Pr(Y_i^* > 0 \mid \beta) = \int_0^\infty Logistic(Y_i^* \mid m_i) dY_i^* = \frac{1}{1+e^{-x_i\beta}},$$

where parameters are calculated using maximum likelihood, assuming independence over the observations. The rare events logit usually yields small estimates of $\Pr(Y_i = 1 \mid x_i) = \pi_\iota$, unless the model has a very good explanatory power.

A *multinomial logit model* is also utilized as a robustness check to explore the various factors affecting a producer's decision to adopt PF for environmental reasons. For an individual *i* we assume a random utility model $V_{ij}^* = X_i'\beta_j + u_{ij}$ associated with the following alternatives: *j*=1, if the farmer is profit-oriented, *j*=2 if he/she values profit and environmental benefits equally and *j*=3 if the farmer is environmentally conscious. Again, X_i' reflects the set of observed characteristics, β the vector of parameters to be estimated and u_{ij} the stochastic error term. Assuming that the disturbances of the different combinations are independent and identically distributed the probability of choosing alternative *j* is specified as (Greene 1997):

(9) $$P_{ij} = \frac{\exp(X_i'\beta_j)}{\sum_{l=1}^{k}\exp(X_i'\beta_l)}, \text{ j=0, …, k (k=2)}$$

From equation (9) we can derive

(10) $$\frac{P_{ij}}{P_{ik}} = \exp(X_i^{'}(\beta_i - \beta_k)) \text{ , k}\neq\text{j,}$$

which holds for every subset of eligible combinations, including *k* and *j*. To ensure identification, β_j is set to zero for one of the categories, and the coefficients are then interpreted with respect to this base category (Cameron and Trivedi, 2009). Again, maximum likelihood procedure is applied to estimate the parameters of the model.

3.2.1.4. Empirical Specification: Adoption due to Environmental Reasons

To empirically estimate equation (1) and determine the characteristics of farmers who adopt PF for environmental reasons, we need to specify the explanatory variables to be included in vector *X*. Based on the precision farming literature (Banerjee et al. 2004, Roberts et al. 2008, Pandit et al. 2011), we first include socio-demographic variables and farm characteristics as possible factors that influence the decision to adopt PF for environmental reasons. Socio-economic variables included in the specification are: age (*AGE*), years of farming experience (*EXPERIEN*), and years of education (*EDUC*). Farm characteristics in the specification are: farm size (*ACRES*), previous years' yield (*YIELDS*), and percentage of total household income from farming (*INCOME*). See Table 1 for detailed variable definitions.

Second, we include variables associated with different management practices that a farmer utilizes in his/her operation. Farm management variables included in the specification are: use of extension publications (*PUBLICAT*), use of computers (*COMPUTER*), use of agricultural easements (*AG EASE*), variable rate input application (*VRT*), use of manure as fertilizer (*MANURE*), and number of years in their farm planning horizon (*PLAN*).

Lastly, farmer perceptions about various aspects of precision farming are also included as covariates in the specification. Perception variables included in the specification are: perceived importance of precision farming in the future (*IMPORTA*), and whether they believe precision farming will be profitable in the future (*PROFIT*). Note that state dummy variables were also included in the specification to account for regional variations.[8]

3.2.2. Empirical Approach for Objective 2: Perceived Environmental Improvements

3.2.2.1. Conceptual Framework: Perceived Environmental Improvements

Based on our conceptual framework in the previous section, we show that the systematic component of a strictly concave utility of the representative producer is a function of the potential environmental (*EB*) and profit (*PB*) benefits of precision technologies. Since the precise effects of variables *X* on *EB* and *PB* are unknown, the expected utility function is:

(11) $$E_{\varepsilon_1,\varepsilon_2} U[EB(X;\varepsilon_1), PB(X;\varepsilon_2)] = \beta \mathrm{E}_{\varepsilon_1} \mathrm{EB}(X;\varepsilon_1) + (1-\beta) E_{\varepsilon_2} PB(X;\varepsilon_2),$$

where β is a constant assigning the producer's relative weight on potential environmental and profit benefits of precision farming $(\beta \in (0,1])$. If $\beta = 1$ then the adoption decision depends entirely on potential environmental benefits. For values of β less than 1, the profit benefits following the precision technologies also enter the adoption decision (Amacher and Feather, 1997). The term *X* is a vector containing farm and farmer characteristics (see Empirical Specification discussion below). The independent random parameters ε_1 and ε_2 reflect the

[8] The state dummy variables included in the specification are: AL, AR, FL, GA, LA, MS, MO, NC, SC, TN, VA; with TX as the "omitted" state to assure identification in the regression.

uncertainty associated with SSIG technologies and VRT adoption on environmental (EB) and profit (PB) benefits.

In this framework, the true *EB* is typically not perfectly observable such that perceptions about *EB* (e.g., EB^*) are the real "drivers" of farmer choice rather than the true *EB* and *PB*. Suppose the producer have adopted at least one precision technology (i.e., one of the SSIG technologies and/or VRT), then the producer can utilize these technologies to update his/her beliefs about EB^*. This implies that we can define EB^* as:

(12a) $$EB^* = f(VRT, X),$$

where VRT is a dummy variable indicating whether or not the producer adopted VRT, and X is a vector of farm/farmer characteristics.

Equation (12a) can then be re-written in linear form such that:

(12b) $$EB^*_i = \beta' X_i + \varepsilon_i \qquad i = 1, \ldots, n,$$

where X_i is a vector that includes all the independent variables that are hypothesized to influence EB^*. Expected changes in EB are assumed to be an increasing function of SSIG and VRT use:

(13) $$E_{\varepsilon_1} = \frac{\partial \mathrm{EB}(VRT, X; \varepsilon_1)}{\partial VRT} > 0$$

3.2.2.2. Estimation Method: Perceived Environmental Improvements

Note that perceived environmental benefits in (12a) are not observable (i.e., it is a latent variable). What is observable from the survey is the farmers' answer to the question "Have you experienced any improvements in environmental quality through the use of precision technologies?" (i.e., the *ENVIRON* variable). Hence, the variable EB_i is then defined as a dummy variable that takes on the value one if the answer is "yes" or zero if the answer is "no" or "do not know". Empirically, this dependent variable is linked to the latent variable as follows:

(14) $$EB_i = 1 \quad \text{if} \quad EB^*_i > 0$$

$$EB_i = 0 \quad \text{otherwise}$$

Equations (12) and (14) represent a dichotomous qualitative response model. The observable dependent indicator variable Y_i is 1 with probability p_i, and 0 with probability $1 - p_i$.

Observed values of EB_i reflect a binomial process with probabilities that change from observation to observation from changes in X_i. Thus, equations (12) and (14) describe the probability that a farmer observes environmental benefits after adopting precision farming, i.e.:

(15) $$\text{Prob}(EB_i = 1) = \text{Prob}(u_i > -\beta' X_i) = p_i$$

$$= 1 - F(-\beta' X_i),$$

where F is the cumulative distribution function for the random error u, that is assumed to be independently and identically distributed logistically such that:

(16) $$F(-\beta' X_i) = \frac{1}{1 + \exp(\beta' X_i)}.$$

Thus,

(17) $$1 - F(-\beta' X_i) = \frac{\exp(\beta' X_i)}{1 + \exp(\beta' X_i)}.$$

One advantage to using this distribution is that *F* can be represented in a closed-form expression that can be used to evaluate the likelihood function by substitution:

(18) $$L = \prod_{Y_i=0} F(-\beta' X_i) \prod_{Y_i=1} [1 - F(-\beta' X_i)]$$

The unknown parameters can be estimated using maximum likelihood to achieve consistent and unbiased estimates. We applied a pooled logistic regression for the three cross section surveys, controlling for the year the observation was taken (year fixed effects). We then compare estimation results from the pooled regression with results from three separate binary logit models, one for each year.

3.2.2.3. Empirical Specification: Perceived Environmental Improvements

To empirically implement the estimation procedure described in the previous section and estimate the parameters in (12b), the variables in *X* need to be specified. Similar to the empirical specification for objective 1 (See section 3.3.1.4), we first include socio-demographic variables and farm characteristics as possible determinants of whether or not farmers perceive environmental improvements from precision technology use. Based on previous literature (Larkin et al. 2005, Roberts and Larson, 2004 and Hite et al 2002), the following socio-demographic variables and farm characteristics variable are included in the specification: age (*AGE*), years of farming experience (*EXPERIEN*), whether or not the

farmer attended college (*COLLEGE*)[9], farm size (*ACRES*), previous years' yield (*YIELDS*), and percentage of total household income from farming (*INCOME*).

We also incorporate the following farm management practices in the specification: use of computers (*COMPUTER*) and use of manure as fertilizer (*MANURE*). The variables related to extension publications (*PUBLICAT*), use of agricultural easements (*AG EASE*), and number of years in their farm planning horizon (*PLAN*) are not included in the pooled regression, but were included in the 2009 run of the logit model since data for these variables are only available for the 2009 crop year. Moreover, as explained in Larkin et al. (2005) and shown in (12a), the use of VRT would also likely influence whether a farmer perceive environmental improvements from precision farming and a variable representing this (VRT) is also included in the specification.

Consistent with Larkin et al. (2005), farmer perceptions about various aspects of precision farming are also included as covariates in the specification. Perception variables included in the specification are: perceived importance of precision farming in the future (*IMPORTA*) and whether they believe precision farming will be profitable in the future (*PROFIT*). Note that state dummy variables were also included in the specification to account for regional differences.[10]

[9] For this objective, the variable COLLEGE instead of the EDUC is used, so that our result can be easily compared to the earlier study by Larkin et al. (2005).

[10] The state dummy variables included in the specification for the pooled regression are: AL, FL, GA, MS, NC; with TN as the "omitted" state to assure identification in the regression. These are the states that are consistently in the data set from 2001 to 2009. For the separate logit regressions, we include state dummies for all the states in the data for each year and omitting the following: TX for 2009, FL for 2005, and TN for 2001.

3.3 Survey and Data Description

3.3.1 Description of Multi-Year Surveys

We use survey data from three questionnaires sent to farmers in the Southeastern region of the U.S. in 2001, 2005 and 2009. The sample from the 2001 survey included farmers from Alabama, Florida, Mississippi, North Carolina and Tennessee. They were asked questions about precision farming technologies for each of seven primary crops (i.e., cotton, tobacco, peanuts, soybeans, corn, wheat and rice). Following Dillman's general mail survey procedures, the questionnaire, a postage-paid return envelope, and a cover letter explaining the purpose of the survey were mailed on January 16, 2001, and a reminder postcard was sent on January 23, 2001. Of the 6,423 questionnaires sent, 1,131 were returned (19% response rate).

For the 2005 survey, the States of Arkansas, Georgia, Louisiana, Mississippi, Missouri, South Carolina and Virginia were added to the states included in the 2001 survey. This increased the number of states in the study to eleven. The first 12,243 questionnaires were sent on January 28, 2005 and reminders followed on February 4, 2005 and February 23, 2005, respectively. The individuals who provided usable responses were 1,215 (10% response rate). For the 2009 survey, a total of 1,692 surveys were returned out of 14,089 questionnaires that were mailed in February 20, 2009, along with the reminder post card on March 5, 2009. Texas was added to the sample of states included in the prior 2005 survey, thereby increasing the number of states to twelve. The response rate improved to 12.5% for this survey year (Mooney et al., 2010).

3.3.2 Data Description for Objective 1: Adoption due to Environmental Reasons

To systematically explore the characteristics of farmers who adopt precision technologies mainly for environmental reasons (objective 1), our analysis only utilizes the 2009 survey, in order to make comparable inferences with Pandit et al. (2011), who utilized the same data[11]. Of the 665 farmers who ranked the three reasons to adopt precision agriculture (i.e., profit, environmental benefits, and being at the forefront of technology) in 2009, 62.5% of them ranked profits strictly higher than any other reason for adoption (See Figure 1). About 34.1% of farmers valued environmental benefits equally with profit, and only 3.3% ranked the environmental motives strictly higher than profit. These were considered to be the environmentally motivated farmers in our sample. Regarding the *2005 survey*, 57.9% valued profits higher than environment, 39% were indifferent, and again 3% were environmentally motivated. Last, for the *2001 survey*, the profit-oriented were 57.3%, the indifferent between profits and environmental benefits consisted of 38.8% of the respondents, and similarly only 3.8% were the environmentally conscious.

Table 3 summarizes the various characteristics that distinguish the more environmentally motivated farmers from the other groups and how these have changed over time on average. Environmentally conscious farmers had relatively smaller farms,

[11]Moreover, 2001 and 2005 surveys did not have questions that are identical to the 2009 questions, i.e., they both included the extra choice of "adopt in order not to be left behind" in addition to the other three reasons for adoption included in 2009 (profit, environmental benefits and being at the forefront of technology). Thus omitting the responses of that question in order to create an identical variable might create additional bias. Nevertheless, we estimated the model using previous years' data but the marginal effects of all variables were not statistically significant.

participated more in agricultural easement programs, they had more experience in farming and they were older. Farmers who adopted PF mainly for environmental reasons tend to use computer in their farm management less, and a higher percentage of their income comes from agricultural sources. Their average yields were slightly lower than the other groups, but they all had higher expectations regarding the future importance of precision agriculture. Producers who ranked profit higher than the other reasons, in contrast, were younger, used University publications to obtain information about precision farming, had larger farms, and more years of formal education.

3.3.3 Data Description for Objective 2: Perceived Environmental Improvements

To more carefully analyze the factors influencing perceived environmental improvements (objective 2), we utilize all three surveys in 2001, 2005, and 2009. Use of multi-year survey data allows us to build on the work of Larkin et al. (2005) to determine whether the factors that influenced perceived environmental improvements in 2001 hold through time. All survey questionnaires asked farmers who adopted at least one precision farming technology whether they had experienced any improvement in environmental quality in their fields. Of the 1668 farmers who responded to this question, 26.4% of them (442 farmers) replied that they had observed environmental improvements, and the rest either did not perceive any improvement or "did not know" whether they did. Table 2 shows the descriptive statistics (i.e., mean and standard deviation) of each variable used to achieve objective 2.

3.4 Results

3.4.1 Objective 1 Results: Adoption due to Environmental Reasons

3.4.1.1. Results of the Proportional Odds Model (Ordered Logit)

To determine the characteristics of farmers who adopt PF for environmental reasons, we estimate the proportional odds and the partial proportional odds model, both of which are nested in the non-proportional (generalized ordered logistic) model. The likelihood ratio test of proportionality of odds across response categories is statistically insignificant (χ^2 (25) = 25.02 with Prob> χ^2 = 0.4048), indicating that the parallel regression assumption has not been violated. The statistics under the gamma parameterization suggest that the partial proportional odds model (PPOM) may not be appropriate to use (χ^2 (28) = 9.76 with Prob> χ^2 = 0.0076). Moreover, the Wald tests indicate that all variables satisfy the proportionality tests (i.e., variables whose effects significantly differ across equations).Given the results of the Wald tests, the proportional odds model (POM) or the cumulative logit model may be the best alternative to use. To further test the specification of the model, we conducted a RESET test. The RESET test indicates a non significant χ^2 statistic for specification error (chi-squared of 0.06 with a p-value of 0.8140) and suggests that the POM model provides a good fit with low specification error.

The average marginal effects along with their delta standard errors in parentheses are presented in Table 4. The parameter estimates cannot reveal the effect of changes in explanatory variables on the dependent variable, holding other factors constant. Thus, we calculated the marginal effects of the independent variables on the probability of reporting

environment as the most important reason to adopt precision technologies. The high number of discrete, and particularly binary variables, raised an issue of multicollinearity. Multicollinearity diagnostics indicated a mean VIF (Variance Inflation Factor) of 1.35 and Tolerance levels between 0.74 and 0.94[12]. The only correlation coefficients that did not follow the condition indices were *AGE* and *EXPERIEN*, both of which were statistically insignificant in our estimation analysis.

Of the statistically significant marginal effects, expected importance of precision agriculture 5 years from now (*IMPORTAN*), and farmers that have agricultural easements (*AG EASE*), are more likely to make their PF adoption decisions based mostly on environmental reasons. Farmers, who participate in agricultural easement programs, may be less concerned about losses that would risk their farm's economic viability, thus value environmental motivations higher. In contrast, the use of university publications (*PUBLICAT*) as a means to obtain PF information, as well as the use of computer in farm management (*COMPUTER*) both negatively affect the probability that a farmer would adopt precision farming technologies for its potential to improve environmental outcomes. Interestingly, more educated farmers (*EDUC*) are less likely to adopt for environmental reasons. We would expect that college degree respondents are more aware of the potential environmental benefits of precision technologies and would more likely adopt for this reason.

Farmers who expect that precision technologies will be important five years from now (*IMPORTA*) and those who use agricultural easements (*AG EASE*) are also the ones

[12] A commonly given rule of thumb is that VIFs of 10 or higher (or equivalently, tolerances of .010 or less) may be reason for concern (Ender, P., UCLA)

more likely to adopt PF for environmental reasons based on the marginal effects in Table 4. The positive effect of *IMPORTA* suggests that the importance of PF in the future may be linked to environmental outcomes. The observed positive *AG EASE* is reasonable since farmers that have agricultural easements are typically more inclined to protect the environment, and consequently adopt environmentally-friendly practices.

The negative sign of the variable signifying use of university publications is somewhat unexpected. A priori we expect this variable to increase the likelihood of adopting PF for environmental reasons because these types of publications often emphasize the potential positive environmental benefits of the technology (i.e., minimization of over or under application of chemical inputs based on location-specific conditions). Nevertheless, the negative relationship may have resulted from the way we constructed the variable *PUBLICAT*. There were a substantial number of farmers who answered "do not know" in the question of whether they used University publications in order to obtain information about precision farming. These respondents were not dropped from the model but were incorporated to the "no" respondents (i.e., no use of publications), taking on the value of zero.

3.4.1.2. Robustness Check Results: Rare Events Logit and Multinomial Logit

Robustness checks using the rare events logit and multinomial logit approaches provide results that are fairly consistent with the POM results above. In the rare events logit, along with *PUBLICAT*, the variable *COMPUTER* had a statistically significant negative effect on the likelihood of a farmer adopting PF for environmental reasons, while the *AG EASE*

variable still exhibited a statistically significant positive effect (Table 5). The negative parameter estimate for the *COMPUTER* is somewhat expected given the results in Pandit et al. (2011) that computer use is more likely to be associated with the profit motive rather than the environmental goals for adopting precision technologies. Farmers who use computers for farm management purposes are typically the ones who only adopt new technologies if these contribute positively to profits. In addition, a shorter planning horizon is more likely to be associated with environmentally conscious farmers. For the multinomial logit estimates, presented in Table 6, *COMPUTER*, *PUBLICAT*, *EDUC* and *AG EASE* are still statistically significant and follow the same sign as in the POM approach. These robustness check results suggest that these variables consistently have a strong statistically significant effect on the likelihood of adopting PF for environmental reasons, regardless of the estimation approach.

3.4.2 Objective 2 Results: Perceived Environmental Improvements

3.4.2.1. Results of the Pooled Logistic Regression

The results of the pooled estimation to determine the characteristics of farmers who perceive environmental improvements from PF are reported in Table 8. Based on the marginal effect calculations, we find that the variables *INCOME* and *MANURE* are consistently significant across all three periods, whereas *ADOPT_2* (Adoption due to environmental reasons) and *VRT* are positive and statistically significant for the 2005 and 2009 periods. This suggests that farmers, who applied their inputs at a variable rate (*VRT*), did not rely on organic fertilizers (*MANURE*), adopted PF mostly due to its environmental potential benefits

(*ADOPT_2*), and whose income came mainly from farming sources (*INCOME*), were more likely to perceive environmental improvements following the use of precision technologies. On the contrary, 2001 individuals who used manure as a farm management practice (*MANURE*) and whose income did not come mainly from farming sources (*INCOME*) were more likely to observe improvements in environmental quality after the PF adoption. The impact of *VRT* in the latest studies reveals a more environmentally conscious profile of farmers.

3.4.2.2. Robustness Check Results: Separate Logit Models

As a robustness check, we estimated three separate logit models for the three different data-sets. Note that pooling three separate years of cross section data is typically favored over separate regressions for each year because one can get a larger sample size. By pooling the independent cross sections, one may be able to get more precise estimates and test statistics will have more power (Wooldridge, 2006, p. 449). In this study, however, the practical shortcoming of pooling the data is that some variables that can be observed in later surveys may not have been available in older surveys. For example, the variable *AG EASE* was only available in the 2009 data and it is not available in the 2005 and 2001 data (i.e. the question about agricultural easement use was not asked in the earlier surveys). Hence, this variable cannot be included in the pooled regression since it is missing in the earlier years. Running separate regression for each year, where the variables *AG EASE*, *PUBLICAT* and *PLAN* are included in 2009, would then be informative in this case. Calculated marginal effects based on separate logit regressions for 2001, 2005, 2009 are presented in Table 10.

As per the 2009 survey, the PF adoption due to environmental reasons (*ADOPT_2*), the use of university publications to obtain information about precision agriculture (*PUBLICAT*), the input application at a variable rate (*VRT*), farmers' perceptions about future PF profitability (*PROFIT*), and the planning horizon (*PLAN*) all positively affected the probability of reporting environmental quality improvements from the use of PF. Likewise, the variables *ADOPT_2*, *VRT*, and *PROFIT* also positively influence perceived improvements in environmental quality in the 2005 survey. On the contrary, *ADOPT_2* and *VRT* had negative signs but were statistically insignificant in the 2001 survey. Farmers, whose incomes were less dependent on farming (*INCOME*), used computer in their farm management (*COMPUTER*) and applied manure on their fields (*MANURE*), were more likely to observe improvements in environmental quality.

The differences between the three separate yearly runs may result from the fact that we could not use the exact set of explanatory variables for 2009 and older surveys (only 2001 and 2005 models have identical regressors). Note that the 2001 logit estimation in our study is not a replication of the logit estimation in Larkin's paper (2005), since we used a different set of explanatory variables (e.g., *ACRES* in our model includes only cotton production, whereas Larkin's study accounts for "other crops" such as wheat, peanuts, soybeans, tobacco, corn, and rice), in order to achieve comparable results among the three surveys in this study. To reveal differences across time, first, we found that the use of *VRT* was not a statistically significant factor in perceived improvement in environmental quality in 2001, but it positively and significantly affected perceived environmental improvements in 2005 and 2009. The use of university publications (*PUBLICAT*), and the farming horizon (*PLAN*) were

also critical in positively influencing the perceptions, but we only had available data for 2009, so we could not compare across the three surveys. Farmers who used computer in their farm management (*COMPUTER*) were more likely to observe improvements in 2001, but not in 2009 and 2005. The perceptions for future profitability of precision technologies (*PROFIT*) positively affect the perceptions about environmental improvement in all years. This was the only variable whose impact was statistically significant and of the same direction for all years. Our estimation indicates minimum regional differences, thus the results of location dummies are not reported, but are available upon request.

3.5 Conclusion

Our study provides further understanding about two key environmental aspects of precision technology adoption: adoption driven by environmental motivations and perceived improvements in environmental quality following adoption of precision agriculture. An advantage of this study is that farmers were asked about reasons driving "real" adoption that had already occurred, contrary to most studies which focus on factors affecting farmers' expected adoption. Exploring the financial and socio-economic factors affecting farmers' technology adoption decisions and their perceptions towards the technology and environment, can help policy makers design schemes that would improve adoption rates of precision agriculture and the effectiveness of policies aimed at environmental awareness.

First, we examined characteristics of producers who adopt precision farming primarily for environmental reasons. Cotton farmers from the Southeastern region were

asked about the importance of potential profit and environmental benefits of the technology in their adoption decisions. Based on the ranking, we constructed a variable that measured the degree of farmers' environmental responsibility (i.e., how they value environmental benefits compared to profit maximization), and we then related these to farm characteristics through various regression methods. In particular, a proportional odds model (POM) was utilized to estimate the factors affecting the role of environmental responsibility on the technology adoption. Our analysis showed that personal and structural factors play an important role in the adoption of precision technologies for environmental reasons. The estimated marginal effects indicate that the participation in agricultural easement programs, the perceived importance of PF in the future, as well as the perceived improvement in environmental quality following the PF use, all positively influence the decision to adopt for environmental reasons. On the other hand, educational attainment only had a positive impact on adoption based on profit motives, although educated farmers are better informed not only about technologies itself, but also about the detrimental effects of unsustainable practices (Ervin and Ervin, 1982). Similarly, farmers who used University Publications to acquire information about precision agriculture are more likely adopt based on profit maximizing criteria. These results suggest that there may be a need for further technical advice and information from Extension focusing on environmental benefits of precision agriculture. Regarding the importance of perceptions on decision making, farmers' perceptions can be shaped from regional policy makers or other networks towards environmental awareness, thus knowing whether they play a significant role in adoption can influence the effectiveness of informal information as well as social networks (Defrancesco et al, 2006). Moreover,

researchers can direct this information to the social channels that would make farmers more aware of the environmental benefits of PF.

The second environmental issue examined in this study is to determine whether producers did perceive environmental quality improvements following the adoption of precision technologies, and to explore the characteristics of producers who observed these improvements. Understanding the factors shaping these perceptions can provide insights about the decision making process that affect the practice of precision agriculture. Based on logistic regressions, the probability that a farmer observed any improvements in environmental quality (through the adoption of technology) was higher if the farmer used manure in his/her fields, was less dependent on income coming only from farming sources, and perceived that PF will be profitable in the future. These elements were found to be statistically significant for separate cross-section data collected over an eight year period. For later surveys, the input application at a variable rate and environmentally motivated behavior both positively affect the perceived improvements in environmental benefits. It would have been interesting to know the level of perceptions (i.e., whether the farmer observed little or significant environmental quality improvement) as in the case of preferences with respect to adoption (objective 1). An interesting follow-up study would be to investigate whether the length of use of information gathering technologies affects farmers' perceptions about improvement in environmental quality.

An implication for the policymakers is that while the vast majority of cotton farmers in the Southeastern U.S. region are strongly motivated by profits (as would be expected), there are still environmentally-minded cotton farmers who practice precision farming. For

future work, it may be interesting to explore the underlying motivation for adopting precision technologies based on environmental reasons. Are these farmers truly altruistic such that they want to adopt precision technologies purely for environmental reasons and therefore providing positive externalities to society? Or are there still long-term, private motives driving these decisions such as the desire to bequeath a high quality (i.e., non-degraded) and environmentally sustainable farm to future generations (i.e., their heirs). Are the farmers who adopted for environmental reasons doing this to avoid future regulations? Exploring these issues in the future may require a more dynamic framework. Future research may also explore the role of social capital in farmers' level of environmental consciousness in addition to the human capital and farm physical characteristics. One can investigate whether farmers with more social capital (i.e., social networking coming from farm dealers, crop consultants, other farmers, news/media, etc.) and better community organization are more willing to adopt based on environmental criteria. Extending our study to account for knowledge of marketing and pricing methods (i.e., whether the farmer used conventional prices, including future prices or cost of production as a source of pricing information) would help also help further understand precision farming producers who are motivated by environmental goals.

Table 3.1 Summary Statistics of the Variables used in Objective 1 (Adoption due to Environmental Reasons)

Variables	**Description**	**Mean**	**Std. Dev.**	**Min**	**Max**
ADOPT	Farmer adopted PF because he ranks environment higher than profit (yes=1; no=0)	0.033	0.178	0	1
ADOPT_2	Farmer adopted PF because he ranks profits higher than environment (y=1), ranks environment equal to profit (y=2), and ranks environment higher than profit (y=3)	1.407	0.555	1	3
ACRES	Total acreage of dry land (sum of rented and owned acres) for the 2007 crop season	653.88	957.22	0	18425
YIELDS	Estimate of average cotton lint yield per acre for 2007 crop season	837.29	735.38	0	3600
EDUC	Number of Years of Formal Education excluding kindergarten	14.16	2.521	0	25
AGE	Age of the farm operator (as of the 2009 survey year)	56.09	12.69	23	95
EXPERIEN	Number of Years farming	31.63	13.52	0	79
IMPORTA	Farmer perceived that precision farming would be important in five years from now (yes=1; no=0)	0.846	0.360	0	1
PROFIT	Farmer perceived that PF would be profitable to use in the future (yes=1; no=0)	0.534	0.498	0	1
INCOME	Percentage (%) of 2007 taxable household income coming only from farming sources	72.24	29.45	0	100
COMPUTER	Farmer uses computer for farm management (yes=1; no=0)	0.537	0.498	0	1
MANURE	Farmer applied manure on his/her fields (yes=1; no=0)	0.181	0.385	0	1
PUBLICAT	Farmer used University publications to obtain PF information (yes=1; no=0)	0.348	0.476	0	1
AG EASE	The farm currently has agricultural easement (yes=1; no or don't know=0)	0.085	0.279	0	1
VRT	Farmer applied his inputs at a variable rate (yes=1; no=0)	0.249	0.432	0	1
PLAN	Years to plan farming in the future	3.749	1.553	1	5

Table 3.2 Summary Statistics of the Variables used in Objective 2 (Perceived Improvements in Environmental Quality)

Variables	Description	Mean	Std. Dev.	Min	Max
ADOPT	Farmer adopted PF because he ranks environment higher than profit (yes=1; no=0)	0.033	0.179	0	1
ADOPT_2	Farmer adopted PF because he ranks profits higher than environment (y=1), ranks environment equal to profit (y=2), and ranks environment higher than profit (y=3)	1.431	0.558	1	3
ENVIRON	Farmer perceived improvement in environmental quality through the PF use (yes=1; no=0)	0.264	0.441	0	1
ACRES	Total acreage of dry land (sum of rented and owned acres) for the 2007 crop season	795.26	1012.7	5	20400
YIELDS	Estimate of average cotton lint yield per acre for 2007 crop season	1023.21	705.73	1	10100
COLLEGE	Farmer attended College	0.641	0.479	0	1
AGE	Age of the farm operator (as of each survey year)	53.087	12.507	20	95
EXPERIEN	Number of Years farming (yes=1; no=0)	29.185	13.047	0	79
IMPORTA	Farmer perceived that precision farming would be important in five years from now (yes=1; no=0)	0.837	0.369	0	1
PROFIT	Farmer perceived that precision farming would be profitable to use in the future (yes=1; no=0)	0.563	0.496	0	1
INCOME	Percentage (%) of each year's taxable household income coming only from farming sources	71.525	29.747	0	100
COMPUTER	Farmer uses computer for farm management (yes=1; no=0)	0.549	0.497	0	1
MANURE	Farmer applied manure on his/her fields (yes=1; no=0)	0.188	0.390	0	1
VRT	Farmer applied his inputs at a variable rate (yes=1; no=0)	0.277	0.447	0	1

Table 3.3 Comparison of Variable Statistics of the 3 Groups of Farmers

	Profit Oriented (Y=1)			Indifferent (Y=2)			Environ Motivated (Y=3)		
	2009	2005	2001	2009	2005	2001	2009	2005	2001
Variables	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
FARM SIZE	1161.6	1208.5	997.76	1012.3	936.1	1039.1	907.05	1534.4	909
YIELDS	1315.4	1286.4	998.70	1202	1144.4	1105.4	1311.9	1192.4	968.14
PUBLICAT	0.512	N/A	N/A	0.504	N/A	N/A	0.318	N/A	N/A
COMPUTER	0.731	0.730	0.755	0.740	0.624	0.709	0.454	0.6	0.875
IMPORTAN	0.940	0.943	0.929	0.963	0.936	0.892	1	0.727	0.9
VRT	0.435	0.530	0.708	0.476	0.507	0.763	0.636	0.272	0.7
PROFIT	0.788	0.780	0.860	0.795	0.751	0.873	0.75	0.7	0.777
INCOME	77.55	77.25	73.15	74.65	78.46	69.90	81.27	81.5	75.55
AG_EASE	0.086	N/A	N/A	0.122	N/A	N/A	0.181	N/A	N/A
PLAN	3.953	N/A	N/A	4.045	N/A	N/A	3.318	N/A	N/A
MANURE	0.242	0.212	0.262	0.216	0.185	0.231	0.227	0.5	0
EXPERIEN	28.24	24.30	25.95	29.34	25.84	26.95	32.31	25.3	26.6
AGE	51.74	47.01	48.47	51.88	48.47	48.97	55.13	48.72	46.9
COLLEGE	0.75	0.758	0.724	0.69	0.671	0.702	0.727	0.727	0.5

Table 3.4 Marginal Effects of the Covariates using Ordered Logit

Variables	**Average Marginal Effects (St.E)**		
	Profit Oriented (Y=1)	**Indifferent (Y=2)**	**Environ Motivated (Y=3)**
ACRES	1.26e-06	-1.04e-06	-0.0001
	(0.00002)	(0.00001)	(0.0006)
YIELDS	-9.98e-06	8.22e-06	1.77e-06
	(0.00003)	(0.00002)	(5.83e-06)
PUBLICAT	0.051	-0.042	-0.009
	(0.045)	(0.037)	(0.008)
COMPUTER	0.058	-0.048	-0.010
	(0.049)	(0.041)	(0.009)
VRT	-0.020	0.016	0.003
	(0.046)	(0.038)	(0.008)
IMPORTAN	-0.272 **	0.224 **	0.048 **
	(0.115)	(0.095)	(0.023)
PROFIT	0.020	-0.016	-0.003
	(0.057)	(0.047)	(0.010)
INCOME	0.0006	-0.0004	-0.0001
	(0.0008)	(0.0006)	(0.0001)
AG_EASE	-0.173 **	0.142 **	0.030 **
	(0.069)	(0.057)	(0.014)

Table 3.4 continued

PLAN	0.009	-0.007	-0.001
	(0.013)	(0.011)	(0.002)
MANURE	0.046	-0.037	-0.008
	(0.049)	(0.040)	(0.008)
EXPERIEN	-0.001	0.001	0.0002
	(0.003)	(0.002)	(0.0006)
AGE	0.0007	-0.0005	-0.0001
	(0.003)	(0.002)	(0.0006)
EDUC	0.021 **	-0.018 **	-0.003 **
	(0.009)	(0.007)	(0.001)

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 Marginal Effects of the Covariates for each Outcome using Ordinal Logistic Regression Models

	NPOM (Generalized Ordered Logit)			**PPOM (Gamma)**		
Variables	**Profit Oriented (Y=1)**	**Indifferent (Y=2)**	**Environ Motivated (Y=3)**	**Profit Oriented (Y=1)**	**Indifferent (Y=2)**	**Environ Motivated (Y=3)**
ACRES	2.77e-06	-2.31e-06	-4.63e-07	2.77e-06	-2.31e-06	-4.63e-07
	(0.00002)	(0.00001)	(3.97e-06)	(0.00002)	(0.00001)	(3.97e-06)
YIELDS	-0.00001	0.00001	2.25e-06	-0.00001	0.00001	2.25e-06
	(0.00003)	(0.00002)	(5.51e-06)	(0.00003)	(0.00002)	(5.51e-06)
PUBLICAT	0.043	-0.036	-0.007	0.043	-0.036	-0.007
	(0.045)	(0.038)	(0.007)	(0.045)	(0.038)	(0.007)
COMPUTER	0.033	0.018	-0.051 **	0.033	0.018	-0.051 **
	(0.050)	(0.047)	(0.019)	(0.050)	(0.047)	(0.019)
VRT	-0.001	-0.036	0.037 **	-0.001	-0.036	0.037
	(0.047)	(0.045)	(0.018)	(0.047)	(0.045)	(0.018)
IMPORTAN	-0.267 **	0.223 **	0.044 **	-0.267 **	0.223 **	0.044 **
	(0.116)	(0.096)	(0.021)	(0.116)	(0.096)	(0.021)
PROFIT	0.025	-0.021	-0.004	0.025	-0.021	-0.004
	(0.057)	(0.048)	(0.009)	(0.057)	(0.048)	(0.009)

Table 3.5 continued

INCOME	0.0006	-0.0005	-0.0001	0.0006	-0.0005	-0.0001
	(0.0008)	(0.0007)	(0.0001)	(0.0008)	(0.0007)	(0.0001)
AG_EASE	-0.162 **	0.135 **	0.027 **	-0.162 **	0.135 **	0.027 **
	(0.070)	(0.058)	(0.012)	(0.070)	(0.058)	(0.012)
PLAN	0.008	-0.006	-0.001	0.008	-0.006	-0.001
	(0.013)	(0.011)	(0.002)	(0.013)	(0.011)	(0.002)
MANURE	0.041	-0.034	-0.006	0.041	-0.034	-0.006
	(0.049)	(0.041)	(0.008)	(0.049)	(0.041)	(0.008)
EXPERIEN	-0.001	0.001	0.0003	-0.001	0.001	0.0003
	(0.003)	(0.002)	(0.0005)	(0.003)	(0.002)	(0.0005)
AGE	0.0009	-0.0008	-0.0001	0.0009	-0.0008	-0.0001
	(0.003)	(0.002)	(0.0006)	(0.003)	(0.002)	(0.0006)
EDUC	0.022 **	-0.018 **	-0.003 **	0.022 **	-0.018 **	-0.003 **
	(0.009)	(0.008)	(0.001)	(0.009)	(0.008)	(0.001)

Table 3.6 Marginal Effects of the Covariates of Each Outcome using Multinomial Logit Model

	Profit Oriented (Y=1)	**Indifferent (Y=2)**	**Environ Motivated (Y=3)**
Variables	**Average Marginal Effects (St.E)**	**Average Marginal Effects (St.E)**	**Average Marginal Effects (St.E)**
ACRES	8.95e-07 (.00002)	-0.0005 (0.003)	-3.13e-06 (0.00001)
YIELDS	-0.00001 (0.00003)	0.00001 (0.00003)	-5.76e-07 (0.00001)
PUBLICAT	0.037 (0.046)	-0.004 (0.045)	-0.033 * (0.020)
COMPUTER	0.027 (0.051)	0.013 (0.050)	-0.041 ** (0.019)
IMPORTAN	-0.513 (34.07)	-0.013 (25.48)	0.526 (59.55)
PROFIT	0.022 (0.058)	-0.011 (0.058)	-0.010 (0.021)
INCOME	0.0006 (0.0008)	-0.001 (0.0008)	0.0005 (0.0004)
AG_EASE	-0.155 ** (0.072)	0.103 (0.071)	0.052 ** (0.025)
PLAN	0.003 (0.014)	0.006 (0.014)	-0.010 * (0.005)

Table 3.6 continued

VRT	-0.001 (0.047)	-0.037 (0.046)	0.039 * (0.020)
MANURE	0.035 (0.050)	-0.025 (0.050)	-0.010 (0.020)
EXPERIEN	-0.001 (0.003)	0.0009 (0.003)	0.0006 (0.001)
AGE	0.0006 (0.003)	-0.0005 (0.003)	-0.0001 (0.001)
EDUC	0.027 ** (0.009)	-0.029 ** (0.009)	0.001 (0.004)

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3.7 Parameter Estimates of the Covariates using Rare Events Logit & Binary Logit

Variables	**Rare Events Logit (N=491)**	**Binary Logit (N=491)**
CONSTANT	-4.468 * (2.528)	-5.820 * (3.092)
ACRES	0.00006 (0.0003)	-0.0004 (0.0004)
YIELDS	-3.02e-06 (0.0004)	-0.00002 (0.0004)
PUBLICAT	-0.850 * (0.487)	-1.254 ** (0.622)
COMPUTER	-1.135 ** (0.491)	-1.464 ** (0.599)
PROFIT	-0.108 (0.518)	-0.434 (0.687)
IMPORTAN	N/A	N/A
VRT	0.999 ** (0.489)	0.955 (0.632)
EXPERIEN	0.013 (0.048)	0.012 (0.047)
INCOME	0.010 (0.009)	0.014 (0.012)
AG_EASE	1.485 ** (0.618)	1.618 ** (0.773)
PLAN	-0.251 * (0.136)	-0.300 * (0.163)
MANURE	-0.113 (0.650)	-0.695 (0.668)
AGE	0.004 (0.045)	0.014 (0.052)
EDUC	0.072 (0.125)	0.125 (0.123)

Table 3.8 Logit Parameter Estimates of the Covariates using a Pooled Regression (N=738)

Pseudo R^2 = 0.1834 -- LR chi2(52) = 179.51

Prob > chi2 = 0.0000 -- Log likelihood = -399.614

Variables	**Coefficients (St.E)**	**Average Marginal Effects (St.E)**
CONSTANT	-3.101 (2.875)	---
ADOPT_2	-0.040 (0.562)	-0.007 (0.102)
VRT	-1.052 (0.775)	-0.192 (0.140)
ACRES	0.0006 (0.001)	0.0001 (0.0002)
YIELDS	-0.0005 (0.001)	-0.00009 (0.0002)
COMPUTER	1.187 (0.732)	0.216 (0.132)
IMPORTAN	-0.383 (1.239)	-0.070 (0.226)
PROFIT	3.346 ** (1.531)	0.610 ** (0.276)
INCOME	-0.036 ** (0.012)	-0.006 ** (0.002)
MANURE	1.632 ** (0.775)	0.297 ** (0.140)
EXPERIEN	0.022 (0.055)	0.004 (0.010)
AGE	0.033 (0.058)	0.006 (0.010)
COLLEGE	-1.025 (0.796)	-0.187 (0.144)

Table 3.8 continued

2005 Interaction Effects

Year 2005	-0.186 (3.301)	-0.033 (0.602)
ADOPT_2_05	1.464 ** (0.660)	0.267 ** (0.119)
VRT_05	1.836 ** (0.865)	0.335 ** (0.156)
ACRES_05	-0.0005 (0.001)	-0.0001 (0.0002)
YIELDS_05	0.0008 (0.001)	0.0001 (0.0002)
COMPUTER_05	-1.532 * (0.854)	-0.279 * (0.154)
IMPORTAN_05	1.439 (1.643)	0.262 (0.299)
PROFIT_05	-2.156 (1.621)	-0.393 (0.294)
INCOME_05	0.040 ** (0.013)	0.007 ** (0.002)
MANURE_05	-1.726 * (0.895)	-0.315 * (0.161)
EXPERIEN_05	-0.013 (0.064)	-0.002 (0.011)
AGE_05	-0.054 (0.066)	-0.009 (0.012)
COLLEGE_05	0.539 (0.904)	0.098 (0.164)

Table 3.8 continued

2009 Interaction Effects

Year 2009	-1.304 (3.183)	-0.238 (0.580)
ADOPT_2_09	1.018 * (0.598)	0.185 * (0.108)
VRT_09	1.840 ** (0.810)	0.335 ** (0.146)
ACRES_09	-0.0006 (0.001)	-0.0001 (0.0002)
YIELDS_09	0.0006 (0.001)	0.0001 (0.0002)
COMPUTER_09	-0.766 (0.782)	-0.139 (0.142)
IMPORTAN_09	1.611 (1.648)	0.294 (0.300)
PROFIT_09	-2.412 (1.575)	-0.440 (0.286)
INCOME_09	0.034 ** (0.012)	0.006 ** (0.002)
MANURE_09	-1.754 ** (0.818)	-0.320 ** (0.147)
EXPERIEN_09	-0.019 (0.058)	-0.003 (0.010)
AGE_09	-0.047 (0.062)	-0.008 (0.011)
COLLEGE_09	1.175 (0.839)	0.214 (0.152)

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3.9 Coefficient estimates of the covariates for each outcome using Binary Logit

	2009 (N=440)	**2005 (N=202)**	**2001 (N=85)**
	LR chi2(26) = 98.03 Pseudo R^2 = 0.1767	LR chi2(17) = 54.85 Pseudo R^2 = 0.1962	LR chi2(17) = 33.25 Pseudo R^2 = 0.2871
Variables	**Coefficients (St.E)**	**Coefficients (St.E)**	**Coefficients (St.E)**
CONSTANT	-5.413 *** (1.474)	-3.705 ** (1.611)	-3.101 (2.875)
VRT	0.888 *** (0.273)	0.852 ** (0.379)	-1.052 (0.775)
ADOPT_2	0.996 *** (0.215)	1.553 *** (0.350)	-0.040 (0.562)
ACRES	0.0001 (0.0001)	0.0001 (0.0001)	0.0006 (0.001)
YIELDS	0.0001 (0.0002)	0.0002 (0.0003)	-0.0005 (0.001)
PUBLICAT	0.538 ** (0.254)	N/A	N/A
COMPUTER	0.280 (0.297)	-0.292 (0.440)	1.187 (0.732)
IMPORTAN	1.186 (1.104)	0.935 (1.066)	-0.383 (1.239)
PROFIT	0.943 ** (0.381)	1.214 ** (0.532)	3.346 **(1.531)
INCOME	-0.001 (0.004)	0.004 (0.006)	-0.036 ** (0.012)
AG_EASE	0.113 (0.402)	N/A	N/A
PLAN	0.171 ** (0.084)	N/A	N/A
MANURE	-0.009 (0.279)	-0.082 (0.453)	1.632 ** (0.775)
EXPERIEN	0.00005 (0.020)	-0.014 (0.028)	0.022 (0.055)
AGE	-0.008 (0.021)	-0.003 (0.027)	0.033 (0.058)
COLLEGE	0.123 (0.280)	-0.385 (0.416)	-1.025 (0.796)

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3.10 Average marginal effects of each outcome using Binary Logit Models

	2009 (N=440)	**2005 (N= 202)**	**2001 (N=85)**
	LR chi2(26) = 98.03 Pseudo R^2 = 0.1767	LR chi2(17) = 54.85 Pseudo R^2 = 0.1962	LR chi2(17) = 33.25 Pseudo R^2 = 0.2871
Variables	**Average Marginal Effects (St.E)**	**Average Marginal Effects (St.E)**	**Average Marginal Effects (St.E)**
VRT	0.153 *** (0.045)	0.160 ** (0.068)	-0.169 (0.120)
ADOPT_2	0.172 *** (0.033)	0.292 *** (0.053)	-0.006 (0.090)
ACRES	0.00002 (0.00002)	0.00002 (0.00002)	0.0001 (0.0001)
YIELDS	0.00002 (0.00003)	0.00005 (0.00006)	-0.00008 (0.0001)
PUBLICAT	0.093 ** (0.043)	N/A	N/A
COMPUTER	0.048 (0.051)	-0.055 (0.082)	0.191 * (0.111)
IMPORTAN	0.205 (0.190)	0.176 (0.199)	-0.061 (0.199)
PROFIT	0.163 ** (0.064)	0.228 ** (0.095)	0.539 ** (0.222)
INCOME	-0.0002 (0.0008)	0.0009 (0.001)	-0.005 *** (0.001)
AG_EASE	0.019 (0.069)	N/A	N/A
PLAN	0.029 ** (0.014)	N/A	N/A
MANURE	-0.001 (0.048)	-0.015 (0.085)	0.263 ** (0.112)
EXPERIEN	9.81e-06 (0.003)	-0.002 (0.005)	0.003 (0.008)
AGE	-0.001 (0.003)	-0.0007 (0.005)	0.005 (0.009)
COLLEGE	0.021 (0.048)	-0.072 (0.077)	-0.165 (0.124)

Note: *** p<0.01, ** p<0.05, * p<0.1

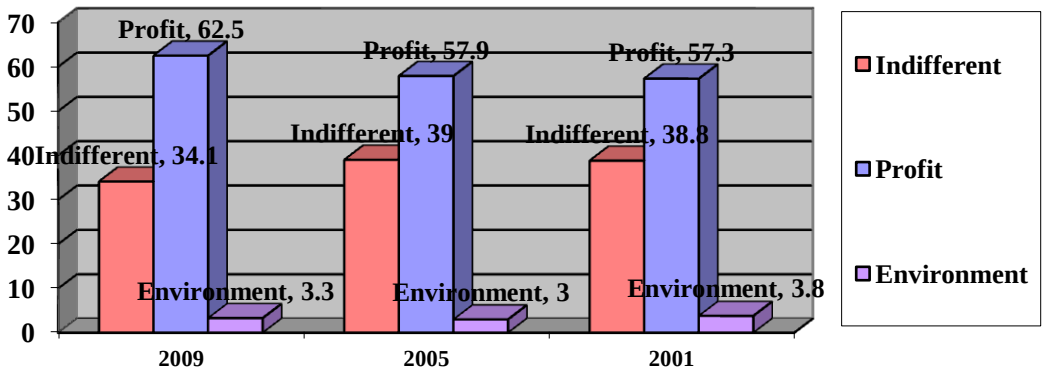

Figure 3.1: Percentage of Responses for the Reasons to Adopt Precision Technology

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CHAPTER 4

WHAT MAKES CERTAIN PRECISION TECHNOLOGIES MORE DURABLE THAN OTHERS

4.1 Introduction

In this chapter, we want to investigate the factors affecting the duration of site specific information gathering (SSIG) technology use. The first application of duration analysis in social sciences was Lancaster's study (1972) that explained the duration of unemployment before workers enter the job market. Recently, there have been studies in the agricultural economics literature that utilized duration analyses to study the length of time before adopting a technology, or the "speed of adoption" (Burton et al., 2003, Dadi et al., 2004, Odendo et al., 2010). Our paper tries to explain the length of time before precision technologies are abandoned (i.e. speed of abandonment). In the context of the above duration models, the entrance or start time in our study is the date when precision technology adoption first took place, whereas the exit date is the time the farmer discontinued the use of the specific technology. To the best of our knowledge, this issue has not been investigated before and we contribute to the literature in this regard.

Previous cross sectional studies have focused on the adoption and abandonment decisions within a static framework (i.e., at a certain point in time) using binary choice models such as logit and probit (Roberts et al., 2004, Khanna, 2001, Banerjee et al., 2008). Walton et al. (2008) identified the factors affecting the abandonment of precision soil

sampling, but no study has yet examined what specific factors affect the amount of time precision technologies are utilized (i.e., their duration of use over time). Our study will try to fill this gap in the literature about the dynamics of technology adoption, and estimate the effect of time-varying and time-independent variables on duration (Dadi et al., 2004, Odendo et al., 2010).

The importance of the duration analysis lies in the fact that it is not a one-time event such as the adoption or the abandonment choice. Farmers' decision on whether they will continue using the technology requires a comparison between the prior expected net benefits before the adoption, and the observed net benefits following the adoption (Walton et al., 2008). Moreover, the use of time-dependent variables helps explain whether and when a farmer adopts a technology, thereby accounting for the growth of adoption over time. This has been ignored in cross sectional studies that estimate adoption and abandonment decisions separately (D'Emden et al., 2006). In our case, where adoption of SSIG technologies requires accumulation of information, technical skills, and physical capital, various economic and social variables may not be adequate to capture the abandonment choice at the time of abandonment. It would be interesting to see whether variables such as education, income, age etc. that affect the SSIG technology adoption also influence the time taken to abandonment. Built on dichotomous choice tools, the duration methods combine both individual adoption decisions as well as the cumulative aspect of innovation diffusion (Feder et al., 1985).

Given the cost of technology diffusion and farmers' costs in learning the new technologies, it is useful to know which future SSIG technologies are more likely to be discontinued (i.e., abandoned faster) and what type of farmers discontinue different types of

SSIG technologies first. Velandia et al. (2010) found that 75% of farmers used combined information about precision farming from Extension and private sources (e.g., consultants, farm dealerships, media and other farmers). Thus, from an extension programming perspective, knowing the characteristics of farmers who give up earlier on essentially effective SSIG technologies would help agents and specialists target educational modules that can help improve technology retention rates, as well as provide better information about precision technologies.

4.2 Conceptual/Empirical Framework

4.2.1 Utility Theory

In this study, we focus on farmers who at some point in the past (t_0) have already adopted SSIG technologies and decide at some future period (t) whether or not to abandon its use. At time t_0, given that the farmer adopted SSIG, we can posit that the expected utility from adopting SSIG technologies at time t_0 (U_{s0}) is greater than the expected utility from not adopting SSIG (U_{n0}), i.e. $U_0^* = U_{s0} - U_{n0} > 0$.[13] The utility from not adopting SSIG (U_{n0}) can be interpreted as the opportunity cost of SSIG adoption (i.e., the foregone utility from using the next best alternative technology). After adoption in time t_0, the farmers then have a series of one-period decisions as to the best technology to use in subsequent periods. The farmer

[13] By choosing to adopt SSIG, the producer self-selects into a non-random sample of famers that in subsequent periods will have to decide whether to continue adopting SSIG or discontinue its use. This characteristic of the sample suggests that the estimation approaches should account for selection bias (see p. 10 in the estimation procedures section).

abandons the SSIG technology at time *t* if the expected utility from SSIG (U_{st}) becomes less than the expected utility from not using SSIG (U_{nt}), i.e., $U_{st} < U_{nt}$ or $U_t^* = U_{st} - U_{nt} < 0$.

The utility from adopting SSIG technology is assumed to be driven by monetary benefits (i.e. direct monetary or profit benefits) and non-monetary benefits (i.e., environmental or cotton quality benefits) such that $U_{st} = M_{st} + E_{st}$, where M_{st} is monetary benefits and E_{st} is non-monetary benefits. Further assume that M_{st} is a function of observable (possibly time-varying) variables (X) that represent farmer/farm characteristics, and unobservable variables (ε) that affect the monetary benefits from SSIG, such that $M_{st} = \alpha X_{st} + \varepsilon_{st}$ (where α is a parameter). The non-monetary benefits from SSIG (E_{st}) is not directly and perfectly measured such that $E_{st} = \bar{E}_{st} + e_{st}$ where $\bar{E}_{st}$ is the observable or perceived non-monetary benefit from the perspective of the producer and e_{st} is an error term that represents the uncertain or unobserved factors affecting the non-monetary benefits of SSIG. The utility from not adopting SSIG (or the opportunity cost of SSIG) is also not perfectly observable such that $U_{nt} = \bar{U}_{nt} + \mu_{st}$, where $\bar{U}_{nt}$ is the perceived utility derived from an alternative technology and μ_{st} represents uncertainty in the perceived benefit from not adopting SSIG. The term μ_{st} can also be considered as unobserved improvements in alternative technologies that evolve through time.

Based on the definitions above, we can represent the decision to abandon SSIG technology as follows:

(1) $$U^* = \alpha X_{st} + \bar{E}_{st} - \bar{U}_{st} + u_{st} < 0,$$

where $u_{st} = \varepsilon_{st} + e_{st} - \mu_{st}$. Equation (1) implies that observed farm/farmer characteristics, perceived non-monetary benefits of SSIG, and perceived opportunity costs of SSIG determines whether to continue the use of SSIG *t* years after adoption. In particular, higher perceived non-monetary benefits would make it more likely to continue the use of SSIG, while higher perceived opportunity cost reduces the probability that an SSIG adopter would continue the use of the technology. More unobserved improvements in the alternative technology would also lead to lower probability of continued SSIG use. Equation (1) then serves as a good point of departure for the empirical specification in this study.

Given the constant period-by-period review of the expected utility from SSIG, the question of abandonment probability in each period essentially becomes a question of time to abandonment. Note that the latent variable *U** in each period is not observable, but our data allow us to observe the period from adoption until the data was collected (2009) and then whether or not SSIG was abandoned at this point in time (2009). Hence, duration time in the context of our study is the period from SSIG adoption until abandonment or, in the case of farmers who have not abandoned at the time of data collection, the period from adoption through when the data was collected (2009).[14] We can consider this period of use as our dependent variable in the empirical specification, and variables that represent the other terms in (1) as possible independent variables (i.e., X_{st}, $\bar{E}_{st}$, $\bar{U}_{st}$) where its hypothesized effects can then be tested.

[14] In the latter case, the farmers have not yet abandoned SSIG at the time of data collection (2009). The time of abandonment is unknown (although it may occur in the future) and the data is effectively right-censored. Empirical approaches for this type of duration data should take this in to account (see p. 10 in the estimation procedures section).

4.2.2 Duration Analysis

In light of the expected utility framework described above (and the available data on right-censored data on abandonment period), duration analysis (or duration models) is an appropriate empirical framework to examine factors affecting the period of use for SSIG technologies (i.e., from time of adoption to their abandonment). In our duration model, we define the hazard function $h(t)$ as the probability that a farmer will abandon the SSIG technology at time t, conditional on him/her being a SSIG user up to that point in time (t). The hazard function can then be expressed as follows:

(2) $$h(t) = \frac{f(t)}{S(t)},$$

where $f(t)$ is the probability density function of abandoning the technology at time t, and $S(t)$ is the survival function, i.e., the probability that someone will use SSIG technologies up to at least time t. In estimating duration models, the density function $f(t)$ is used for uncensored observations, for which we observe their actual time of abandonment, and the survival function $S(t)$ is used for censored observations, for which we only observe that SSIG technologies have been used at least up to time t.

The hazard function can be thought of as the continuous time version of a sequence of conditional probabilities (in this case, conditional probabilities of abandonment) (Burton et al., 2003). The cumulative distributions, e.g., the survivor and hazard functions, are equivalent ways of expressing the distribution of the period until abandonment. Note that for an individual farmer, 1 - $S(t)$ is gives the probability that an individual will have abandoned

SSIG by time *t*, but if one considers a population of SSIG adopters, it will also represent the expected abandonment rate through that population, that is, the share of the population that has abandoned the technology.

To analyze explanatory variables that affect the time from SSIG adoption until abandonment, the hazard function needs to be specified to allow observable variables to affect the hazard function. The most common way of expressing such a hazard function is as follows:

(3) $$h(t, X, \theta, \beta) = h_0(t, \theta) g(X, \beta),$$

where $h_0(t, \theta)$ denotes the baseline hazard which is independent of *X* (i.e., it represents the hazard for the individual under "standard" conditions, say *X* = 0), *X* is a vector of observable variables, β is a vector of parameters associated with the observable variables, θ is a vector of parameters associated with the baseline hazard, and the function $g(X, \beta)$ acts multiplicatively on the baseline hazard.

The most widely-used and convenient specification of the function $g(X, \beta)$ is:

(4) $$g(X, \beta) = \exp(x\beta),$$

which ensures non-negativity of $g(X, \beta)$ without imposing restrictions on β. This also makes the function easier to estimate because it becomes linear in logarithms. Once $g(X, \beta)$ is specified, the baseline hazard function $h_0(t, \theta)$ also needs to be specified so that the hazard function in (3) follows a particular parametric shape (i.e., a parametric approach).

One of the more popular functional forms used for the baseline hazard is $h_0(t, p)$ = pt^{p-1} where *p* is the shape parameter to be estimated from the data. This specification of the

baseline hazard and the specification $g(X,\beta)$ in (3), results in the Weibull model/distribution for the hazard function, as follows:

(5) $$h(t, X, \theta, \beta) = pt^{p-1}\exp(X\beta).$$

If $p > 1$ there is increasing duration dependence, while $p < 1$ means there is decreasing duration dependence. In the context of this study, $p > 1$ suggests that the likelihood of a farmer abandoning SSIG will increase the longer he has used SSIG (or alternatively it becomes less likely that the farmer will continue to use SSIG if he has already used it for a long time). The reverse holds for $p < 1$. When $p = 1$, the hazard function would then be considered the exponential model/distribution:

(6) $$h(t, X, \theta, \beta) = \exp(X\beta).$$

Hence, the exponential form is nested within the Weibull model for the hazard function. Other commonly used parametric functional forms to specify the hazard function are lognormal, loglogistic, and Gompertz model.[15] In empirical applications, a best-fitting distribution based on the data is chosen using tests or criteria (i.e. Akaike Information Criteria, below in estimation procedures section).[16]

The fully parametric specification of the hazard function in (5) and (6) that allows for explanatory variables to affect the hazard rate is commonly called a proportional hazard (PH)

[15] The detailed specifications for these distributions are not discussed here in detail in the spirit of conciseness. But the interested reader can refer to Cleves et al (2008) for the specific details on each functional form.

[16] Note that when a particular parametric distribution is used to specify the hazard function this is called the parametric approach. The success of the parametric approach greatly depends on how correctly we specified the distribution based on the data. A semi-parametric approach, called the Cox proportional hazard model, could also be an alternative where the baseline hazard is left unspecified. The benefit of this semi-parametric approach is that no assumptions are made about the shape of the hazard function. However, the semi-parametric approach is less efficient than the parametric approach since the Cox proportional hazard model ignores what happens to the explanatory variables when no "failures" occur (or abandonments in our case). Also, to the best of our knowledge, there has been no approach yet that controls for selection issues for the Cox proportional hazard model.

model. In the PH model, a positive coefficient associated with the explanatory variables means that an increase in the explanatory variable increases the hazard rate (i.e., in our case, increases the probability of abandonment or decreases the likelihood of continued SSIG use). An alternative to the PH model is the Accelerated Failure Time (AFT) model. In an AFT specification, the Weibull hazard function can specified as follows:

(7) $$h(t, X, \theta, \beta) = pt^{p-1} \exp(-pX\beta),$$

and the exponential specification (when p =1) can be specified as:

(8) $$h(t, X, \theta, \beta) = \exp(-X\beta).$$ [17]

In the AFT model, a positive coefficient associated with an explanatory variable suggests that the waiting time for failure is increased. In the context of our study, a positive β coefficient in the AFT model indicates that an increase in the explanatory variable will increase the waiting time until abandonment is observed (i.e., or alternatively increase the likelihood of continuing to use SSIG). In the present study, a PH specification is used and interpretations of the duration model coefficients are based on this specification.

4.3 Data, Estimation Procedures, and Empirical Specification

4.3.1 Data Description

Our data for this study were collected from a 2009 survey sent to cotton farmers in 12 Southeastern states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas and Virginia. This survey was developed

[17] The interested reader is again referred to Cleves et al. (2008) for the detailed functional forms of the other distributions (e.g., lognormal and loglogistic) in an AFT specification.

to query cotton producers about their attitudes toward and use of precision farming technologies (i.e., SSIG and VRT). Following Dillman's (1978) general mail survey procedures, the questionnaire, a postage-paid return envelope, and a cover letter explaining the purpose of the survey were sent to each producer. The initial mailing of the questionnaire was on February 20, 2009, and a reminder post card was sent two weeks later on March 5, 2009. A follow-up mailing to producers not responding to previous inquiries was conducted three weeks later on March 27, 2009. The second mailing included a letter indicating the importance of the survey, the questionnaire, and a postage paid return envelope. A mailing list of 14,089 potential cotton producers for the 2007-2008 marketing year was furnished by the Cotton Board in Memphis, Tennessee. Among responses received, 1981 were counted as valid, and thus used in our study. We only have responses regarding the duration of use of site specific information gathering (SSIG) technologies, but not for the variable rate input practices.

The survey conveys information about a) the physical characteristics of the farm (e.g., location, acres); b) demographics (e.g., income, education, experience); c) input management decisions (e.g., fertilizers, irrigation, drainage); d) sources of information (dealers, university extension); and e) farmers perceptions about environmental and cotton quality issues. An adopter of at least one SSIG technology is identified as everyone who assesses his within field yield variability either with yield monitors, soil sampling, maps, aerial photography, or combinations of the above technologies. In this context, the duration of interest is the length of time it takes a farmer to discontinue a SSIG technology. Among the SSIG technologies,

soil sampling and maps are being used for a longer period (see Table 2), possibly because farmers had sufficient time to evaluate benefits and costs (Walton et al., 2008).

For the variable of interest -- the expected duration -- we utilized questions 19 and 20 from the survey (See Figure 4.2). We only considered data for which the length of use did not exceed 30 years, since precision agriculture was introduced in the early 80s.

4.3.2 Estimation Procedures

Duration models allow corrections for censoring and duration dependence. Censoring and particularly *right censoring* is a problem of incomplete observations for the farmers who have not experienced the event of interest by the end of the observation period (i.e., abandonment in our case). We can only observe the actual time of SSIG use (or duration of use) for those who abandoned SSIG technologies prior to or during the 2009 crop year, which is the year for which we have available survey data (see footnote 14). Thus, the survival time is not completely determined, because there are farmers who still use the technology but may abandon in the future. For these individuals, the statistical process is to right censor the duration at the end of the observation period (Burton et al, 2003). In this case, we assume that the probability of remaining SSIG users is greater than the censored value (i.e., the time of survey). Standard models of duration data are built on the assumption that everyone will eventually “fail”, or in our case “abandon” (Jones, 2006). As for the issue of *duration dependence*, it occurs when the risk of a farmer abandoning the technology depends on how long s/he has been in the non-abandonment stage, a case where the standard

logit/probit models fail to account (Botelho et al., 2008, Beck et al., 1998). Again, duration analysis is more appropriate in this case.

Sample selection is an additional problem we may encounter, when dealing with the survey data we have. Sample selection problems occur when observations selected are not independent of the outcome variable, causing biased inferences (Berk, 1983). In our case, selection problem arises because our "full" sample includes farmers who adopted in the past, and not the entire population of cotton producers at the moment of abandonment. This is a self-selected sample in itself, because farmers made this choice based on their awareness for precision technologies and other factors (See footnote 1). Moreover, producers may not be aware of all the technology aspects and those aware are not likely to represent a random sample of population (McBride and Daberkow, 2003). Thus, factors that affect duration of SSIG technologies might also affect the farmer's decision to abandon SSIG technologies. To address this problem, previous literature has typically employed dummy variables of soil type, weather, climate, availability of information, etc. to represent location factors that affect adoption of precision agriculture (Khanna, 2001, Daberkow and McBride, 2003).

Given the potential issues with regards to right-censoring, duration dependence, and selection problems, a duration model that accounts for sample selection is the estimation procedure of choice in this study. To more formally present this estimation approach, we follow Boehmke et al. (2006), where we first define Y_i as a continuous variable[18] that follows density $f(Y_i)$. The outcome depends on a set of covariates, by letting $y_i = \exp(-X_i\beta)\varepsilon_i$. The selection process leads us to observe Y_i only for the observations for which the binary

[18] Our data only provide integer values, although duration in years could be continuous. However other studies (Boehmke et al., 2006, Dadi et al., 2004, Martins et al., 2010) have essentially used integer values as well.

censoring variable c_i takes on the value of 1 (abandon) and d is an indicator of right-censoring. Thus, the probability of uncensored observations is $\Pr(Y_i=y_i, c_i=1)$, whereas for censored is $\Pr(c_i=0)$. Combining the two probabilities yields

(9) $$\Pr(Y,c) = \prod_{i=1}^{n} (\Pr(c_i = 1 \mid Y_i = y_i) f(y_i))^{c_i=1} (\Pr(c_i = 0))^{c_i=0}$$

To calculate the above probabilities, Gumbel (1960) developed a bivariate exponential model with the following joint and cumulative density functions:

(10) $$f(x,y) = \exp(-x-y)(1 + a(2\exp(-x)-1)(2\exp(-y)-1))$$

$$F(x,y) = (1-\exp(-x))(1-\exp(-y))(1 + a\exp(-x-y))$$

The model can be written as a function of systematic and stochastic components as $c_i^*=\exp(w_i,\gamma)u_i$, where $c_i=0$ if $c_i^* \le 1$ or $c_i=1$ if $c_i^* > 1$

Thus the probability that an observation is censored becomes $\Pr(\exp(w_i\gamma)u_i \le 1)$ and $F(1 \mid \exp(w_i\gamma)) = (1-\exp(-\exp(-w_i\gamma))$. Using the bivariate exponential distribution above, the conditional cumulative density is:

(11) $$F(x \mid Y = y) = 1 - \exp(-x)(1 + a(2\exp(-y)-1)(\exp(-x)-1))$$

By substituting $c_i^*=\exp(w_i,\gamma)u_i$ and $y_i=\exp(-x_i\beta)\varepsilon_i$ and defining $\lambda_{1i}=\exp(-w_i,\gamma)$ and $\lambda_{2i}=\exp(x_i\beta)$, the cdf in (11) can be rewritten as:

(12) $$F(u_i \mid \lambda_{1i}, \varepsilon_\iota = y_i\lambda_{2i}) = 1 - \exp(-\lambda_{1i}u_i)(1 + a(2\exp(-\lambda_{2i}y_i)-1)(\exp(-\lambda_{1i}u_i)-1))$$

The joint probability that an observation selects in and has duration greater than the right censoring point, y_i^0 is calculated as:

(13) $$\begin{aligned}\Pr(y_i \ge y_i^0, u_i > \exp(-w_i\gamma)) &= 1 - F(y_i^0 \mid \lambda_{2\iota}) - F(1 \mid \lambda_{1i}) + F(1, y_i^0 \mid \lambda_{1i}, \lambda_{2i}) \\ &= \exp(-\lambda_{1i} - \lambda_{2i}y_i^0)[1 + \alpha(1-\exp(-\lambda_{2i}y_i^0))(1-\exp(-\lambda_{1i}))]\end{aligned}$$

Combining uncensored observations with an observed failure time, uncensored observations that are right censored, and censored observations yields the exponential likelihood function: (14)

$$\begin{aligned}\ln(\beta,\gamma,\alpha,p \mid X,W,Y,c,d) &= \sum_{i=1}^{n} c_i(1-d_i)[-\lambda_{1i} - \lambda_{2i}y_i + \ln(\lambda_{2i}) \\ &+ \ln(1+\alpha(1-2\exp(-\lambda_{2i}y_i))(1-\exp(-\lambda_{1i})))] \\ &+ c_i d_i[-\lambda_{1i} - \lambda_{2i}y_i^0 + \ln(1+\alpha(1-\exp(-\lambda_{2i}y_i^0))(1-\exp(-\lambda_{1t})))] + (1-c_i)[\ln(1-\exp(-\lambda_{1i}))]\end{aligned},$$

where d_i is an indicator for whether an observed duration is right-censored or not.

The Weibull likelihood with right censoring is derived by repeating the same steps as with the exponential above, and substituting this into the bivariate exponential cdf:

(15) $$F(x,y) = (1-\exp(-x^p))(1-\exp(-y))(1+\alpha\exp(-x^p - y))$$

To get the following: (16)

$$\begin{aligned}\ln(\beta,\gamma,\alpha,p \mid X,W,Y,c,d) &= \sum_{i=1}^{n} c_i(1-d_i)[-\lambda_{1i} + \ln(1+\alpha(2\exp(-\lambda_{2i}Y_i)^p)-1)\exp(\lambda_{1t})-1)) \\ &+ \ln(p)\ln(\lambda_{2i}) + (p-1)\ln(\lambda_{2i}Y_i) - (\lambda_{2t}Y)^p] + c_i d_i[-\lambda_{1i} - (\lambda_{2i}Y_i^0)^p \\ &+ \ln(1+\alpha(1-\exp(-\lambda_{2i}Y_i)^p)(1-\exp(-\lambda_{1i})))] \\ &+ (1-c_i)[\ln(1-\exp(-\lambda_{1i}))]\end{aligned}$$

where β, γ, α are parameters to be estimated; p is the Weibull distribution shape parameter, when the error term ε follows an exponential distribution; X is the vector of explanatory variables; W is the Weibull distribution, Y is the duration of SSIG technologies use; c is a censoring binary variable, and $\lambda_{1i} = \exp(-w_i\gamma)$ and $\lambda_{2i} = \exp(\mathrm{X}_i\beta)$.

4.3.3 Empirical Specification

We assume that the conditional probability of duration, given the time invariant regressors X_i, the time varying regressors $Z_i(t_i)$, and errors θ_i is:

(17) $$f(t_i) = Z_i(t_i)b + X_i(t_i)c + \theta_i,$$

where t denotes the duration of a particular site-specific information gathering technology s for an individual farmer i. Last, we assume that X_i and $Z_i(t_i)$ are exogenously determined and observable, while θ is unobserved. In (17), perceptions about non-monetary benefits (i.e., $\bar{E}_{st}$ in the utility theory discussion above) and opportunity costs of SSIG (i.e., $\bar{U}_{st}$ in the utility theory discussion) are included as part of the vector of time-invariant regressors.

Due to lack of a sufficient number of observations for all individual technologies, we grouped them in 4 categories as follows: MONITORS include the yield monitors with GPS and yield monitors without GPS, SAMPLING consists of grid soil sampling and zone soil sampling, PHOTOS reflect aerial photos and satellite images, and MAPS account for soil survey maps, COTMAN plant mapping, and digitized mapping (See Figure 4.1). This grouping would account for cases of farmers who may have abandoned yield monitors without GPS, by adding a GPS to their yield monitor[19]. Therefore, this study considers the period of use of the aforementioned groups of technologies as the dependent variable of interest in our models.

For our duration analysis, we specifically focus on the duration of use of SAMPLING because it has been the most widely adopted precision farming technology, for which farmers

[19] The survey does not provide information on whether farmers, who discontinued a specific type of technology, later adopted another precision technology.

had sufficient time to evaluate its benefits and costs (Walton et al., 2008). Along with variable rate P and K application, soil testing has been the most offered service since the introduction of precision agriculture technologies. Then we compare our results with the duration of use of MONITORS, which is the most recent SSIG technology that became commercially viable in 1997. Fertilizer management through the soil sampling method is recommended when there is no history of livestock or manure influence on the field, and when yield maps or other sources of spatial information show consistency from one layer to another. On the other hand, grid sampling is preferred when fields with different crop histories have been merged into one, or livestock, heavy manure application and irrigation have taken place (Ferguson Hergert, undated).

We decided on the explanatory variables X_i and $Z_i(t_i)$ to be included in the specification based on the utility theory presented above (See Section 4.2.1) and also on previous literature (Walton et al., 2008, Roberts et al., 2004, Velandia et al., 2010). The utility theory discusses the importance of observable characteristics that influence the period-by-period decision to whether or not abandon the use of SSIG technology. Hence, we include farmer and farm characteristics that could potentially influence the period of use of SSIG technologies.

With regards to the *farmer characteristics* included in our empirical model, we first consider human capital variables such as age, years of experience and education level. These factors have previously been considered as important determinants in the theory of technology adoption (Khanna et al., 2001, Feder et al., 1985). Younger farmers have both longer life and planning horizons (*PLAN*) in which they can make changes, and are likely to

invest on precision technologies over a longer period of time. On the contrary, there are farmers who invest more on minimizing the time spent on farming rather than maximize their farm's profits (Nehring, Fernandez-Cornejo, and Banker, 2002). Hence the expected sign of *PLAN* coefficient is indeterminate.

Increased farming experience may indicate better skills on how to manage the field, thus the sign of *EXPERIEN* could be expected as negative (longer duration). Experienced farmers may be more reluctant to invest in new technologies, but those who have already adopted will more likely use it for a longer period of time. Regarding the years of formal education (*EDUC*), we would expect the more educated farmers to abandon SSIG technologies slower, due to their human capital that recognizes the benefits of precision farming. Moreover, higher levels of education indicate increased analytical ability of managing the massive amount of data generated by precision agriculture (Batte, Jones, and Schnitkey 1990). Hence, the expected sign of the variable *EDUC* would be negative, as well. From a different aspect, more educated farmers would be more likely to experiment and continuously adopt improved technologies. Hence, they tend to abandon older technologies faster in order to adopt newer technologies or advanced versions of the same technology (e.g., incorporate GPS in the same SSIG technology). Furthermore, since most of these technologies are interrelated with computer systems, farmers who use computer or handheld devices in their farm management (*COMPUTER*) will likewise preserve the precision farming for a longer period of time, thus we would expect negative correlation with the hazard rate. The effect of percentage of farm income (*INCOME*) is difficult to be determined a priori. Farmers who are more dependent on farming may be more willing to invest their

financial resources on precision technologies, thus abandon the technologies at a slower rate. In a different perspective, a large percentage of income coming from farming may indicate a more risk-averse behavior. Hence, a farmer may abandon the technology faster if it does not yield the expected benefits.

Indicator variables that represent whether farmers participate in agricultural easement programs (*AG_EASE*) and whether farmers have access to university publications and extension (*PUBLICAT*) are also included in the empirical specification as part of the group of farmer characteristics that can potentially affect duration of SSIG use. Exposure to university publications would likely lead farmers to adopt as well as use technologies for a longer period (Hall et al., 2003, Velandia et al., 2010). Those farmers who participate in easement programs will also more likely acknowledge the environmental benefits of precision farming apart from the potentially increased profitability from adoption. Hence, it is reasonable to expect that they would be more eager to rely on these technologies for a longer period of time.

Farmer perceptions about the spatial yield variability of their fields, perceptions about the environmental and quality benefits of SSIG, and opinions about the future profitability/importance of precision technologies are additional farmer characteristics included in the empirical specification. Perceptions about spatial yield variability (*SYVAR*) may be another factor affecting duration of SSIG use. If farmers realize or perceive lack of yield variability in their fields, they will more likely discontinue the use of SSIG technology more rapidly. In order to calculate the perceived Spatial Yield Variability (*SYVAR*) variable, we utilized the spatial variability formula used in Larson and Roberts (2004):

(18) $$SYVAR = 0.33 \times (Y_{LOW} - Y_{AVG})^2 + 0.33 \times (Y_{MID} - Y_{AVG})^2 + 0.33 \times (Y_{HIGH} - Y_{AVG})^2,$$

where Y_{LOW} is the estimate for the yield of the least productive portion of field, Y_{AVG} is the estimated average yield for the typical field, Y_{HIGH} is the estimated yield for the most productive portion, and Y_{MID}=3* Y_{AVG} - Y_{LOW} – Y_{HIGH}. We, then, used the *SYVAR* and Y_{AVG}, in order to create the coefficient of spatial yield variability ($SYCV_i$) statistic based on the following formula:

(19) $$SYCV_i = \frac{SYVAR_i^{0.5}}{Y_{avg}} \times 100,$$

where $SYVAR_i^{0.5}$ is the standard deviation of spatial yield variability estimated using (18).

Previous studies (Walton et al., 2008, Roberts et al., 2003) have pointed out the importance of perceptions about precision farming on technology adoption and technology abandonment. Hence, variables that represent these perceptions are included in the empirical specification. Farmers, who perceive that precision agriculture will be profitable (*PROFIT*) and important (*IMPORTA*) in the future will more likely utilize technologies for a longer time, thus abandon at a slower rate. Therefore, the sign of *PROFIT* and *IMPORTA* would be expected to be negative under the expectation of future payoffs (Napier et al., 2000, Roberts et al., 2004). Note that the *PROFIT* dummy variable can also be interpreted as a crude proxy for the opportunity costs of SSIG (i.e., $\bar{U}_{st}$ in the utility theory discussion) because if one views precision farming to be profitable in the future it suggests that he/she views the opportunity costs of precision farming to be low (i.e., the expected utility or benefits from using alternative technologies are perceived to be low). However, caution must be taken in interpreting the PROFIT variable this way because it refers to the profitability of "precision

technologies" in general (not just SSIG in particular), and also it asks about "future" profitability rather than the profitability perception during the *t* periods when the producer decides whether or not to abandon the technology.

As explained in the utility theory section, non-monetary benefits may also play a role in the decision to whether or not to continue use of SSIG technologies. Burton et al. (2003) also found that farmers' attitude towards the environment affects the adoption decisions, and likewise the length of use. Hence, dummy variables that reflect producer opinions about the potential environmental and quality benefits of SSIG are included in the empirical specification. Producers who perceived improvements in cotton quality (*QUALITY*) and environmental benefits (*ENVIRON*) through the use of PF will more likely retain the technology for a longer term.

Farm characteristics included in our specification are farm size and average cotton yields (in the past crop year). Large farm size (*ACRES*) is associated with easier investment in new technologies as well as economies of scale. Thus, we expect higher adoption rates in this case (Larkin et al., 2005). This implies that a farmer will less likely abandon the technology fast. Likewise, farmers whose average yields are high (*YIELDS*) will more likely adopt (Banerjee et al., 2008) and utilize the technology for a longer period of time. Farmers who apply manure in their fields are relatively more concerned about water pollution that would be caused by the excessive use of chemical fertilizers. Thus they would be more willing to adopt precision technologies that are environmentally friendly (Torbett et al., 2007). Hence, we would expect *MANURE* to have a positive influence both on adoption as well as duration.

To evaluate the degree of correlation between the covariates, we checked for collinearity diagnostics. The values of the *Variance Inflation Factors* (VIF) are all very small (below 4), so the inclusion of the above variables in our estimation does not seem to be worrisome in terms of multicollinearity. Table 4.1 contains a description of the variables along with their hypothesized signs and the descriptive statistics of the sample. Note that the hypothesized signs in the table reflect the impact on SSIG duration and not the hazard rate (which, in this case, would be the opposite).

4.4 Results and Discussion

4.4.1 Nonparametric Analysis: Kaplan-Meier Curves

Before presenting the results of our duration model estimation, it is important to discuss some results that give a broad overview about the abandonment behavior of farmers in our sample. Aside from the summary statistics that provide the average abandonment periods of farmers in the survey (See Table 2), the non-parametric Kaplan-Meier curve would be another method to show general trends in the abandonment behavior of producers in the sample. The nonparametric Kaplan-Meier method (1958), the life table method, and the Nelson-Aalen method (1978), do not make assumptions about the distribution of failure time and how covariates shift the survival experience (Stevenson, 2009). Moreover, they assume that censoring is independent of survival time. In this study, we use the Kaplan-Meier (1958) estimator since it is the most often used non-parametric method in previous duration analysis

studies. The Kaplan-Meier approach non-parametrically estimates the probability of surviving past time *t*.

The Kaplan-Meier estimates of the survival functions for the five different groups of SSIG technologies are depicted in Figures 3 through 6, respectively. The horizontal axis reflects the number of years that passed from the date the farmer started using a particular technology to the time of abandonment. The time interval goes from 1 to 16 years for yield monitors and from 1 to 30 years for soil sampling, which is the longest duration period taken into consideration (we excluded observations for which farmers reported soil sampling use greater than 30 years). Note that the starting year is 1 instead of 0, since the sample contains only SSIG adopters. The vertical axis represents the estimated probability of SSIG continuation for a hypothetical cohort (and not the actual probability of survival). All technologies' slopes except from the yield monitors are relatively flat, indicating that the speed of abandonment was not rapid. People seem to abandon yield monitors faster compared to soil sampling. The first drop in the monitors' survival function is observed at year 5, and abandonment becomes even more frequent after this. On the other hand, 25% will abandon sampling technologies in 20 years, whereas 25% will quit monitors in less than 10 years of use. This implies that farmers seem to be pleased with sampling, and monitors' users either abandoned precision farming completely or switched to a different technology. A similar situation to soil sampling holds for the other two SSIG technologies -- PHOTOS and MAPS -- which also tend to be more likely abandoned after 20 years of use.

4.4.2 Parametric Duration Analysis

Tables 3 and 4 present the results of the estimated Weibull model with sample selection. We focus on SAMPLING and MONITORS only. The dependent variable is the length of use of each SSIG technology, and is measured in years. It should be noted that each equation has been estimated independently. Positive values of the parameters have a positive impact on the hazard, thus the time until failure (in our case SSIG abandonment) is shorter.

We first needed to determine the most appropriate parametric functional form for the baseline hazard function. The Akaike Information Criterion (AIC) is utilized in this study to find the functional form that best fits our data. The distributions taken into consideration were the Weibull, the Exponential, the lognormal, the loglogistic, and the Gompertz (see Table 3). For MONITORS, the AIC yields the smallest value for the Weibull distribution. Thus, the Weibull functional form is preferred. For SAMPLING, the AICs for Weibull and the other distributions almost coincided. For consistency, we still proceeded with the Weibull model for the SAMPLING duration model because the divergence in the AICs above was small. Thus, in this study we only focus on the estimates of Weibull model with sample selection[20]. Results of the Wald test indicate that the null hypothesis that all slope coefficients equal to zero can be rejected at less than a 0.01 significance level.

The next step is to address the selection problems inherent in our abandonment data. As suggested in Section 4.3.2, previous studies typically use locational factors that affect

[20] The Cox semi-parametric model does not facilitate control of selectivity issues. Thus it was not used in our analysis, since we believe that sample selection is a problem in our case. The results from Cox regressions are consistent with Weibull regressions without selection (see tables 3 and 4), meaning that the bias arising from unobserved heterogeneity or misspecified baseline hazard may not be significant.

technology adoption to control for selection issues in a first-stage probit model. Hence, we control for the: a) July humidity (*HUMIDITY*), since in cotton, heavy humidity could spoil production and reduce quality, and b) July temperature (*TEMPERA*) (Walton et al., 2008), since high temperature is a primary controller for rapid cotton growth. However, excessive temperatures have an adverse effect on cotton development. These variables were collected from the USDA/ERS website (2004 ERS County Typology), and were considered to be exogenous and beyond farmers' control. Parameter estimates of the selection equations are also presented in Tables 3 and 4 (labeled "Selection"). Most of the coefficients in the selection equations in both the SAMPLING and MONITORS duration models are statistically significant (except for temperature in the MONITORS equation). Cotton farmers facing less favorable environmental conditions (i.e., lower temperatures and/or higher humidity) will more likely adopt precision farming technologies. Higher temperatures and low humidity would make for ideal cotton growing conditions, thus farmers in low temperature and high humidity counties have more incentives to use technologies that would benefit them.

On the basis of the log-likelihood statistic, the Weibull model with sample selection provides a better fit to the data for both soil sampling and yield monitors. This implies that sample selection represents unobserved characteristics that influence the conditional probability of the length of use and the probability of being in the sample, which are not taken into account in the explanatory variables (Boehmke et al. 2006). By accounting for selection in soil sampling the constant term increases from -14.96 in the independent Weibull model to -4.082 in the Weibull with selection. Likewise for yield monitors, it increases from

-4.606 in the independent Weibull model to 4.519 in the Weibull model with selection. Thus, the Weibull model with sample selection indicate a larger hazard rate and hence shorter times until abandonment for both SSIG technologies. The positive duration dependence (p= 1.371) for soil sampling implies that the risk of discontinuing soil sampling increases over time at a decreasing rate, $1<p<2$. Likewise, the positive duration dependence for yield monitors (p= 1.952) implies that the risk of discontinuing yield monitors increases over time at decreasing rate $1<p<2$. These results are consistent with the non-parametric analysis (Kaplan- Meier curves) that indicated faster rate of "failure" (i.e., abandonment) for yield monitors compared to soil sampling. Parameters with different signs among the two models indicate possible endogeneity for the respective variables.

In the soil sampling model (SAMPLING), the variable *ACRES* is statistically significant and positively affects the hazard of SSIG technology's length of use (Table 3). A large farm size may positively affect technology adoption, but we have no evidence that suggests that it lengthens the use of soil sampling. A possible explanation for the estimated sign of the farm size variable could be that larger farmers may not have the managerial time to conduct precision soil sampling, thus have a higher probability of abandonment (Walton et al., 2008).

Other statistically significant variables in the SAMPLING model are *EXPERIEN* and *PLAN*. Both had a negative impact on the proportional hazard (i.e., less likely to abandon). Farmers with longer planning horizons tend to utilize the sampling technology longer. For technologies requiring long-term investments, longer planning horizons are usually related with younger farmers who have a longer time frame in which to gain benefits (Lapar, 1999).

Similarly, farmers with more experience will more likely use the technology for a longer period. This could be interpreted that often experienced farmers report that they plan on farming for a long time in the future.

In Table 4, the *IMPORTA*, *EDUC*, *EXPERIEN* and *INCOME* variables have a negative impact on the yield monitors' hazard (MONITORS). This means that farmers who believe that precision farming will be important in the future, are more experienced, have attained a higher level of education, and farmers whose income comes mainly from agriculture will most likely use the yield monitors for a longer period of time. More educated farmers possess the human capital to recognize the benefits of precision farming, and thus will more likely use it for a longer period. Similarly to soil sampling, the years of farming experience *EXPERIEN* have a negative effect on hazard, which implies that more experienced farmers will more likely use yield monitors for a longer period of time. We would expect that farmers who are more dependent on farm income will more likely use soil sampling for a longer period. We attribute this finding to farmers with income mainly from farming sources being more likely to be more risk averse, thus continue using a technology for which they made a significant investment.

In Section 4.3.3, we posit that *PROFIT* can be considered a crude measure of farmer perception about the opportunity cost of SSIG. Farmers that think precision technologies would be profitable in the future are the ones who believe that the opportunity costs of SSIG would be low (and hence continue adopting SSIG). But this does not seem to be the case here. As we cautioned in Section 4.3.3, it could be that the *PROFIT* variable in this case is a very crude proxy such that it does not capture the opportunity cost of SSIG per se since it

asks about the profitability of precision technologies in general (not just SSIG) and also pertains to future profitability rather than the *t* periods where one needs to decide whether or not to abandon the technology. However, *PROFIT* does not seem to significantly influence the duration of neither soil sampling nor yield monitors. Likewise, perceived improvements in environmental and cotton quality do not seem to significantly affect the length of either soil sampling or yield monitors. This is consistent with the profile of farmers in our sample. Our survey respondents consisted of only 3.3% of farmers who valued environmental benefits more than profit, whereas 62.5% of farmers in the sample were more profit oriented and the rest ranked environment and profit equally. Our regressions (from Chapter 3 of this dissertation) indicates that farmers who perceived that precision farming would not be important in the future, acquired information about precision technologies from University publications, and were more educated, would more likely adopt based on monetary reasons. On the contrary, farmers who participated in agricultural easement programs, expected PF to be important in the future and experienced improvements in environmental quality, would more likely be environmentally motivated, that is adopt PF mostly because of its potential environmental benefits.

4.5 Conclusions

In this study, we examined the factors determining the length of use of selected cotton precision farming technologies. A duration analysis that accounts for selectivity bias is used to investigate the impact of different variables on the speed of abandonment of precision technologies for cotton farmers in the Southeastern US. We focus on soil sampling, which is considered the most widely used SSIG technology, and we compared our findings with yield monitors, which are the most recently introduced precision technologies. The estimated Weibull model for soil sampling suggests that farm size, experience, and farm planning are important determinants in the duration of soil sampling usage. Cotton producers with larger farms tend to use soil sampling technologies for a shorter period of time. On the other hand, farmers with longer planning horizons, and more experience will more likely use soil sampling for a longer duration. We also find that the length of use of yield monitors tend to be longer for farmers who believe that precision farming will be important in the future, are more educated and more experienced, and whose income comes mainly from farming.

Our results could provide insights about designing policies that would increase the duration of use of these technologies (or slow down their abandonment). Regarding the yield monitors, when formulating educational programs, it may be more beneficial to target less experienced farmers, those with lower educational attainment, those do not believe that PF will be important in the future, and farmers whose income is not mainly dependent on farming. Farmers with these characteristics are the ones less likely to use SSIG technologies and targeting these producers may encourage them to continue use of these technologies. In

addition, further study of the behavior of these producers may be worthwhile in the future to further understand why they abandon SSIG technologies faster.

Although this study provides some inferences about the factors influencing how long cotton producers use precision technologies, there are still several interesting topics that can be pursued in the future. An extension of this study would be to explore potential substitution effects among different SSIG technologies, i.e., study whether farmers who used a specific technology in the survey conducted in 2005, still continue its use in the survey conducted in 2009 or quit and/or switched to another SSIG technology. Unfortunately, we do not have adequate information from our sample since the 2005 survey respondents do not necessarily coincide with the 2009 respondents. On the other hand, we observed complementarities within technologies, and this justified the grouping of technologies we made in this study (e.g., use of grid along with zone soil sampling). Another issue to be investigated is whether there has been a change in start-up costs of the technologies that induced farmers to discontinue specific technologies faster (e.g., whether specific precision technologies have advanced such that start-up costs are low, or whether certain technologies were promoted more). Last, there is always the effect of obsolescence risk, as it is the case with all technologies. The constant creation and promotion of software advancements may create incompatibility issues with older precision hardware, which has not been improved dramatically since the introduction of precision farming. Hence the farmer may end up buying hardware that will be obsolete sooner because of software incompatibilities, and even if he wants to use that technology, the newer software may no longer be supported by the hardware company from which he purchased it. A limitation of our study is that we cannot

account for joint usage of technologies, for example a simultaneous application of monitors along with aerial photos. Moreover, our results are based on a relatively small sample of cotton farmers located in a specific geographic region.

For technologies that farmers abandon faster, Extension can focus their training programs that would increase awareness about the potential environmental and financial benefits of precision farming. Likewise, other outlets (e.g., dealers, crop consultants, media, etc.) could make information about precision technologies more available, since higher accessibility may reflect slower abandonment rate. At this point, we have no evidence whether the distance from the markets affects speed of abandonment decisions.

Table 4.1 Descriptive Statistics of the Variables

Variables	Description	Hypothesized Sign		Mean	Std. Dev
		Adoption	Duration		
HUMIDITY	Mean Hours of Humidity in July, 1941-70	+/-		56.13	16.32
TEMPERA	Mean Temperature for July, 1941-70	+/-		177.82	28.98
MONITORS	Number of years farmer used yield monitors (with and/or w/o GPS)			3.89	3.17
SAMPLING	Number of years farmer used soil sampling (grid and/or zone)			9.340	8.161
ACRES	Total acreage of dry land (sum of rented and owned acres) for the 2007 crop season		+	663.2	859.2
YIELDS	Estimate of average cotton lint yield per acre for 2007 crop season		+	1407.2	449.9
EDUC	Number of Years of Formal Education excluding kindergarten		+	14.15	2.52
AGE	Age of the farm operator (as of the 2009 survey year)		+/-	58.08	12.70
EXPERIEN	Number of Years farming		+	31.63	13.52
SYVAR	Perceived Spatial Yield Variability (lbs. lint/acre)		+		
IMPORTA	Farmer perceived that precision farming would be important in five years from now (yes=1; no=0)		+	0.696	0.459
PROFIT	Farmer perceived that precision farming would be profitable to use in the future (yes=1; no=0)		+	0.431	0.495
INCOME	Percentage (%) of 2007 taxable household income coming only from farming sources		+/-	72.24	29.46
COMPUTER	Farmer uses computer for farm management (yes=1; no=0)		+	0.128	0.335
MANURE	Farmer applied manure on his/her fields (yes=1; no=0)		+	0.181	0.385
PUBLICAT	Farmer used University publications to obtain precision farming information (yes=1; no=0)		+	0.348	0.476
AG EASE	The farm currently has agricultural easement (yes=1; no or don't know=0)		+	0.085	0.279

Table 4.1 continued

QUALITY	Farmer experienced improvement in cotton quality (yes=1; no or don't know=0)	+	0.137	0.344
PLAN	Years to plan farming in the future	+/-	3.748	1.553
ENVIRON	Farmer perceived improvement in environmental quality through the PF use (yes=1; no=0)	+	0.202	0.401

Table 4.2 Summary Statistics for the two categories of farmers (Abandon vs Continue)

Variables		**Obs**	**Mean (years)**	**Min (years)**	**Max (years)**	**Std. Deviation**
MONITORS	Abandon	7	6.285	1	12	4.151
	Continue	102	3.735	1	16	3.050
SAMPLING	Abandon	17	8.882	1	26	7.261
	Continue	321	9.364	1	30	8.215
PHOTOS	Abandon	8	2.75	1	6	1.581
	Continue	81	9.777	1	30	9.521
MAPS	Abandon	7	8	2	30	10.082
	Continue	93	3	1	30	9.486

Table 4.3 Akaike Information Criterion for different distributions

Distribution	**AIC Sampling**	**AIC Monitors**
Exponential	95.24	84.63
Weibull (w/o selection)	**95.60**	**50.23**
Loglogistic	95.67	70.02
Lognormal	95.14	70.28
Gompertz	96.68	61.57

Table 4.4 Weibull Model Estimates for SAMPLING (N=977)

	Sampling		
Variables	**β (Robust S.E)**	**β (Robust S.E)**	**β (S.E)**
Selection			
INTERCEPT	3.793 * (2.028)		
HUMIDITY	0.018 *** (0.024)		
TEMPERA	-0.071 ** (0.024)		
Weibull (with Selection)		**Naïve Duration Models**	
		[1] Weibull	**[2] Cox**
INTERCEPT	-2.561 (1.343)	-13.661 *** (3.400)	---
EDUC	0.029 (0.059)	-0.358 ** (0.167)	-0.325 ** (0.159)
EXPERIEN	-0.027 ** (0.010)	0.065 (0.050)	0.080 (0.051)
PUBLICAT	-0.113 (0.278)	0.726 (0.720)	0.735 (0.712)
SYVAR	0.004 (0.007)	0.004 (0.007)	0.005 (0.006)
COMPUTER	0.084 (0.254)	0.458 (1.064)	0.379 (0.944)
IMPORTAN	-0.066 (0.525)	17.65 *** (1.580)	36.724 *** (2.413)
PROFIT	0.476 (0.299)	-0.512 (0.827)	-0.479 (0.797)
INCOME	-0.006 (0.004)	-0.006 (0.018)	-0.007 (0.015)
AG_EASE	0.009 (0.361)	-1.196 (1.653)	-0.931 (1.434)

Table 4.4 continued

PLAN	-0.185 * (0.095)	-0.268 (0.306)	-0.180 (0.306)
MANURE	-0.102 (0.263)	-17.994 *** (0.746)	-45.31 *** (0.687)
ACRES	0.0003 ** (0.0001)	-0.0003 (0.0006)	-0.0003 (0.0006)
YIELDS	0.0001 (0.0003)	-0.001 (0.001)	-0.001 (0.001)
QUALITY	-0.394 (0.304)	0.679 (1.291)	0.538 (1.073)
ENVIRON	0.157 (0.254)	1.867 (1.662)	2.000 (1.340)
rho (error correlation)	-0.050 (0.069)	---	---
ln_p	0.312 *** (0.061)	0.371 (0.272)	---
p (duration dependence)	1.366 *** (0.084)	1.449 (0.394)	---
N_U (Uncensored)	99	177	177
Log Likelihood	-581.24	-29.801	-29.905
Wald	55.05 ***	1573.22 ***	8552.50 ***

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 4.5 Weibull Model Estimates for MONITORS (N=919)

	Monitors		
Variables	**β (Robust S.E)**	**β (Robust S.E)**	**β (Robust S.E)**
Selection			
INTERCEPT	1.487 (2.524)		
HUMIDITY	0.017 *** (0.002)		
TEMPERA	-0.045 (0.031)		
Weibull (with Selection)		**Naïve Duration Models**	
		[1] Weibull	**[2] Cox**
INTERCEPT	4.519 (2.786)	-4.606 (11.197)	---
EDUC	-0.219 * (0.127)	0.538 ** (0.206)	0.356 * (0.196)
EXPERIEN	-0.061 ** (0.031)	0.231 * (0.132)	0.173 (0.109)
PUBLICAT	0.923 (0.812)	-0.255 (2.195)	-0.641 (2.369)
SYVAR	0.018 (0.019)	---	---
COMPUTER	-0.520 (0.604)	-0.908 (2.296)	-0.540 (1.342)
IMPORTAN	-2.894 ** (1.301)	7.270 (9.643)	(omitted)
PROFIT	0.316 (0.684)	-0.055 (3.398)	-0.374 (2.657)
INCOME	-0.026 ** (0.010)	-0.079 * (0.047)	-0.046 (0.059)
AG_EASE	-0.484 (1.493)	-0.521 (2.757)	0.523 (0.868)
PLAN	-0.069 (0.267)	N/A	N/A

Table 4.5 continued

MANURE	0.650 (0.674)	-0.926 (1.894)	-0.522 (2.134)
ACRES	0.0002 (0.0002)	-0.0001 (0.0003)	-0.00006 (0.0002)
YIELDS	0.0005 (0.0006)	-0.002 (0.003)	-0.002 (0.002)
QUALITY	-0.516 (0.926)	0.711 (4.136)	0.796 (3.366)
ENVIRON	-0.178 (0.675)	0.092 (5.089)	-0.234 (3.732)
rho (Error Correlation)	-0.107 (0.124)	---	---
ln_p	0.669 *** (0.104)	1.158 (0.708)	---
p (Duration Dependence)	1.952 *** (0.204)	3.185 (2.256)	---
N_U (Uncensored)	41	57	57
Log Likelihood	-228.42	-9.117	-9.976
Wald	39.74 ***	150.45 ***	38.66 ***

Note: *** p<0.01, ** p<0.05, * p<0.1

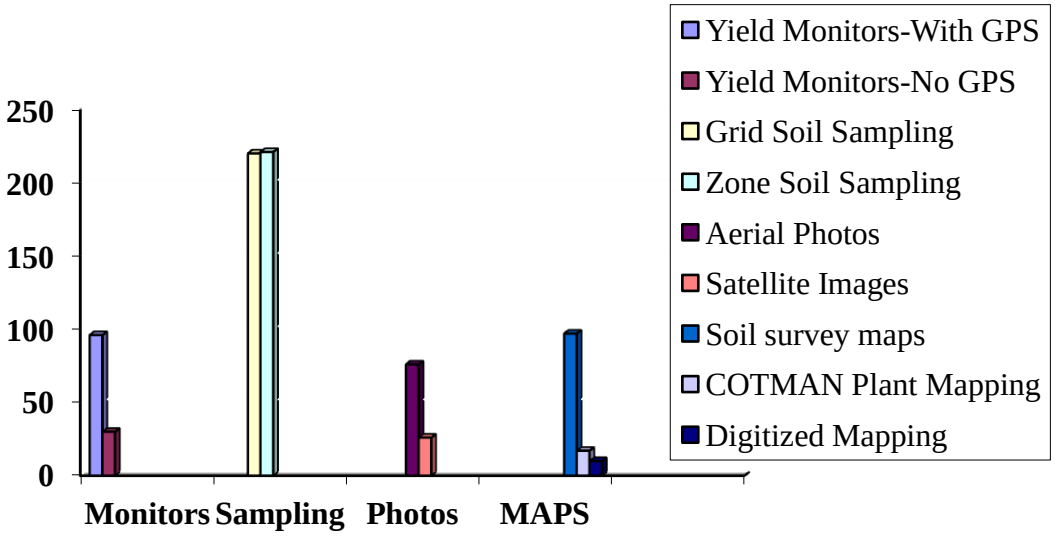

Figure 4.1: Number of farmers using different SSIG technologies

Use of Information Gathering Technology for Crop Production Q19	Number of years used
Yield monitor – with GPS	a_i
Yield monitor – no GPS	b_i
Soil sampling – grid	c_i
Soil sampling – zone	d_i
Aerial photos	e_i
Satellite images	f_i
Soil survey maps	g_i
Handheld GPS/PDA	h_i
COTMAN plant mapping	i_i
Digitized mapping	j_i
Electrical conductivity	k_i

Figure 4.2A: Length of use of each SSIG Technology

20. Of the technologies in Question 19 you have used, which have you abandoned (list the letters of any you no longer plan to use)?

Q20a through Q20k

_____

Figure 4.2B: Abandonment of each SSIG Technology

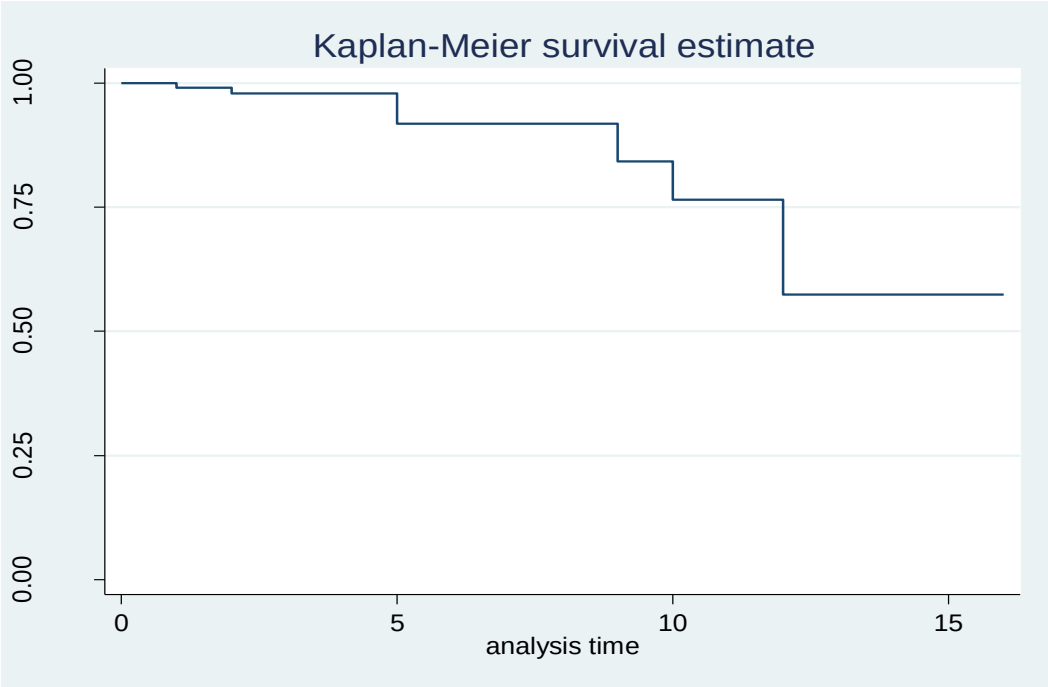

Figure 4.3: Kaplan-Meier survival curve of MONITORS' duration

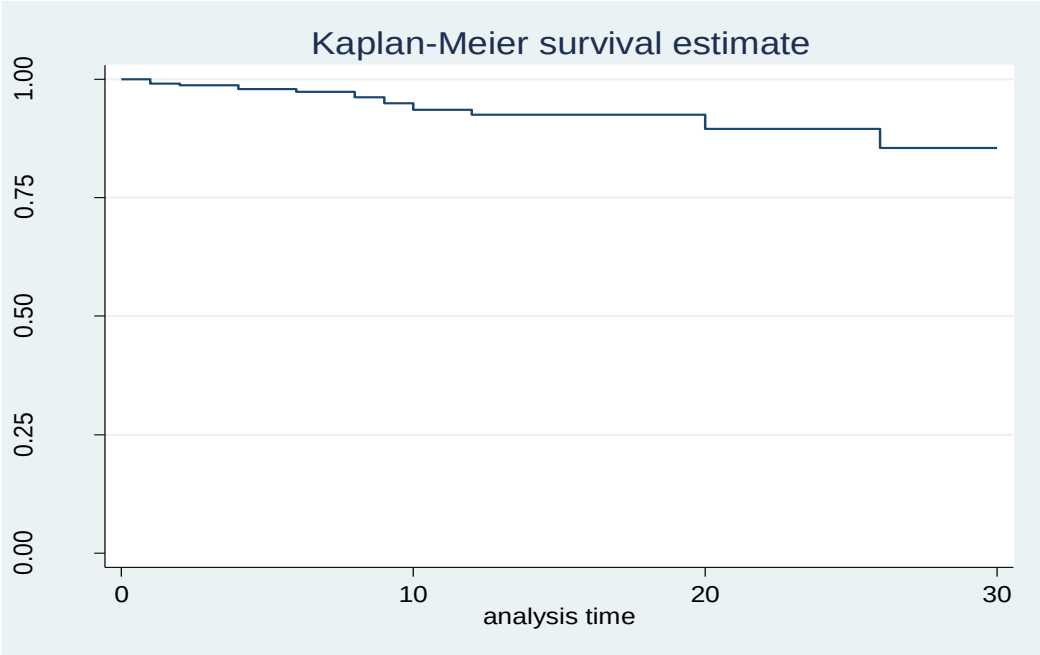

Figure 4.4: Kaplan-Meier survival curve of SAMPLING' duration

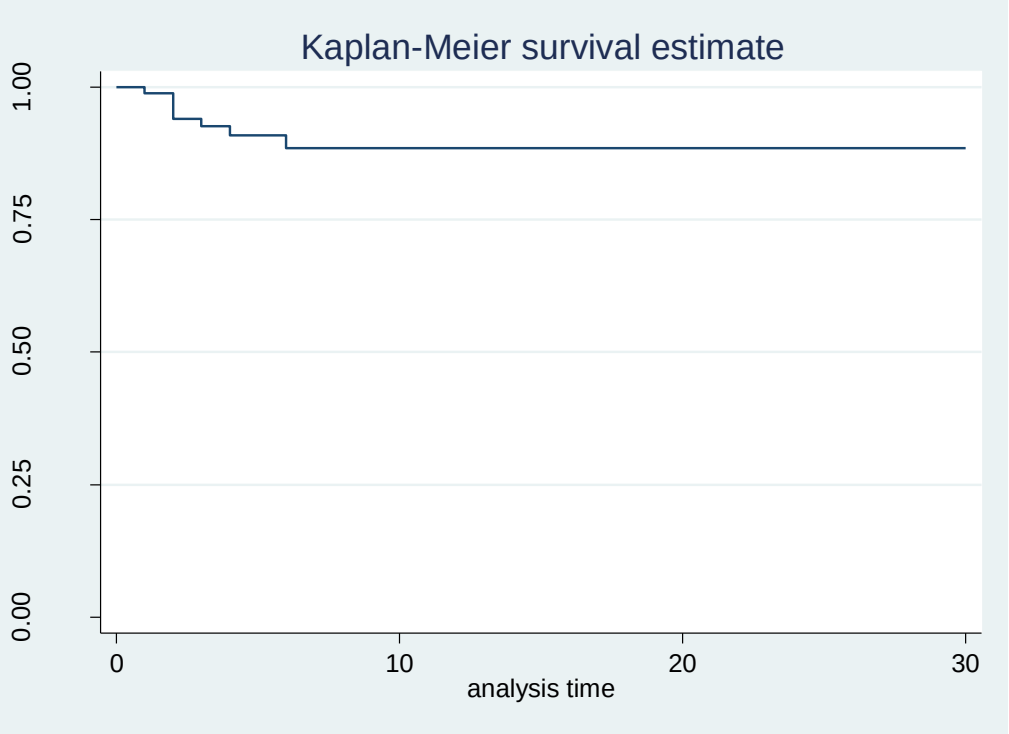

Figure 4.5: Kaplan-Meier survival curve of PHOTOS' duration

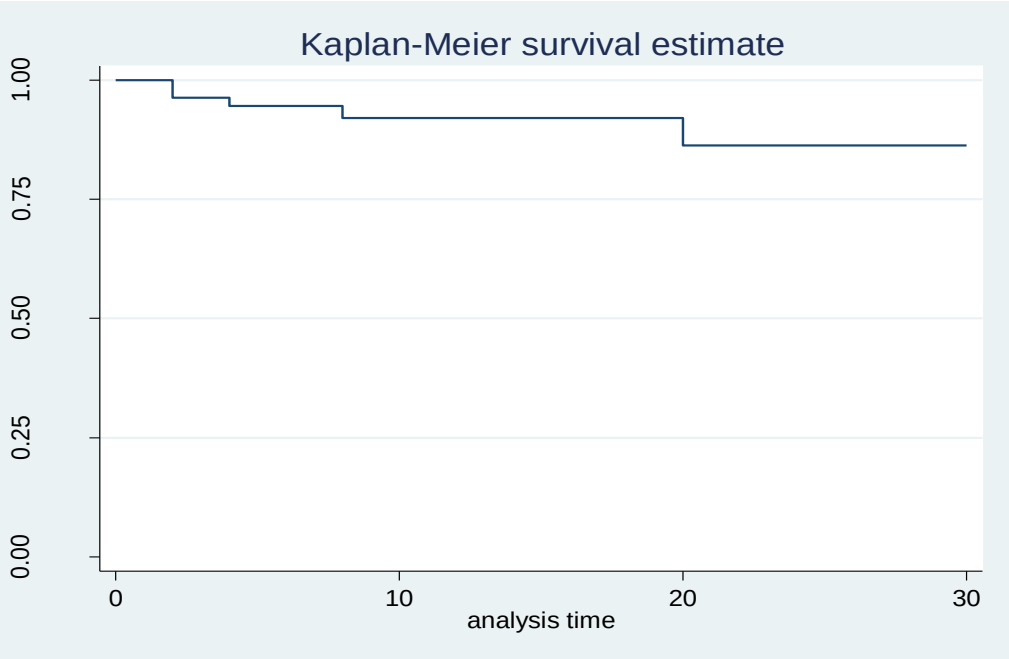

Figure 4.6: Kaplan-Meier survival curve of MAPS' duration

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CHAPTER 5

CONCLUSIONS

In this study we explored economic issues related to precision farming technologies in cotton production. The first essay investigated the effect of farmers' perceived yield variability on technology adoption. Our results indicate that the higher the perceived yield variation is, the more likely that the farmer will adopt at least one of precision farming's components, i.e., either site-specific information gathering (SSIG) technologies only, or combine with variable rate input applications (VRT). Furthermore, higher likelihood of adopting precision technologies is associated with age, information about precision agriculture through University Publications, plans about farming, use of computer, and perceptions about expected profitability and importance of precision technologies. The impact of perceptions on precision farming makes the role of Extension, and social networks even more critical in providing information and training about the benefits of precision agriculture. If we neglect to account for the factors affecting the subjective beliefs, then estimated perceptions may be inaccurate and the decision to adopt precision technologies may be affected.

The second essay investigated the factors affecting cotton farmers' decision to adopt based on either environmental reasons or profit maximization reasons or either of the two (i.e., the producer values them equally). Our results indicate that the participation in agricultural easement programs, the perceived importance of PF in the future, as well as the perceived improvement in environmental quality following the PF use, all positively influence the decision to adopt for environmental reasons. On the other hand, educational

attainment and use of University publications had a positive impact on adoption based on profit motives. Moreover, we examined how farmers' perceptions about improvement in environmental quality following adoption change over an 8-year period. Based on logistic regressions, the probability that a farmer observed any improvements in environmental quality (through the adoption of technology) was higher if the farmer used manure in his/her fields, was less dependent on income coming only from farming sources, and perceived that PF will be profitable in the future. These elements were found to be statistically significant for separate cross-section data collected over an eight year period.

The third essay applied a duration analysis to study the factors affecting farmers' length of use of soil sampling and yield monitors. Using a parametric Weibull model that accounts for sample selection bias, we found that cotton producers with larger farms tend to use soil sampling technologies for a shorter period of time. On the other hand, farmers with longer planning horizons, and more experience will more likely use soil sampling for a longer duration. We also find that the length of use of yield monitors tend to be longer for farmers who believe that precision farming will be important in the future, are more educated and more experienced, and whose income comes mainly from farming.

This thesis provided some insights about economic issues that farmers face with respect to precision farming technologies. Our results could be used by Extension and educational targeted programs in order to design policies that would disseminate the importance of precision agriculture and help farmers who would be more benefited by the use of technology. Further research could incorporate data from more years and possibly farmers' behavior throughout the years. This would also improve the duration analysis by

estimating potential substitution effects among different SSIG technologies, for example whether farmers who used a specific technology in the survey conducted in 2005, still continue its use in the survey conducted in 2009 or quit and/or switched to another SSIG technology. With respect to the environmental aspects of precision farming, future research could investigate whether there are still truly altruistic such that they want to adopt precision technologies purely for environmental reasons and therefore providing positive externalities to society, or they adopted for environmental reasons in order to avoid future regulations.

APPENDIX

APPENDIX

Derivation of the Quasi-Rent Differential Needed to Evaluate Equations (16) and (17)
(To Derive Equation (18) and (19))

Consider a first order Taylor series approximation of the marginal utility U_W (as seen in (5)) about the expected wealth $\bar{W} = W_0 + E(A\pi^j) - K^l$, where l = (S, V) and j = (U, V). Using a first-order Taylor series approximation, one can obtain the quasi-rents associated with VRT adoption as follows:

(A.1) $$A\pi^j \cong \sum_{i \in N} A_i [Pf(x_i^j, z_i) - wx_i] + P \sum_{i \in N} A_i z_i \varepsilon f_z(x_i^j, z_i)].$$

The variance of $A\pi^j$ can then be expressed as $\sigma_j^2 = P^2 \sigma_\varepsilon^2 [\sum_{i \in N} A_i z_i f_z(x_i^j, z_i)]^2$ .The marginal utility U_W can then be rewritten as:

(A.2) $$U_w(W) = \bar{U}_W(\bar{W}) + \bar{U}_{WW}(\bar{W})[\sum_{i \in N} A_i z_i \varepsilon f_z(x_i^j, z_i)].$$

Similar to (A.1), the first-order approximation of the marginal product in (5) (e.g., $f_x(\cdot)$) can be expressed as:

(A.3) $$f_x(x_i^j, z_i + z_i \varepsilon_i) \cong f_x(x_i^j, z_i) + z_i \varepsilon_i f_{xz}(x_i^j, z_i).$$

To simplify equation (5), we plug A.2 and A.3 into equation (5) to obtain:

(A.4) $$\frac{\partial U}{\partial x^j} = E\{[\bar{U}_W(\bar{W}) + \bar{U}_{WW}(\bar{W}) \sum_{i \in N} A_i z_i \varepsilon f_z(x_i^j, z_i)](Pf_x(x_i^j, z_i + z_i \varepsilon_i)) - w\} = 0.$$

Given the following definition of risk aversion to $\varphi = {-\bar{U}_{WW}}/{\bar{U}_W}$ (such that $\bar{U}_{WW} = -\varphi \bar{U}_W$) we can re-write A.4 as:

(A.5) $$\frac{\partial U}{\partial x^j} = E\{[\bar{U}_W(\bar{W}) - \varphi \bar{U}_W(\bar{W}) \sum_{i \in N} A_i z_i \varepsilon f_z(x_i^j, z_i)](P f_x(x_i^j, z_i + z_i \varepsilon_i)) - w\} = 0.$$

Taking the expectation of A.5 and with further simplification, we get:

(A.6) $$\frac{\partial U}{\partial x^j} \frac{1}{\bar{U}_W(\bar{W})} = P f_x(x_i^j, z_i) - w - \varphi P^2 \sigma_\varepsilon^2 z_i f_{xz}(x_i^j, z_i) \sum_{i \in N} A_i z_i \varepsilon f_z(x_i^j, z_i) = 0.$$

Simplifying and manipulating terms in A.6, we can obtain:

(A.7) $$P f_x(x_i^j, z_i) - \varphi P^2 \sigma_\varepsilon^2 z_i f_{xz}(x_i^j, z_i) \sum_{i \in N} A_i z_i \varepsilon f_z(x_i^j, z_i) = w.$$

At this point, we now define the output elasticity with respect to soil conditions as:

(A.8) $$\in_{Yi} = \frac{z_i f_z(x_i^j, z_i)}{f(x_i^j, z_i)} > 0.$$

This elasticity indicates how the level of soil characteristics affects output. Similarly, the elasticity of the marginal product (f_x) with respect to soil conditions can be expressed as follows:

(A.9) $$\in_{Mi} = \frac{z_i f_{xz}(x_i^j, z_i)}{f_x(x_i^j, z_i)},$$

which is negative (positive) when the input is risk decreasing (risk increasing) represented by $f_{xz} < (>) 0$.

Using the elasticity expression in A.8 and A.9, we can then define the following:

(A.10) $$F_i = \varphi P \sigma_\varepsilon^2 \in_{Mi} \in_{Yi} Y.$$

Using A.10 and the production function $Y_i = \sum_{i \in N} A_i f(x_i^j, z_i)$, equation A.7 can be re-written and simplified as follows:

(A.11) $$Pf_x(x_i^{\,j}, z_i) - \varphi P^2 \sigma_\varepsilon^2 \in_{Mi} \in_{Yi} Y = w$$

(A.12) $$Pf_x(x_i^{\,j}, z_i) - PF_i = w$$

(A.13) $$Pf_x(x_i^{\,j}, z_i)[1 - F_i] = w$$

(A.14) $$Pf_x(x_i^{\,j}, z_i) = \frac{w}{1 - F_i}.$$

Using the profit-maximizing condition for scenario 1 and plugging it in equation A.14:

(A.15) $$Pf_x(x_i^{\,j}, z_i) = \frac{Pf_x(x^U, \overline{z})}{1 - F_i}.$$

The difference in input use for precision technology adoption (e.g., scenarios 2 and 3) and non-adoption (e.g., scenario 1) can then be obtained by taking the first order Taylor series expansion of A.15 around $\overline{z}$:

(A.16) $$x_i^j(z_i) - x^U(\overline{z}) \cong \frac{f_x F_i}{[1 - F_i] f_{xx}} + (z_i - \overline{z}) \frac{dx}{dz} + \frac{1}{2}(z_i - \overline{z})^2 \frac{d^2 x}{dz^2},$$

where $\frac{dx}{dz} = -\frac{f_{xz}}{f_{xx}}$, and summing it over all sites:

(A.17) $$\Delta x = \frac{1}{A} \sum_{i \in N} A_i (x_i^j - x^U) = \frac{1}{A} \sum_{i \in N} A_i \frac{f_x F_i}{[1 - F_i] f_{xx}} + \frac{1}{2} \sigma_z^2 \frac{d^2 x}{dz^2}.$$

Note that the variable of interest here is the within field spatial variability of the soil attribute σ_z^2.

Similarly, the aggregate yield difference between precision technology adoption (e.g., scenarios 2 and 3) and non-adoption (e.g., scenario 1) can be obtained by taking a second

order Taylor series expansion, plugging A.16 into this approximation, and summing over all sites:

(A.18) $$\Delta y = \frac{1}{A}\sum_{i\in N} A_i (y_i^j - y^U) = -\frac{1}{2f_{xx}}[\sigma_z^2 (f_{xz})^2 - \frac{(f_x)^2}{A}\sum_{i\in N} A_i (\frac{F_i(2-F_i)}{(1-F_i)^2})].$$

Using (A.17) and (A.18) , we obtain the per acre quasi-rent (or profit) differential between precision technology adoption (e.g., scenarios 2 and 3) and non-adoption (e.g., scenario 1):

(A.19) $$\Delta\pi = -\frac{P}{2f_{xx}}[\sigma_z^2 (f_{xz})^2 - \frac{(f_x)^2}{A}\sum_{i\in N} A_i (\frac{F_i^2}{(1-F_i)^2})].$$