A Bayesian Analysis of GPS Guidance System in Precision Agriculture: The Role of Expectations

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Abstract

Farmer's post adoption responses about technology are important in continuation and diffusion of a technology in precision agriculture. We studied farmer's frequency of application decisions of GPS guidance system, after adoption. Using a Cotton grower's precision farming survey in the U.S. and Bayesian approaches, our study suggests that 'meeting expectation' plays an important positive role. Farmer's income level, farm size, and farming occupation are other important factors in modeling GPS guidance system adoption and application.

Key words: Precision agriculture, GPS guidance system, cotton farms, Bayesian, expectation, adoption, application, technology

1. Introduction

Precision agriculture (PA) is a system approach to managing variation in crop production (Dobermann et al. 2004; Ebel and Schimmelpfennig, 2012) using site-specific information technologies and practices (Paxton et al., 2011). The agricultural economics literature suggests a number of demographic, socioeconomic, and financial factors influence the adoption of agricultural technologies. Broadly, the areas dealt in most of these studies include factors influencing the adoption decision; information sources and their relevance in relation to adoption, perceptions about precision farming, and cost savings. Many analyses have focused on decisions to adopt these technologies. However, few studies have analyzed the post-adoption features of the technology, such as whether the technologies meet the expectations of producers and if producers continue to use or abandon precision agriculture technologies (exceptions include Walton et al., 2008). This process plays a key role in technology diffusion.

Farmers are assumed to continue using a technology if it meets their expectation. As defined in most of the previous adoption studies, factors such as education, age, information access, perception about cost and return of a technology, cost savings due to adoption are considered some general factors that may determine an adopter's decisions about application and hence diffusion of a particular technology. Once adopted, a rational decision maker is assumed to judge about the technology based on his/her criteria about evaluating it and whether a technology meets his/her expectation. Motivation for this study primarily comes from the general hypothesis that a technology adopted in one cultivation practice and that meets an adopter's expectation is more likely to be used in other cultivation practices where it can be applied. This study considers application of GPS guidance system in precision agriculture.

The ultimate aim of the empirical analysis is to identify a causal relationship between the variables of interest. There are substantial challenges to this task. Angrist and Pischke (2009) describe 'cause and effect' as a fundamental question of interest in social science. Empirical studies attempt to capture cause-effect relationships by deriving statistical inferences under a different set of assumptions. Econometric models using observational data usually places broadly assumptions on the distribution, dependence, and heterogeneity of data (Spanos, 2007). Statistical inference can be drawn using different approaches, namely classical (frequentist), Neyman-Pearson, and Bayesian approaches. In classical and Bayesian approaches, researchers aim to learn more about an unknown set of parameters. A distinguished feature of the Bayesian approaches is that it applies prior information about parameter distributions along with the information from observed data to make inferences. Scholars suggest a major limitation of classical approach is its reliance on asymptotics for making inferences about estimates. Yet, these properties are in fact unknown for given, finite samples. Further, in empirical studies, researchers face practical problems such as low sample size, high dimensional parameterizations, and less tractable likelihood functions. In such cases, Bayesian models are preferred for computational reasons, or model selection and searching, or to add additional information about observational data using priors. Even in the situations with limited sample sizes and noninformative (diffuse) priors, different approaches are employed in Bayesian simulation-based econometrics to estimate posterior distributions (Koop et al. 2007). The model search and Bayesian model averaging procedures allow the investigation of wider set of possible models.

In modeling the farmer's adoption decision of GPS guidance system in cotton precision farming using the 2009 Cotton Incorporated data set (Mooney et al., 2010), we face the similar constraints of low sample size due to missing information. We take a Bayesian simulation and model averaging approach towards specifying and estimating our econometric model explaining the decision to adopt GPS guidance systems. Specifically, among the factors that are broadly defined by economic theory and used in similar previous studies, we explore the relationships between key farm business and operator characteristics and the adoption of GPS guidance in cotton production. Based on the data for respective variables, we employ a different set of draws for resampling and simulation. We derive the parameter's posterior densities specifying priors and a likelihood function. Next, using posterior predictive densities (PPD) and highest posterior density intervals (HPDI), we present our results graphically. For two groups of adopters—those met expectation about GPS guidance system and those who did not and also allowing for interaction of farm size and income, we compare predictive densities of GPS guidance adoption decision. Our findings suggest that "whether GPS guidance system met farmer's expectation'' plays a role in frequency of application of such technology, following adoption.

2. Data and Variable Definitions

Data for this study comes from 2009 cotton precision farming survey conducted among Southern cotton growers of the 12 states (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas, and Virginia) in the United States. In 2009, cotton farmers were asked to complete the Southern Cotton Precision

Farming survey to determine their use of PA technologies during 2007-2008 (Mooney et al. 2010). The questionnaire was mailed to cotton growers according to the list provided by Cotton Board, Memphis, TN. From 13,579 mailed surveys, 1,692 surveys were returned.

Our emphasis is to assess the role of expectations on technology application and diffusion. Only the farmers who adopt GPS-guidance system can apply it to other aspects of their operation and can answer the question of whether this technology met their expectation. For the purpose of this research there were 545 records suitable for analysis. Around 88% of the GPS guidance system adopters met their expectation about GPS guidance in 2008.

Our dependent variable of interest is a count variable, number of different farm activities that use GPS guidance system, which ranges from 1 to 5. Decision about involving GPS guidance system in such activities is estimated as a function of demographic and socio-economic variables including age, level of education, use of a computer in farm management, income, farm size, and farmer's additional information sources about GPS guidance. Summary statistics and variable definitions are shown in table 1. The average age of the farm operator is about 51 years, with about 15 years of formal education. To account for the computer use in farming, we include a dummy variable indicating whether computers are used in farm management activities. Farm household income was captured by the level of taxable income range that household earns from both farm and non-farm sources. Farmers chose among 6 income ranges. These include: (1) less than $50,000 (2) $50,000-99,999 (3) $100,000- $149,999; (4) $150,000-$199,999; (5) $200,000-$499,999; (6) $500,000 or greater. As an indicator of farmer's additional information sources and participation in extension programs, we include number of university events attended by farmers as *extension* variable. On average, farmers attended 4 university events. However, this variable has large variation as indicated by large standard deviation of 6.62. Farm size is an important variable in adoption and application studies. We captured farm size variation by including a dummy variable defining whether farm size is small (less than 1,000 acres of cultivated land in 2008) (D'antoni et al., 2012). We also include a dummy variable *occupation* to define whether farming is a main occupation. In this study, if more than 50% of the total income comes from farming, then we consider farming as main occupation. Using such definition, around 89% of the GPS guidance adopters have farming as main occupation.

The *importance of cost saving* variable is created to determine the farmer's perception about importance of input cost savings due to adoption. In the survey, farmers ranked the relative importance of fuel cost savings, labor cost savings, more time to do other things, and reduced operator fatigue/longer operating hours. Following D'antoni et al. (2012), we computed the average ranking and relative importance of cost savings as follows:

$$R_1 = \frac{1}{3}(fuel\ cost\ savings + labor\ cost\ savings + input\ cost\ savings)$$

Where R_1 represents the average ranking of fuel cost, labor cost, and input cost ranks directly accrued to the farmer (operator). Similarly, average ranking for savings are computed as,

$$R_2 = \frac{1}{2}(More\ time\ for\ other\ activities + Reduced\ fatigue)$$

Importance of cost savings variable is defined as:

$$Importance\ of\ cost\ savings = \begin{cases} 1\ if\ R_1 > R_2 \\ 0\ if\ R_1 \leq\ R_2 \end{cases}$$

When average rank of cost savings is greater than average rank of benefits directly related to operator, then $Importance\ of\ cost\ savings$ variable is equal to one.

Another interesting variable is perception about *importance of precision agriculture*. We created dummy variable based on farmer's response in the question "Will Precision farming be important five years from now?" Farmers that respond "yes" were assigned a value of one (zero otherwise).

3. Empirical approach

3.1 Conceptual framework

Adoption and frequency of application of a technology within a farm and whether continuation or abandonment of a technology is affected by various economic, demographic, and social factors. Let y represent number of activities involving GPS guidance system in a farm (applications), after adoption. Then the decision about number of such activities involving GPS guidance in a farm can be represented as:

$y_i = f(E_i, I_i, S_i, Z_i)$ where E_i represents expectation of firm *i* about GPS guidance system (whether technology met expectation upon initial adoption), I_i and S_i represent income and size of the cotton farm, respectively. All other factors are included in vector Z_i including farmer characteristics, (age, education level etc.), access to additional information, costs, and farmer's perception etc. Let us represent set of right hand side variables (vector of independent variables) as X_i.

In our study, the variable of interest is the number of applications of GPS guidance system in a cotton farm. Thus instead of treating y_i as continuous variable, it is more appropriate to account for its count nature. A common method is to adopt a Poisson model assuming y_i is independent and Poisson distributed.

$$E(y_i|X_i) = \lambda_i = \exp(\beta' X_i), i = 1, \ldots\ldots N$$

Probability density function of Poisson model is $\Pr(y_i = y) = f(y_i) = \left[\frac{e^{-\lambda_i} \ {\lambda_i}^{y_i}}{y_i\,!}\right]$

3.2 Empirical methods

We use Bayesian methods in estimating our model. Bayesian econometrics is based on rules of probability – usually the fundamental derived from joint, conditional, and marginal probability theories. In a regression model, researcher aims to assess the effect, often a coefficient of the variable(s) of interest. Coefficients are thus the parameters under study. Let y represent vector or matrix of data and θ be vector or matrix of parameters. We are interested to learn about θ based on the data, y. Bayes rule, the foundation of Bayesian econometrics, computes parameter vector/matrix as follows: $p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)}$ where $p(\theta|y)$ is the fundamental interest. Bayesian econometrics is a subjective view of probability where we argue that our uncertain about anything unknown can be expressed in terms of something known (data) and the conditional probability of the unknown given the known, a usual expression for posterior in terms of prior and likelihood function (Koop, 2003) as: $p(\theta|y) \propto p(y|\theta)p(\theta)$, where posterior density $p(\theta|y)$ is represented as proportional to probability density function (pdf) for the data given parameters of the model $p(y|\theta)$ (refer as likelihood function) and $p(\theta)$ as prior density. Any non-data information (what we already have information about θ) about θ is referred as prior. In summary, the fundamental computation (posterior) is computed in Bayesian framework combining the likelihood function derived from data (pdf, $p(y|\theta)$) and prior (adding information that we have about distribution of θ) (Koop, 2003). Prediction of Bayesian econometrics is based on *predictive densities* often derived from the computational approaches of posterior simulations.

Discussing the practical implication of a choice between estimation procedures, Moeltner (2012) lays out three points: 1) under large sample size and well behaved likelihood function, classical and Bayesian are under same fundamentals, may be producing more or less identical results; 2) under large sample size but high dimensionality of θ, a Bayesian approach is preferable to derive posterior because it can be very difficult to derive estimates using maximum likelihood estimations alone; 3) under small sample size, Bayesian approaches can have substantial advantages, as we do not need to evoke asymptotics for interpretation and they can combine sparse data with subjective priors.

Under Bayesian theories, many computational tools have been developed, mainly based on resampling, redrawing, and simulations. In computational practice using Bayesian tools, some less informative/ flat (or diffused priors) are also being used in different classes of models (Koop, 2003). The Bayesian computational tools implemented in this study are described as follows.

Independence chain Metropolis Hasting algorithm

Generally, in the cases where conditional posterior kernel for the set of parameters is unknown, we need to approximate the unknown density and thus we cannot draw from usual Gibbs sampler. MH algorithm allows us to approximate those. We give a starting value, approximate the density, and draw the unknown parameter set (θ). Since our dependent variable is count, we consider a parameterized Poisson model. Basic Poisson density has a single parameter λ to represent both mean and variance of the distribution.

$$f(y_i|\lambda_i) = \frac{\exp(-\lambda_i){\lambda_i}^{y_i}}{y_i!}, \text{ where } \lambda_i = \exp(x_i'\beta) \qquad (1)$$

X represents set of explanatory variables. We interpret parameter β as a fractional change in expected outcome as a unit change in explanatory variable.

Likelihood function is given as:

$$p(y|\beta) = \frac{\exp(-\exp(x_i'\beta))(-\exp(x_i'\beta))^{y_i}}{y_i!} \qquad (2)$$

Using a multivariate normal prior for β, *i.e*,

$$p(\beta) = (2\pi)^{-k/2}|v_0|^{-1/2}\exp(-\frac{1}{2}(\beta-\mu_0)'V_0^{-1}(\beta-\mu_0) \qquad (3)$$

where *k* represents the dimension of β, along with other usual defined parameters in multivariate normal density, posterior kernel is given as $(posterior = prior * Likelihood)$:

$$p(\beta|y,X)\ \alpha\ \exp(-\frac{1}{2}(\beta-\mu_0)'^{V_0^{-1}}(\beta-\mu_0) * \prod_{i=1}^{N}\frac{\exp(-\exp(x_i'\beta))(-\exp(x_i'\beta))^{y_{ij}}}{y_i!} \qquad (4)$$

Since this is not the kernel of well-known density function, we cannot derive analytical results by deriving direct draws from it. We can apply Metropolis Hasting (MH) procedure. The idea of MH procedure is that we draw a candidate vector β_c from known generating function $q(\beta_c)$ and retain it with acceptance probability $\alpha\ (\beta_0 -\!\!\rightarrow \beta_c)$, where β_0 is old or current draw such that candidate generating function can be function of β_0 and/or the data, $q(\beta_c) = q(\beta_c|\beta_0, y, X)$ (Koop 2003; Moeltner, 2012). In this study, we used independence chain MH where candidate generating function is no longer a function of current draw but is indirectly the function of the data (y, X). We used a t-density with a mean equal to mode of posterior kernel and variance set to MLE solution scaled by some scalar *c* (variance-covariance is inverted negative hessian matrix in MLE). We used *t* with 10 degrees of freedom (v in t-density). In each round of sampling, MH runs a MLE procedure and collects $\widehat{\beta}$ such that $\beta_c \sim mvt\left(\widehat{\beta}, cV_c, v\right) = q(\beta_c|y, X)$. We used the independence chain MH in parameterized Poisson model. We followed a general convention of the procedure as suggested in (Koop et al., 2007; Moeltner, 2012).

Markov Chain Monte Carlo Model composition (MC^3)

This is one of the popular methods used in Bayesian econometrics for model search and selection. We used this approach to assess key factors, top models, and present the model averaged results. Models are defined as different combinations of included variables. With possibilities of very big model space, $2^{(k-1)}$, MC^3 visits more relevant models (those with more relevant variables) more frequently and thus allows identifying top models and inclusion probabilities of each variable. After running MH algorithm to approximate the density of the posterior in application decision, we used the result draws of MH in MC^3 framework to find the top models and inclusion probabilities. We present the top models each with frequency of model visited and the posterior results. Further, we compare posterior model probabilities those computed empirically and analytically to check convergence.

Notice that demeaning the regressors, i.e., subtracting the mean from all of the explanatory variables, implies an orthogonality of intercept (i, column of ones) with all remaining regressors: $i'X = 0$. Demeaning does not change the interpretation of slope coefficients. Following standard convention (Fernandez et al., 2001), we chose an improper prior to the error variance and conjugate g-prior for our 10 by 1 coefficient vector.

Thus, we can have prior for sigma: $p(\sigma^2) \propto \frac{1}{\sigma^2}$ and $p(\beta|\sigma^2) = n(\mu_0, g\sigma^2(X'X)^{-1})$. We set $\mu_0 = 0$, n denotes k-1 variate normal density. If γ is the representation of k-1 by 1 vector of binary indicators such that $\gamma_j = 1$ indicates covariate x_j be included in the model and $\gamma_j = 0$ indicating it is excluded from the model, we can express conditionality on a specific model (i.e, combination of specific mix of regressors) as conditionality on γ. This allows us to search and select for top models defined on the basis of combination (mix) of covariates, *i.e*, most probable models from combination of specific variables. For detail derivations, I refer to Bayesian econometrics chapters (Koop, 2003; Koop et al., 2007). In MC^3 algorithm, g is shown to be a tuning parameter. Fernandez et al. (2001) discuss about different options of g finding that $g = n$ is performing well in most cases. We follow $g = n$ convention in defining our codes.

Summarizing the role of this procedure, γ can be used as showing indicator for which variable combination of model is appropriate. Draws of γ can be utilized to examine the posterior inclusion probabilities for each coefficient, identify most probable models, and perform convergence check comparing empirical and analytical model probabilities (Fernandez et al., 2001). Ideally, the correlation coefficient between these set of probabilities should be close to one for well convergence.

In defining algorithm and codes for empirical Bayesian tools, we used software Matlab, Mathworks. The ideas for our empirical models are based on the suggestions and ideas presented as examples in lecture notes (Moeltner, 2012) and as Matlab exercise presented in textbook website (Koop et al., 2007).

Posterior Predictive Density (PPD) plots and Highest Posterior Density Intervals (HPDI)

Posterior predictive density plots are predictive density plots of dependent variable based on the repeated draws while plugging representative values of variables defined as per interest. This allows us to check the prediction difference due to certain specific effect. Highest posterior density intervals (HPDI) are considered as methods to check linear restrictions of parameters (hypothesis testing). HPDI finds the bounds for a specific parameter, such that we can be $(1-\alpha)100\ \%$ sure that the parameter lies between them. This allows us to checking our general hypothesis. Interpretation of PPD and HPDI will be clearer in results section.

4. Results and Discussion

We have utilized both numerical and graphical methods to present our results. Posterior estimation results in table 2 and 3 include posterior mean, standard deviation, p> 0 diagnostics, numerical standard errors (NSE), and inefficiency factor (IEF) obtained from posterior simulator. The measures NSE and IEF are considered as indicators of efficiency diagnostics in Bayesian models. The NSE captures simulation noise or error around a posterior construct of interest (usually mean) of given parameter. An efficient simulator has low correlation across draws. Chib (2001) defines IEF as the ratio of squared nse under correlation over the squared nse under independence and thus low IEF values implies more efficiency, the ideal being an IEF close to 1. Another interesting diagnostic we present is “p> 0”, which represents relative significance of the estimate. For instance, if posteerior mean is positive and p> 0 is high, it may imply higher significance. From the same logic, a low p>0 value and a negative posterior mean also indicates the left tail significance (negative effect) of the variable.

Table 2 presents posterior results from independence chain metropolis hasting algorithm. This estimation is based on total 60,000 draws through MH and discards the first 10,000 draws (referred as burn-ins). Results based on posterior mean estimates in combination with p>0 value suggests a strong positive effect of *expectation met*. Further result suggests positive effects of income level, perceived importance of PA, farming as main occupation, and education on application decisions of GPS guidance system.

Table 3 presents the posterior results obtained by MC^3 conducting total 60,000 iterations while burning-in 50,000 and retaining 10,000. Last column of table 3 labeled as “inclusion probabilities” can be interpreted as the probability that the corresponding variable should be included. As suggested in Koop et al., (2007), this is an informal but useful diagnostic in deciding whether the included variable has explanatory role in application decision. Results suggest that ‘*expect’* has highest explanatory power followed by variables income, farm size, education, and occupation. Thus, we can conclude that these variables are important in modeling application decisions of GPS guidance system.

First two columns of the table 3 represent posterior mean and standard deviations of each regression coefficient, averaged across models. Apparently, table 4 suggests that the average posterior mean and standard deviations of table 3 are average of 190 models. Out of total 512 model space, the MC^3 procedure visits 190 models. Posterior mean, standard deviation and p>0 measures in the table highlighted the strong positive effect of *expect* variable. Other important variables that have positive effects are: level of income and education. Notice a strong negative effect of farm size in model averaged result in table 3 while its effect was not strong in table 2. This indicates that in the most of the models, having a small farm size negatively impacts application decisions. Posterior density plots for each coefficient are shown in figure 1. We presented highest posterior density intervals (HPDI) at 95% confidence level around the posterior mean in figure 2. A HPDI bound [0.3957, 1.082] around coefficient of *expect* suggest that it has clearly a positive and significant effect since "no effect" (*i.e.*, $\beta_1 = 0$) is clearly outside and left to the bound. HPDI of [-0.0004, 0.15358] on income level coefficient (β_2), [-0.0008, 0.354] on β_3, [-0.0005, 0.5386] around β_4, and a [-0.0001, 0.09] bound on β_8 suggest more likely positive effects of income level, importance of PA, farming occupation, and education, respectively in usual cases. We can infer this because the left bound is almost zero while rest of the greater share of coefficient distribution is in positive range. The effect of farm size, on the other hand is strong negative as indicated by [-0.447, 0.0002] HPDI. This reinforces notion of negative impact on application due to small farm size.

Table 4 shows most probable ten models based on frequency of model visited. Frequencies are included in last column. Notice all ten models include the *expect* variable. The most probable model includes expectation, income, and size variables. It's worth discussing the result of table 5 in-lieu of the results in table 4. First column of table 5 shows model probabilities calculated by analytical method (by exact formula for posterior model probabilities, see Koop et al., 2007, equation 16.12 and 16.13) while second column present the probabilities estimated by MC^3. Table suggests that the model averaged results are more or less accurately estimated and the problem of non-convergence is not detected.

Further we present predictive density plots for representative values of interesting variables in figures 3 and 4. These plots allow us to examine the role of expectation and interactions of it with income and farm size on GPS guidance application decision within the farm, following adoption. Figure 3 (top panel) compares the predicted density of number of applications of GPS guidance adopters for large farms who met expectation *versus* who did not meet expectation. Figure 3 (bottom panel) compares the same for adopters of small farms. Both predictive densities suggest the role of meeting farmer's expectation on number of application decisions. Notice that when lower range of number of application, probability of application is higher for those do not met expectation (this may indicate initial adoptions) but the probability drops down quickly when it comes to more number of applications. In other words, predictive density plots of those 'who met expectation' is towards right side of the density for those 'who did not meet expectation.' In both small and larger cotton farms, adopters who met expectation are likely have more frequency of application within the farm, for instance more applications—number of applications such as 4,5,6, 7 in the figures. Further, predictive densities presented in figure 4 suggest the notion that the role of expectation interacted with larger farm size and high income level is even more persistent towards higher diffusion (more applications). Overall these figures reinforce the conclusion of important positive and significant effect of 'technology meeting expectation' as suggested by estimates, HPDI test, and inclusion probabilities.

5. Conclusions

Post-adoption features play crucial role in technology diffusion both within and across the farm. Thus there is an inherent interest in post-adoption features of precision technologies. However, very few studies have analyzed such features. Utilizing a Cotton grower's precision farming survey in 12 Southern states of the U.S., we assessed GPS guidance system adopter's application decisions, a post-adoption feature leading to within farm diffusion of a technology. Special attention is given to the role of farmer expectations, following adoption. We explore important factors influencing application decisions, testing the hypothesis that application decisions are influenced by expectations. We employed Bayesian approaches in model estimations.

We expect this study to contribute at least in two ways. Firstly, it contributes to existing precision agriculture literature and adoption literature by including 'farmer's expectation' variable in assessing post adoption features, particularly in assessment of within farm diffusion, which was not considered in most of the previous studies. We adapt inclusion of *expectation* in the model that defines farmer's decision about number of activities involving GPS guidance system (applications). Secondly, it introduces a Bayesian approaches and tools in precision technology adoption studies. The study introduces the applications of new alternative estimation procedures utilizing Bayesian simulation, search, and selection procedures which are getting popular in recent computational literature. While facing with empirical difficulties such as low sample sizes, less tractable likelihood functions, or higher dimensionality of parameters in the model, we can effectively utilize alternative Bayesian procedures to draw statistical inferences.

Overall, our study suggests a significant positive role of meeting 'farmer's expectation' about GPS guidance system in application decisions and its further diffusion within a cotton farm. This implies that the adopters of GPS guidance system and who met expectation are likely to apply the system more widely in their farm than those adopters who did not meet expectation. More or less consistent with previous studies, we found income level, farm size, and farming occupation as other important factors in modeling GPS guidance system adoption and application.

However, what factors a farmer considers in defining the expectation about a particular technology is yet interesting study as it could be more guided by psychological settings, his available information, or other determinants from socio-economic settings. We do not explore that in this study. Nevertheless given the perception about meeting farmer's expectation, our study provides useful suggestions: technology meeting expectation is important in diffusion and thus farming technology developers, social researchers, and modelers need to account for this.

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Table 1: Summary statistics and variable definitions

Variable	Definition	Mean	Std. Dev.
Application	Number of applications of GPS guidance system adopted in a farm (dependent variable, 1-5)	2.41	1.30
Expect	Whether GPS guidance met farmer's expectation, following adoption (=1 if expectation met)	0.88	0.32
Income	Farmer's level of income (1-6)	3.17	1.6
Importance of PA	Farmer's perception about importance of precision agriculture (=1 if farmer perceives precision agriculture will be important, 0 else)	0.95	0.22
Occupation	Whether farming is a main occupation (=1 if more than 50% of income is coming from farming)	0.89	0.31
Age	Age of farm operator (in years)	51.32	11.90
Education	Level of education (in years)	14.71	2.27
Computer use	Whether computer is used in farm management (=1 if used, 0 else)	0.74	0.43
Extension	Number of university events related to farming, attended by farmer	3.66	6.62
Farm size (Small)	Whether farm size is small (<1000 acres under cultivation in 2008)	0.45	0.49
Importance of cost saving	Farmer's perception about cost saving (=1 if operator considers cost savings is important)	0.26	0.44

Table 2: Posterior results (Independence chain Metropolis Hasting results)

Variables	Posterior Mean	Standard Deviation	P > 0	nse	IEF
Expect	0.341	0.105	1.000	0.001	4.661
Income	0.034	0.018	0.971	0.000	4.569
Importance of PA	0.160	0.148	0.864	0.001	4.579
Occupation	0.159	0.100	0.950	0.001	4.659
Age	0.000	0.002	0.864	0.000	4.527
Education	0.024	0.013	0.950	0.000	4.670
Computer Use	0.032	0.069	0.563	0.001	4.958
Farmer’s participation in Extension	-0.002	0.005	0.970	0.000	4.831
Farm Size (small)	-0.099	0.059	0.672	0.001	4.902
Importance of Cost Savings	0.006	0.064	0.368	0.001	4.525
Total Number of Iterations	60,000				
Burn-in Iterations	10,000				
Acceptance Rates in MH part	0.330				

Table 3: Posterior results from MC^3 (Model averaged results)

Variables	Posterior Mean	Standard Deviation	P > 0	nse	IEF	Inclusion Probabilities
Expect	0.727	0.177	0.997	0.002	1.077	0.997
Income	0.075	0.054	0.731	0.002	12.654	0.732
Importance of PA	0.030	0.122	0.083	0.004	12.788	0.091
Occupation	0.097	0.187	0.257	0.006	9.318	0.262
Age	0.000	0.001	0.020	0.000	1.114	0.035
Education	0.027	0.034	0.461	0.001	8.731	0.464
Computer Use	0.008	0.043	0.051	0.001	9.083	0.062
Farmer's participation in Extension	-0.000	0.002	0.017	0.000	3.865	0.050
Farm Size (small)	-0.158	0.168	0.002	0.006	11.532	0.538
Importance of Cost Savings	-0.000	0.026	0.021	0.000	1.000	0.041
Sigma-squared	1.597	0.100	1.000	0.001	1.027	
Total Number of Iterations		60,000				
Burn-in Iterations		50,000				

Table 4: Top ten most probable models based on frequency of model visited

Expect	Income	Importance of PA	Occupation	Age	Educ.	Computer Use	Extension	Farm Size	Cost Saving	Frequency of Model Visited
1	1	0	0	0	0	0	0	1	0	1193
1	1	0	0	0	0	0	0	0	0	1089
1	1	0	0	1	0	0	0	0	0	1059
1	1	0	0	1	0	0	0	1	0	930
1	0	0	0	0	0	0	0	1	0	615
1	0	0	0	0	1	0	0	1	0	421
1	1	0	1	0	1	0	0	0	0	400
1	1	0	1	0	0	0	0	0	0	353
1	0	0	1	0	0	0	0	1	0	289
1	1	0	1	0	0	0	0	1	0	271
Total model space				512						
Number of visited models				190						
Fraction of model visited				0.371						

"1" indicates inclusion of respective variable in the model; "0" indicates non-inclusion

Table 5: Posterior model probabilities for top ten models

	Analytical	MC^3 estimate (empirical)
1	0.1193	0.1196
2	0.1089	0.1064
3	0.1051	0.1005
4	0.0930	0.0783
5	0.0615	0.0633
6	0.0421	0.0444
7	0.0400	0.0533
8	0.0353	0.0378
9	0.0289	0.0214
10	0.0271	0.0264

Correlation of empirical and analytical model probabilities, all visited model: 0.993

Figure 1: Posterior density plots for estimated parameters

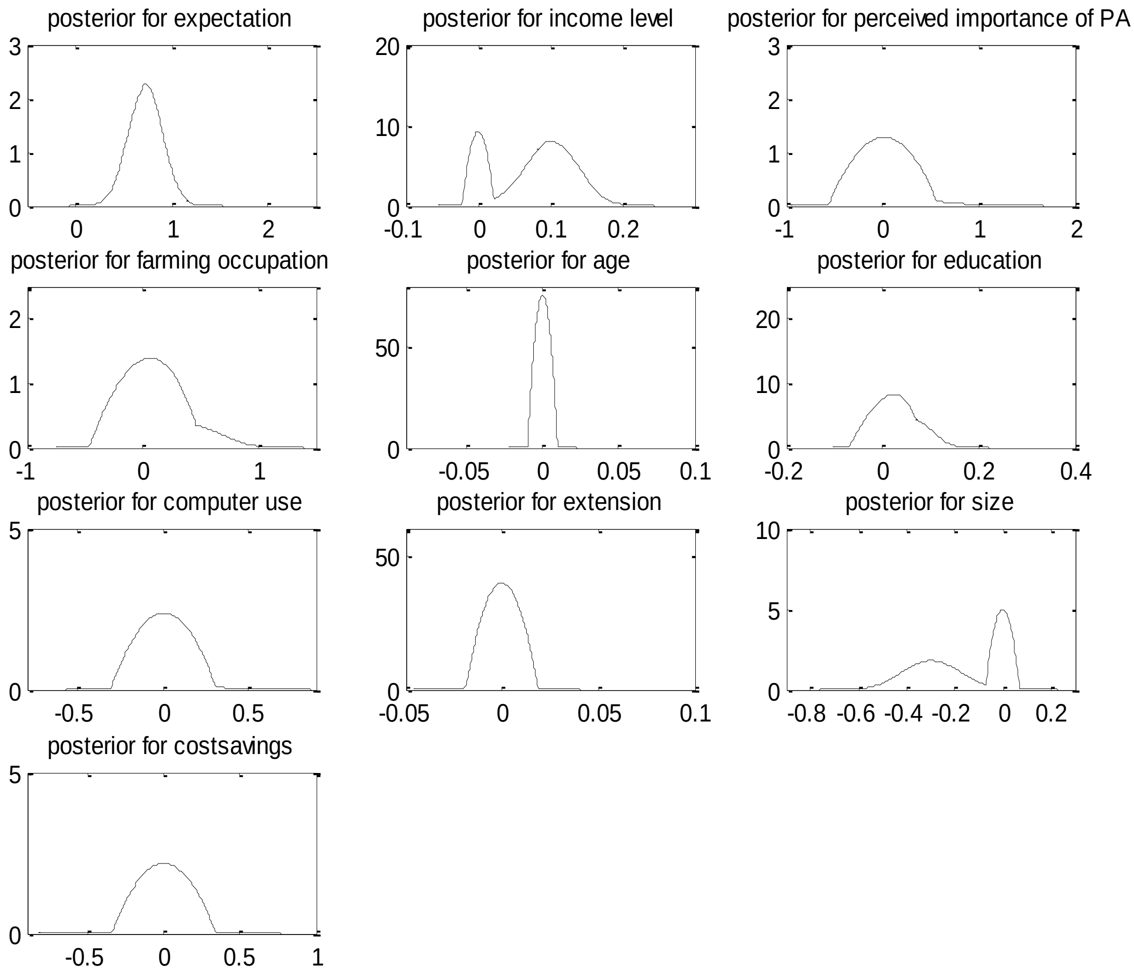


Figure 2: Posterior densities with Highest Predictive Density Interval (HPDI, 95% confidence level)

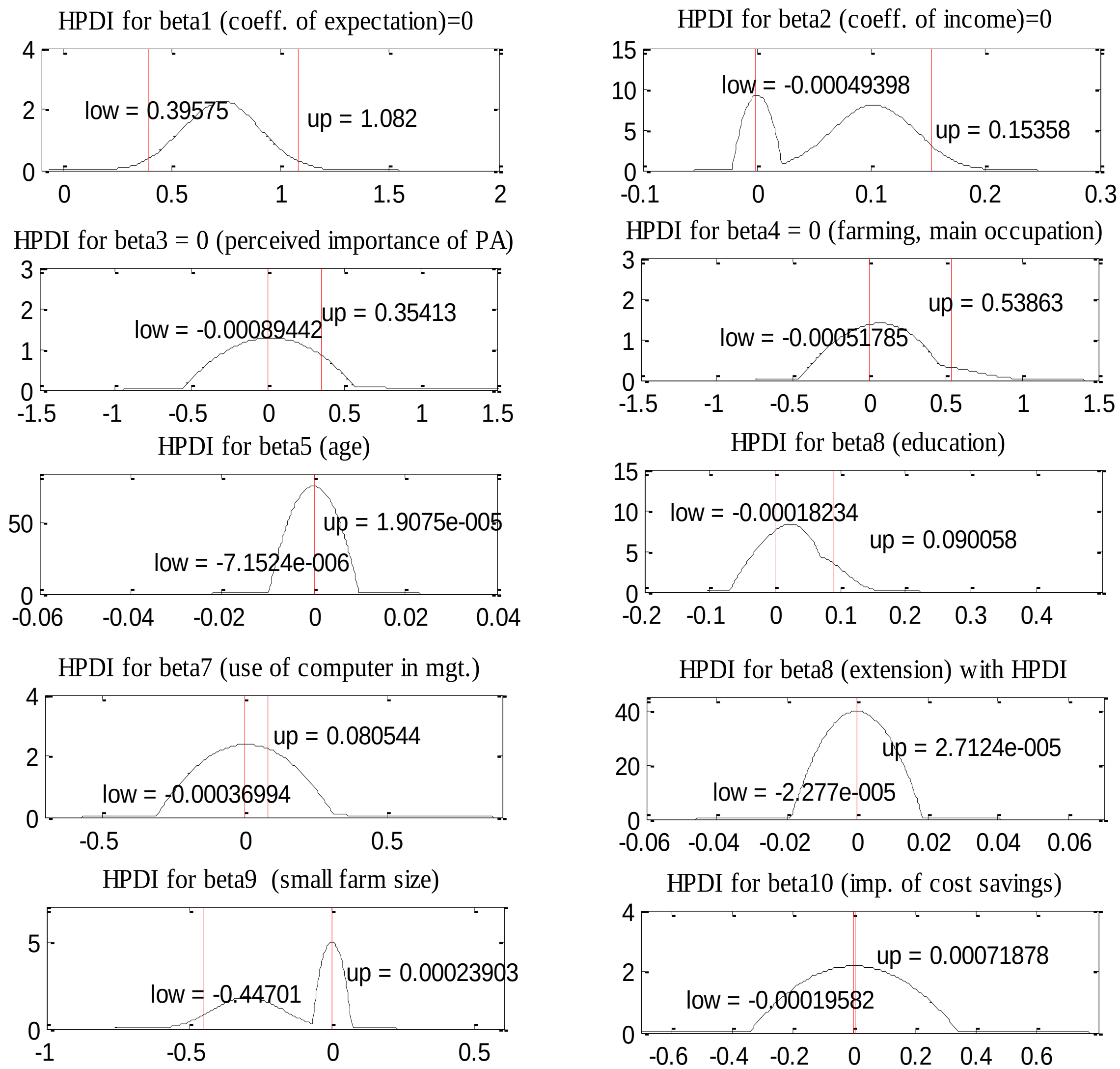
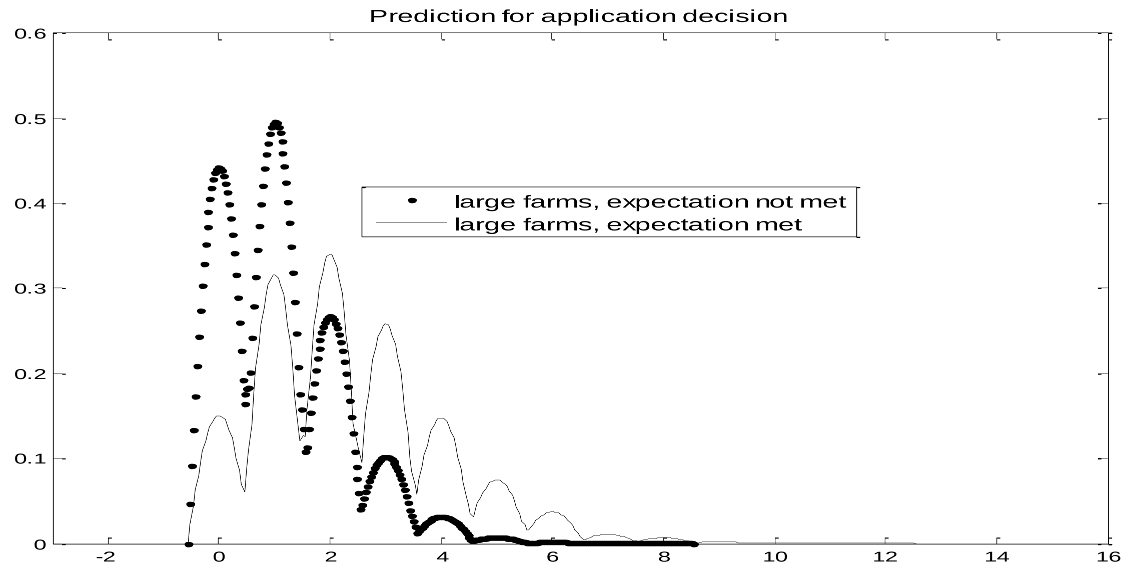


Figure 3: Posterior predictive density (PPD) plots showing GPS guidance system application decisions: Effect of expectation



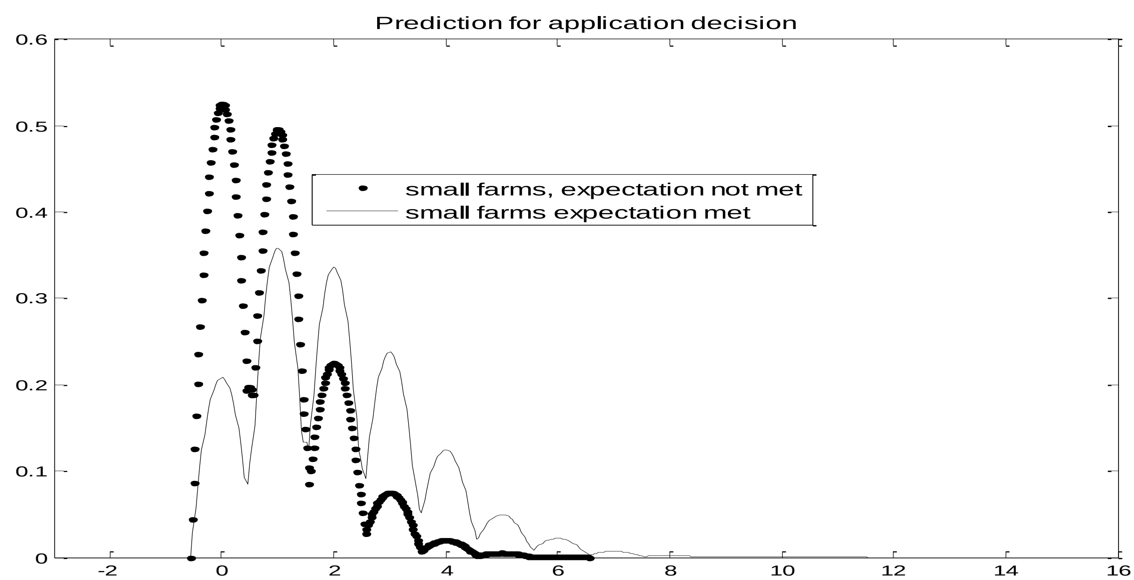


Figure 4: Posterior predictive density (PPD) plots of GPS guidance system application: Effect of expectation interacted with different level of income and farm size