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

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1. Introduction

Precision agriculture (PA) encompasses many technologies that use field-level data in order to improve input application efficiency, which potentially reduces the environmental impact of agricultural production (National Research Council, 1997). Changes in the input costs of crop production, particularly seed, fertilizer, and chemical costs influence farmer use of PA technologies.

The application of an input in sections of a field where that input has already been applied (e.g., seed, chemicals) is one example of input application inefficiency (Larson et al., 2016). Automatic section control (ASC) and auto-guidance (AG) systems are PA technologies that can reduce this type of inefficiency. ASC turns planter/sprayer sections or rows off in areas of the field where inputs have been previously applied or on and off at headland turns, point rows, terraces, and/or waterways, reducing or eliminating input overapplication (Fulton et al., 2011). AG systems complement ASC technologies by allowing producers to maintain a desired path through fields which can reduce application overlap and skips. In addition, AG systems reduce fatigue from operating machinery, giving producers the ability to extend their working hours (Shockley et al., 2011). Conversely, AG systems may decrease operator hours by helping them navigate through a field more efficiently (McDonald, 2015). Previous research has evaluated the economic benefits 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). However, while some research has evaluated the factors influencing the adoption of GPS auto-guidance systems (Martin et al., 2007; Banerjee et al., 2008), no studies have evaluated the factors influencing the adoption of ASC technologies. Furthermore, no studies have evaluated the factors influencing the adoption of ASC

and GPS auto-guidance systems simultaneously, a desirable approach considering the complementary relationship between these technologies.

Both ASC technologies and AG systems have been quickly adopted by producers due to their relatively low cost compared to other PA technologies. Despite their popularity, the factors that influence the adoption of ASC and AG among cotton producers are unknown. While previous research has evaluated the economic benefits of jointly adopting ASC and GPS guidance systems (Shockley et al., 2012), no study has evaluated the factors influencing the adoption of these two technologies simultaneously. Thus, this study will address a gap in the literature by using a bivariate probit regression to evaluate factors influencing the adoption of these technologies.

Information about the factors that influence the adoption of ASC and AG systems would be beneficial to several groups, particularly producers and machinery dealers. This research can be used in combination with decision-aid tools and extension publications to aid producers in evaluating the benefits of adopting these technologies. For example, calculations from the Automatic Section Control for Planters Cost Calculator (ASCCC)[1] indicate that the impact of field geometry on seed savings due to ASC for planters adoption decreases as total farm size increases; this result could be confirmed or contradicted by the results presented in this study. For machinery dealers, results from this study can assist the development of marketing strategies that target clientele more likely to adopt ASC technologies and AG systems.

2. Literature Review

The existing literature in the field of PA technologies is quite extensive and includes both the evaluation of factors influencing the adoption of various technologies as well as the economic benefits of adopting these technologies. Some of the past research has evaluated the

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

adoption of all PA technologies as a whole (Napier, Robinson, and Tucker, 2000; McBride and Daberkow, 2003), while other studies have evaluated the factors influencing the adoption of specific technologies (Napier, Robinson, and Tucker, 2000; McBride and Daberkow, 2003; Roberts et al., 2004; Larson et al., 2008; Walton et al., 2008; Walton et al., 2010; Lambert et al., 2014). In regards to the technologies being evaluated here, few studies have evaluated factors influencing the adoption of GPS guidance systems, (Martin et al., 2007; Banerjee et al., 2008; D'Antoni, Mishra, and Joo, 2012) while no studies have evaluated the adoption of ASC technologies. Rather, the research on ASC has focused on the economic benefits of adopting this technology (Batte and Ehsani, 2006; Shockley et al., 2012; Velandia et al., 2013; Larson et al., 2016).

Martin et al. (2007) evaluated the adoption of GPS guidance systems using results from a 2005 survey of cotton producers. Survey results indicated about 23% of cotton producers used GPS guidance systems (Martin et al., 2007). Martin et al. (2007) found that adopters of GPS guidance systems were younger, more likely to use portable laptop computers, and more likely to use other PA technologies. In addition, adopters of these technologies had higher levels of education, more acres of cropland, higher yields, and less farming experience than non-adopters.

Banerjee et al. (2008) evaluated the factors influencing the decision to adopt GPS guidance systems. Similar to Martin et al. (2007), Banerjee et al. (2008) found that farm size, yield, years of formal education, age, use of computers for farm management, and use of other PA technologies affect the decision to adopt GPS guidance systems. In addition, the results from Banerjee et al. (2008) indicated that household income and state where farm operation is located can influence a producer decision to adopt these technologies.

D'Antoni, Mishra, and Joo (2012) assessed the factors influencing the decision to adopt autosteer or lightbar GPS guidance systems. Results indicated that producer expectations of input cost savings from the adoption of these technologies affect the decision to adopt GPS guidance systems. Likewise, producer expectations of the importance of PA technologies in the future also affected the decision to adopt GPS guidance systems (D'Antoni, Mishra, and Joo, 2012). Computer use for farm management, type of cotton picker (e.g., 4-row, 5-row, and 6-row), and farm size positively affected the decision to adopt GPS guidance systems, while producer age and age of the picker used in harvesting activities negatively impacted the adoption decision (D'Antoni, Mishra, and Joo, 2012).

Previous research about ASC technologies have evaluated the economic benefits of ASC adoption and potential factors influencing the size of these benefits (Batte and Ehsani, 2006; Shockley et al., 2012; Smith et al., 2013; Velandia et al., 2013; Larson et al., 2016). Shockley et al. (2012) found that small and irregularly shaped fields yielded larger cost savings from the adoption of ASC for sprayers. They also noted that the effect of irregularity on savings decreases as field size increases. Similarly, results from Velandia et al. (2013) indicated that the economic benefits from ASC adoption for planters will be greater when producers are farming small, irregularly shaped fields. Smith et al. (2013) evaluated the economic benefits of adopting ASC and AG systems. They evaluated field shape by calculating the average angle of machinery approach at headlands of a particular field. This angle of approach decreases as field irregularity increases (Smith et al., 2013). They found that irregularly shaped fields experienced larger economic benefits from ASC adoption and smaller economic benefits from GPS guidance systems adoption than regularly shaped fields (Smith et al., 2013).

Recently, Larson et al. (2016) used a sample of fields in west Tennessee to evaluate the effects of field geometry as measured by the perimeter-to-area ratio (P/A) on the profitability of ASC. The reduction in overlap from the adoption of ASC was measured for three different P/A levels. Consistent with previous research, Larson et al. (2016) found that the economic benefits from the adoption of ASC were higher for more irregularly shaped fields. Additionally, Larson et al. (2016) noted that P/A is a reliable measure of field irregularity and could be considered for use in future research evaluating field geometry.

Luck et al. (2010) used three fields in Kentucky to evaluate the input application reduction when using automatic boom section control, and Batte and Ehsani (2006) analyzed the economic benefits from the adoption of ASC for sprayers. Both studies noted the potential environmental benefits from the reduction of chemical runoff (Batte and Ehsani, 2006; Luck et al., 2010).

3. Conceptual Framework

Modeling the decision to adopt PA 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 (Rahm and Huffman, 1984; Roberts et al., 2004; Larson et al., 2008; Walton et al., 2008; Jara-Rojas et al., 2013; Lambert et al., 2014), 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, μ_{AG}, μ_{ASC} are random disturbance terms. While U^*_{AG} and U^*_{ASC} are unobservable, but the decision to adopt any of these technologies can be observed such that

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

4. Data and Methods

Data

The data used in this study is from the 2013 Southern Cotton Farm Survey mailed in February of that year to 13,566 cotton producers in 14 states in the United States Southern region. A total of 1,810 surveys were found to be appropriate for analysis after those that were returned undeliverable or from producers who were no longer growing cotton were eliminated, resulting in a 14% response rate (Zhou et al., 2015). The survey followed the Dillman's Tailored

Design Method, using reminder cards and a second mailing of surveys to those producers who did not respond to the first wave of surveys sent in February (Dillman, 2000).

The survey was divided into four sections: "You and Your Farm," "General Questions about Precision Agriculture," "Variable Rate Application on Cotton," and "Information about Your Household." These sections contained questions about adoption and abandonment of PA technologies, sources used to obtain information about PA technologies, producer opinions about PA technologies' importance and profitability, and farm and producer characteristics.

The survey did not include questions that could help assess farm field geometry; thus, secondary data was used to create field shape measures. Perimeter (p_i) and area (a_i) field data used to estimate shape indexes 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, hedgerows, trees, or waterways, and 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.

Bivariate Probit Regression

The adoption decisions for ASC and AG systems technologies are not considered to be mutually exclusive; thus, a farmer can adopt the two technologies simultaneously. This study hypothesizes that the unobserved factors influencing the decisions to adopt ASC and AG systems may be correlated. Further, we emphasize that ASC adoption does not require the previous adoption of AG systems; thus, a producer can adopt ASC without adopting AG. If a producer adopts ASC without AG systems, machinery dealers recommend using a high accuracy GPS correction services such as OmniSTAR HP[2] or OmniSTAR XP[3]. Therefore, a bivariate probit regression was used to evaluate the factors influencing the adoption decisions (Greene, 2003). The error terms in equations (1) and (2) are assumed to be normally distributed and correlated ($Corr(\mu_{AG}, \mu_{ASC}) = \rho$). The null hypothesis to be tested associated with ρ assumes the model consists of independent probit regressions $(\rho = 0)$; 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.

Random Intercept Probit Regression

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,

[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

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 result in the violation of strict exogeneity (Wooldridge, 2002).

In the case where a variable capturing specific individual characteristics affecting the adoption of ASC technologies is not available, a random-intercept probit regression like 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,

$$U^{*}_{icASC} = x'_{icASC}\beta_{ASC} + \varsigma_{cASC} + \varepsilon_{icASC}, \quad (4)$$

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 a vector of unknown parameters associated with the explanatory variables. Finally, ς_{cASC} is 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). We hypothesized that the unobserved factors influencing the adoption of ASC by farms located in the same county (i.e., group *c*) may be correlated; thus, we relax the random disturbance independence assumption using cluster-robust standard errors. The AG systems adoption decision is represented as,

$$U^{*}_{icAG} = x'_{icAG}\beta_{AG} + \varepsilon_{icAG}, \quad (5)$$

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_{AG} is a vector of unknown parameters associated with the explanatory variables. Finally, ε_{icAG} is a vector of random disturbances for equation (5). The error terms ε_{icASC} and ε_{icAG} are assumed to be bivariate normally distributed with a zero mean and a correlation ρ.

Empirical Model

Existing research on the adoption of PA technologies guides the consideration of variables that may influence the adoption of ASC and AG systems. Variables that have been previously identified as factors influencing the decision to adopt PA technologies include age, computer use, education, sources used to obtain PA information, and farm size. McBride and Daberkow (2003), Roberts et al. (2004), Martin et al. (2007), Banerjee et al. (2008), Larson et al. (2008), Walton et al. (2008), D'Antoni, and Mishra, and Joo (2012), included age in the adoption equations and found that younger farmers with longer planning horizons were more likely to adopt PA technologies than older producers. Based on this previous literature, farmer age (*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 PA technologies by previous studies including McBride and Daberkow (2003), Roberts et al. (2004), Martin et al. (2007), Banerjee et al. (2008), Larson et al. (2008), Walton et al. (2010), D'Antoni, Mishra, and Joo (2012), and Lambert et al. (2014), . These studies hypothesized that farmers using computers for farm management 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 farm management were more likely to adopt remotely sensed imagery.

Past research suggests that producer education level may influence the decision to adopt PA technologies (Napier, Robinson, and Tucker, 2000; McBride and Daberkow, 2003; Roberts et al., 2004; Martin et al., 2007; Banerjee et al., 2008; Larson et al., 2008; Walton et al., 2010; Lambert et al., 2014). Farmers with more education are hypothesized to have the skills to understand more complex technologies and their potential benefits.

Farm size is hypothesized to have a positive influence on the decisions to adopt ASC technologies and AG systems (Napier, Robinson, and Tucker, 2000; McBride and Daberkow, 2003; Roberts et al., 2004; Martin et al., 2007; Banerjee et al., 2008; Larson et al., 2008; Walton et al., 2010; D'Antoni, Mishra, and Joo, 2012; Lambert et al., 2014). A larger farm operation implies more crop area over which to spread investment costs. McBride and Daberkow (2003) found that farm size positively influenced the likelihood of PA technologies 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).

Information sources used to obtain precision agriculture information have also been identified as factors that may influence the adoption of PA technologies (McBride and Daberkow, 2003; Velandia et al., 2010). For instance, McBride and Daberkow (2003) found that information obtained from extension personnel has a smaller impact on a producer decision to adopt PA technologies compared to that obtained from crop consultants or machinery dealers. 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 them and also provide support to producers who purchase these technologies. In contrast, crop consultants handle other issues such as map development, using yield information to set recommendations for variable rate application. 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. A farm dealer variable (*FARMDEALER*) is included in the ASC and AG adoption equations. This variable is hypothesized to have a positive effect on the likelihood of adopting both ASC and AG technologies.

Shockley et al. (2012), Velandia et al. (2013), and Larson et al. (2016) found that producers with irregularly shaped fields will experience the highest cost savings (e.g., saved seed and saved chemicals associated with overlap reduction) from the adoption of ASC technologies. Perimeter-to-area ratio (P/A) was used by Velandia et al. (2013) and Larson et al. (2016) as a measure of field irregularity, where lower P/A levels represent more regularly shaped fields. Previous research suggests that P/A positively impacts the potential input costs savings from the adoption of ASC; thus, P/A measures were included among the shape variables considered in this research. The median perimeter-to-area ratio of a county (*MEDIANIRR*) was considered, as well as a modified sum of perimeter-to-area ratio per county (*SUMOFIRR*),

$$SUMIRR = \frac{\sum_{i=1}^{N_C} p_i}{\sum_{i=1}^{N_C} a_i}, \tag{6}$$

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 *MEDIANIRR* and *SUMOFIRR* are expected to be higher in counties with a larger percentage of irregularly shaped fields.

We also considered an alternative measure 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, 2014). In the current study, we focus specifically on plot shape.

The area weighted mean shape index (*AWMSI*) is a measure of plot shape used in previous research evaluating land fragmentation (Aslan, Gundogdu, and Arici, 2007; Latruffe and Piet, 2014). This measures was included in this study as a measure of field shape irregularity and it is defined as,

$$AWMSI = \frac{1}{A_c}\sum_{i=1}^{N_c} a_i \frac{p_i}{4\sqrt{a_i}}, \tag{7}$$

where p_i and a_i are perimeter and area of field *i* in county *c*, N_c is the number of fields in a specific county, and A_c is the total area of county *c*. Higher values of *AWMSI* indicate a county has more irregularly shape fields than a county with a lower *AWMSI.* The shape measures presented above are expected to positively influence the likelihood of adopting ASC technologies. We took the natural logarithm of all the variables presented above (i.e., *LOGMEDIANIRR, LOGSUMOFIRR,* and *LOGAWMSI*) to simplify the interpretation of their marginal effects.

Descriptive Statistics and Multicollinearity Tests

The producer and farm characteristics for ASC adopters and non-adopters and AG system adopters and non-adopters were compared using independent sample t-tests (Tables 2 and 3). 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).

Model Selection Criteria

Because there are three different field shape irregularity measures considered in this study, there are a total of six different regressions (i.e., two per measure, associated to the bivariate probit regression and the random intercept bivariate probit regression) to be evaluated and compared. For this purpose, the Akaike Information Criterion (AIC) (Akaike, 1974), the Bayesian Information Criterion (BIC) (Schwarz, 1978), and likelihood-ratio tests were used to compare the different approaches and select the approach that best fits the data used in this study.

5. Results

Descriptive Statistics

Table 1 presents variable definitions and descriptive statistics for the 1,145 observations that were included for analysis after eliminating those with missing values. The average crop acres harvested between 2011 and 2012 were 976, and 36% of producers were using cover crops on their fields. The average producer was 57 years old; 58% had used farm dealers to obtain information about PA technologies and 41% had a bachelors or graduate degree. Field shape irregularity measures were estimated at the county level. About 31% of respondents had adopted ASC technologies 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 indicating 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 suggest that ASC adopters are more likely to use farm dealers to obtain

information about PA technologies and use cover crops. Statistically, field shape measure values were not significantly different between 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 technologies.

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). In addition, AG adopters harvest more crop acres and are more likely to use farm dealers for information about PA technologies than non-adopters. Lastly, about 48% of AG systems adopters also use ASC technologies, while only about 4% of the AG systems non-adopters use ASC technologies.

Multicollinearity Tests

The condition indexes revealed a potential correlation between the variables representing computer use for farm management and 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 regressor matrix when evaluating the random intercept probit regressions. While previous studies have incorporated both variables in the adoption equations (McBride and Daberkow, 2003; Roberts et al., 2004; Banerjee et al.,2008; Larson et al.,2008; Walton et al., 2010; Lambert et al., 2014), we decided to include education but not computer use in both ASC and AG adoption equations to avoid potential multicollinearity problems. 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

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; and 2) a bivariate probit regression with a shape measure but no random-intercept included in the ASC equation. The correlation coefficients between residuals (ρ) from both adoption equations 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. Therefore, a bivariate probit-regression approach is appropriate for this analysis. The estimation of marginal effects on the probability of adoption of ASC and AG systems are presented in Tables 5 and 6. Marginal effects are presented for the marginal probabilities of ASC and AG.

The likelihood-ratio test was used to evaluate model fit between regression models with and without the random intercept for each field shape measure; this resulted in the selection of the random-intercept approach 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 the six regression approaches evaluated. AIC and BIC values were used to compare random-intercept regression models using different shape measures. The bivariate regression including a random intercept and *LOGSUMIRR* as a measure of field shape irregularity have the smallest AIC and BIC values. Field shape irregularity measure *LOGSUMIRR* is the most appropriate measure of field shape irregularity for this analysis according to these statistics. Results from the bivariate

probit regressions including random intercepts, and *LOGSUMIRR* and *LOGAWMSI* as measures of field shape irregularity are presented in Tables 5 and 6.

Table 5 contains the parameter estimates and marginal effects of the regression approach evaluating the factors influencing the adoption of ASC technologies and AG systems including *LOGSUMIRR* as a shape field irregularity measure and a county-level random intercept. The overall regression model is significant at the 1% level. Results suggest that farm business characteristics positively influencing the decision to adopt ASC technologies and AG systems include farm size and field shape irregularity. Producers with additional 100 acres of cropland harvested are 1% more likely to adopt ASC technologies and AG systems, and a 1% increase in *SUMIRR* increases the likelihood of adopting ASC by 8%.

Producer characteristics influencing the decision to adopt ASC technologies and AG systems include education level, age of producer, the use of farm dealers to gather information about PA technologies, and use of cover crops. Producers with a bachelors or graduate degree are more likely to adopt ASC and AG (Table 5). Likewise, the use of farm dealers to obtain PA information increases the probability of adopting AG systems by 14% and the probability of adopting ASC technologies by 19%. Consistent with previous literature, older producers are less likely to adopt ASC and AG systems. The signs of all variables are consistent with the hypotheses presented in this research.

The parameter estimates and marginal effects for the bivariate probit regression with random intercepts and *LOGAWMSI* as a measure of field shape irregularity are presented in Table 6. The overall regression model is significant at the 1% level. Producer characteristics influencing the adoption of ASC and AG include age, education attainment, and use of farm dealers to obtain PA information. For example, a producer using farm dealers to obtain

information about PA technologies is 14% more likely to adopt AG and about 19% more likely to adopt ASC.

Farm and business characteristics influencing the adoption of ASC and AG systems include crop acres harvested and field shape irregularity measure *LOGAWMSI*. For example, additional 100 acres of crop harvested increases the probability of ASC and AG adoption by 1%. While field shape irregularity was hypothesized to have a positive impact on the adoption of ASC, results indicate a 1% increase in *AWMSI* actually, decreases the probability of adopting ASC by 9% (Table 6).

Overall, the results from the regressions presented above indicate that adopters of ASC and AG are likely to be more educated, younger, harvest more crop acres, and more likely to use farm dealers as a PA information source than non-adopters. When considering the two regression approaches that fit best the data use in this study, results from the regression approach considering *AWMSI* as a measure of field shape irregularity seem to contradict the hypothesis that farms with more irregularly shaped fields are more likely to adopt ASC technologies. This result may be explained by the facts that this field shape irregularity measure is taken out of the context of land fragmentation which is a concept including various dimensions other than field shape. Therefore, this measure in itself may not be capturing field shape irregularity as an individual measure that could potentially affect the adoption decision considered in this study. From these results we infer that a good measure of field shape irregularity when farm-level data is not available is *SUMIRR*. As hypothesized, farm operations located in counties that are more likely to have fields with higher levels of shape irregularity may be more likely to adopt ASC technologies.

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 fertilizer 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 regression 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. Not only do findings from this study clarify the understanding of the factors influencing the adoption of these technologies, but they may also contribute to the discussion about measurements of field shape irregularity at a county-level when field shape measures are not available at the farm level.

A producer decision to adopt ASC and AG is influenced by farmer and farm business characteristics. These include crop acres harvested, age of the producer, educational attainment, and the use of farm dealers to obtain PA information. Producers who are older are less likely to adopt ASC or AG, which follows the hypothesis that these producers have shorter planning horizons than younger producers and are, therefore, 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.

Although results from this study suggest farms located in counties with more irregularly shape fields are more likely to adopt ASC technologies, the variable used in this analysis to measure field shape irregularity should be used with caution. The lack of farm-level data on field shape irregularity led to the creation of shape measures using the CDL data. This approach was not validated matching fields obtained from CDL data with actual field data from individual

farms, as this data was not available. Further, the aggregation of the shape measures by county may not be an appropriate approach when attempting to measure field shape irregularity at the farm-level. Until the procedure used in this study to create field shape irregularity measures is validated, *SUMIRR* should be used with caution when evaluating field shape irregularity at the farm-level.

References

Akaike, H. 1974. A New Look at the Statistical Model Identification. *IEEE Transactions on Automatic Control* 19(7): 716–723.

Aslan, S .T., K. S. Gundogdu, and I. Arici. 2007. Some Metric Indices for the Assessment of Land Consolidation Projects. *Pakistan Journal of Biological Sciences* 10 (9): 1390–97.

Banerjee, S., S. W. Martin, S. L. Larkin, M. C. Marra, K. W. Paxton, R. K. Roberts, J. A. Larson, B. C. English, and J. M. Reeves. 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.

Batte, M.T., and M.R. Ehsani. 2006. The Economics of Precision Guidance with Auto-boom Control for Agricultural Sprayers. *Computers & Electronics in Agriculture* 53 (1):28-44.

Belsley, D.A. 1991. A Guide to Using the Collinearity Diagnostics. *Computer Science in Economics and Management* 4: 33-50.

Belsley, D.A., E. Kuh, and R.E. Welsch. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York: John Wiley & Sons.

Zhou, X., B. C. English, C. Boyer, R. K. Roberts, J. A. Larson, D. M. Lambert, M. Velandia, L. L. Falconer, S. W. Martin, S. L. Larkin, K. P. Paudel, R.M. Rejesus, C. Wang, and J.M. Reeves. 2015. Precision Farming by Cotton Producers in Fourteen Southern States. Research series, Department of Agricultural and Research Economics at University of Tennessee, Knoxville. Research Series 15-001. http://economics.ag.utk.edu/publications/precisionag/CottonSurveyReport_Sept2015.pdf

D'Antoni, J. M., A.K. Mishra, and H. Joo. 2012. Farmers' Perception of Precision Technology: The Case of Autosteer Adoption by Cotton Farmers. *Computers and Electronics in Agriculture* 87: 121-28.

Dillman, A. 2000. *Mail and Internet Surveys: The Tailored Design Method.* 2nd Edition. New York: John Wiley & Sons, Inc.

Fulton, J., D. Mullenix, A. Brooke, A. Winstead, and B. Ortiz. 2011. Automatic Section Control (ASC) Technology for Planters. Paper presented at Precision Agriculture Series: Timely Information, Agriculture, Natural Resources & Forestry, Alabama Cooperative Extension Service, Auburn, AL.

Greene, W.H. 2003. *Econometric Analysis - 5th Edition*. Upper Saddle, NJ: Prentice Hall.

Jara-Rojas, R., B.E. Bravo-Ureta, A. Engler, and J. Díaz. 2013. An Analysis of the Joint Adoption of Water Conservation and Soil Conservation in Central Chile. *Land Use Policy* 32: 292-301.

Lambert, D. M, B. C. English, D. C. Harper, S. L. Larkin, and J. A. Larson, D.F. Mooney, R.K. Roberts, M. Velandia, and J.M. Reeves. 2014. Adoption and Frequency of Precision Soil Testing in Cotton Production. *Journal of Agricultural and Resource Economics* 39 (1): 106-23.

Larson, J.A., M. Velandia, M.J. Buschermohle, and S.M. Westlund. 2016. Effect of Field Geometry on Profitability of Automatic Section Control for Chemical Application Equipment. *Precision Agriculture* 17 (1): 18-35.

Larson, J.A., R.K. Roberts, B.C. English, S.L. Larkin, M.C. Marra, S.W. Martin, K.W. Paxton, and J.M. Reeves. 2008. Farmer Adoption of Remotely Sensed Imagery for Precision Management in Cotton Production. *Precision Agriculture* 9 (4):195-208.

Latruffe, L. and L. Piet. 2014. Does Land Fragmentation Affect Farm Performance? A Case Study from Brittany, France. *Agricultural Systems* 129: 68-80.

Luck, J.D., S.K. Pitla, S.A. Shearer, T.G. Mueller, C.R. Dillon, J.P. Fulton, and S.F. Higgins. 2010. Potential for Pesticide and Nutrient Savings via Map-based Automatic Boom Section Control of Spray Nozzles. *Computers and Electronics in Agriculture* 70 (1):19-26.

Martin, S. W., S. Banerjee, J. M. Reeves, R. K. Roberts, B. C. English, J. A. Larson, S. L. Larkin, K. W. Paxton, and M.C. Marra. 2007. Revealed Characteristics of Guidance Systems Adopters in Cotton Production. *Crop Management* 6. doi:10.1094/CM-2007-1116-01-RV.

McBride, W.D., and S.G. Daberkow. 2003. Information and the Adoption of Precision Farming Technologies. *Journal of Agribusiness* 21 (1): 21-28.

McDonald, G. 2015. Personal Communication. June 10.

McFadden, D. 1974. Conditional Logit Analysis of Qualitative Choice Behavior. *Frontiers in Econometrics, Economic Theory and Mathematical Economics*. New York: Academic Press.

Napier, T., J. Robinson, and M. Tucker. 2000. Adoption of Precision Farming with Three Midwest Watersheds. *Journal of Soil and Water Conservation* 55 (2): 135-47.

National Research Council. 1997. Precision Agriculture in the 21st Century: Geospatial and Information Technologies in Crop Management. Washington DC: National Academy Press.

Rabe-Hesketh, S., and A. Skrondal. 2012. *Multilevel and Longitudinal Modeling Using Stata. Volume II: Categorical Responses, Counts, and Survival*. Third Edition. College Station, Texas: Stata Press.

Rahm, M. and W. Huffmann. 1984. The Adoption of Reduced Tillage: the Role of Human Capital and Other Variables. *American Journal of Agricultural Economics* 66 (4): 405–413.

Roberts, R. K., B.C. English, J.A. Larson, R.L. Cochran, W.R. Goodman, S.L. Larkin, M.C. Marra, S.W. Martin, W.D. Shurley, and J.M. Reeves. 2004. Adoption of Site-specific Information and Variable-rate Technologies in Cotton Precision Farming. *Journal of Agricultural and Applied Economics* 36 (1): 143–58.

Schwarz, G. 1978. Estimating the Dimension of a Model. *Annals of Statistics* 6 (2): 461–64.

Shockley, J.M., C.R. Dillon, and T.S. Stombaugh. 2011. A Whole Farm Analysis of the Influence of Auto-Steer Navigation on Net Returns, Risk, and Production Practices. *Journal of Agricultural and Applied Economics* 43 (1): 57-75.

Shockley, J.M., C.R. Dillon, T. Stombaugh, and S. Shearer. 2012. Whole Farm Analysis of Automatic Section Control for Agricultural Machinery. *Precision Agriculture* 13(4): 411-20.

Smith, C.M., K.C. Dhuyvetter, T.L. Kastens, D.L. Kastens, and L.M. Smith. 2013. Economics of Precision Agricultural Technologies across the Great Plains. *Journal of the American Society of Farm Managers and Rural Appraisers* 76(1): 185-206.

Velandia, M., D.M. Lambert, A. Jenkins, R.K. Roberts, J.A. Larson, B.C. English, and S.W. Martin. 2010. Precision Farming Information Sources Used by Cotton Farmers and Implications for Extension. *Journal of Extension* 48 (5): 1-7.

Velandia, M., M.J. Buschermohle, J.A. Larson, N. Thompson, and B. Jernigan. 2013. The Economics of Automatic Section Control Technology for Planters: A Case Study of Middle and West Tennessee Farms. *Computers and Electronics in Agriculture* 95: 1-10.

Walton, J.C., D.M. Lambert, R.K. Roberts, J.A. Larson, B.C. English, S.L. Larkin, S.W. Martin, M.C. Marra, K.W. Paxton, and J.M. Reeves. 2008. Adoption and Abandonment of Precision Soil Sampling in Cotton Production. *Journal of Agricultural and Resource Economics* 33(3): 428-48.

Walton, J.C., R. K. Roberts, D. M. Lambert, J. A. Larson, B. C. English, S.L. Larkin, S.W. Martin, M.C. Marra, K.W. Paxton, and J.M. Reeves. 2010. Grid Soil Sampling Adoption and Abandonment in Cotton Production. *Precision Agriculture* 11(2):135-147.

Wasserstein, R. L., and N. A. Lazar. 2016. The ASA's Statement on P-values: Context, Process, and Purpose. *The American Statistician*. doi: 10.1080/00031305.2016.1154108.

Wooldridge, Jeffrey M. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Appendix

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, divided by 100	9.75	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
LOGAWMSI	Area Weighted Mean Shape Index of the county a producer operates within	2.72	1.98	1.15	15.14

Table 1 Continued.

Variables	Description	Mean	Standard Deviation	Min	Max
SUMIRR	The sum of the perimeter-to-area ratio of the county a producer operates within	50.51	31.84	0.32	173.77

Table 2. Summary Statistics of Variables by ASC Adoption

Variable	ASC=1	ASC=0
*AVACRES****	15.17	7.37
*BGDEDUCATION****	0.48	0.39
*AGE****	52.39	58.82
*COVER****	0.40	0.32
*FARMDEALER****	0.78	0.50
LOGAWMSI	2.70	2.74
LOGSUMIRR	52.08	49.82
*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****	12.54	5.64
*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 Intercepts	Sign	AIC	BIC	Log-Likelihood	Condition Index
LOGAWMSI	No	(-)	44101.41	44170	-22132.93	14.5735
LOGAWMSI	Yes	(-)	2998.518	3072.38	-1485.2591	14.5735
LOGSUMIRR	No	(+)	44132.27	44200.86	-22053.14	26.4532
LOGSUMIRR	Yes	(+)	2997.293	3071.155	-1484.6466	26.4532
LOGMEDIANIRR	No	(+)	44257.32	44325.9	-22115.65	25.5774
LOGMEDIANIRR	Yes	(+)	3002.113	3075.975	-1487.0563	25.5774

Table 5. Parameter Estimates and Marginal Effects for ASC and AG Adoption Equations from a Bivariate Probit Regression with *LOGSUMIRR*, County-level Random Intercepts, and Cluster Robust Standard Errors Included (n=1445)

	Adoption Equations		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	Coefficient	Coefficient	AG=1	ASC=1
AVACRES	0.0300***	0.0300***	0.0100***	0.0100***
	(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 6. Parameter Estimates and Marginal Effects for ASC and AG Adoption Equations from a Bivariate Probit Regression with *LOGAWMSI*, County-level Random Intercepts, and Cluster Robust Standard Errors Included (n=1445)

	Adoption Equation		Marginal Effect	Marginal Effect
	AG	ASC		
Independent Variables	**Coefficient**	**Coefficient**	**AG=1**	**ASC=1**
AVACRES	0.0300***	0.0300***	0.0100***	0.0100***
	(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)		
Constant	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.

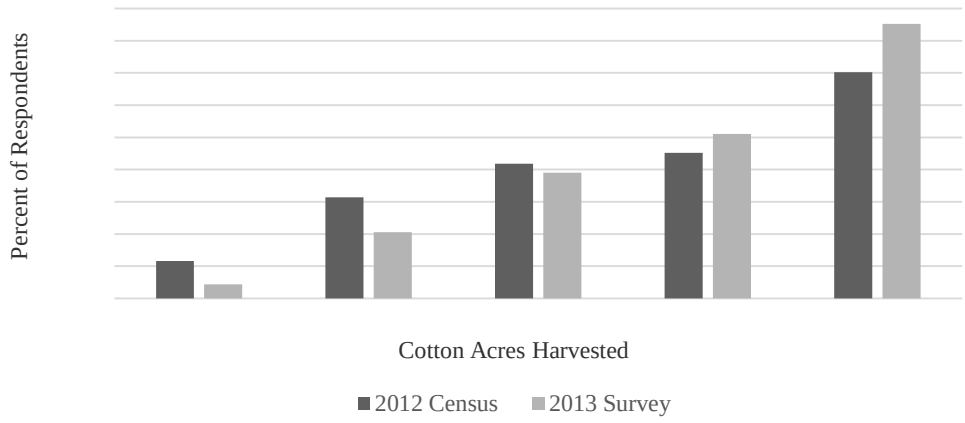

Figure 1. Cotton Acres Harvested from Agricultural Census vs. Survey Data