Precision Farming Technology Adoption in Cotton Farming: Duration Analysis

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Introduction

Precision agriculture (PA) refers to an information based agricultural production system that applies right amount of inputs on right place at right time. PA which has been in existence in agriculture since mid-1980 has helped farmers realize increased profit and reduced environmental concerns by applying right amount of inputs (Bullock, Lowenberg-DeBoer,and Swinton, 2002; Bongiovanni and Lowenberg-DeBoer, 2004; Roberts, English, and Larson, 2002; Watson, Segarra, Lascano, Bronson and Schubert, 2005; Torbett, Roberts, Larson, and English, 2007).

PA uses several component technologies -- of these some farmers only use a few but others adopt all. Some of these component technologies include yield monitor with or without GPS, soil sampling done using grid or zone method, aerial photos, satellite images, soil survey maps, handheld GPS/PDA, COTMAN plant mapping, digitized mapping, and electrical conductivity. Although PA has been common in cereal crops, it's component technologies are slowly becoming popular in cotton production.

Our interest is to find out why some farmers use all component technologies and others do not. While it is true that cotton farmers do adopt technology for profit, to be at the forefront of technology and for environmental benefits reasons, it is still puzzling to see why where and when related questions on technology adoption. Considering the adoption process as survival of technologies, we can analyze duration for technology adoption using available methodology from survival analysis literature. The commonly used methodologies for survival analysis are Cox-proportional hazard (Cox, 1972), Andersen-Gill (1982), shared frailty, and conditional frailty models. In simple survival model, we assume that there is no individual difference among farmers; however, this is not a case in real analysis. The cotton farmers have different intuition on farming and have their own specific farm and individual characteristics. These condition leads to heterogeneity across individual cotton producers and produces within-subject correlation in the occurrence and timing of recurrent events with in the given subject. At the same time, response rate can be homogeneous within individuals producing within-subject correlation in event times.

Objectives

The main objective of this paper is to apply the conditional frailty model for precision agricultural technology adoption that can address both the individual heterogeneity as well as event dependence among multiple precision farming technology.

Methods

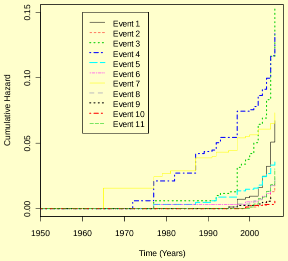
A single technology adoption/nonadoption behavior of a cotton farmer can be modeled using a probit/logit model. When concern is about adopting multiple technology and the time it takes to adopt these technologies once they are available can be modeled as a duration model. In literature, a Cox proportional hazard model (CPHM) is used to model the duration of technology adoption. When there are multiple technologies involved, CPHM does not give right type of variance and parameters are also biased. The model does not recognize individual heterogeneity or correlated events. One way to overcome efficiency problem is to correct variance and estimate CPHM using Wei et al.'s (1989) variance corrected model. This model does not give consistent parameters and also cannot address individual heterogeneity. Other alternative model are shared frailty and conditional frailty models. Shared frailty model can handle only individual heterogeneity. Therefore, we used a conditional frailty model which addresses both individual heterogeneity and correlated events. Additionally, this model gives efficient and consistent parameters. Under the conditional frailty model, the chance of adoption of a particular technology k completed for a specific individual i, (A_{ik}) is

$$A_{ik} = A_{0k}(t - t_{k-1})e^{X_{ik}\beta + w_i}$$

Here, k denotes number of precision technology adoption, A0k is the baseline adoption rate and varies by with the number of technologies adopted by cotton producer. $t - t_{k-1}$ represents a gap time from (k-1)th technology adoption to kth technology adoption. Then the parameters are estimated by maximizing following partial likelihood function:

$$L(\beta) = \prod_{i}^{n}\prod_{k=1}^{K}\left(\frac{e^{X_{ik}\beta + w_i}}{\sum_{i=1}^{n}\sum_{k=1}^{K} Y_{ik}e^{X_{ik}\beta + w_i}}\right)^{\delta_{ik}}$$

Figure 3: Cumulative hazard function



ABSTRACT

We used survey data collected from cotton producers in eleven U.S. states to address the issues of correlated events and individual heterogeneity in multiple precision technologies adoption. Results from a conditional frailty model indicated that younger, better educated cotton producer adopted precision technology quickly once those technologies were available. Further, farm size and farm income have positive influence on a chance of technology adoption by the cotton farmers. Moreover, the conditional frailty model addresses for both heterogeneity and event dependence allowing different baseline hazards for each group of precision technology adopters.

Data

The data for this study were obtained from a survey of cotton producers located in 11 U.S. states (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, and Virginia). The purpose of this survey was to obtain information about the cotton producers' attitude towards the adoption of precision agricultural technology. Data consists of 7456 observation for 681 cotton farmers who adopted technologies between 1966 and 2007. Considering, year as a unit of duration for technologies adoption, we observed whether the cotton producer adopt the technologies or not in a particular year. Each cotton producer can adopt one or more than one technology as a case of multiple technologies adoption. There are total of 474 events with each farm experiencing an average of 0.70 events. The events in this data set range from 1 to 11 for 11 technologies. Figures 1 and 2 give summary representation of adoption behavior of these cotton producers. We found that 255 farmers adopted only one technology; 97 farmers adopted exactly two technology; 55 farmers adopted exactly 3 technology; 24 farmers adopted only four technology, 9 farmers adopted exactly 5 technology, 4 farmers adopted exactly 6 technology. Further there is exactly one farmer who adopts 7 to 10 technology. Finally, no farmer adopted all 11 technologies.

Table 1. Parameter estimates under three different duration models

	Conditional gap time			Shared frailty			Conditional frailty		
	Coef.		Haz. R.	Coef.		Haz. R.	Coef.		Haz. R.
age	-0.01280	.	0.9873	-0.01654	***	0.984	-0.01699	**	0.983158
	(0.00729)			(0.00487)			(0.00686)		
education	0.03617		1.0368	0.05782	**	1.06	0.06704	**	1.069334
	(0.03172)			(0.02320)			(0.03441)		
profitable	1.05084	***	2.8601	0.99544	***	2.706	1.00933	***	2.74376
	(0.32483)			(0.26635)			(0.31475)		
farm_income	0.00358		1.0036	0.00531	**	1.005	0.00644	***	1.006457
	(0.00277)			(0.00223)			(0.00314)		
com	0.88357	***	2.4195	0.89639	***	2.451	0.94803	***	2.580612
	(0.17754)			(0.14389)			(0.18602)		
ayield	0.00088	***	1.0009	0.00097	***	1.001	0.00102	***	1.001017
	(0.00026)			(0.00021)			(0.00031)		
size	0.16726	***	1.1821	0.17196	***	1.188	0.19301	***	1.212899
	(0.04162)			(0.03068)			(0.05447)		
share_rented	-0.00403	*	0.996	-0.00316		0.997	-0.00296		0.99704
	(0.00222)			(0.00167)			(0.00240)		
Θ				1.381501***			1.691786***		
N	7456			7456			7456		
Number of failure	474			474			474		
Likelihood ratio for theta				138.7489			178.5928		
I-Likelihood				-3699.284			-2602.899		
Log-Likelihood for model	-2692.195			-3441.592			-2316.038		
Wald chi-square	108.6***			129***			134***		

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Results and Conclusions

A likelihood ratio test is performed to determine the presence of heterogeneity among farmers which is determined by variance component of the random effect. The likelihood ratio test determines whether the variance component is significantly different from zero at a 5% level of significance. Our results show that the test statistics value is 138.7489, which is highly significant. The significant likelihood ratio test implies the presence of the random effect in the model, so we concluded that unobserved heterogeneity affects the model possibly from two possible reasons: individual heterogeneity and event dependence. Hence, the random effect can either be attributed to individual heterogeneity or event dependence or both. The values of random effect for the conditional frailty and shared frailty model are 1.38 and 1.69, respectively and those are statistically significant suggesting heterogeneity is present among cotton producers adopting component precision technologies. Following Box-Steffebsneuer and Boef (2006), we can argue that the difference in the estimated effect of covariates in these two models imply that either heterogeneity or event dependence or both are present in the data. A graph of cumulative hazard function by event number from conditional gap time model suggests that the baseline hazard is different for different technology. From the comparison of this graph with conditional frailty model (Figure 3), we noted that cumulative hazard lines are not significantly different. Moreover the two graphs suggest that except for few technologies, there is no technology dependence. In order to account for the event dependence, we considered a conditional frailty model as our final model.

Our results from conditional frailty model show that variable *profitable* has the highest effect on the risk of technology adoption, which implies that farmers who think that precision farming technologies would be profitable in future are likely to adopt technology in short time period than who do not think so. This result is consistent with the result obtained from (Paxton et. al, 2010). Age shows negative and significant effect on the hazard of adoption of technology. Therefore, an additional year of *age* reduces the estimated hazard of technology adoption by two percent, which is consistent with our expectation that older farmers are less likely to adopt new technology because of a lower expectation from cumulative return from the cotton farming in future. Results suggest that education attainment (*educ*) has a positive effect on the hazard of adoption. Therefore, an additional year of formal education increases the conditional probability of adoption by 6%. This implies that the duration for adoption of technologies decreases with an increase in the number of formal education. The significant positive effect of farm income on the likelihood of precision technology adoption indicates that a $1,000 increase in farm income increase the chance of adoption of technology by 0.6%. Cotton producers whose farm income is higher can afford to new precision technology so they do not wait long time to adopt a new technology. Cotton producers, who use computer for farm management (such as computerized financial records) were most likely to be successful (Mishra, El-Osta and Johnson, 1999). Consistent with their findings, our results shows that computer use in farming has positive and significant impact on the adoption of technology. Cotton producers who use computer for farm management has a conditional probability of adoption is 1.58 times greater than those operators who have not use computer. Adoption of technology by cotton producer also depends on the productivity of their land. Our results suggest that one lb/acre increase in cotton yield per acre of land increases the hazard of technology adoption by 1%. This means that cotton producer adopt technologies faster if the average yield of land is higher compare to other farm.

The most important issue addressed in this paper is the multiple precision technologies adoption by some cotton producers. Hypothesis test for individual heterogeneity shows that presence of heterogeneity in the data, so we implemented a conditional frailty model which handles for both heterogeneity and event dependence allowing different baseline hazards for each precision technology. Hence, the bias and inefficiency originates from individual level heterogeneity and/or from event dependence in the presence of multiple precision technology adoption are corrected in this study. In conclusion, the results help to formulate an effective policy to increase adoption of precision technologies by cotton producers.

Figure 1. Number of farmers adopting different precision farming technologies in cotton production

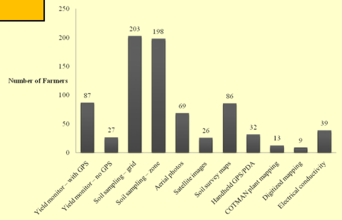

Figure 2. Multiple technology adoption pattern by farmers