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Event dependence and heterogeneity in the adoption of precision farming technologies: A case of US cotton production

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ABSTRACT

This study aims to examine event dependence and heterogeneity in the adoption of precision farming (PF) technologies. The study uses farm-level data and a conditional frailty model to estimate the empirical model. A novelty of this study is the introduction of a group level heterogeneity in the traditional conditional frailty model. The simulation model shows that the conditional frailty model addresses both event dependence and heterogeneity related issues in technology adoption. Results indicate that farmers with large farms, a higher share of total cultivated farmland, a higher percentage of income from farming, and farmers using computers for farm management are more likely to adopt PF technologies early on after a technology becomes available. Further, cotton producers who think that PF technology would be valuable in the future and those receiving farming information from university publications are more likely to adopt PF technologies soon after the technologies become available.

1. Introduction

The decision to adopt new precision technologies is influenced by farm and operator characteristics and other factors. High cost and low personal profit, for example, cause farmers to delay precision farming (PF)[1] technology adoption (Gillespie et al., 2007; Watcharaanantapong et al., 2014). Other factors include risk aversion and perception of farmers (Liu, 2013; Chavas and Nauges, 2020), disposition effect (Vollmer et al., 2019), cognitive ability and receptiveness (Barham et al., 2018), and heterogeneity in returns (Suri, 2011). Previous studies (Roberts et al., 2004; Walton et al., 2010; Paudel et al., 2020) have examined the factors associated with adopting PF technology in cotton. However, these studies have not addressed factors affecting the time it takes for farmers to adopt PF technologies once those become available to them.

PF uses several technologies, and some farmers use only a few, while others adopt PF technologies and practices in the bundle (Lambert et al., 2015). PF technologies include yield monitor with or without global positioning system (GPS), soil sampling using a grid or a zone method, aerial photos, satellite images, soil survey maps, handheld GPS/PDA, COTMAN plant mapping, digitized mapping, and electrical conductivity. Although PF technologies have been used by corn and soybean producers in the US, there has been a significant lag in the timing of adoption and acceptance among US cotton farmers. Cotton farmers in the US have also adopted several PF technologies, including the GPS guidance system (Khanal et al., 2019), precision nutrient management technology (Boyer et al., 2016), and variable rate nitrogen management technology (Stefanini et al., 2019). Ever-evolving progress in PF technologies has contributed to environmentally sound and profitable farming systems (Finger et al., 2019). Considering that adoption is an observation of an event, the lack of adoption of PF is a failure to observe the event.

Only limited studies have analyzed the time taken to adopt a technology using the duration model. For instance, Gao et al. (2019), using the discrete-time hazard method (cloglog function) investigated the time taken by Chinese farmers from awareness of the technology to adopting

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[1] Precision farming (PF) refers to an information-based agricultural production system that helps to apply the right amount of inputs on crop production in the right place at a suitable time. PF, which has been in existence in agriculture since the mid-1980s, has helped farmers to realize increased profit and a better environment by applying the right amount of inputs (Bongiovanni et al., 2004, Roberts et al., 2004, Torbett et al., 2007, Watson et al., 2005).

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green control techniques. The authors found that, among other things, education, risk, easiness to adopt, and government service involvement expedite the adoption while the household head being male slows down the adoption of green control techniques. In a recent study, Canales et al. (2020) investigated the time to adopt cover crops, variable rate technology, and no-till practices using data from farmers in Kansas, US. The authors found that complementarity was the main reason why farmers adopt new practices. Finally, Ofori et al. (2020) used panel data and semiparametric Cox proportional hazard model to study the time taken (time elapsed) by Kansas farmers in adopting technologies from the availability to the adoption of the PF technologies. The authors found that farming experience, farm size and crop insurance affected the timing of adoption of PF technologies. However, the above studies, including PF technology-related studies, have not considered correlated events and heterogeneity in modeling PF technology adoption decisions. Further, previous studies have not tested the suitability of models using empirical simulation. The present study fills these voids in the PF literature.

The Cox proportional hazard model ([CPHM], Cox, 1972) and its extensions have been extensively used to model events in the duration analysis. The commonly used methods for duration analyses are Cox-proportional hazard (Cox, 1972, Andersen and Gill, 1982), shared frailty, and conditional frailty models (Box–Steffensmeier and Boef, 2006). In the simple survival model, we assume no individual difference among farmers; however, this is not a case in applied work. Farmers have different intuitions regarding farming and have a specific farm and individual characteristics. These conditions lead to heterogeneity across individual cotton producers and result in a within-subject correlation in the occurrence and timing of recurrent events (adoption of new technology). Within-subject correlation implies that once a farmer adopts one PF technology, the farmer is more likely to adopt another PF technology. PF technology adoption in cotton production suggests that heterogeneity is present among farmers. Hence, this study addresses both heterogeneity and event dependence issues associated with technology adoption.

Herein lies the objectives of this study. First, we identify the factors affecting farmers' waiting time to adopt multiple-precision farming technologies. While it is true that farmers adopt technology for profit, to be at the forefront of technology and environmental benefits (Paudel et al., 2020), it is still puzzling why farmers wait to adopt seemingly promising technologies (Wozniak, 1993; Liu, 2013; Suri, 2011). Second, we analyze the duration of technology adoption that addresses heterogeneity and event dependence between PF technology adoptions among the US cotton farmers. A conditional frailty model accounts for heterogeneity with stratification and event duration dependence (Box-Steffensmeier and Boef , 2006). Other commonly used survival models are variance corrected, frailty, and shared frailty models (Paudel et al., 2016). Frederiksen et al. (2007) address duration dependence and group heterogeneity in the duration model. Thus, the contribution of this study to the literature is on multiple fronts. First, the study adds a group-specific effect on the conditional frailty model to estimate the empirical model. Second, from a policy perspective, findings can induce policymakers and technology firms to design incentives and policies to increase the PF technology adoption rate, simultaneously improving environmental quality and increasing farm profit (Finger et al., 2019). Third, the findings from this study could help in targeting PF technologies to the right group of farmers.

The rest of the paper proceeds as follows. Section 2 introduces the concept of the hazard model and how heterogeneity and event dependence necessitates the estimation of a conditional frailty model. After that, the study compares the performance of several different hazard models using the empirical simulation method. The simulation focuses on heterogeneity (in terms of PF technology adoption and dependency) among US cotton producers. Section 3 presents data, variable choice, and descriptive statistics. Section 4 estimates the model suggested by the empirical simulation results and shows the results of the study. Section 5 concludes the paper. Supporting materials are relegated to the Appendix.

2. Empirical framework

A binary choice modeling procedure models a single PF technology adoption behavior of a cotton farmer. The binary modeling approach has several limitations. For example, a binary choice modeling approach does not provide a measure of the waiting time in the adoption of PF technology. In other words, how long do farmers wait to adopt PF technology once the technology becomes available in the market? A CPHM can be used when there are concerns regarding adopting multiple PF technologies and the time taken to adopt these technologies. A summary of the CPHM and its relevance to this study is presented in Appendix A.1. CPHM assumes that the baseline hazard does not vary across precision farming technologies. Another commonly used survival model is a frailty model, the details of which are presented in Appendix A.2.

2.1. Individual heterogeneity

Individual heterogeneity refers to a condition where some farmers adopt more PF technologies than other farmers for unknown or unmeasurable reasons. For instance, Fig. 1 shows the number of cotton farmers adopting different numbers of PF technologies. The figure is based on the data used in the present study. The figure shows that 1,533 cotton producers did not adopt any PF technology. In contrast, it shows that 225 farmers adopted only one PF technology, 97 farmers adopted two PF technologies, and 55 farmers adopted three PF technologies. A smaller number of farmers adopted four or more PF technologies—24 farmers adopted four PF technologies, nine farmers adopted five PF technologies, and four farmers adopted six PF technologies. Interestingly, one farmer adopted 7–10 PF technologies. No farmers adopted all eleven PF technologies. Thus, the above analysis shows heterogeneity in the adoption of PF technologies.

2.2. Event dependence

Event dependence refers to a condition where the probability that a PF technology is adopted is related to whether another PF technology was adopted earlier. Adoption and non-adoption of PF technologies is a

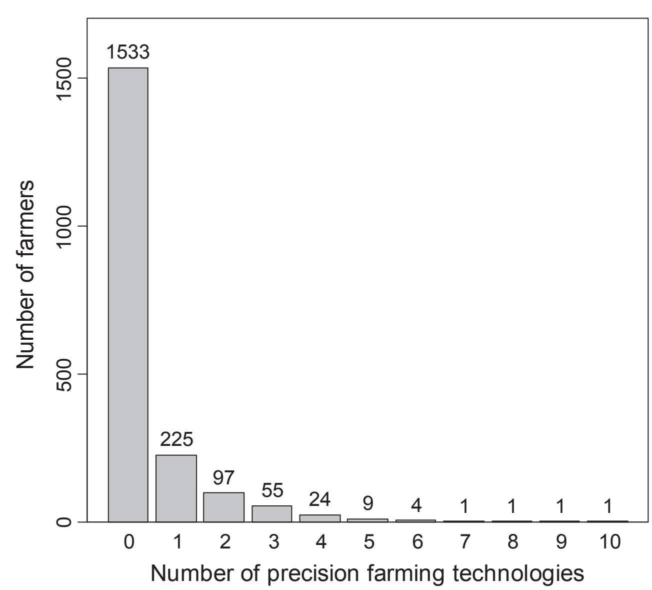

Fig. 1. The number of PF technologies adopted by cotton farmers in the United States.

binary variable, so Pearson's correlation coefficient is not an appropriate indicator to check the dependence between adoptions of one precision farming to other PF technologies. Kendall's tau (τ) is a suitable method to measure dependence. Let (X_1, X_2) and (Y_1, Y_2) be independent random pairs from a continuous bivariate pdf $F(x_1, x_2)$

$$\tau = P[(X_1 - Y_1)(X_2 - Y_2) > 0] - P[(X_1 - Y_1)(X_2 - Y_2) < 0] \tag{1}$$

If $(X_1 - Y_1)(X_2 - Y_2) > 0$, then (X_1, X_2) and (Y_1, Y_2) are concordant pairs. If $(X_1 - Y_1)(X_2 - Y_2) < 0$, then (X_1, X_2) and (Y_1, Y_2) are discordant pairs. A nonparametric estimate of Kendall's tau is used to determine the dependence of PF technologies:

$$\hat{\tau} = \frac{(C - D)}{n(n-1)/2}. \tag{2}$$

where C is the number of concordant pairs, D is the number of discordant pairs, and n represents the sample size. Table 1 shows the estimated Kendall's tau correlation between adoptions of different PF technologies used by US cotton producers. PF technologies (PF1 to PF11) are provided in a sequential order consistent with Fig. 2. Many of Kendall's tau correlation coefficient values are significant, indicating event dependence among PF technologies; therefore, there is the need to address event dependence in our model.

Parameters and standard errors estimated by the CPHM are inconsistent and biased when heterogeneity among farmers and event (PF technology adoption) dependence[2] in the presence of different PF technologies. Some variance-corrected models (Box-Steffensmeier and Boef, 2006, Box-Steffensmeier et al., 2007) address this problem. Variance-corrected models adjust event dependence and heterogeneity by adjusting the variance–covariance matrix. However, Box-Steffensmeier et al. (2007) show that variance-corrected models perform poorly in the presence of heterogeneity and event dependence. The authors suggest using the conditional frailty model as an alternative method because it is more efficient and consistent than other variance-corrected models.

Heterogeneity and event dependence are not the only problems in the duration model estimation. Another factor is duration dependence (Frederiksen et al., 2007). The current probability of adopting a PF technology might depend not only on whether the cotton farmer has not adopted PF technology in the last period but also on how long they have not adopted the PF technology. That is, the length of past non-adoption of PF technology might be an essential determinant of the current likelihood of adoption in addition to the last period's realization. Frederiksen et al. (2007) address the duration dependence issue using a duration dependence parameter. Given the conditional frailty model is estimated on gap time, it easily handles the duration dependence. The probability of adopting PF technology in a region[3] might be higher or lower than in the other areas—group-specific effect. The group-specific impact can be solved by including a regional dummy variable in the conditional frailty model.

2.3. Model and estimator

We analyze the duration for adopting PF technologies in terms of the adoption hazard, representing the instantaneous adoption rate of PF technologies by US cotton farmers. We define some terminology related to survival analysis relevant to the present study (see Appendix A.3). Fig. 1 and Table 1 show that the conditional frailty model captures heterogeneity across individuals and event dependence via a random effect. The model is formulated in gap time so that parameter estimates can be interpreted as the probability of adopting a technology given that the PF technology was not adopted in the previous period. Let's define the adoption hazard (likelihood of adopting) of a particular technology k by an individual i belonging to the group j ish_{ijk}. Using the method suggested by Box-Steffensmeier et al. (2007) and considering the group-specific effect offered by Honoré and Hu (2010) and Frederiksen et al. (2007), the conditional frailty model can be presented as:

$$h_{ijk}(t) = h_{0k}(t - t_{k-1})\exp(X_{ijk}\boldsymbol{\beta} + \alpha_j + \omega_i) \tag{3}$$

where h_{0k} is the baseline hazard rate that varies by the number of precision agricultural practices adopted by a cotton producer i, $(t - t_{k-1})$ represents the likelihood of adopting kth practice since the adoption of $(k-1)^{th}$ practice, X_{ijk} is a matrix of explanatory variables, $\boldsymbol{\beta}$ represents vector parameters, and α_j represents the group-specific (group = j) effects, and ω_i is the random effects or frailties. This model addresses duration dependence and group-specific effects and includes time-varying variables. Parameters $\boldsymbol{\beta}$ are estimated by maximizing the following partial likelihood function

$$L(\beta) = \prod\nolimits_{i=1}^{n}\prod\nolimits_{k=1}^{K}\left(\frac{\exp(X_{ijk}\beta + \alpha_j + \omega_i)}{\sum_{i=1}^{n}\sum_{k=1}^{K} Y_{ijk}\exp(X_{ijk}\beta + \alpha_j + \omega_i)}\right)^{\delta_{ijk}} \tag{4}$$

where δ is a censoring variable equal to 1 if observed and 0 if censored, Y_{ijk} is an at-risk indicator equal to 1 when a farmer is likely to adopt current PF technology k and 0 otherwise, and K represents the total number of PF technologies. The above equation allows for estimating fixed and random effects separately from the survival function (Cox and Oakes, 1984).

2.4. Empirical simulation

Box–Steffensmeier and Boef (2006) use theoretical simulations to show that the conditional frailty model performs better than other duration models. This study extends Box–Steffensmeier and Boef's model by using time-varying independent variables and group heterogeneity, as suggested by Frederiksen et al. (2007) and Honoré and Hu (2010). Recall that we are interested in empirical simulations to identify the appropriate model that best fits the data. In this study, we selected eight independent variables to generate the duration variable for simulation purposes. The data was created by drawing the time to an individual i's k^{th} event t_{ijk} adoption, using an exponential distribution with rate $h_{ijk}(t)$ and is expressed as:

$$h_{ijk}(t) = h_{0k}(t)\exp(X_{ijk}\beta + \alpha_j + \omega_i) \tag{5}$$

where h_{0k} is the baseline hazard rate which depends on k and$t$; α_j a group-specific effect; $\omega_i$is a random effect that allows for heterogeneity; X is a matrix of the independent variables from our model, and β is a vector of parameters corresponding to the independent variables. The variance of $\omega_i(\sigma_\omega^2)$is set to 0.001 in case of no observed heterogeneity and $\sigma_\omega^2 = 10$ to account for heterogeneity in the data. The larger variance represents more significant heterogeneity and results in a higher correlation among event times. The event dependence is created by setting $h_{0k} = kh_0$. Also, setting parameter value $\beta = 1$, the baseline hazard $h_0 = 1$ and the maximum number of the event is set to11 (recall that a maximum of 11 component PF technologies is available for cotton farmers). The data is generated with 1,000 observations following Eq. (5) and estimate three variances-corrected models (Andersen-Gill, conditional elapsed time, and conditional gap time), a shared frailty model, and the conditional frailty model. The conditional frailty model uses a

[2] Some individual farmers or group of farmers might have higher or lower adoption rate of precision technology adoption than other farmers due to unknown, unmeasured or unmeasurable effects. See details in Box-Steffensmeier et al. (2007).

[3] Frederiksen et al. (2007) suggested that group could be observed by focusing on geographical location, by household, by employer in empirical setting, so we chose region as our group specific effects.

Table 1
Kendall's tau coefficient of precision farming technology adoptions by US cotton producers.

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF11
PF1	0.117										
PF2	0.027	0.061									
	(0.00)										
PF3	0.039	0.019	0.311								
	(0.00)	**(0.01)**									
PF4	0.026	0.016	0.039	0.281							
	(0.01)	**(0.02)**	**(0.01)**								
PF5	0.011	0.006	0.022	0.067	0.144						
	(0.09)	(0.25)	**(0.04)**	**(0.00)**							
PF6	0.012	0.006	0.035	0.059	0.067	0.135					
	(0.07)	(0.20)	**(0.00)**	**(0.00)**	**(0.00)**						
PF7	0.003	0.004	0.002	0.009	0.002	0.007	0.041				
	(0.46)	(0.12)	(0.68)	(0.12)	(0.62)	(0.05)					
PF8	0.012	0.004	0.032	0.023	0.017	0.017	0.009	0.051			
	(0.00)	(0.21)	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**				
PF9	0.014	0.004	0.015	0.021	0.008	0.019	0.005	0.010	0.031		
	(0.00)	**(0.06)**	**(0.00)**	**(0.00)**	**(0.02)**	**(0.00)**	**(0.01)**	**(0.00)**			
PF10	0.004	−0.001	0.007	0.013	0.009	0.009	0.000	0.015	0.005	0.016	
	(0.05)	(0.76)	**(0.04)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.81)	**(0.00)**	**(0.00)**		
PF11	0.043	0.008	0.034	0.030	0.016	0.026	0.004	0.014	0.020	0.010	0.065
	(0.00)	**(0.01)**	**(0.00)**	**(0.00)**	**(0.00)**	**(0.00)**	(0.15)	**(0.00)**	**(0.00)**	**(0.00)**	

Note: The precision farming technologies are: Yield monitor-with GPS (PF1), Yield monitor-no GPS (PF2), Soil sampling-grid (PF3): Soil sampling-zone (PF4) Aerial photos (PF5), Satellite images (PF6), Soil survey maps (PF7), Handheld GPS/PDA (PF8), COTMAN plant mapping (PF9), Digitized mapping (PF10), and Electrical conductivity (PF11). The values in parenthesis are p-values. The bolded value in parentheses indicates a Kendell's tau correlation coefficient is significant. Kendall's tau coefficient (Kendell rank correlation) is a nonparametric measure of the relationship between PF_i and PF_j where $i \neq j$. Kendall's tau coefficients are calculated based on concordant and discordant pairs.

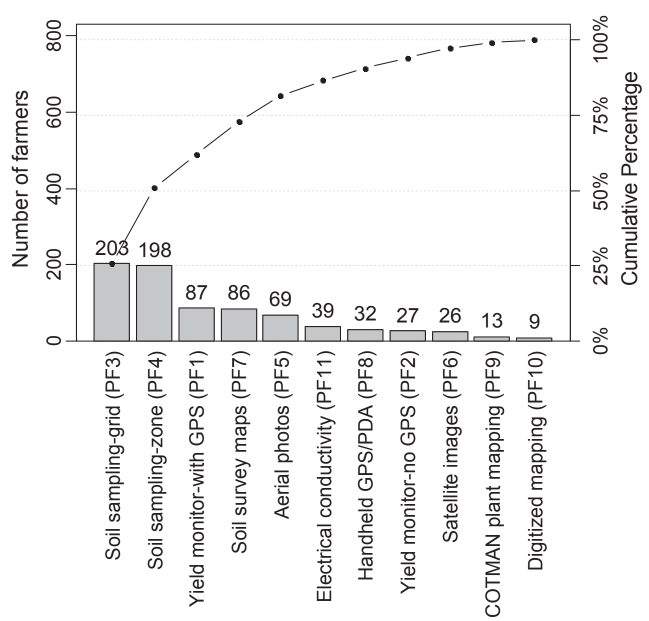

Fig. 2. The number of cotton producers adopting each PF technology in the US.

random gamma effect.[4] The simulation is replicated 100 times. For evaluation, we calculated the root mean square error (RMSE) for each model using the following expression:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\widehat{\beta}_i - 1\right)^2}. \tag{6}$$

In Eq. (6), N is the number of simulations. The R-software and the survival package was used for the model simulation.

Following Box–Steffensmeier and Boef (2006), we compare five different duration models in empirical simulation: shared frailty, conditional frailty, Anderson-Gill conditional gap, and conditional elapsed. The result of the simulation is shown in Table 2. Results show that parameters estimated from the conditional frailty model are closer to the real parameter value ($\boldsymbol{\beta} = 1$) for all dependent variables. Other variance-corrected models result in parameter estimates that are much smaller than the true parameter values. In contrast, the shared frailty model result gives much higher parameter estimates than the true parameter values. For the conditional frailty model, the RMSE is very low, indicating that the model performs very well, and the RMSE is smaller compared to the RMSE from the other models. A density plot of the estimated parameters of a variable (say farm income) is shown in Fig. 4. This density plot is calculated from the 100 estimated coefficients from the empirical simulation for each model. Fig. 4 also shows that the conditional frailty model has an average mean value closer to the true parameter. Thus, the conditional frailty model performs better under heterogeneity and event dependence conditions than the other two models. Hence, the final model that fits the data can be expressed as:

$$h_{ijk}(t) = h_{0k}(t - t_{k-1})\exp\left(X_{ijk}\boldsymbol{\beta} + \alpha_j + \omega_i\right). \tag{7}$$

In the above equation, X represents the matrix of explanatory variables (see Table 3), $\alpha_j$represents the group-specific regions (Delta, Cornbelt, Appalachia, Southeast), and ω represents frailty or random effect. For the interpretation of the model, we are interested in the hazard ratio. Let $h_1(t, X, \omega, \alpha)$ represent a hazard for the first set of variables defined as:

$$h_1(t, X, \omega, \alpha) = h_{0k}(t - t_{k-1})exp\left(X_{1,ijk}\beta + \alpha_j + \omega_i\right), \tag{8}$$

And $h_2(t, X_N, \omega, \alpha)$ be the hazard for the second set of variables given by:

$$h_{2(t,X_N,\omega,\alpha)} = h_{0k}(t - t_{k-1})exp\left(X_{N,ijk}\beta + \alpha_j + \omega_i\right), \tag{9}$$

with $X_N = X + \delta_i, \delta_i = (0,...,1,...,0)$, then the hazard ratio (hr) is defined as:

$$hr = \frac{h_2(t, X_N, \omega, \alpha)}{h_1(t, X, \omega, \alpha)} = exp(\beta_i) \tag{10}$$

The hazard ratio shows the chance of PF technology adoption in one

[4] Note that these models differ from Box-Steffensmeier et al. (2007) as we incorporate time-varying covariates and group heterogeneity.

Table 2
Results from empirical simulations.

Model	Statistics	Age	Education	Profitable	Farm income	Computer	Syield	Farm size	Land tenure
Conditional frailty	$\widehat{\beta}$	0.979	0.957	0.981	0.996	1.005	1.107	0.947	0.974
	SD	0.383	0.551	0.153	0.153	0.094	0.506	0.446	0.153
	RMSE	0.380	0.547	0.153	0.151	0.093	0.512	0.445	0.154
Shared frailty	$\widehat{\beta}$	2.097	1.676	2.150	2.112	2.097	2.141	1.720	1.927
	SD	1.127	1.674	0.456	0.608	0.289	1.305	1.279	0.423
	RMSE	1.565	1.790	1.235	1.264	1.134	1.723	1.457	1.017
Andersen-Gill	$\widehat{\beta}$	0.674	0.741	0.654	0.685	0.691	0.790	0.776	0.725
	SD	0.271	0.368	0.091	0.110	0.073	0.464	0.351	0.113
	RMSE	0.423	0.447	0.358	0.333	0.317	0.505	0.413	0.297
Conditional gap	$\widehat{\beta}$	0.611	0.653	0.605	0.638	0.636	0.739	0.686	0.657
	SD	0.235	0.327	0.079	0.100	0.059	0.384	0.302	0.097
	RMSE	0.453	0.475	0.403	0.376	0.369	0.460	0.434	0.357
Conditional elapsed	$\widehat{\beta}$	0.269	0.284	0.289	0.305	0.298	0.366	0.300	0.297
	SD	0.128	0.189	0.051	0.065	0.036	0.220	0.169	0.057
	RMSE	0.742	0.740	0.713	0.698	0.703	0.671	0.719	0.705

Note: Variable definitions are given in Table 3. RMSE stands for root mean square error.

Table 3
Variable definition and summary statistics.

Variable	Variable definition	Average	SD	Min	Max
Tech	Technologies	6.00	3.16	1.00	11.00
Start	Year when technology started	1987.88	11.41	1957.00	2004.00
Tadopt	Year when technology adopted	2006.50		1957.00	2007.00
Event	=1 if technology adopted, 0 otherwise	0.06	0.24	0.00	1.00
Age	Age of farm operator (years)	51.35	11.47	11.00	84.00
Education	Formal education of farm operator (years)	14.77	2.13	5.00	23.00
Farm size	Cotton acreage in 2007 (1,000 s acres)	1.29	1.40	0.01	16.00
Farm income	Percentage income from farm	73.85	27.61	0.00	100.00
Land tenure	Owned acres divided by owned acres plus rented acres	34.55	35.14	0.00	108.14
Computer	=1 if farmer uses computer for farm management	0.65		0.00	1.00
Farming information	=1 if the farm uses university publication to obtain precision farming information	0.42		0.00	1.00
Important	=1 if the farm think PF is important for future	0.90		0.00	1.00
Cons easement	=1 if the farm currently have conservation easement	0.17		0.00	1.00
Syield	Spatial yield variability	37.59	24.99	0.00	296.00
Livestock	=1 if farm own livestock, 0 otherwise	0.32		0.00	1.00
Delta	=1 if a farm is located in Delta region (Louisiana, Arkansas, Mississippi), 0 otherwise	0.16		0.00	1.00
Cornbelt	=1 if a farm is located in Corn belt region (Missouri), 0 otherwise	0.02		0.00	1.00
Appalachia	= 1 if a farm is located in Appalachia region (Tennessee, North Carolina, Virginia), 0 otherwise	0.21		0.00	1.00
Southeast	=1 if a farm is located in Southeast region (South Carolina, Alabama, Georgia, Florida), 0 otherwise	0.19		0.00	1.00
Southplain	=1 if a farm is located in Southplain region (Texas), 0 otherwise	0.42		0.00	1.00

Source: 2009 Southern Cotton Precision Farming Survey.

group compared to the other group. If two groups are separated by only treatment vs. no treatment, $\exp(\beta)$ with β being the treatment coefficient results in a hazard ratio.

3. Data

The study uses the 2009 Southern Cotton Precision Farming Survey data collected from farmers in twelve US states (Alabama, Arkansas, Florida, Georgia, Louisiana, Missouri, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia) (see Fig. 3). A survey implementation method suggested by Dillman (1978) was used to collect information about precision farming technologies adoption. The mailing list of potential cotton farmers for the 2007–08 marketing year was obtained from the Cotton Board in Memphis, Tennessee (Mooney et al., 2010). The survey was mailed in February of 2009. Of the 14,089 questionnaires sent, 306 were returned undeliverable, 204 respondents were no longer cotton farmers, and 1,692 respondents provided useful information for a response rate of 12.5 percent, which is considered a valid response rate for conducting this type of analysis.

These data were coded in an extended format by farmers' ID and technologies, which is required to estimate the conditional frailty model. We observe whether the cotton producer adopted a given technology in

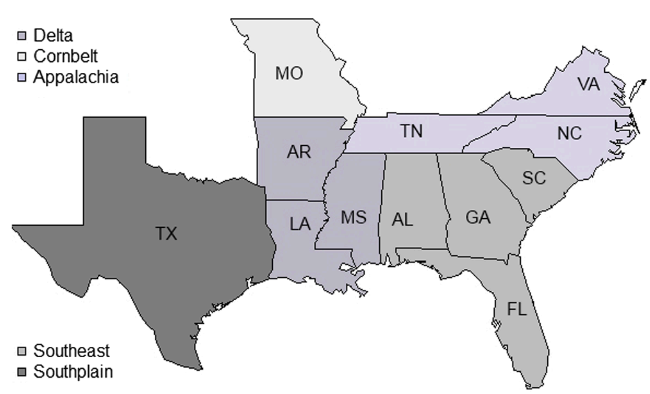

Fig. 3. Precision farming survey states with division of regions. U.S. states and regions are defined as: Delta region (LA = Louisiana, AR = Arkansas, MS = Mississippi), Corn belt region (MO = Missouri), Appalachia region (TN = Tennessee, NC = North Carolina, VA = Virginia), Southeast region (SC = South Carolina, AL = Alabama, GA = Georgia, FL = Florida), Southplain region (TX = Texas).

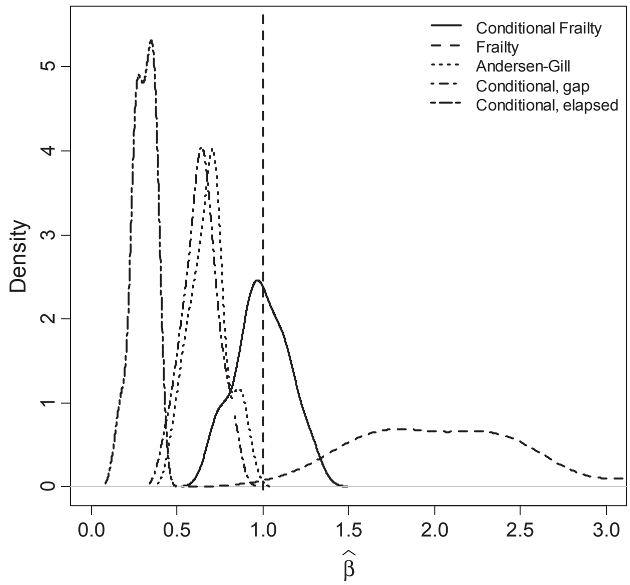

Fig. 4. Densities of parameter $\widehat{\beta}$ estimated under heterogeneity and event dependence in different survival models. Note the true parameter value is $\beta = 1$.

a particular year by considering a year as a unit of technology adoption duration. Each producer can adopt one or more than one technology as a case of multiple technology adoptions. There are 474 events (total precision farming technologies adopted by farmers), with each farmer adopting an average of 0.70 technologies. Farmers have adopted 11 different PF technologies. Cotton producers adopting each PF technology are given in Fig. 2. This figure shows that the soil sampling grid and soil sampling zone are the two most common PF technologies adopted by cotton producers.

The variables used to explain the adoption pattern are based on human capital theory, farm and production characteristics, and other variables used in the technology adoption literature. Education and farming experience are measures of human capital that reflect the ability to innovate and adopt new ideas. The human capital variable has a positive influence on adoption hazard. Since there is no study done on duration analysis in cotton PF, we expect that the variables used on adoption decisions also have a similar effect on PF duration. Previous studies (Gargiulo et al., 2018; Paustian and Theuvsen, 2017; Paxton et al., 2011; Roberts et al., 2004; Tamirat et al., 2018; Velandia et al., 2010; Walton et al., 2010) have shown that farm size, age, income, and farming experience are widely accepted variables that affect precision technology adoption decisions. Most of these studies have shown that the operator's age has a negative influence on technology adoption (Soule et al., 2000). Young and educated farmers are willing to innovate and adopt new technologies that reduce the time spent on farming (Mishra et al., 2002). Therefore, education is expected to have a positive influence on PF technology adoption hazard because farmers with those attributes are exposed to more ideas and efficiently use different information sources (Caswell et al., 2001).

Farm characteristics are essential variables for understanding a farmer's decision to adopt PF technology (Prokopy et al., 2008). As with other studies, this study uses financial and location variables for the duration to adopt precision agriculture technology. University publications are helpful to cotton producers in obtaining precision farming information. Extension services convey information about university research and publication that help farmers make an informed decision to enhance profitability (Hall et al., 2003). Producers tend to use multiple sources of information to increase their knowledge of precision agriculture (Velandia et al., 2010). Therefore, information is expected to be positively related to the adoption likelihood of farming technology (Gupta et al., 2020; Buchkin and Kerret, 2020). Paxton et al. (2011) find that spatial yield is one of the critical factors on the PF adoption in cotton. In their study, spatial yield variability is defined as:

$$FSV = 0.5\left(Yield_{low} - Yield_{avg}\right)^2 + 0.5\left(Yield_{high} - Yield_{avg}\right)^2 \tag{11}$$

where the coefficient of the field spatial yield variability:

$$(CVFSV) = 100 \times FSV_i^{0.5} / Yield_{avg}$$

Farmers with larger farms are more likely to believe they will observe positive externalities associated with precision farming (Larkin et al., 2005). Also, Larkin et al. (2005) find that farmers who found PF to be profitable or who believed input (e.g., fertilizer and pesticides) reduction was important had a higher probability of adopting PF technologies. Farmers with larger farms and higher than average county yields were more likely to adopt precision technology (Banerjee et al., 2008). Computers are essential to keep financial records and to find information about the use of precision agriculture. It has been found that farmers who kept computerized financial records were more likely to be financially successful (Mishra et al., 1999). Table 3 provides definitions and summary statistics of the variables used in the empirical model. Since some observations in the original data were missing, only 1,650 completed surveys were deemed useable in our analysis. PF technology in cotton farming was first used in 1957. Summary statistics show that the average age of cotton farmers in the twelve states is 51 years, with 15 years of schooling. Seventy-four percent of household income comes from cotton farming. Cotton farmers own 34% of the total farming land. Sixty-five percent of cotton producers use computers for their farm management.

A study by Zhou et al. (2015) using more recent data than ours has found that 73.5% of US cotton farmers have adopted one or more precision agricultural technologies. This adoption proportion is about 10% more than what we have found in our survey of similar technologies adopted by cotton farmers in the U.S. Zhou et al. (2015) find that georeferenced soil sampling grid, yield monitor with GPS, soil survey maps, and aerial photos are the top four precision farming technologies adopted by US cotton farmers.

4. Results and discussion

The empirical simulation (see Fig. 4 and Table 2) shows that the conditional frailty model performs better under heterogeneity and correlated events than other models. The results are consistent with the findings of Box-Steffensmeier and Boef (2006) and Box-Steffensmeier et al. (2007). A likelihood ratio test was used to determine the heterogeneity among farmers, determined by the variance component of the random effect. The likelihood ratio test shows that the variance component is significantly different from zero at the 5% level of significance. The values of random effects for the conditional frailty is 7.90 (Table 4), and the likelihood ratio test value for the variance component is 607.76 and is highly significant. This result justifies the presence of the random effect in the model. A Weibull probability plot of adoption for each PF technology by cotton producers from the conditional frailty model is given in Fig. 5. Fig. 5 suggests that the probability of PF technology adoption is different by event number. Correlated events are found to be present since the likelihood of PF technologies for each stratum is distinct.

Table 4 provides the parameter estimates and hazard ratios obtained from the conditional frailty models. Age has a negative and significant effect on the hazard of the adoption of technology. An additional year in the age of cotton producer reduces the estimated hazard of technology adoption by 5.0%. Our finding is consistent with our expectation that older farmers are less likely to adopt new technologies. A plausible explanation is that older farmers have lower expectations from the expected cumulative returns from cotton farming in the future. This result is consistent with Roberts et al. (2004), who found that older farmers do

Table 4
Parameter estimates and hazard ratios obtained from the conditional frailty models.

Variables	Coefficients	Hazard Ratio
Age	−0.0499 (0.00)	0.951
Education	0.068 (0.64)	1.071
Farm size	0.227 (0.05)	1.255
Farm income	0.016 (0.06)	1.016
Land tenure	0.019 (0.02)	1.019
Computer	0.865 (0.08)	2.376
Farming information	1.485 (0.00)	4.413
Important	2.286 (0.04)	9.836
Cons Easement	0.169 (0.83)	1.184
Syield	−0.007 (0.53)	0.993
Livestock	1.516 (0.00)	4.552
Delta	4.072 (0.00)	58.671
Cornbelt	3.404 (0.03)	30.094
Appalachia	2.030 (0.00)	7.613
Southeast	1.889 (0.00)	6.614
Random effects (θ)		7.90
N		8016
Number of failures		453.00
Likelihood ratio for theta		607.76
I-likelihood		−2272.75
Log likelihood for model		−1580.78
Wald χ^2(15,457)		1465.00

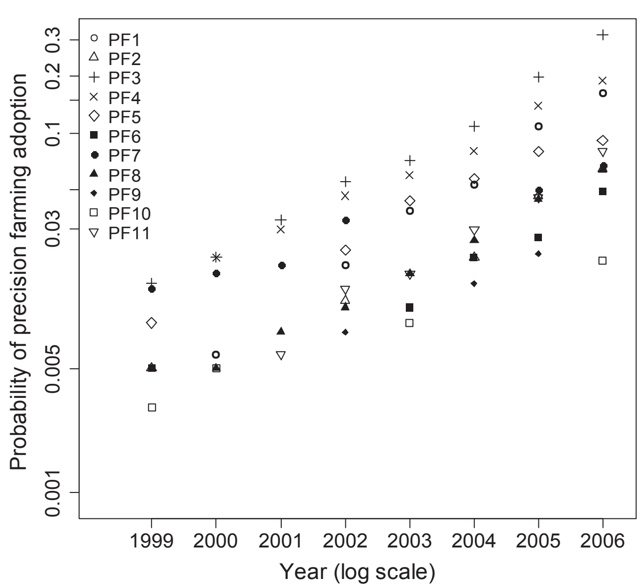

Fig. 5. A Weibull probability plot of adoption for each precision farming technology by US cotton producers.

not adopt variable rate technology than younger farmers. The significant positive effect of farm income on the hazard of technology adoption indicates that for each $1000 increase in farm income increases, the probability of adopting PF technology by about 1.6%. Higher farm income affords farmers with the cash that is needed to adopt new PF technologies. Thus, farmers with higher farm incomes do not have to wait a long time to acquire new PF technologies. Our finding is consistent with Isgin et al. (2008), who reported a positive effect of income (lack of indebtedness) on adopting PF technology in Ohio, United States. Results in Table 4 suggest that cotton producers, who own a higher percentage of the land they farm, are more likely to adopt PF technologies. A 1% increase in land tenure increases the likelihood of adopting PF technologies by 1.9%. Our finding is consistent with Isgin et al. (2008) and Roberts et al. (2004) have also found that an increase in the proportion of ownership of land compared to the total operated area increases the adoption of PF technologies.

Table 4 reveals that a cotton producer who uses a computer for farm management is about 1.34 times more likely to adopt PF technologies than their counterparts. Our result is consistent with Mishra et al. (1999), who found that computer use in farming has a positive and significant impact on farm earnings and more likely to adopt new technologies. Table 4 shows that cotton producers using PF technology information (university publication, journal articles, and other sources) are 3.41 times more likely to adopt PF technology than their counterparts. Our finding is consistent with Larson et al. (2008). They argue that farmers who perceive extension service as providing pertinent information related to PF technology are more likely to adopt the technology.

Cotton producers who think that PF will be important in the future are likely to adopt PF. The result in Table 4 shows that cotton producers who think PF is essential in the future are 8.83 times more likely to adopt PF technologies than their counterparts. Further, we found similar results for cotton producers who own livestock. The probability of adoption of PF is 3.55 times greater when compared to those who do not own livestock. The above results are consistent with findings reported in Tey and Brindal (2012). Regional dummy variables in Table 4 are significant, which implies that the group-specific effect is present in our data. Thus, the farm's geographical location is also an essential factor affecting the adoption hazard of PF in the Southern US states. Results show that farms located in the Delta, Corn Belt, Appalachia, and Southeast regions are more likely to adopt PF technologies than farms located in the Southern Plains region. The study finds that farms located in the Delta region have the highest adoption effects (58.76). Further, the results show that farms situated in the Corn Belt region have the second-highest adoption effect (30.09) for the likelihood of adopting PF technologies.

5. Conclusions and policy implications

The study conducted empirical simulations to identify an appropriate model that can address event dependence and heterogeneity associated with adopting multiple-precision farming technologies by US cotton farmers. Variance corrected models resulted in parameter estimates much smaller than the true parameter values. In contrast, the shared frailty model result gave much higher parameter estimates than the true parameter value. For the conditional frailty model, RMSE was smaller compared to the RMSE from the other models. The conditional frailty model has an average mean value closer to the true parameter. Thus, the conditional frailty model performed better under heterogeneity and event dependence conditions than the other models. These findings were consistent with Box-Steffensmeier and Boef (2006). Therefore, we estimated the conditional frailty model to estimate the empirical model to understand the waiting time to adopt precision farming practices by cotton farmers in the US.

The findings from this study show the existence of event dependency among PF technologies. Results reveal that farmers observe a waiting time or duration to adopt PF technologies. Further, the time taken to adopt PF technologies depends on the individual farmer and farm-specific characteristics of cotton farmers in the US. The duration model was used to measure the time taken by a cotton producer to adopt a PF technology given the technology is available. The adoption hazard of PF technologies is negatively correlated with age. Thus, younger cotton producers are more likely to adopt PF faster. Farmers with large acreage, higher land ownership, higher farming income, and use of information technology, such as the use of computers for farm management, are more likely to adopt PF technology. Further, cotton producers who think that PF will be valuable in the near future and use farming-related information from university publication are more likely to adopt PF shortly after a new PF technology is available. Finally, cotton producers located in the Delta region have the highest probability of adopting PF technology than farms located in other areas.

We found that only a few cotton farmers have adopted yield monitors compared to the US national average of 40–50 percent adopting the same technology by corn and soybean producers. At least in our case, Cotton farmers seem to equally adopt soil mapping and yield monitoring technology compared to other grain farmers. Yield monitoring and soil mapping are two essential technologies for the adoption of precision farming technologies. Given the almost equal adoption of the above technologies by cotton farmers, tandem promotion of PF technologies and variable rate technology (VRT) is warranted. Policymakers could design policies to increase the adoption of PF technologies that target farmers who say precision farming is essential, those using information management technology like computers in agriculture and farm management, and those using university publication in the farm decision-making process. Readers should be cautioned that 92% of cotton farmers did not adopt any PF technology. Therefore, this study's results may have been affected by fewer observations of adopters of PF technologies. Future studies should use a larger-scale survey to collect information on more PF related technologies.

Many of the PF technologies require technical sophistication to operate. Publications from university research and extension can provide detailed workings of the technology. Additionally, extension personnel can help to train farmers on how to manage the technology appropriately. Another way to increase adoption is to provide subsidized capital to facilitate the adoption process. This is because the equipment used in precision agriculture technology is expensive. Better data on environmental benefits from precision agriculture and proper documentation of this information may convince farmers to adopt the technology. Of course, these recommendations should be carefully evaluated before developing a final policy to increase the adoption rate of precision farming technologies in cotton production.

CRediT authorship contribution statement

Krishna Paudel: Conceptualization, Methodology, Original draft preparation, Coordination and Validation. **Ashok Mishra:** Conceptualization, Writing-Reviewing and Editing, Visualization. **Mahesh Pandit:** Analysis, contribution to the initial draft. **Eduardo Segarra:** Review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

A.1. Cox proportion hazard model

In a Cox Proportion Hazard Model (CPHM), baseline hazard can be of any functional form, noninformative censoring should be followed, and a proportional hazard assumption should hold. The number of cotton producers is stratified according to the number of individual precision technologies they have adopted in light of the above assumptions. Suppose there are k different types of technologies that can be adopted. The hazard (adoption) function is obtained by multiplying the baseline hazard function (h_{0k}) and some functional form of covariates. The CPHM is expressed as:

$$h_{ik}(t) = h_{0k}(t)\exp(X_{ik}\beta). \tag{A1}$$

Here h_{0k} is the baseline adoption rate, varies according to events; X is the matrix of independent variables, which may have time varying variables, and β is a vector of parameter estimates. Under the assumption of no tie among event times, parameters are estimated using a partial likelihood function suggested by Cox (1972) and given by:

$$L(\beta) = \prod_i^n \prod_{k=1}^K \left(\frac{(\exp(X_{ik}\beta)}{\sum_i^n \sum_{k=1}^K Y_{ik}\exp(X_{ik}\beta)} \right)^{\delta_{ik}}. \tag{A2}$$

Here, r indexes D_i, which is the set of d_i tied events for the i^{th} risk set. Since the parameter estimates are obtained from the maximum likelihood estimation, the variance is the Cramer-Rao lower bound, which is the inverse of second the derivative of the likelihood function (Hessian matrix) and equal to the following expression.

$$Var(\hat{\beta}) = -\left[\frac{d^2 \log L(\beta)}{d\beta^2}\right]^{-1}_{\hat{\beta}} \tag{A3}$$

A.2. Frailty model

The variance corrected CPHM cannot address the heterogeneity effect on the estimates and remains inconsistent (Kelly and Lim, 2000). The frailty model incorporates heterogeneity into the model estimator by treating the frailty term randomly drawn from a known parametric distribution. Then, the hazard function and likelihood function to estimate the shared model are given below:

$$h_{ik}(t) = h_{0k}(t)\exp(X_{ik}\beta + \omega_i) \tag{A4}$$

Here, w_i is the vector of unknown random effects or frailty for the i^{th} individual and k^{th} represents the number of possible technology combinations adopted by each cotton producers. The frailty is assumed to follow a gamma distribution. So, the heterogeneity in the model is estimated by the variance of error term$\theta(=exp(w_i))$. Then, the parameters are estimated by maximizing the following likelihood function:

$$L(\beta)=\prod_{i=1}^{n}\left(\frac{\exp(X_{ik}+w_i)}{\sum_{i=1}^{n}\exp X_{ik}+w_i}\right) \tag{A5}$$

It is important to highlight here that this model does not simultaneously address the correlation between event dependence and individual heterogeneity.

A.3. Terminologies

Below, we define some terminology related to survival analysis as these are relevant to our study.

1. *Cumulative Distribution Function,*$F(t)$: The cumulative distribution function of T, $F(T)=P(T\le t)$ gives the probability that technology will be adopted before time t.

2. *Probability Density Function,* $f(t)$: The probability density function for a continuous random variable T is the derivative of $F(t)$with respect to t : $f(t)=\frac{dF(t)}{dt}$

3. *Event*: An event is the adoption of technology at time$t$.

4. *Non-adoption (Survival)*, $S(t)$: The non-adoption function is the probability that the adoption of precision farming occurs after t, and given by

$$S(t)=P(T\ge t)=1-F(t) \tag{A6}$$

Here, the adoption (hazard) function,$h(t)$, is proportional to the probability of adoption of technology in the interval $[t,t+\delta]$ given that it has not been adopted up to time t:

$$h(t)=f(t)/S(t) \tag{A7}$$

and

$$\delta h(t)\doteq P(t<T\le t+\delta|T>t).$$

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