Environmentally Responsible versus Profit Oriented Farmers: Evidence from Precision Technologies in Cotton Production

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ABSTRACT

This article examines what differentiates "socially responsible" 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. 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.

Keywords: socially conscious, profit oriented, Likert style ranking, precision farming, ordered logit, rare events logit

JEL Codes: Q13, Q15, Q16

Introduction

This study is part of the precision farming (PF) 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 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 responsible" 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 responsible (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.

Our study 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.[1] What are the characteristics of farmers who adopt precision 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 responsible" or "environmentally conscious" farmers (i.e., those who prioritize potential environmental improvements over profits as the reason for adopting the technology). The definition of an environmentally responsible or environmentally conscious 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. 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.

Having knowledge of farmers' characteristics who adopt precision technologies for environmental reasons 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

[1] 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 responsible farmer). The Pandit et al. (2011) study does not make 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).

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 there are other important elements that affect environmental motives.

Empirical Approach

Conceptual Framework

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:

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

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:

$$
\begin{aligned}
(2) \qquad & Y_{\mathrm{i}} = 1 \quad && \text{if} \quad Y_{\mathrm{i}}^* < \mu_1 \\
& Y_{\mathrm{i}} = 2 \quad && \text{if} \quad \mu_1 < Y_{\mathrm{i}}^* < \mu_2 \\
& Y_{\mathrm{i}} = 3 \quad && \text{if} \quad \mu_2 < Y_{\mathrm{i}}^*.
\end{aligned}
$$

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.

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 responsible" 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) $$\Pr[Y_i = j] = \Pr[\mu_{j-1} < Y_i^* \le \mu_j] = \Pr[\mu_{j-1} < X_\iota^{'}\beta + \varepsilon_i \le \mu_j]$$

$$= \Pr[\mu_{j-1} - X_\iota^{'}\beta < \varepsilon_i \le \mu_j - X_\iota^{'}\beta]$$

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

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

where the odds ratio $\frac{\Pr[Y_i > j]}{\Pr[Y \le j]}$ 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.

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*.

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

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.

Empirical Specification

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, such as: 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*).

Last, farmer perceptions about various aspects of precision farming are also included as covariates, and more specifically: whether farmers perceive environmental improvements after the use of precision technologies (*ENVIRON*), 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.[2]

Survey and 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 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.

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

[2] 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.

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 responsible farmers in our sample.

Table 3 summarizes the various characteristics that distinguish the more environmentally responsible farmers from the other groups and how these have changed over time on average. Environmentally conscious farmers had relatively smaller farms, participated more in agricultural easement programs, they had more experience in farming and they were older. As expected, the farmers who adopted PF mainly for environmental reasons had experienced improvement in environmental quality through the use of precision technologies. They 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.

Results

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) = 30.94 with Prob> χ^2 = 0.1911), 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 be as well appropriate to use (χ^2 (28) = 13.34 with Prob> χ^2 = 0.9603). 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 0.11 with a p-value of 0.7387) 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 2. 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[3]. 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, perceived improvements in environmental quality (*ENVIRON*), 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

[3] 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)

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.

The positive effect of the *ENVIRON* variable suggests that farmers that perceive improvements in the environment due to precisions technologies are the ones that adopt these same technologies for environmental reasons. This is consistent with the work of Pandit et al. (2011) where they also found a strongly significant positive coefficient. Although there seem to be a strong relationship between these two variables, one has to question whether this is more of "correlation" rather than "causation". That is, there could be simultaneity such that the "flipside" relationship may be true as well – farmers who adopt for environmental reasons are the ones more likely to perceive environmental improvements. This may be a topic for future study because we cannot address this issue here due to data constraints (i.e., lack of instrumental variables).

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 more likely to adopt PF for environmental reasons based on the marginal effects in Table 2. 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.

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 4, *ENVIRON*, *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.

Summary and Conclusions

Our study provides further understanding about the environmental aspect of precision technology adoption: adoption driven by environmental motivations. 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.

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. In contrast, 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.

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 could 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.

References

Amacher, G., S., and Feather, P., M., (1997) “Testing Producer Perceptions of Joint Beneficial Best Management Practices for Improved Water Quality”, *Applied Economics,* 29:2, 153-159

Auernhammer, H., (2001) “Precision Farming – The Environmental Challenge”, *Computers and Electronics in Agriculture*, 30, 31-43

Balderjahn, I., (1988) “Personality Variables and Environmental Attitudes as Predictors of Ecologically Responsible Consumption Patterns”, *Journal of Business Research*, 7: 51-56

Banerjee, S.B., Martin, S.W., Roberts, R.K., Larkin, L.S., Larson, J.A., Paxton, W.K., English, B.C., Marra, M.C., Reeves, M.J., (2008) “A Binary Logit Estimation of Factors Affecting Adoption of GPS Guidance Systems by Cotton Producers”, *Journal of Agricultural and Applied Economics*, 40, 1: 345-355

Bosch, D., Cook, Z., and Fuglie, K., (1995) “Voluntary versus Mandatory Agricultural Policies to Protect Water Quality: Adoption of Nitrogen Testing in Nebraska”, Review of Agricultural Economics, 17: 13-24

Cameron, C.A., Trivedi, P.K., (2005) “Microeconometrics: Methods and Applications”, *Cambridge University Press*

Defrancesco E., Gatto, P., Runge, F., Trestini, S., (2006) “Factors affecting Farmers’ Participation in Agri-Environmental Measures: Evidence from a Case Study”, *10th Joint Conference on Food, Agriculture and the Environment*, Duluth, Minnesota

Drake, L., Bergström, P., and Svedsäter, H., (1999) “Farmers’ attitudes to and uptake of countryside stewardship policies”, Organized Session, *IXth European Congress of Agricultural Economics*, Warsaw, Poland

Ender, P., Multicollinearity Test in STATA, UCLA

Ervin, C. A., and Ervin, D. E., (1982) “Factors affecting the use of soil conservation practices - Hypotheses, evidence and policy implications”, *Land Economics,* Vol 58, No 3, pp 277–292

Fernandez-Cornejo, J., Beach, E.D., & Huang, W.-Y., (1994) “The adoption of IPM techniques by vegetable growers in Florida, Michigan, and Texas”, *Journal of Agricultural and Applied Economics, 1*, 158-72

Gould, W., (2005) “Pooling Data and Performing Chow Tests in Linear Regression”, *StataCorp*

Greene W.H., (1997) *Econometric Analysis.* 3rd ed. Prentice-Hall International, Inc.

Hatfield, J., (2000) "Precision Agriculture and Environmental Quality: Challenges for Research and Education", *national workshop prepared for The National Arbor Day Foundation held in cooperation with USDA's Natural Resources Conservation Service and Agricultural Research Service*

Hite, D., Hudson, D., Intarapapong, W., (2002) "Willingness to Pay for Water Quality Improvement: The Case of Precision Application Technology", Journal of Agricultural and Resource Economics, 27 (2), 433-449

King, Gary, and Langche Zeng, (2001) Logistic regression in rare events data, *Political Analysis* 9(2): 137-163

Knowler, D., Bradshaw, B., (2007) "Farmers' Adoption of Conservation Agriculture: A Review and Synthesis of Recent Research", Food Policy, 32, 25-48

Larkin, S.L., Perruso, L., Marra, M.C., Roberts, R.K., English, B.C., Larson, J.A., Cochran, R.L., Martin, S., W., (2005) "Factors Affecting Perceived Improvements in Environmental Quality from Precision Farming", *Journal of Agricultural and Applied Economics*, 37, 3, 577-588

Lohr, L., Parker, T., and Higley, L., (1999) "Farmers Risk Assessment for Voluntary Insecticide Reduction", *Ecological Economics*, 30 (1), 121-30

Lynne, G.D., and Casey, C.F., (1998), "Regulation of Technology Adoption when Individuals Pursue Multiple Utility", *Journal of Socio-Economics* 27: 701-19

MacDonald, J.M., Ribaudo, M.O., Livingston, M.J., Beckman, J., Huang, W., (2009) "Manure Use for Fertilizer and for Energy", Economic Research Service, U.S. Department of Agriculture

McBratney, A., B. Whelan, and T. Ancev, (2005) "Future directions of precision agriculture", Precis. Agric. 6:7-23

McCullagh, P. and Nelder, J.H., (1989) *Generalized Linear Models*. 2nd ed. London, UK: Chapman and Hall

Morris C. and Potter C., (1995) "Recruiting the new conservationists: farmers' adoption of agri-environmental schemes in the U.K.", *Journal of Rural Studies*, 11 (1), pp. 51-63

Mudalinge, U.J., and Weersink, A., (2004) "Factors affecting the Adoption of Environmental Management Systems by Crop and Livestock Farms in Canada", *Sri Lankan Journal of Agricultural Economics*, Vol. 6, No1

Napier, T. L., and Brown, D.E., (1993) “Factors affecting attitudes toward groundwater pollution among Ohio farmers”, *Journal of Soil and Water Conservation*, 48 (5), 432-438

Pandit, M., Mishra, A., Larkin, S., Rejesus, R., Lambert, D., Kotsiri, S., (2011) “Reasons for Adopting Precision Farming: A Case Study of U.S. Cotton Farmers”, *Paper Presented at the Southern Agricultural Economics Association Annual Meeting*, Corpus Christi, TX, February 5-8

Payne, J., Fernandez-Cornejo, J., and Daberkow, S., (2003) “Factors affecting the Likelihood of Corn Rootworm Bt Seed Adoption”, *AgBioForum*, 6(1&2): 79-86

Peterson, B. and Harrell, Jr., F., (1990) “Partial Proportional Odds Models for Ordinal Response Variables”, *Applied Statistics*, 39(2), 205-217

Risse, L.M., Gaskin, J.W., Radcliffe, D.E., Cabrera, M.L., Gilley, J. E., Tollner, W.E., Franzluebbers, A.J., Killorn, J., and Zhang, H., (2006) “Land Application and Manure for Beneficial Reuse”, *Biological Systems Engineering: Papers and Publications*

Roberts, R.K., English, B.C., Larson, J.A., Cochran, R.L., Goodman, R.W., Larkin, S.,L., Marra, M.C., Martin, S.W., Shurley, W.D., Reeves, J.M., (2004) “Adoption of Site Specific Information and Variable Rate Technologies in Cotton Precision Farming,” *Journal of Agricultural and Applied Economic.*, 36,1, 143-158

Schear P., and Blaine, T.W., “Conservation Easements”, Ohio State University Fact Sheet, Land Use Series, CDFS-1261-98

Swinton, S., and Lowenberg-DeBoer, J., (1998) “Evaluating the Profitability of Site Specific Farming”, Journal of Production Agriculture, 11, 439-446

Torbet, J.C., Roberts, R.K., Larson, J.A., English, B.C., (2007) “Perceived importance of precision farming technologies in improving phosphorus and potassium efficiency in cotton production”, *Precision Agriculture* 8:127-137

Traoré, N., Landry, R., Amara, N., (1998) “On-Farm Adoption of Conservation Practices: The Role of Farm and Farmer Characteristics, Perceptions, and Health Hazards”, Land Economics, Vol.74, No.1, pp.114-127

Van Kooten, G.C., Ward, P.W., Chinthammit, D., (1990) “Valuing trade-offs between net returns and stewardship practices: the case of soil conservation in Saskatchewan”, *American Journal of Agricultural Economics* 72, 104–113

Verbeek M., (2008) *A Guide to Modern Econometrics*, 3rd ed. John Wiley & Sons, Ltd

Williams, R., (2006) “Generalized Ordered Logit/Partial Proportional Odds Models for Ordinal Dependent Variables”, *The Stata Journal*, 6(1), 58-82

Wilson G.A. and Hart K., (2001) “Farmer participation in agri-environmental schemes: towards conservation oriented thinking?” *Sociologia ruralis*, 41 (2), pp. 254-274

Wynn G., Crabtree B. and Potts J., (2001) “Modelling farmer entry into the environmentally sensitive area schemes in Scotland”, *Journal of Agricultural Economics*, 52 (1), pp. 65-82

APPENDIX

Table 1: Summary Statistics of the Variables

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
ENVIRON	Farmer perceived improvement in environmental quality through the PF use (yes=1; no=0)	0.202	0.402	0	1
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 2: Parameter Estimates and Marginal Effects of the Covariates using Ordered Logit Model

Variables	**Coefficients (St.E)**	**Average Marginal Effects (St.E)**		
		Profit Oriented (Y=1)	**Indifferent (Y=2)**	**Socially Responsible (Y=3)**
ACRES	-0.00006	0.00001	-0.00001	-2.49e-06
	(0.0001)	(<0.001)	(<0.001)	(4.20e-06)
YIELDS	0.00004	-9.47e-06	7.77e-06	1.69e-06
	(0.0001)	(<0.001)	(<0.001)	(5.70e-06)
PUBLICAT	-0.424 *	0.085 *	-0.070 *	-0.015 *
	(0.224)	(0.044)	(0.036)	(0.008)
COMPUTER	-0.347	0.070	-0.057	-0.012
	(0.243)	(0.048)	(0.040)	(0.009)
ENVIRON	1.121 ***	-0.226 ***	0.185 ***	0.040 ***
	(0.226)	(0.041)	(0.034)	(0.011)
VRT	0.005	-0.001	0.0009	0.0002
	(0.228)	(0.046)	(0.037)	(0.008)
IMPORTAN	1.122 *	-0.226 **	0.185 **	0.040 *
	(0.573)	(0.114)	(0.093)	(0.022)
PROFIT	-0.286	0.057	-0.047	-0.010
	(0.284)	(0.057)	(0.046)	(0.010)
INCOME	-0.003	0.0006	-0.0005	-0.0001
	(0.004)	(0.0008)	(0.0006)	(0.0001)
AG EASE	0.769 **	-0.155 **	0.127 **	0.027 **
	(0.342)	(0.067)	(0.055)	(0.013)

PLAN	-0.082	0.016	-0.013	-0.002
	(0.067)	(0.013)	(0.011)	(0.002)
MANURE	-0.226	0.045	-0.037	-0.008
	(0.243)	(0.048)	(0.040)	(0.008)
EXPERIEN	0.003	-0.0007	0.0006	0.0001
	(0.016)	(0.003)	(0.002)	(0.0005)
AGE	0.003	-0.0006	0.0005	0.0001
	(0.017)	(0.003)	(0.002)	(0.0006)
EDUC	-0.102 **	0.020 **	-0.017 **	-0.003 **
	(0.046)	(0.009)	(0.007)	(0.001)
Cutoff_1	-0.317 (1.055)			
Cutoff_2	2.758 (1.073)			

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

Table 3: 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)**	**Socially Responsible (Y=3)**	**Profit Oriented (Y=1)**	**Indifferent (Y=2)**	**Socially Responsible (Y=3)**
ACRES	0.00001	-0.00001	0.0001	0.00001	-0.00001	-2.55e-06
	(<0.001)	(<0.001)	(0.0006)	(<0.001)	(<0.001)	(4.16e-06)
YIELDS	-9.84e-06	8.09e-06	1.75e-06	-9.84e-06	8.09e-06	1.75e-06
	(<0.001)	(<0.001)	(5.65e-06)	(<0.001)	(<0.001)	(5.65e-06)
PUBLICAT	0.084 *	-0.069 *	-0.015 *	0.084 *	-0.069 *	-0.015 *
	(0.044)	(0.036)	(0.008)	(0.044)	(0.036)	(0.008)
COMPUTER	0.040	0.021	-0.062 **	0.040	0.021	-0.062 **
	(0.049)	(0.047)	(0.021)	(0.049)	(0.047)	(0.021)
ENVIRON	-0.229 ***	0.188 ***	0.040 ***	-0.229 ***	0.188 ***	0.040 ***
	(0.041)	(0.034)	(0.011)	(0.041)	(0.034)	(0.011)
VRT	-0.001	0.0008	0.0001	-0.001	0.0008	0.0001
	(0.046)	(0.037)	(0.008)	(0.046)	(0.037)	(0.008)
IMPORTAN	-0.223 **	0.183 **	0.039 *	-0.223 **	0.183 **	0.039 *
	(0.113)	(0.093)	(0.021)	(0.113)	(0.093)	(0.021)
PROFIT	0.058	-0.047	-0.010	0.058	-0.047	-0.010
	(0.056)	(0.046)	(0.010)	(0.056)	(0.046)	(0.010)
INCOME	0.0006	-0.0005	-0.0001	0.0006	-0.0005	-0.0001
	(0.0008)	(0.0006)	(0.0001)	(0.0008)	(0.0006)	(0.0001)
AG EASE	-0.156 **	0.128 **	0.027 **	-0.156 **	0.128 **	0.027 **
	(0.068)	(0.056)	(0.013)	(0.068)	(0.056)	(0.013)
PLAN	0.014	-0.012	-0.002	0.014	-0.012	-0.002
	(0.013)	(0.011)	(0.002)	(0.013)	(0.011)	(0.002)

MANURE	0.044	-0.036	-0.007	0.044	-0.036	-0.007
	(0.049)	(0.040)	(0.008)	(0.049)	(0.040)	(0.008)
EXPERIEN	-0.0007	0.0006	0.0001	-0.0007	0.0006	0.0001
	(0.003)	(0.002)	(0.0005)	(0.003)	(0.002)	(0.0005)
AGE	-0.0006	0.0005	0.0001	-0.0006	0.0005	0.0001
	(0.003)	(0.002)	(0.0006)	(0.003)	(0.002)	(0.0006)
EDUC	0.024 **	-0.028 **	0.003	0.024	-0.028 **	0.003
	(0.009)	(0.009)	(0.004)	(0.009)	(0.009)	(0.004)

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

Table 4: Marginal Effects of the Covariates of Each Outcome using Multinomial Logit Model

	Profit Oriented (Y=1)	Indifferent (Y=2)	Socially Responsible (Y=3)
Variables	**Average Marginal Effects (St.E)**	**Average Marginal Effects (St.E)**	**Average Marginal Effects (St.E)**
ACRES	0.00001 (<0.001)	2.94e-06 (<0.001)	-0.00001 (<0.001)
YIELDS	-9.16e-06 (<0.001)	0.00001 (<0.001)	-3.53e-06 (<0.001)
PUBLICAT	0.073 (0.046)	-0.035 (0.046)	-0.037 * (0.020)
COMPUTER	0.035 (0.050)	0.010 (0.050)	-0.045 ** (0.019)
ENVIRON	-0.230 *** (0.042)	0.206 *** (0.042)	0.023 (0.017)
IMPORTAN	-0.413 (24.648)	-0.064 (22.862)	0.478 (47.509)
PROFIT	0.057 (0.058)	-0.047 (0.058)	-0.010 (0.022)
INCOME	0.0007 (0.0008)	-0.001 (0.0008)	0.0004 (0.0004)
AG EASE	-0.133 * (0.071)	0.084 (0.070)	0.049 ** (0.025)
PLAN	0.010 (0.014)	-0.001 (0.014)	-0.008 * (0.005)
MANURE	0.030 (0.050)	-0.008 (0.050)	-0.022 (0.021)
EXPERIEN	-0.0009 (0.003)	0.0004 (0.003)	0.0004 (0.001)
AGE	-0.0003 (0.003)	0.00001 (0.003)	0.0003 (0.001)
EDUC	0.026 ** (0.009)	-0.030 *** (0.009)	0.004 (0.003)

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

Table 5: Parameter Estimates of the Covariates using Rare Events Logit & Binary Logit Model

Variables	**Rare Events Logit (N=491)**	**Binary Logit (N=491)**
CONSTANT	-5.510 ** (2.591)	-6.409 ** (2.992)
ACRES	-0.0002 (0.0003)	-0.0003 (0.0004)
YIELDS	-0.00001 (0.0004)	-0.00001 (0.0004)
PUBLICAT	-1.055 ** (0.501)	-1.291 ** (0.613)
COMPUTER	-1.233 ** (0.534)	-1.425 ** (0.590)
ENVIRON	0.673 (0.598)	0.777 (0.583)
PROFIT	-0.156 (0.582)	-0.103 (0.675)
IMPORTAN	N/A	N/A
VRT	0.831 (0.520)	1.016 (0.620)
EXPERIEN	0.013 (0.050)	0.023 (0.046)
INCOME	0.011 (0.009)	0.015 (0.012)
AG EASE	1.472 ** (0.656)	1.660 ** (0.771)
PLAN	-0.240 (0.150)	-0.282 * (0.162)
MANURE	-0.388 (0.667)	-0.542 (0.652)
AGE	0.013 (0.048)	0.006 (.049)
EDUC	0.114 (0.112)	0.133 (0.121)

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