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Factors Influencing the Adoption of Automatic Section Control Technologies and GPS Auto-Guidance Systems in Cotton Production

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To the Graduate Council:

I am submitting herewith a thesis written by Brittani Kimberlyn Edge entitled "Factors Influencing the Adoption of Automatic Section Control Technologies and GPS Auto-Guidance Systems in Cotton Production." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

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Abstract

Precision agriculture (PA) technologies allow producers to obtain information about their fields and use this knowledge to apply inputs and manage time more efficiently. PA technologies such as Automatic-Section Control (ASC) reduce inefficiencies such as overlapping application of inputs (e.g., seed, chemicals). Additionally, technologies such as Auto-Guidance (AG) systems complement ASC technologies and allow producers to work longer hours by reducing fatigue. Both ASC and AG technologies appear to be quickly adopted by producers because of their relatively low cost compared to other precision farming technologies.

The objective of this study is to determine the factors influencing the adoption of Automatic Section Control (ASC) technologies and GPS Auto-guidance (AG) systems among cotton producers. Using data from a survey of cotton producers in 14 states, this study evaluates the effect of age, education, farm size, use of information sources, and the use of specific production practices on the adoption decisions. Additionally, various field shape measures created using data from the NASS Crop Data Layer are included in the ASC equation to evaluate the influence of field shape on ASC adoption.

Results suggest that younger, more educated producers, managing larger farming operations, and consulting farm dealers for information about PA technologies are more likely to adopt ASC and AG technologies. The influence of field shape on the adoption of ASC technologies is inconclusive.

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CHAPTER 1: PROBLEM IDENTIFICATION AND EXPLANATION

Precision Agriculture uses information technologies to gather specific data from a field that could be used to improve input application efficiency, and potentially, reduce the environmental impacts of crop production (National Research Council, 1997). Increasing input costs in crop production, especially those costs associated with seed, fertilizers, and chemicals, influences farmer use of Precision Agricultural (PA) technologies.

Application of inputs in areas of fields where inputs have already been applied (e.g., seed, chemicals) is one example of input application inefficiency (Larson et al., 2016). PA technologies that could reduce this type of inefficiency are Automatic Section Control (ASC) and auto-guidance (AG) systems. ASC reduces or eliminates input over-application by turning planter/sprayer sections or rows off in areas where inputs have been previously applied or on and off at headland turns, point rows, terraces, and/or waterways (Fulton et al., 2011). AG systems complement ASC technologies because they help producers maintain a desired path while navigating through fields thereby reducing application overlap and skips. Additionally, Auto-guidance systems provide producers the ability to work longer hours while reducing fatigue (Shockley et al., 2011). AG systems may also reduce machinery and operator hours because these systems allow producers to follow designated paths more efficiently and reduce operator error (McDonald, 2015). Previous studies evaluated the economics of ASC technologies and GPS guidance systems (Batte and Ehsani, 2006; Shockley et al., 2011; Shockley et al., 2012, Velandia et al., 2013, Larson et al., 2016). In contrast, although few studies have evaluated the factors influencing the adoption of GPS auto-guidance systems (Banerjee et al., 2008; Martin et al., 2007), no research has evaluated adoption patterns and factors influencing ASC technology adoption. Furthermore, no studies have evaluated the factors influencing the adoption of ASC and GPS auto-guidance systems simultaneously, a desirable approach given the complementary nature of these two technologies.

Although ASC and AG systems appear to be readily adopted among producers because of their relatively low cost compared to other precision farming technologies, it remains unclear which factors influence the adoption of these technologies among cotton producers. Additionally, previous studies (Shockley et al., 2012) evaluated the economic benefits of jointly adopting ASC and GPS guidance systems, but no study has evaluated the factors influencing the adoption of these technologies. In this regard, this research addresses a gap in knowledge by applying a bivariate probit regression to model the joint adoption of these technologies.

A better understanding of the factors influencing the adoption of ASC technologies and GPS auto-guidance systems would be advantageous to several groups, including producers and machinery dealerships. This information along with information provided through decision aid tools and extension publications could help producers better evaluate potential benefits of adopting these technologies. For example, the Automatic Section Control for Planters Cost Calculator (ASCCC)[1] suggests the impact of field geometry on savings associated with ASC adoption may decrease as farm size increases. This result may be confirmed or rejected by results obtained from this study. On the other hand, machinery dealerships selling these technologies may be able to improve marketing strategies to better target clientele more likely to adopt ASC and GPS auto-guidance systems.

Research Objectives

The objective of this research is to determine the factors influencing the adoption of ASC technologies and GPS auto-guidance systems (AG systems).

[1] http://economics.ag.utk.edu/asccc.html

CHAPTER 2: LITERATURE REVIEW

Extensive literature exists in the field of precision farming technologies, both in factors influencing adoption decisions and economic evaluation of technologies. While some studies focused on the adoption of precision agriculture technologies as a whole (McBride and Daberkow, 2003; Napier and Tucker, 2000) others have looked at the factors influencing the adoption of specific technologies (Lambert et al., 2014; Larson et al., 2010; McBride and Daberkow, 2003; Napier et al., 2000; Roberts et al., 2004; Walton et al., 2008; Walton et al., 2010). Few studies have evaluated factors influencing the adoption of GPS guidance systems (Banerjee et al., 2008; D'Antoni et al., 2012; Martin et al., 2007) while no studies have evaluated the adoption of ASC technologies.

GPS Guidance Systems and Automatic Section Control Technologies

In the context of AG systems and ASC technologies, factors influencing the adoption of GPS guidance systems have been studied without the consideration of potential correlation between unobserved factors influencing both the decisions to adopt ASC technologies and GPS guidance systems (Martin et al, 2007; Banerjee et al., 2008; and D'Antoni et al., 2012). On the other hand, studies evaluating ASC technologies have focused on the economic benefits of adopting ASC rather than the factors influencing adoption decisions (Batte and Ehsani, 2006; Shockley et al., 2012; Velandia et al., 2013).

Martin et al. (2007) evaluated the adoption of GPS guidance systems, characteristics of operators adopting these types of technologies, and the economic value operators attribute to and satisfaction they receive from using these technologies. Results from a survey of cotton producers from 11 states conducted in 2005 revealed that about 23% of cotton producers used GPS guidance systems (Martin et al., 2007). Martin et al. (2007) indicated that adopters of these technologies were younger, with less years of farming experience, and more educated than non-adopters. Adopters were more likely to use laptop computers they could carry to the field, more likely to use other precision farming technologies (e.g., yield monitors, grid and soils sampling, aerial photos, satellite images, and PDA handheld devices), have larger farming operations, larger cotton acreage, and higher yields than non-adopters.

Banerjee et al. (2008) evaluated the factors influencing the decision to adopt GPS guidance systems. Banerjee et al. (2008) also found that farm size, yield, years of formal education, age, use of computers for farm management, household income, state where farm operation is located, and use of other precision farming technologies affect the decision to adopt GPS guidance technologies. Although both Martin et al. (2007) and Banerjee et al. (2008) evaluated the effect of other precision farming technologies on the decision to adopt GPS guidance systems, ASC was not included as one of those other technologies.

D'Antoni et al. (2012) used a multinomial logit regression to assess the factors affecting farmer decisions to adopt autosteer or lightbar GPS guidance systems. Results from this study suggest that producers who expect higher potential input cost savings from the use of precision farming technologies were more likely to adopt autosteer or lightbar technologies. Older producers and those producers using older cotton pickers were less likely to adopt any of these guidance systems. On the other hand, producer expectation regarding the importance of precision farming technologies in the near future, type of the cotton picker (e.g., 4-row, 5-row, and 5-row) used, the use of computers for farm management, and farm size positively influenced the decision to adopt autosteer but not the decision to adopt GPS lightbar guidance systems.

Recent research on ASC technologies measured the economic benefits from using these technologies and the factors influencing the magnitude of these economic benefits (Batte and

Ehsani, 2006; Larson et al., 2016; Shockley et al., 2012; Smith et al., 2013; Velandia et al., 2013). Velandia et al. (2013) suggested that adoption of ASC technology for planters may bring substantial monetary savings for those producers farming small and irregularly shaped fields. Larson et al. (2016) evaluated the effect of field geometry on the profitability of ASC, using perimeter to area ratio (P/A) as a measure of field irregularity to evaluate the profitability at different irregularity levels. Larson et al. (2016) analyzed 44 fields in middle and west Tennessee to estimate the reduction in chemical input application overlap with ASC as a percent of the total field size for three perimeter to area ratio (P/A) groups. This reduction in overlap was then used to evaluate the profitability of ASC for three field geometry categories. Results were consistent with previous research, indicating that more irregular fields result in the greatest savings. Larson et al. (2016) indicated that P/A is a good measure of field irregularity and a potential variable to be included when evaluating the profitability of ASC technologies.

Shockley et al. (2012) suggested that savings associated with the adoption of ASC for sprayers may be higher when field shapes are irregular and small, with the effect of field irregularity decreasing as field size increases. Luck et al. (2010) used three different fields in Shelby County, Kentucky to evaluate the reduction in input application when using automatic boom section control. Luck et al. (2010) noted that benefits associated with the adoption of ASC for sprayers include the potential reduction of negative environmental impacts associated with agricultural chemical runoff. In an economic evaluation of ASC for sprayers, Batte and Ehsani (2006) acknowledged the potential environmental benefits of ASC for sprayers, but the evaluation of these benefits was not included in the technology assessment.

Smith et al. (2013) evaluated the economic impact of adopting ASC and GPS guidance systems, including lightbar and AG systems using 533 fields in Colorado, Kansas, and Nebraska.

Field shape was approximated by calculating the average approach angle of headlands on a particular field, where this angle decreases as field shape "irregularity" increases (Smith et al., 2013). Smith et al. (2013) found that the potential economic benefits from the adoption of GPS guidance systems were larger for more regularly shaped fields while the potential economic benefits from the adoption of ASC were larger for producers with more irregularly shaped fields. Similar to previous literature (Shockley et al., 2012), Smith et al. (2013) noted that the effect of field shape decreases as field shape increases.

CHAPTER 3: CONCEPTUAL FRAMEWORK

Modeling the decision to adopt precision farming technologies begins with the assumption that farmers maximize the discounted expected benefits from production over a time horizon (Walton et al. 2008). Previous studies have used the random utility model framework to study adoption decisions (Jara-Rojas et al., 2012; Lambert et al., 2014; Larson et al., 2008; Rahm and Huffman, 1984; Roberts et al., 2004; Walton et al., 2008), where a producer adopts a technology when the expected utility of profits is higher for the adoption scenario compared to the non-adoption scenario. Let $E[U(\pi_{AG})]$ ($E[U(\pi_{NAG})]$) be the expected utility of adopting (non-adopting) AG systems for producer *i*. Defining $U^*_{AG} = E[U(\pi_{AG})] - E[U(\pi_{NAG})]$, the expected utility-maximizing producer will choose to adopt GPS auto-guidance systems if $U^*_{AG} > 0$. Likewise, let $E[U(\pi_{ASC})]$ ($E[U(\pi_{NASC})]$) be the expected utility of profits of adopting (non-adopting) ASC technologies. Defining $U^*_{ASC} = E[U(\pi_{ASC})] - E[U(\pi_{NASC})]$, the utility maximizing producer will choose to adopt ASC when $U^*_{ASC} > 0$.

As presented in Roberts et al. (2004) and Walton et al. (2008) and originally by McFadden (1974), the unobservable latent variables U^*_{AG} and U^*_{ASC} are hypothesized to be random functions of exogenous variables x_{AG} and x_{ASC}, representing farmer and farm business characteristics,

(1) $$U^*_{AG} = x_{AG}\beta_{AG} + \mu_{AG},$$

(2) $$U^*_{ASC} = x_{ASC}\beta_{ASC} + \mu_{ASC},$$

where β_{AG} and β_{ASC} are vectors of unknown parameters associated with the explanatory variables, and μ_{AG} and μ_{ASC} are random disturbance terms. While U^*_{AG} and U^*_{ASC} cannot be observed, a farmer's decision to adopt any of these technologies can be observed such that

$$y_j = \begin{cases} 1 & if\ U^*_j > 0 \\ 0 & otherwise \end{cases} \quad . \qquad (3)$$
$$for\ \ j = ASC, AG$$

Empirical Model

Factors Influencing Precision Agriculture Adoption Decisions

Both studies regarding all precision farming technology adoption and the adoption of specific precision farming technologies guides the identification of variables that influence the adoption of AG systems and ASC technologies. Variables identified as factors influencing PA adoption decisions include age, computer use, education, information sources use, and farm size. Banerjee et al. (2008), D'Antoni et al. (2012), Larson et al. (2008), Martin et al. (2007), McBride and Daberkow (2003), Roberts et al. (2004), and Walton et al. (2008) included age in the empirical models identified to evaluate the adoption of various precision farming technologies. These studies found that older farmers with shorter planning horizon were less likely to adopt these technologies compared to younger farmers. Based on previous literature, this variable (i.e., *AGE*) is hypothesized to have a negative effect on the adoption of ASC technologies and AG systems.

Computer use has been considered as a variable influencing the adoption of precision farming technologies by previous studies including Banerjee et al. (2008), D'Antoni et al. (2012), Lambert et al. (2014), Larson et al. (2008), Martin et al. (2007), McBride and Daberkow (2003), Roberts et al. (2004), and Walton et al. (2010). These studies hypothesized that farmers using computers are more likely to be interested in new farming technologies. For example, Larson et al. (2008) found that cotton producers who used a computer or handheld device for field management were more likely to adopt remotely sensed imagery.

Education influences precision farming adoption decisions (Banerjee et al., 2008; Lambert et al., 2014; Larson et al., 2008; Martin et al., 2007; McBride and Daberkow, 2003; Napier et al., 2000; Roberts et al., 2004; Walton et al., 2010). Farmers with more education are hypothesized to have the skills to understand more complex technologies and their potential benefits. For example, Larson et al. (2008) found that those cotton producers with more years of formal education were more likely to adopt remotely sensed imagery.

Farm size is hypothesized to influence ASC and AG adoption decisions (Banerjee et al., 2008; D'Antoni et al., 2012; Lambert et al., 2014; Larson et al., 2008; Martin et al., 2007; McBride and Daberkow, 2003; Napier et al., 2000, Roberts et al., 2004; and Walton et al., 2010). A larger farm operation implies more acres over which to spread investment costs. McBride and Daberkow (2003) found that farm size positively influenced the likelihood of precision farming adoption. Farm size (*AVACRES*), rather than cotton acres farmed, is hypothesized to have a positive effect on the adoption of ASC and AG systems as cotton producers are able to benefit from the use of these technologies on other crops (e.g., corn, soybeans).

Other factors considered to influence the adoption of PA technologies include sources used to obtain information about precision farming technologies (McBride and Daberkow, 2003; Velandia et al., 2010). For instance, McBride and Daberkow (2003) found the information from crop consultants and input suppliers had a more significant influence on precision agriculture technology adoption than other information sources such as mass media or extension services. Use of farm equipment providers to obtain PA information may be the most appropriate variable to be included in the adoption equations for both ASC technologies and AG systems due to the fact that equipment providers distributed these technologies and also provide support to producers who purchase the technology. In contrast, crop consultants handle other issues such as map development, using yield information to set recommendations for variable rate application (Buschermohle, 2015). Extension agents and specialists provide research based information regarding the economic benefits of adopting these technologies but may not be the first source producers consult when making PA technology purchasing decisions (Buschermohle, 2015). A farm dealer variable (*FARMDEALER*) is included in the ASC and AG systems adoption equations. This variable is hypothesized to have a positive effect on the likelihood to adopting both ASC and AG technologies.

Previous literature suggests that producers with irregularly shaped fields would benefit the most from the adoption of ASC for sprayers or planters, including Velandia et al. (2013), Larson et al. (2016), and Shockley et al. (2012). Perimeter-to-area ratio has been used as a measure of field irregularity by two of these three studies. This measure had a positive effect on the potential savings (e.g., saved seed and saved chemicals associated with overlap reduction) from the adoption of ASC for sprayers or planters. The variations of perimeter-to-area ratio measures that were evaluated here include the average perimeter-to-area ratio of a county (*AVGIRR*),

(4) $$AVGIRR = \frac{\sum_{i=1}^{N_c} \frac{p_i}{a_i}}{N_c},$$

where p_i and a_i are perimeter and area of field *i* in county *c*, respectively, and N_c is the number of fields in a specific county. The median perimeter-to-area ratio of a county (*MEDIANIRR*) was also considered, as well as the sum of perimeter-to-area ratios in a county (*SUMOFIRR*),

(5) $$SUMIRR = \frac{\sum_{i=1}^{N_C} p_i}{\sum_{i=1}^{N_c} a_i}.$$

It is expected that *AVIRR*, *MEDIANIRR*, and *SUMOFIRR* will be larger for counties with a greater percentage of irregular fields. A drawback of these measures is that all of them may be influenced by the number of fields identified within a county.

We also considered alternative measures of irregularity borrowed from the land fragmentation literature. There are five dimensions used to describe the complexity of farm land fragmentation: 1) the number of plots farmed; 2) plot size; 3) plot shape; 4) plot distance to the farm buildings; and 5) plot scattering (Latruffe and Piet, 2013). In the current study, we focus specifically on the third dimension (i.e., plot shape).

Measures used by previous studies to evaluate parcel irregularity in the context of land fragmentation include shape index (*SI*), weighted fractal dimension (*FDWTED*), and area weighted mean shape index (*AWMSI*) (Latruffe and Piet, 2013; Aslan et al., 2007). The SI index is defined as,

(6) $$SI = \sum_{c=1}^{lc_i} \frac{p_i}{4\sqrt{a_i}} Nc$$

A county with a larger *SI* suggests that parcels in that county are more irregular than a county with a smaller *SI*. Additionally, *AWMSI* is defined as,

(7) $$AWMSI = \frac{1}{A_c} \sum_{i=1}^{i_c} a_i \frac{p_i}{4\sqrt{a_i}},$$

where A_c is the total area of county *c*. Counties with large values of *AWMSI* have more irregular fields than counties with lower *AWMSI* values. The final measure considered in this study to measure field irregularity is *FDWTED*. Fractal dimension measures the degree of shape complexity in a land parcel (Aslan et al., 2007) and is defined as,

$$FDWTED = \frac{1}{A_c} \sum_{i=1}^{i_c} a_i \frac{2\ln(p_i)}{\ln(a_i)}. \quad (8)$$

In this study we hypothesized the adoption of ASC to be positively correlated with these shape measures. All shape measures have been transformed using the natural log in order to have marginal effects that are easy to interpret.

Figure 1 is a map of AVGIRR for all counties in the United States. Red counties indicate those with higher values of AVGIRR and, thus, more irregularly shape fields. The map reveals patterns that are expected based on the PLSS systems. Counties located in the Midwest have generally lower values of AVGIRR while counties in states with the PLSS system and near the Appalachian Mountains have higher values of AVGIRR.

CHAPTER 4: METHODS AND PROCEDURES

Data

A survey was mailed in February of 2013 (i.e. the 2013 Southern Cotton Farm Survey) to 13,566 cotton producers in Alabama, Arkansas, Florida, Georgia, Kansas, Louisiana, Mississippi, Missouri, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia. After eliminating those surveys from producers who were no longer growing cotton and those surveys returned undeliverable, 1,810 of the returned surveys were considered appropriate for analysis for a 14% response rate (Boyer et al., 2014). The survey was conducted using Dillman's Tailored Design Method, which emphasizes the use of multiple contacts through reminder cards and second waves of surveys to non-respondents (Dillman, 2000).

Survey

The 2013 Southern Cotton Farm Survey asked questions regarding the use of precision farming technologies as well as farm and producer characteristics. The survey was divided into four sections: "You and Your Farm", "General Questions about Precision Farming", "Variable Rate Application on Cotton", and "Information about Your Household".

The first section of the survey collected information regarding producer characteristics (e.g., age of primary operator, highest education level attained) and farm characteristics (e.g., acreage on cotton and other crops).

The "General Questions about Precision Farming" section, asked producers whether they have used precision farming in cotton production and what improvements they have noticed as a result of this adoption decision. This section also includes questions about the sources used to attain information about precision farming and the importance farmers place on profitability, environmental benefits, and being at the forefront of technology in their decision to adopt precision farming technologies. Finally, this section asked questions regarding the use of various precision farming technologies, excluding Variable Rate Application (VRA) technologies, such as year a producer began using a technology, when and why he/she stopped using it.

The “Variable Rate Application on Cotton” section contains questions about producer use of variable rate technology on their cotton acreage. Specifically this section contains questions about who puts together the information and maps used to implement VRA, what inputs are applied using this technology, producer perceptions of the effect of VRA on yield, and perceived changes in input use as a result of VRA use.

The last section, “Information about Your Household”, asked producers questions regarding household income and percentage of income from farming.

Secondary Data

Field shape for individual farms was not available. Secondary data were used to create field shape measures. Perimeter (p_i) and area (a_i) field data used to estimate shape indexes presented in equations 4 to 8 were created using the NASS Crop Data Layer (CDL). The crop map was uploaded in ArcGIS, and various procedures were used to generate a coverage of field polygons that allowed for the shape assessment. We used the field boundaries typically formed along roads, hedge rows, trees, or waterways, all non-cropland pixels, to break down the CDL into small land parcels that resembled a field rather than several parcels of land put together. Finally, a raster-to-vector conversion was performed on the remaining cropland dataset. The end result was a set of vector field boundaries that aligned with actual field boundaries.

Post-Stratification Survey Weights

A comparison of the survey data with data from the 2012 USDA Census of Agriculture indicates the distribution of survey respondents is skewed towards those farms with larger cotton acres planted (Figure 1). Using Lambert et al.'s (2014) approach, post-stratification survey weights were estimated to account for this difference in a way that the central tendency measures of the survey data approach the distribution of cotton farms from the 2012 Census of Agriculture.

Estimation Methods: Bivariate Probit Regression

The decisions to adopt the two precision agriculture technologies evaluated in this study (i.e., ASC and AG) are considered to be not mutually exclusive (i.e., a farmer can adopt ASC and AG simultaneously), and it is hypothesized that unobserved factors influencing both adoption decisions may be correlated. Additionally, it is important to notice that the adoption of ASC does not require for AG to be already adopted; thus, it is possible to adopt ASC without adopting AG. When running ASC without AG systems equipment providers recommend producers to use a higher accuracy GPS correction services such as OmniSTAR HP[2] or OmniSTAR XP[3] (Buschermohle, 2015). Therefore, a bivariate probit regression was used to evaluate the factors influencing these decisions (Greene, 2003).

The error terms in equations (1) and (2) are assumed to be normally distributed and correlated ($Corr(\mu_{AG}, \mu_{ASC}) = \rho$). For the likelihood function, let $q_{iASC} = 2y_{iASC} - 1$ and $q_{iAG} = 2y_{iAG} - 1$. Thus,

[2] For information about this correction service visit: http://www.omnistar.com/SubscriptionServices/OmniSTARHP.aspx
[3] For information about this correction service visit: http://www.omnistar.com/SubscriptionServices/OmniSTARXP.aspx

(9) $$q_{ij} = \begin{cases} = 1 \; if \;\; y_{ij} = 1 \\ = -1 \; if \;\; y_{ij} = 0 \end{cases} \quad j = ASC, AG$$

Also, let $z_{ij} = x'_{ij}\beta_j$, $w_{ij} = q_{ij} z_{ij}$, and $\rho_i^* = q_{i1ASC} q_{iAG} \rho$. Therefore, the probabilities entering the likelihood function from Greene (2003) are:

(10) $$\text{Prob}\left(Y_{ASC} = y_{iASC}, Y_{AG} = y_{iAG} \mid x_{iASC}, x_{iAG}\right) = \Phi_2\left(w_{iASC}, w_{iAG}, \rho_i^*\right),$$

where Φ_2 denotes the bivariate normal cumulative distribution function. Therefore, the log-likelihood function can be defined as:

(11) $$\log L = \sum_{i=1}^{n} \ln \Phi_2\left(w_{iASC}, w_{iAG}, \rho_i^*\right)$$

Derivatives of the log-likelihood function with respect to β_{ij} and ρ are:

(12) $$\frac{\partial \ln L}{\partial \beta_j} = \sum_{i=1}^{n} \left(\frac{q_{ij} g_{ij}}{\Phi_2}\right) x_{ij,} \;\; for \;\; j = ASC, AG$$

(13) $$\frac{\partial \ln L}{\partial \rho} = \sum_{i=1}^{n} \frac{q_{iASC} q_{iAG} \phi_2}{\Phi_2} \;\; ,$$

where ϕ_2 denotes the bivariate normal density function and g_{iASC} is defined as

(14) $$g_{iASC} = \phi(w_{iASC}) \Phi\left[\frac{w_{iAG} - \rho_i^* w_{iASC}}{\sqrt{1 - \rho_i^{*2}}}\right],$$

where ϕ denotes the univariate standard normal density and Φ represents the univariate standard normal cumulative distribution function. Subscripts are reversed to obtain g_{iAG}. The maximum likelihood estimates for β_{ij} and ρ are obtained by setting (12) and (13) equal to 0. Note that if $\rho = 0$, then $\rho_i^* = 0$ and thus,

(15) $$g_{iASC} = \phi(w_{iASC}) \Phi(w_{iAG}).$$

Replacing (15) in (12) reduces the expression in (12) to the first order condition of a probit regression. The null hypothesis to be tested associated with ρ assumes the model consists of independent probit regressions $(\rho = 0)$ and, therefore, the regressions associated with adoption of ASC technologies and AG systems can be estimated separately. If this null hypothesis is rejected, a bivariate probit regression is appropriate for evaluating the factors influencing the decisions to adopt ASC and AG systems.

Descriptive Statistics

For the analysis of the data, 4 groups of producers were of interest: 1) producers who adopted ASC, 2) producers who did not adopt ASC, 3) producers who adopted AG systems, and 4) producers who did not adopt AG systems. The producer and farm characteristics for ASC adopters and non-adopter and AG system adopters and non-adopters were compared using an independent sample t-test (Tables 2, 3).

Multicollinearity Tests

Multicollinearity can distort results by inflating the estimated variances (Greene, 2003). For the purpose of evaluating multicollinearity, the condition index was used to compare the models in this study (Belsley, Kuh, and Welsch, 1980). Condition indexes between 30 and 80 are considered to be an indication of moderate to strong collinearity among covariates (Belsley, 1991).

Considering Unobserved Individual Farm Characteristics Affecting the Adoption of ASC Technologies

As suggested by previous literature, field geometry may affect the potential economic benefits from the adoption of ASC (Velandia et al., 2013; Larson et al., 2016). Field geometry may be unique for each farm. If information regarding field geometry for each farm is available, then this information should be included in the ASC adoption decision equation. If this information is not available or a good proxy measuring field shape is not available for each farm, omitting this variable from the ASC adoption equation may result in inconsistent parameter estimates, as this omitted variable will be part of the error term and if correlated with the exogenous variables may results in the violation of strict exogeneity (Wooldridge, 2002). A variable that could capture differences between farms influencing the adoption of ASC included in survey data could be location (i.e., state where farm operation is located). Nonetheless, the state where a farm is located may capture some differences (e.g. weather, landscape) that could affect adoption decisions but may not capture individual differences, such as field shape. An alternative approach is to create a variable that groups states based on the system used to establish property boundaries. The states that have non-rectangular fields (i.e., metes & bounds) would be the territory under the jurisdiction of the Thirteen Colonies at the time of independence that did not adopt the Public Land Survey System (PLSS), with the exception of the area that became the Northwest Territory and some of the Southern states. States not using the PLSS system, and therefore more likely to have farms with irregular shape type fields, include Georgia, Connecticut, Delaware, Kentucky, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Tennessee, Vermont, Virginia, and West Virginia. Nonetheless, similar to including state dummy variables, a variable representing PLSS adoption systems may capture general characteristics, such as farm size, that are not necessarily associated with field shape.

In the case where a variable capturing specific individual characteristics affecting the adoption of ASC technologies is not available, a random-intercept probit regression as the one presented in Rabe-Hesketh and Skrondal (2012) where a producer-specific random intercept is included to capture unobserved heterogeneity may be appropriate to capture farm differences affecting the adoption of ASC technologies. Rabe-Hesketh and Skrondal, (2012) present this approach in the context of longitudinal data with two dimensions (e.g., panel data). This approach is adjusted for the case of cross section data. Using the latent-response formulation we can write the random-intercept model for ASC as,

(16) $$U^*_{icASC} = x'_{icASC}\beta_{ASC} + \varsigma_{cASC} + \varepsilon_{icASC},$$

where U^*_{icASC} is the unobservable latent variable for farm *i* and group *c*, which is expected to be a function of the observable exogenous explanatory variables x_{icASC}; β_{ASC} is the vector of unknown parameters associated with the explanatory variables. Finally, ς_{cASC} represents the group specific random intercept that is assumed to be independent and identically distributed across group *c* and independent of covariates x_{icASC}, and ε_{icASC} (i.e., random disturbances vector assumed to have a normal standard distribution). The assumption of random disturbance independence between farms within a county is relaxed using the cluster-robust standard errors available in STATA (STATA, 2013) as we believe that the unobserved factors influencing farms decisions to adopt ASC in a specific county may be correlated. For the case of the GPS auto-guidance adoption decision,

(17) $$U^*_{icAG} = x'_{icAG}\beta_{AG} + \varepsilon_{icAG},$$

where U^*_{iAG} is the unobservable latent variable for farm *i*, which is expected to be a function of the observable exogenous explanatory variables x_{iAG}; β_{iAG} is the vector of unknown parameters associated with the explanatory variables. Finally, ε_{icAG} is the vector of random disturbances for equation (17). The error terms ε_{icASC} and ε_{icAG} are assumed to have a bivariate normal distribution with a zero mean and a cross-equation correlation of ρ.

CHAPTER 5: RESULTS

Sample Overview and Descriptive Statistics

A total of 1,145 observations were included in this analysis after eliminating observations with missing values. Table 1 presents variable definitions and descriptive statistics. The average age of respondents was 57 years old and 41% had a bachelors or graduate degree. Reported average crop acres harvested between 2011 and 2012 were about 976, 36% of respondents indicated using cover crops, and about 58% of respondents indicated using farm dealers to obtain information about precision agriculture. Field shape measures were estimated at the county level. About 31% of cotton producers had adopted ASC, and 59% had adopted AG systems.

Table 2 and Table 3 present comparisons of operator characteristics, farm business characteristics, and the shape indexes for ASC and AG systems adopters and non-adopters. Results suggest that adopters of ASC technologies are younger and have achieved higher levels of education on average, with 48% having a bachelors or graduate degree compared to 39% of non-adopters indicated having this level of education (Table 2).

Total crop acres harvested were 1,517 and 737 for ASC adopters and non-adopters, respectively. Results also indicate that 40% of ASC adopters used cover crops compared to 32% of non-adopters using this production practice. Additionally, results suggest that ASC adopters are more likely to use farm dealers as precision farming information sources than non-adopters. None of the mean shape measures were significantly different between ASC adopters and non-adopters. This result may reflect that field shape measures used in this study may be imprecise rather than reflecting that there is no relationship between ASC and shape measures (Wasserstein and Lazar, 2016). Finally, 94% of cotton producers who adopted ASC technologies also adopted AG systems compared to 44% of producers who had not adopted ASC.

Similar to ASC adopters, AG adopters are younger and have a higher level of education than non-adopters. About 46% of adopters have a bachelors or graduate degree compared to 34% of non-adopters (Table 3). Adopters and non-adopters of AG systems reported about 1,254 and 564 crop acres harvested, respectively. Similar to ASC adopters, this result suggest adopters of AG systems may harvest more acres than non-adopters.

Results also indicate producers using AG systems are also more likely to use farm dealers for information about precision agriculture technologies (67%) compared to non-adopters (46%). Lastly, about 48% of GPS auto-guidance systems adopters also use ASC technologies, while only about 4% of the GPS auto-guidance systems non-adopters use ASC technologies.

Multicollinearity Tests

The condition indexes for the various covariates revealed some potential multicollinearity issues. For the shape measures, the condition indexes for covariates when including FDWTED or AVGIRR were above 30, being 50 and 42 respectively. In addition, the condition indexes when including SUMIRR and MEDIANIRR were very close to 30, indicating there could be some moderate multicollinearity. The shape measures, AWMSI and MEANSI did not have condition indexes above 20, indicating no considerable multicollinearity.

The condition indexes also revealed a potential correlation between computer use and a producer education level. Although computer use and education have been used in past adoption models, the inclusion of both of these as covariates within the adoption equation led to an increased condition index and suspected ill-conditioning of the repressor matrix when evaluating the random intercept regression models. While previous studies incorporated both variables in the adoption equations (Banerjee et al.,2007; Lambert et al., 2014; Larson et al.,2008; McBride and Daberkow, 2003; Roberts et al., 2004; Walton et al. ,2010), we decided to include education but not computer use in both ASC and AG adoption equations. Education was included as it yielded lower condition indexes compared to those condition indexes obtained when including computer use as a regressor.

Results and Discussion from Bivariate Probit Regressions

Bivariate probit regressions were used to evaluate the factors influencing the adoption of ASC and AG systems. This approach was considered to be appropriate for parameter estimation due to the potential correlation between unobserved variables influencing the adoption decisions of ASC technologies and AG systems. The bivariate probit regressions evaluated include: 1) a bivariate probit regression with a shape measure included as an independent variable and a random-intercept included in the ASC equation; 2) a bivariate probit regression with a shape measure but no random-intercept included in the ASC equation; and 3) a bivariate probit regression with a random-intercept but no shape measure included in the ASC equation. The random-intercept probit regression approach is only used for the ASC adoption equation because it is only in the case of the adoption of this particular technology that we believe there are farm-specific unobserved characteristics influencing the adoption decision. The correlation coefficients between the residuals (ρ) were positive and statistically significant at the 1% level for all evaluated regressions, supporting the hypothesis that the error terms in the ASC and AG equations are correlated. The estimation of marginal effects on the probability of adoption of ASC and AG systems are presented in Tables 5 through 18. Marginal effects are presented for the marginal probabilities of ASC and AG[4].

[4] Marginal effects are only available for the marginal probabilities after using cmp in STATA. The cmp command was used to allow for the random-intercept approach in the bivariate probit regression (Roodman, 2011).

Because there were 6 different shape measures being considered, there were a total of 14 different models to evaluate and compare. We used the Akaike Information Criterion (AIC) (Akaike, 1974), the Bayesian Information Criterion (BIC) (Schwarz, 1978), and likelihood-ratio tests to evaluate goodness of fit of the different regression approaches, and to select among those the regression approach that best represents the data used in this study. We used likelihood-ratio tests to evaluate changes in model fit when using the random intercept approach for each of the shape measures considered in this study. Including random intercepts resulted in a statistically significant improvement in model fit for all shape measures. Table 4 contains the AIC, BIC, values of the log-likelihood function, and condition numbers (i.e., highest condition index) for all the regression approaches evaluated. The AIC and BIC statistics were used to compare random intercept regression models using different shape measures. Regression models with SUMIRR and AWMSI included as measures of field irregularity have the smallest AIC and BIC values, and both values are very close to one another for each shape measure. While SUMIRR has a BIC and AIC that is slightly smaller than those for the model with AWMSI, SUMOFIRR has a condition number of 26 which is close to the threshold of 30. Thus, the random intercept regression model with AWMSI seems to be the most appropriate model among those considered to evaluate the factors influencing the adoption of ASC and AG systems.

Table 5 presents the parameter estimates and marginal effects on the probability of adopting ASC and AG systems from the bivariate probit regression that includes LOGAWMSI (i.e., natural log of AWMSI) and uses county level random-intercepts. Results suggest that the overall model is significant at the 1% level, and the bivariate probit regression is the appropriate estimation approach based on the result, suggesting that the null hypothesis of ρ=0 is rejected at the 1% level and that the unobserved factors influencing the adoption of these two technologies may be correlated. The producer characteristics influencing the adoption of ASC and AG include age, education attainment, and use of farm dealers to obtain precision farming information. For example, a producer with a bachelors or graduate degree is 9% more likely to adopt AG and about 8% more likely to adopt ASC (Table 5). Gathering information about precision farming from farm dealers increases the probability of adopting AG by about 14% and the probability of adopting ASC by 18.8% (Table 5).

Farm characteristics influencing the adoption of ASC and AG systems include crop acres harvested, and shape measure *AWMSI*. For example, a producer with one additional acre of crop harvested is 0.01% more likely to adopt AG or ASC. Despite the hypothesized positive sign of *LOGAWMSI*, results suggest a 1% change in the shape index decreases the probability of adopting ASC by 9% (Table 5). With the exception of *LOGAWMSI*, the signs of the farm and producer characteristics were consistent with previous literature and the hypotheses proposed in this study.

Tables 6 and 7 present the results from two regressions, one without county-level random intercepts and one with county-level random intercepts but no shape measure included, respectively. While some parameter estimates change slightly, the overall regression model and significance of the explanatory variables remains largely the same. For these models, producer characteristics such as age, education attainment, and use of farm dealers to obtain precision farming information seem to significantly influencing the adoption of ASC and AG. Similarly, the farm characteristics that significantly affect the adoption of ASC and AG included crop acres harvested, and the use of cover crops. Farm dealers have a positive and significant impact on the adoption of ASC. Results presented in Table 6 suggest the use of farm dealers to obtain precision farming information increases the likelihood of adopting ASC by about 19%. Similarly, results presented in Table 7 suggest the use of farm dealers will increase the probability of adopting ASC by about 19%.

All the alternative models estimated are presented in the Appendix. When using different measures of field shape, regression results suggest contradicting conclusions regarding the influence of field shape on ASC adoption.

When using measures that aggregate perimeter to area ratios by county such as *AVGIRR*, *SUMIRR*, and *MEDIANIRR* results suggest that field shape has a positive impact on the adoption of ASC. In contrast, when using alternative measures such as *AWMSI* and *FDWTED*, we found that these measure suggest a potential negative impact of field shape on the likelihood of adopting ASC. These results may only suggest that that field shape measures used in this study may be imprecise as suggested above (Wasserstein and Lazar, 2016).

In general, all regressions suggest adopters of ASC and AG are likely to be younger, more educated, with larger farms, and more likely to use farm dealers as a source of precision farming information than non-adopters. Finally, the results from the models indicate the effect of the shape index on the adoption of ASC is inconclusive when using the shape measures suggested in this study.

CHAPTER 6: CONCLUSIONS

Precision agriculture technologies such as ASC and AG will continue to be adopted by producers in the United States as the size of the average farm and fertilizers and seed costs increase. Technologies like the ones evaluated in this study that result in both monetary and time savings may have a particular advantage, specifically for larger farms. A bivariate probit approach was used to evaluate the adoption of ASC and AG, and a county-level random intercept was included to take into account unobserved farm-level heterogeneity. Findings from this study may not only help better understand the factors influencing the adoption of these technologies but they may also contribute to the discussion about measurements of field irregularity at a county-level when field shape measures are not available at the farm-level.

Both farm and producer characteristics influence producer's decision to adopt ASC and AG. These characteristics have been examined in previous studies and include age of the producer, educational attainment, farm size, and the use of information sources to obtain precision farming information. Producers who are older are less likely to adopt ASC or AG, which follows the hypothesis that these producers have shorter planning horizon than younger producers and, therefore, are less likely to make drastic changes in their production systems. Additionally, consistent with previous literature, producers with larger farms are more likely to adopt ASC and AG due to their ability to spread the cost of the technology across more acres. There are several limitations of this study associated with field shape measures. Farm-level field shape information is not available; therefore, field shapes are create based on NASS CDL data. We have not validated the procedures used to identify fields at the county level with actual field data. Additionally, the aggregation of perimeter to area ratios on a county basis may be affected by the number of fields in a county, and it is not clear whether aggregation is a valid approach when trying to measure field irregularity. Alternatively, assuming field shape measures used in this study are accurate measures of actual field irregularity, a producer's decision to adopt ASC may not be affected by the potential cost savings in the way previous studies have hypothesized (Velandia et al., 2013, Larson et al., 2016, and Shockley et al., 2012). There are benefits associated with ASC such as the ability to increase turn speed or work longer hours that are not exclusive to farms with a large percentage of highly irregular fields (Beary 2016). This explains popularity of ASC technologies in the Midwest, where fields tend to be very regular, or perimeter to area ratios tend to be low (Beary 2016). Additionally, as suggested by decision aid tools created to evaluate profitability of adopting ASC such as the Automatic Section Control for Planters Cost Calculator (ASCCC)[5], the effect of field geometry on farm savings associated with ASC adoption may decrease as farm size increases. Therefore, a farmer decision to adopt ASC technologies may be driven by farm size rather than field geometry.

[5] http://economics.ag.utk.edu/asccc.html

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APPENDIX

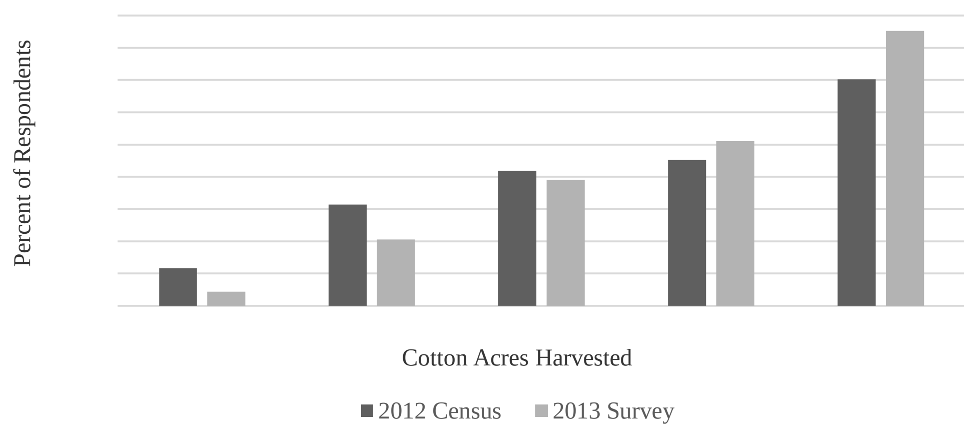

Figure 1. Cotton Acres Harvested from Agricultural Census vs. Survey Data

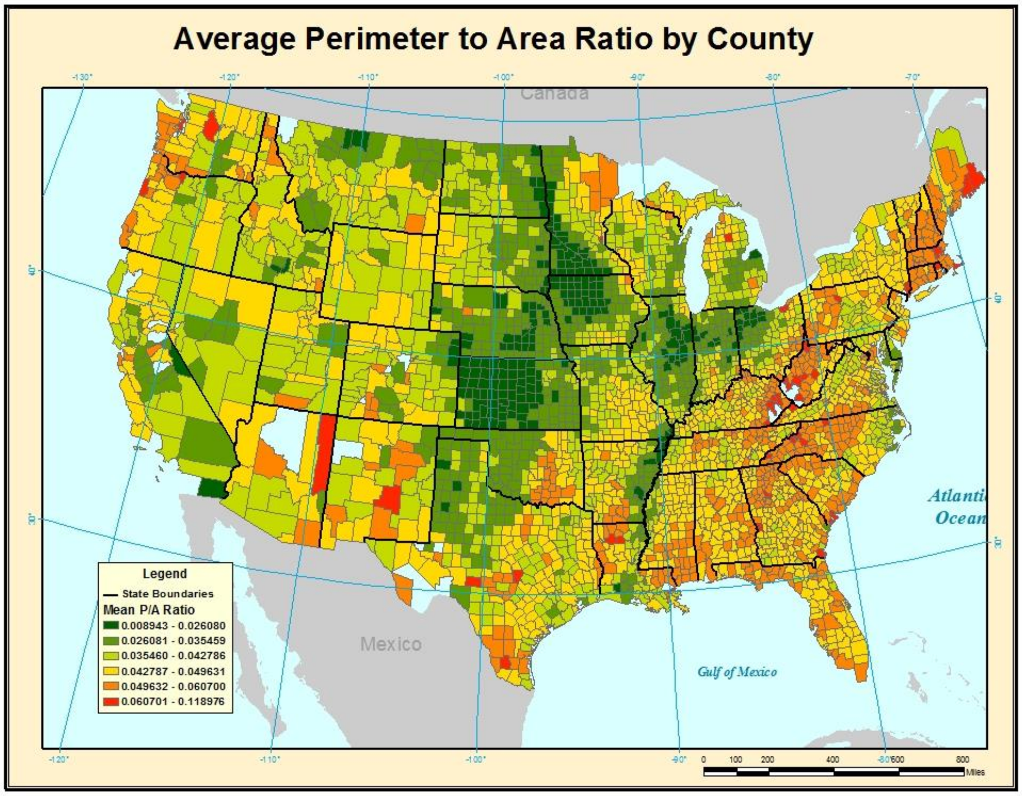

Figure 2. Map of AVGIRR by County

Table 1. Summary Statistics of Variables with Shape Index (n=1445)

Variables	Description	Mean	Standard Deviation	Min	Max
A. Dependent variables:					
ASC	= 1 if producer has adopted ASC for planters or sprayers	0.31		0	1
AG	= 1 if producer has adopted AG auto-guidance systems	0.59		0	1
B. Independent variables:					
AVACRES	Average cotton acres harvested in 2011 and 2012.	975.51	1323.74	2	17500
BGDEDUCATION	= 1 if the producer's highest level of education is a bachelors or graduate degree	0.41		0	1
AGE	Age of primary decision maker as of 2014	56.85	13.32	20	100
FARMDEALER	= 1 if the producer has used a farm dealer as a source of information about precision farming	0.58		0	1
COVER	= 1 if producers uses cover crops, 0 otherwise	0.35		0	1
AWMSI	Area Weighted Mean Shape Index of the county a producer operates within	2.72	1.98	1.15	15.14
SI	Shape Index of the county a producer operates within	1.33	0.35	0.97	4.00

Table 1 Continued.

Variables	Description	Mean	Standard Deviation	Min	Max
FDWTED	Fractal Dimension Weighted of the county a producer operates within.	1.31	0.02	1.24	1.41
AVGIRR	The average perimeter to area ratio of the county a producer operates within.	0.04	0.01	0.01	0.06
SUMIRR	The sum of the perimeter to area ratio of the county a producer operates within.	50.51	31.84	0.32	173.77
MEDIANIRR	The median of the perimeter to area ratio of the county a producer operates within	0.03	0.01	0.01	0.06

Table 2. Summary Statistics of Variables by ASC Adoption

Variable	ASC=1	ASC=0
AVACRES***	1516.56	737.08
BGDEDUCATION***	0.48	0.39
AGE***	52.39	58.82
COVER***	0.40	0.32
FARMDEALER***	0.78	0.50
AWMSI	2.70	2.74
SI	1.34	1.32
FWTED	1.31	1.31
AVGIRR	0.04	0.04
SUMIRR	52.08	49.82
MEDIANIRR	0.03	0.03
AG***	0.94	0.44

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively

Table 3. Summary Statistics of Variables by AG Adoption

Variables	AG=1	AG=0
AVACRES***	1254.05	563.67
BGDEDUCATION***	0.46	0.34
AGE***	54.95	59.36
FARMDEALER***	0.67	0.45
ASC(%)***	0.48	0.04

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively

Table 4. Goodness of Fit Measures for All Models

Shape Variable	Random Effect	Sign	AIC	BIC	Log-Likelihood	Condition Index
None	No		3003.924	3072.51	-1488.9619	
AWMSI	No	(-)	44101.41	44170	-22132.93	14.5735
AWMSI	Yes	(-)	2998.518	3072.38	-1485.2591	14.5735
FDWTED	No	(-)	44220.73	44289.32		50.106
FDWTED	Yes	(-)	3005.129	3078.991	-22097.37	50.106
MEANSI	No	(-)	44163.85	44232.44	-22068.93	17.944
MEANSI	Yes	(-)	3001.549	3075.411	-1486.7747	17.944
SUMIRR	No	(+)	44132.27	44200.86	-22053.14	26.4532
SUMIRR	Yes	(+)	2997.293	3071.155	-1484.6466	26.4532
AVGIRR	No	(+)	44259.52	44328.11	-22116.76	42.329
AVGIRR	Yes	(+)	3002.476	3076.338	-1487.2378	42.329
MEDIANIRR	No	(+)	44257.32	44325.9	-22115.65	25.5774
MEDIANIRR	Yes	(+)	3002.113	3075.975	-1487.0563	25.5774

Table 5. Parameter Estimates and Effects of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit with County-level Random Intercepts and LOGAWMSI with Cluster Robust Standard Errors (n=1445)

	Adoption Equation		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0003***	0.0003***	0.0001***	0.0001***
	(0.0001)	(0.0001)		
BGDEDUCATION	0.2411***	0.2333**	0.0913***	0.0789***
	(0.0791)	(0.1108)		
AGE	-0.0150***	-0.0217***	-0.0057***	-0.0072***
	(0.0026)	(0.0042)		
FARMDEALER	0.3586***	0.5817***	0.1372***	0.1875***
	(0.0739)	(0.1161)		
COVER		0.1577		0.0528
		(0.1097)		
LOGAWMSI		-0.2701***		-0.0904**
		(0.0241)		
_CONS	0.5108***	-0.0508		
Likelihood value	-1485.33			
$\chi^2(10)$	259.70***			
Correlation coefficient	0.80***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 6. Parameter Estimates and Effects of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit with LOGAWMSI and without County-level Random Intercepts with Cluster Robust Standard Errors (n=1445)

	Adoption Equation		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0004***	0.0003***	0.0002***	0.0001***
	(0.0001)	(0.0000)		
BGDEDUCATION	0.2570***	0.2324***	0.0995***	0.0704***
	(0.0856)	(0.0810)		
AGE	-0.0144***	-0.0185***	-0.0056***	-0.0055***
	(0.0028)	(0.0030)		
FARMDEALER	0.3404***	0.6167***	0.1323***	0.1806***
	(0.0809)	(0.0841)		
COVER		0.1278		0.0383
		(0.0814)		
LOGAWMSI		-0.2622**		-0.0785**
		(0.0890)		
_CONS	0.4746**	-0.12443		
Likelihood value	-22037.71			
$\chi^2(10)$	262.89***			
Correlation coefficient	0.75***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively.
Numbers in parentheses are standard errors.

Table 7. Parameter Estimates and Effects of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit with County-level Random Intercepts and Cluster Robust Standard Errors and without Shape Measure (n=1445)

	Dependent Variables		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0003***	0.0003***	0.0001***	0.0001***
	(0.0001)	(0.0000)		
BGDEDUCATION	0.2403***	0.2211*	0.0908***	0.0746**
	(0.0792)	(0.1163)		
AGE	-0.0150***	-0.0221***	-0.0057***	-0.0074***
	(0.0026)	(0.0044)		
FARMDEALER	0.3581***	0.5864***	0.1370***	0.1885***
	(0.0739)	(0.1222)		
COVER		0.2013*		0.0673*
		(0.1143)		
_CONS	0.5103***	-0.1175		
Likelihood value	-1488.96			
$\chi^2(9)$	306.70***			
Correlation coefficient	0.79***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 8. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation without Shape Measure or Random Effect with Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=0
AVACRES	0.0004***	0.0003***	0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BGDEDUCATION	0.2556***	0.2141***	0.0989***	-0.0643
	(0.0790)	(0.0829)	(0.0303)	(0.0252)
AGE	-0.0144***	-0.0189***	-0.0056***	-0.0056
	(0.0029)	(0.0031)	(0.0012)	(0.0009)
FARMDEALER	0.3390***	0.6141***	0.1318***	-0.1784
	(0.0800)	(0.0878)	(0.0310)	(0.0244)
COVER		0.1676**		-0.0498**
		(0.0779)		(0.0231)
Constant	0.47211**	-0.3487**		
Likelihood value	-22132.93			
$\chi^2(9)$	221.73***			
Correlation coefficient	0.73***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 9. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGFDWTED and Cluster Robust Standard Errors (n=1445)

Independent Variables	Adoption Equations AG	Adoption Equations ASC	Marginal Effect	Marginal Effect
	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0004***	0.0003***	0.0001***	-0.0001***
	(0.0000)	(0.0000)		
BGDEDUCATION	0.2571***	0.2208***	0.0672***	-0.0664***
	(0.0856)	(0.0805)		
AGE	-0.0144***	-0.0188***	-0.0053***	-0.0056***
	(0.0028)	(0.0030)		
FARMDEALER	0.3391***	0.6130***	0.1662***	-0.1783***
	(0.0809)	(0.0844)		
COVER		0.1557*		-0.0462*
		(0.0840)		
LOGFDWTED		-4.2743*		-1.2703*
		(2.3174)		
Constant	0.4731*	0.8055		
Likelihood value	-22097.37			
$\chi^2(10)$	255.43***			
Correlation coefficient	0.73***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 10. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGFDWTED, Random Effects, and Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0003***	0.0003***	0.0001***	0.0001***
	(0.0001)	(0.0001)		
BGDEDUCATION	0.2406***	0.2238*	0.0910***	0.0755**
	(0.0778)	(0.1120)		
AGE	-0.0150***	-0.0221***	-0.0057***	-0.0074***
	(0.0024)	(0.0041)		
FARMDEALER	0.3578***	0.5846***	0.1369***	0.1879***
	(0.0691)	(0.1130)		
COVER		0.1938*		0.0647*
		(0.1152)		
LOGFDWTED		-2.4794		-0.8281
		(2.8377)		
Constant	0.5106***	0.5473		
Likelihood value	-1488.56			
$\chi^2(10)$	373.61***			
Correlation coefficient	0.79***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 11. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGSI and Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0004***	0.0003***	0.0002***	-0.0001***
	(0.0000)	(0.0000)		
BGDEDUCATION	0.2551***	0.2285***	0.0987***	-0.0693***
	(0.0858)	(0.0827)		
AGE	-0.0144***	-0.0186***	-0.0056***	0.0056***
	(0.0028)	(0.0030)		
FARMDEALER	0.3408***	0.6119***	0.1325***	-0.1794***
	(0.0809)	(0.0841)		
COVER		0.1425**		-0.0427*
		(0.0813)		
LOGSI		-1.5763**		-0.4723**
		(0.6630)		
Constant	0.4741**	0.1434		
Likelihood value	-22068.93			
$\chi^2(10)$	256.35***			
Correlation coefficient	0.73***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 12. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGSI, Random Effects, and Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0003***	0.0003***	0.0001***	0.0001***
	(0.0001)	(0.0001)		
BGDEDUCATION	0.2401***	0.2300*	0.0908***	0.0777*
	(0.0761)	(0.1076)		
AGE	-0.0150***	-0.0218***	-0.0057***	-0.0073***
	(0.0024)	(0.0039)		
FARMDEALER	0.3590***	0.5830***	0.1370***	0.1877***
	(0.0689)	(0.1086)		
COVER		0.1738*		0.0581*
		(0.1101)		
LOGSI		-1.4773**		-0.4940**
		(0.7494)		
Constant	0.5105***	0.3289		
Likelihood value	-1486.77			
$\chi^2(10)$	335.63***			
Correlation coefficient	0.79***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 13. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGSUMIRR and Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0004***	0.0003***	0.0002***	0.0001***
	(0.0000)	(0.0000)		
BGDEDUCATION	0.2548***	0.2303***	0.0986***	0.0700***
	(0.0857)	(0.0829)		
AGE	-0.0144***	-0.0182***	-0.0056***	-0.0054***
	(0.0028)	(0.0030)		
FARMDEALER	0.3413***	0.6226***	0.1327***	0.1830***
	(0.0809)	(0.0839)		
COVER		0.1231		0.0370
		(0.0810)		
LOGSUMIRR		0.2139***		0.0642***
		(0.0809)		
Constant	0.4740***	0.6205		
Likelihood value	-22053.14			
$\chi^2(10)$	245.50***			
Correlation coefficient	0.74***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 14. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGSUMIRR, Random Effects, and Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0003***	0.0003***	0.0001***	0.0001***
	(0.0001)	(0.0001)		
BGDEDUCATION	0.2399***	0.2320**	0.0906***	0.0786**
	(0.0758)	(0.1040)		
AGE	-0.0150***	-0.0213***	-0.0057***	-0.0072***
	(0.0024)	(0.0038)		
FARMDEALER	0.3597***	0.5864***	0.1369***	0.1893***
	(0.0686)	(0.1046)		
COVER		0.1523		0.0511
		(0.1060)		
LOGSUMIRR		0.2382**		0.0799***
		(0.0784)		
Constant	0.5106***	0.9449**		
Likelihood value	-1484.65			
$\chi^2(10)$	343.87***			
Correlation coefficient	0.79***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 15. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGAVGIRR and Cluster Robust Standard Errors (n=1435)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0004***	0.0003***	0.0001***	0.0001***
	(0.0000)	(0.0000)		
BGDEDUCATION	0.2545***	0.2171***	0.0985***	0.0655***
	(0.0857)	(0.0825)		
AGE	-0.0144***	-0.0186***	-0.0056***	-0.0055***
	(0.0028)	(0.0030)		
FARMDEALER	0.3397***	0.6131***	0.1320***	0.1789***
	(0.0810)	(0.0843)		
COVER		0.1679**		0.0501**
		(0.0828)		
LOGAVGIRR		0.2224		0.0663
		(0.1712)		
Constant	0.4732**	0.3705		
Likelihood value	-22116.76			
$\chi^2(10)$	238.09***			
Correlation coefficient	0.74***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 16. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGAVGIRR, Random Effects, and Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0003***	0.0003***	0.0001***	0.0001***
	(0.0001)	(0.0001)		
BGDEDUCATION	0.2391***	0.2209**	0.0905***	0.0749**
	(0.0762)	(0.1077)		
AGE	-0.0150***	-0.0218***	-0.0057***	-0.0073***
	(0.0024)	(0.0040)		
FARMDEALER	0.3588***	0.5858***	0.1373***	0.1882***
	(0.0692)	(0.1095)		
COVER		0.1966*		0.0656*
		(0.1093)		
LOGAVGIRR		0.3594*		0.1200*
		(0.1864)		
Constant	0.5106***	1.0377*		
Likelihood value	-1487.23			
$\chi^2(10)$	321.17***			
Correlation coefficient	0.79***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 17. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGMEDIANIRR and Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0004***	0.0003***	0.0001***	0.0001***
	(0.0000)	(0.0000)		
BGDEDUCATION	0.2544***	0.2174***	0.0984***	0.0655***
	(0.0857)	(0.0830)		
AGE	-0.0144***	-0.0186***	-0.0056***	0.0056***
	(0.0028)	(0.0030)		
FARMDEALER	0.3398***	0.6094***	0.1321***	0.1778***
	(0.0810)	(0.0840)		
COVER		0.1692**		0.0505**
		(0.0827)		
LOGMEDIANIRR		0.1094		0.0326
		(0.0906)		
Constant	0.4735**	0.0641		
Likelihood value	-22115.65			
$\chi^2(10)$	236.13***			
Correlation coefficient	0.74***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

Table 18. Parameter Estimates and Effect of Independent Variables on the Probability of ASC and AG Adoption from Bivariate Probit Estimation with LOGMEDIANIRR, Random Effects, and Cluster Robust Standard Errors (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0003***	0.0003***	0.0001***	0.0001***
	(0.0001)	(0.0001)		
BGDEDUCATION	0.2391***	0.2220**	0.0906***	0.0749**
	(0.0773)	(0.1083)		
AGE	-0.0150***	-0.0218***	-0.0057***	-0.0073***
	(0.0024)	(0.0039)		
FARMDEALER	0.3592***	0.5827***	0.1374***	0.1874***
	(0.0691)	(0.1089)		
COVER		0.1962*		0.0656*
		(0.1091)		
LOGMEDIANIRR		0.1883**		0.0629**
		(.0944)		
Constant	0.5109***	0.5776		
Likelihood value	-1487.05			
$\chi^2(10)$	385.01***			
Correlation coefficient	0.79***			

*, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively
Numbers in parentheses are standard errors.

VITA

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