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Do Farmers Hedge Optimally or by Habit?

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Do Farmers Hedge Optimally or by Habit?
A Bayesian Partial-Adjustment Model of Farmer Hedging

Hedging is one of the most important risk management decisions that farmers make and has a potentially large role in the level of profit eventually earned from farming. Using panel data from a survey of Georgia farmers that recorded their hedging decisions for four years on three crops we examine the role of habit, demographics, farm characteristics, and information sources on the hedging decisions made by 106 different farmers. We find that the role of habit varies widely. Information sources are shown to have significant and large effects on the chosen hedge ratios. The farmer's education level, attitude toward technology adoption, farm profitability, and the ratio of acres owned to acres farmed also play important roles in hedging decisions.

Key words: Bayesian econometrics, hedging decisions, habit formation, information sources

Introduction

Hedging is an important risk management tool for both farmers and food processors. Farmers are continually being instructed on how to hedge, how much to hedge, when to hedge, etc., by a wide variety of "experts." Just to name a few, extension agents and specialists, consultants, marketing newsletters, and commodities brokers all bombard many farmers with information on optimal hedging strategies. Yet, even with all this information, anecdotal evidence is that farmers still do a poor job of hedging. We suspect that most extension faculty would say that farmers hedge too small a percentage of their crops.

Literature on hedging has a long history but has recently moved into investigating motivations for and influences on farmers' hedging decisions. Pennings and Leuthold (2000) examine the role of producer attitudes and the variation involved in how farmers choose whether or not to hedge. Pennings and Garcia (2004) and Dorfman, Pennings, and Garcia (2005) both study how different firms (Pennings and Garcia) and farms (Dorfman, Pennings, and Garcia) reach hedging decisions in very different manners, showing that allowing for heterogeneity in a model of hedging behavior is an important component of model specification.

In this paper, we examine the role of habit and information sources in farmers' choices of hedging strategies. We use a survey of Georgia farmers that records the annual percent of three crops hedged over a four year period. In our model, we wish to incorporate habit effects, through use of lagged hedge ratios that we have data on due to our rare panel data set. Habit effects have been considered in many areas of economics, particularly in the demand literature (cf. Pope, Green, and Eales, 1980; Blanciforti and Green, 1983; Holt and Goodwin, 1997). However, habit effects have rarely been used in hedging models (an exception is Dorfman, Pennings, and Garcia, 2005). This may be because of the rarity of possessing data on past hedging decisions, but it also may be because of the heterogeneity of habit's role in the decision making process and the inability to estimate farmer-specific habit effects econometrically.

In estimating a model to investigate the role of habit and information sources in farmers' hedging decisions, one would like to allow for different farmers to act differently. Some evidence of the segmentation of methods for farmers to arrive at hedging decisions has been found in Dorfman, Pennings, and Garcia (2005). Because this paper is focused on the relative importance of factors such as information sources, farm characteristics, and habit in the hedging decision, we take a somewhat different approach here and do not estimate a mixture model of different classes of farmers. Instead, we add flexibility to the estimation of model parameters through the use of a smooth coefficient model.

Smooth coefficient models are a class of semi-parametric models that do not fully restrict parameters to be constant over the whole data set, but do not allow for free variation either (Koop and Tobias, 2006). Instead, such models require the "smooth" parameters to vary in some prescribed manner. By linking the variation in the semi-parametric parameter to some ordering of the data and imposing a Bayesian prior distribution over the amount of variation expected between adjacent observations, researchers can control the amount of variation captured by the "smooth" parameter.

The remainder of this paper is organized as follows. In section 2, we discuss data used in our hedging decision model. In section 3, we present the application and estimation details. Section 4 presents econometric results and discusses the implications of our findings. Conclusions follow in section 5.

The Data

The data consist of observations on 106 distinct farmers each growing one or more of the three crops studied: corn, soybeans, and cotton. All farmers own at least 300 acres of land. Information was also collected on basic demographic traits, farm characteristics, information sources for farm management decisions, computer usage, and some farm economic characteristics. The survey was conducted as part of a large research project on farmland preservation, with the hedging questions "piggybacked" onto the survey along with some questions on e-commerce. Hedging questions were asked for the three crops for the years 1999-2002.

To study the role of habit in hedging decisions, we extracted observations on farmers who hedged in at least one of each pair of consecutive years for each of the three crops. The earlier year in each pair is used to create the lagged hedge ratio variable that will allow us to measure the habit effect. This results in an unbalanced panel where a single farmer could represent up to nine observations (three crops, three years

(2000-2002)). After removing observations with missing variables on the desired set of explanatory variables we were left with 379 observations and no farmer with more than eight observations. Observations on corn were 29 percent of the sample, soybeans 14 percent, and cotton the remaining 57 percent.

Explanatory variables to include in the model, other than lagged hedge ratio, include: education level, income range, percent of income from farming, years of farming experience, number of commodities produced, attitude toward technology adoption (early, mid, or late adopter), profitability of the farm (money making, breaking even, or money losing), the ratio of owned acres to farmed acres, and a set of information source dummies. The farmers were asked to report all information sources used to help make hedging decisions from among the following list of choices: consultants, extension, magazines, the internet, field trials, and the local feed & seed store. Some basic statistics on the variables are displayed in table 1.

A Model with Smooth Spatial and Response Characteristics

In this paper we wish to explain hedging decisions based on a range of explanatory variables, but with particular emphasis on the role of habit. We will measure the role of habit by the parameter on the lagged hedge ratio which we will enter in the model as one of the explanatory variables. If we represent the hedge ratio for farmer i in year t by h_{it}, we can write the model of the hedging decision as

$$h_{it} = x_{it}\beta + h_{i,t-1}\gamma_i(z_i) + \epsilon_{it}, \tag{1}$$

where x is a k-vector of explanatory variables some of which may vary by year and all of which vary by farmer, β is a vector of coefficients to be estimated that do not vary by observation, γ_i is the parameter that varies smoothly across farmers, z_i is a variable that determines the ordering of the farmers for the smooth coefficient, and ϵ_{it} is the observation-specific random stochastic term. Note that because of the panel data nature of the observations used here, the model will have n observations, but there are only $n_f < n$ distinct farmers. Thus, there will be n_f different γ_i parameters.

The semi-parametric parameter γ_i designates the expected impact of the lagged hedge ratio on this period's choice of hedge ratio by farmer i. Denoting γ_i as a function of z_i is done to make clear that the variable z_i is used to order the smooth changes allowed across farmers. Since there is no natural way to order the farmers (such as time), we need some method to introduce an ordering. In the application at hand we create a composite variable that incorporates scaled versions of four of the explanatory variables to use in ordering the data. Note that while the smoothing does dampen variation in the habit parameter, the effect of variable z_i on γ_i is not constrained to be linear or even continuous. So given enough information in the data, the habit parameters can still vary fairly freely across farmers.

Introducing the Smooth Coefficient Model

In order to demonstrate the smoothing methodology, it is easier to work with all the observations stacked into matrices. Thus, rewrite the model in (1) as

$$h = X\beta + H\gamma + \epsilon = W\lambda + \epsilon, \tag{2}$$

where h, X, and ϵ are the usual vertical concatenations of the h_{it}, x_{it} and ϵ_{it}, β are the standard regression parameters, H is a block-diagonal non-square matrix of the $h_{i,t-1}$ with a column for each farmer and a row for each observation, and γ is a column vector of the n_f values of the semi-parametric habit parameters.

To accomplish the smoothing of the nonparametric functions, one must first define what is meant by "smooth." In this paper, we will employ the definition that smooth means coefficient changes from farmer to farmer are not "too large" where the farmers will first be ordered by the variable z_i to create a natural ordering where imposing some structure on the varying coefficients makes some sense.

To make this concrete, order the observations so that z_i is increasing from first to last observation. Then the necessary smoothing matrix is

$$D = \begin{bmatrix} 1 & -2 & 1 & 0 & \cdots & & 0 \\ 0 & 1 & -2 & 1 & 0 & \cdots & 0 \\ \vdots & & & \ddots & & & \vdots \\ 0 & \cdots & & \cdots & 1 & -2 & 1 \end{bmatrix}. \tag{3}$$

The reader should note that D is $((n_f - 2) \times n_f)$, not square, because we are preparing to impose a prior that posits minimal or zero changes in second differences between the γ_i's. That is, the γ_i's should lie approximately on a line. Because second differencing requires us to have two free parameters, we do not impose the same smoothing on the first and second γ_i parameters with this approach. To write the idea of smooth coefficients mathematically, define the smoothing matrix R, $R = [0 \quad D]$, which allows for the semi-parametric smoothness to be imposed by the linear approximate restriction

$$R\lambda \approx 0. \tag{4}$$

The above equation imposes $n_f - 2$ restrictions on the n_f parameters in γ. If the restriction in (4) were imposed exactly, the individual effects would fall on a line and the effect of the lagged hedge ratio on the current hedging decision would be represented by a constant part and a "trend" component as the composite variable increases through the data set. By imposing the restrictions embodied in (4) through a Bayesian prior with a nonzero prior variance, we will allow the nonparametric function represented by the vector γ to be smooth, but not completely unfettered. Thus, the model will allow the effect of $h_{i,t-1}$ to vary as z_i increases, but in a gradual, more continuous way than without the smoothness prior.

To simplify the derivation of the posterior distribution of the parameters of interest, it is useful to define a few more subsets of parameters to be estimated and some additional matrices. Let

$$\lambda = \begin{pmatrix} \lambda_1 \\ \lambda_2 \end{pmatrix}, \tag{5}$$

where $\lambda_1 = (\beta', \gamma_1, \gamma_2)'$ and $\lambda_2 = (\gamma_3, \cdots, \gamma_{n_f})'$. Further, define two submatrices of the smoothing matrix, R, $R = [R_1 \quad R_2]$ where $R_1 = [0 \quad D^*]$ where D^* is the first two columns on the left of D, and R_2 is thereby implicitly defined. Partition the matrix W from (2) conformably with the partition of R, $W = [W_1 \quad W_2]$, where $W_1 = [X \quad D^*]$. This leaves $W_2 = D^{**}$, the $(n_f - 2)$ rightmost columns of D.

Now use the above matrices to transform the data matrices as follows:

$$X_1^* = W_1 - W_2 R_2^{-1} R_1, \tag{6}$$

$$X_2^* = W_2 R_2^{-1}, \tag{7}$$

and $X^* = [X_1^* \quad X_2^*]$.

Given these definitions, the transformed model can be written as

$$h = W\lambda + \epsilon = X_1^* \lambda_1^* + X_2^* \lambda_2^* + \epsilon, \tag{8}$$

where $\lambda_2^* = R_2 \lambda_2$. In (8), λ_2^* is the vector of smoothed semi-parametric parameters representing the role of habit in each farmer's hedging decisions (minus the two initial conditions for γ which are in λ_1^*).

A Bayesian Prior Distribution

To analyze this model within a Bayesian framework we need a prior distribution for all the unknown random parameters. To begin with, we need priors for λ^* and for σ_ϵ^2. If we employ the natural conjugate prior, this model can actually be examined analytically in a straightforward manner. We have no strong prior beliefs about any of the structural parameters in β, so this seems reasonable. Therefore, we assume a normal-Gamma prior of the form

$$p(\lambda^*, \sigma_\epsilon^{-2}) \sim NG(m_o, V_o, s_o^{-2}, \nu_o). \tag{9}$$

The prior mean of the regression model parameters, m_o, is set to a vector of zeros since we do not claim to have specific prior information on the β parameters. To implement the smooth parameter model a prior mean for the λ_2^* parameters is critical as that is what imposes the smoothness on the nonparametric functions so the prior mean on λ_2^* should always be set to zero (implying no expected change between $(\gamma_i - \gamma_{i-1})$ and $(\gamma_{i+1} - \gamma_i)$, $\forall i$). The variance of the prior on λ^*, V_o, controls how near to m_o one believes the elements of λ^* to be, as well as whether one believes the parameters to be independent or correlated in some way. Since there are two classes of parameters in

λ^*, smoothed and structural, it is appropriate to specify this matrix in two parts,

$$V_o = \begin{bmatrix} \tau_1 I_{k+2} & 0 \\ 0 & \tau_2 I_{n_f-2} \end{bmatrix}. \tag{10}$$

This partition of the prior variance allows for the researcher to place a loose prior on the structural parameters in λ_1 by setting τ_1 to a relatively large scalar (in our application $\tau_1 = 4$). In turn, τ_2 controls how smooth the changes in the parameter on the lagged hedge ratio are to be; smaller values of τ_2 lead to a smoother nonparametric functions. In the extreme, as τ_2 goes to zero, all observations will share a constant parameter on the lagged hedge ratio. In our application, τ_2 is set to 0.0001 to introduce a definite smoothing of λ_2.

The Gamma prior on the error variance term is a standard one. Common choices of values for s_0^{-2} are on the order of 0.1 or 0.01 or even zero. The degree of freedom hyperparameter ν_o in the Gamma prior is typically set to a small, positive integer representative of the size of an imaginary sample of data used to measure the amount of prior information held about the variance. We use $s_0^{-2} = 0$ and $\nu_o = 0$. These amount to an uninformative prior on the model error variance (a Jeffreys prior).

The Posterior Distributions

If one assumes that the ϵ_{it} are *i.i.d.* as normal random variables with zero mean and constant variance σ_ϵ^2, that is equivalent to specifying the standard normal-Gamma likelihood function for the observations on h_{it}. With such a likelihood function and the prior described in the previous subsection, Bayes' Theorem leads one to a posterior distribution in the normal-Gamma form:

$$p(\lambda^*, \sigma_\epsilon^{-2}) \sim NG(m_p, V_p, s_p^{-2}, \nu_p), \tag{11}$$

where

$$V_p = (V_o^{-1} + X^{*\prime} X^*)^{-1}, \tag{12}$$
$$\nu_p = \nu_o + n, \tag{13}$$
$$m_p = V_p \left(V_o^{-1} m_o + X^{*\prime} h \right), \tag{14}$$

and

$$s_p^2 = \nu_p^{-1} \left(\nu_o s_o^2 + (h - X^* m_p)'(h - X^* m_p) + ((m_o - m_p)' V_o^{-1} (m_o - m_p) \right). \tag{15}$$

Because the conditional posterior distribution of λ^* is normal and the transformation from λ to λ^* was a linear one, it is simple to recover the posterior estimates of the elements of λ and those original, structural parameters will also have conditional posterior distributions that are normal. Also, note that if one chooses to work with the marginal distribution of λ, integrating out σ_ϵ^2 will yield a t-distribution for λ. Either the conditional or marginal distribution makes it easy to construct a variety of probability statements about elements of λ or any linear function of these parameters, say $A\lambda$.

Econometric Results and Implications

For comparison purposes and as a starting point, we estimated the model in (1) with a constant parameter γ by OLS. The results of this estimation are shown in table 2. We find that a total of five parameters are statistically significant, including the γ parameter on the lagged hedge ratio. The OLS estimate of γ is 0.473 with a t-ratio of 9.444, implying that habit plays a significant role in hedging decisions. Other statistically significant variables are the farmer's attitude toward technology adoption, and the uses of consultants, magazines, and the internet as information sources. The model has an R^2 of 0.349 which is not horrible considering the nature of the panel data (small T, fairly large N).

Our composite variable z_i is formed from four variables: percent income from farming, number of commodities produced, profitability of the farm, and the ratio of acres owned to acres farmed. Dorfman, Pennings, and Garcia (2005) found that percent income from farming, profitability of the farm, and the ratio of acres owned to acres farmed played important roles in influencing hedge ratios. The number of commodities produced should also be linked to hedging behavior since diversification of products is another form of risk management. Thus, these four variables were chosen to bring structure to the parameter variation on the habit parameter in this study. Each of the four variables were scaled to have a mean of one and then summed to create our composite sorting index variable.

The results of the smooth coefficient model estimation are shown in tables 3 and 4. Table 3 contains summary measures and statistics on the 106 farmer-specific, smoothed estimates of γ_i, while table 4 contains the Bayesian posterior means and standard deviations for the structural (non-smoothed) parameters of the model.

Allowing the habit parameter to vary by farmer, while being smoothed by our Bayesian estimator in order to remove some of the effect of noise appears to have worked reasonably well. Recall that farmers were ordered by the composite index sorting variable and the smoothing prior tries to reduce variation in the γ_i parameters for farmers with adjacent values for that composite variable. Many of the γ_i's are not estimated very precisely, but 44 have 90% highest posterior density regions (HPDRs, the Bayesian equivalent to confidence intervals) that do not include zero and 55 have 80% HPDRs that do not cover zero. All 106 of the γ_i fall between -1 and 1 (see figure 1) which is important, since values outside that range would be equivalent of nonstationarity.

Since the marginal posterior distributions of the γ_i are in the form of the Student-t distribution, having an 80% HPDR that does not include zero is equivalent to that particular γ_i having a 90% posterior probability of being one sign (either positive or negative). Of these 55 γ_i's, 26 have strong posterior support in favor of being positive and 29 have strong posterior support in favor of being negative. That leaves 51 (roughly half) of the farmer-specific effects of unclear direction. Partially, this is the result of the smoothing, with less smoothing we would have more individually significant parameters and a higher model R^2. We decided to stick with the smoother parameters and give up some model fit in order to maintain all 106 γ_i being between -1 and 1.

Table 4 shows that including farmer-specific habit effects greatly improved the model fit, with the R^2 now equal to 0.608 when taken at the posterior means of the parameter distributions. This is a very large improvement from the 0.349 of the OLS estimates with a single habit parameter. The improvement does not all come from the additional parameters that the farmer-specific effects allow, as the adjusted R^2 also rises from 0.319 to 0.421.

Table 4 reveals that allowing for some sample variation in the habit parameter across farmers has improved the estimation of the remaining, constant parameters. Seven of the parameters have 90% HPDRs that do not include zero. Thus, compared to the four statistically significant parameters (not counting the habit parameter) when estimating by OLS, we now find seven variables to be statistically distinguishable from zero. The new results drop one variable (internet as an information source) from the list of significant variables, but add four new ones to our list of important variables in the hedging decision process. These additional significant variables are education level, the use of field trials as an information source, profitability of the farm, and the ratio of acres owned to acres farmed.

As an additional result of allowing sample variation in the habit parameter, it is worth noting that of the 106 smoothed farmer-specific γ_i's, 44 of them have at least a 90% posterior probability of being either greater or smaller than the constant coefficient estimate of 0.473. That is, almost half the farmers have habit effects significantly different from the estimate when the habit effect is constrained to be constant across the whole sample. Also, the mean of the posterior means of the γ_i's is 0.240 and the median of the posterior means is 0.335. Both of these values are quite different than the constant coefficient estimate suggesting that not only is there significant variation in these parameters if it is allowed, but that constraining it introduces some aggregation bias.

The education level variable is a categorical variable ranging from 1 (some high school) to 6 (Ph.D. degree). The Bayesian posterior mean for this parameter is -3.897, meaning that for every additional education level attained we expect the farmer to hedge about 4 percent less of his crop. This is an intriguing result as one might expect more educated farmers to more actively manage their risk and thus hedge more fully.

The technology adoption variable is also categorical (1 = early adopter, 2 = mid-adopter, 3 = late adopter) and the Bayesian posterior mean is -17.348. Thus, early adopters hedge the most with late adopters hedging almost 35 percent less of their crop than early adopters. Thus, early technology adopters have also more fully adopted hedging in a similar manner.

The results for information sources are particularly interesting. We included six information sources in the farmer survey and farmers were asked to select "all farm-related information sources you use." Thus, these sources may not all be used for hedging decisions, but could represent common sources of farm management or production information as well. In the smooth coefficient model, we find that two of the six information sources have posterior probabilities of having a positive effect on hedge ratios that exceed 95% (consultants and field days) with magazines as an information source having over a 95% posterior probability of having a negative effect on the hedge ratio. All these effects are fairly large with expected changes in hedge ratios ranging from 10 to 12 percent (in amount of crop hedged, not as a percent of the mean hedge ratio). These are very economically significant amounts by which to influence hedge ratios and greatly exceed the magnitude of the effects from any of the other variables in the model except the lagged hedge ratio.

Farm profitability was self-reported as profitable (1), break-even (2), or money-losing (3). This coefficient's posterior mean was quite large at 13.018, so break-even and money-losing farmers hedge significantly more of their crop than profitable farmers. This may be due to these less financially secure farmers feeling a greater need for risk management and the greater revenue certainty afforded by hedging.

Finally, the ratio of acres owned to acres farmed was also estimated to be significantly different from zero, with a posterior mean of 20.110. Thus, a farmer who owned all his acreage would be expected to hedge 20 percent more of his crop than a farmer operating exclusively on rented land. This is a surprising result as we would have expected farmers relying heavily on rented land to be more interested in risk management. Perhaps mortgage debt produces a stronger inclination for risk management than do impending rent payments.

Conclusions

This paper utilized a panel data of Georgia farmers to investigate the role of a variety of factors on the hedging decisions of farmers on three major crops: corn, soybeans, and cotton. Further, the effect of habit on hedging decisions, measured through a parameter that links the current hedge ratio to the lagged hedge ratio, is allowed to vary by farmer in a "smooth" way that allows for heterogeneity of habit effects while dampening the impact of sample noise.

We find that habit plays a quite significant role in hedging decisions for many farmers, but that the heterogeneity of the habit effect is enormous. Even with a Bayesian smoothing prior in place on the 106 farmer-specific habit effect parameters, the parameters vary greatly in sign and magnitude within the range of (-0.63, 1). Across the sample, the median habit effect is 0.335, which differs considerably from the estimate derived from a simple constant coefficient model of 0.473.

The results further show that information sources are powerful explainers of hedging decisions. Three different information sources have effects on hedging decisions that are significant in both statistical and economic senses (and those which are not statistically significant still have posterior means that connote economic importance). Whether a farmer relies on sources such as consultants, magazines, and field days can move the expected hedge ratio of the farmer up or down by over 10 percent for a single source. One can compose two distinct sets of information sources that would produce a difference of over 50% in the expected hedge ratio.

Other important factors in farmer hedging decisions include attitude toward technology adoption (early adopters hedge much more), education levels (more education means lower hedge ratios), farm profitability (more profit, less hedging), and the ratio of acres owned to acres farmed (being more dependent on rented land leads to lower hedge ratios).

Overall, this study has shown that farmer hedging decisions can be reasonably well explained and that a variety of factors influence those decisions. The results also confirmed those in Dorfman, Pennings, and Garcia (2005) that habit effects can be important, but are heterogeneous across farmers.

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Table 1: Summary Statistics

	Mean	Min.	Max.	Std. Dev.
Education	3.309	1	6	1.263
Income	4.937	2	8	1.897
Percent of income from farming	3.298	1	4	0.925
Years of experience	28.340	5	56	10.954
Commodity mix	4.586	2	20	3.466
Technology adoption	1.665	1	3	0.540
Consultants	0.604	0	1	0.490
Extension	0.958	0	1	0.201
Magazine	0.852	0	1	0.355
Internet	0.338	0	1	0.474
Field trial	0.723	0	1	0.448
Feed store	0.375	0	1	0.485
Profitability	1.478	1	3	0.592
Proportion of owned acres to total farmed acres	0.523	0.004	1	0.281
Hedge ratio in previous year	46.815	0	100	29.038

Notes: Summary statistics are computed using all 379 observations. Thus, all the variables for a farmer are counted as many times as the number of observations on that farmer.

Table 2: Ordinary Least Squares Results

	Regression coefficient	t-values
Intercept	-2.507	-0.783
Education	1.175	0.827
Income	1.260	1.299
Percent of income from farming	-1.087	-0.623
Years of experience	0.201	1.188
Commodity mix	-0.650	-1.379
Technology adoption	-7.418	-2.252
Consultants	8.871	2.834
Extension	-0.502	-0.056
Magazine	-9.149	-1.779
Internet	9.372	2.828
Field trial	6.151	1.629
Feed store	-4.262	-1.463
Profitability	0.867	0.282
Proportion of owned acres to total farmed acres	-0.726	-0.115
Years	1.266	0.791
Hedge ratio in previous year	0.473	9.444
R^2	0.3493	
Adjusted R^2	0.3186	

Table 3: Habit Parameter Statistics

	Number of obs. (out of 106)
$\gamma_i > 0$	73
$\gamma_i < 0$	33
$\gamma_i > 1$	0
$0 < \gamma_i < 0.5$	38

Table 4: Bayesian Smoothing Results

	Posterior mean	Posterior std. dev.	Pseudo t-values
Intercept	2.731	2.616	1.044
Education	-3.897	1.886	-2.067
Income	0.143	1.075	0.133
Percent of income from farming	-0.357	1.653	-0.216
Years of experience	-0.206	0.198	-1.043
Commodity mix	1.218	0.937	1.299
Technology adoption	-17.348	3.803	-4.561
Consultants	11.854	3.484	3.403
Extension	13.219	9.665	1.368
Magazine	-12.731	5.477	-2.324
Internet	-5.020	3.704	-1.355
Field trial	10.886	3.966	2.745
Feed store	-2.597	3.440	-0.755
Profitability	13.018	3.508	3.711
Proportion of owned acres to total farmed acres	20.110	7.825	2.570
Years	-1.348	1.308	-1.031
R^2	0.6077		
Adjusted R^2	0.4207		

Notes: R^2 is measured at posterior means.

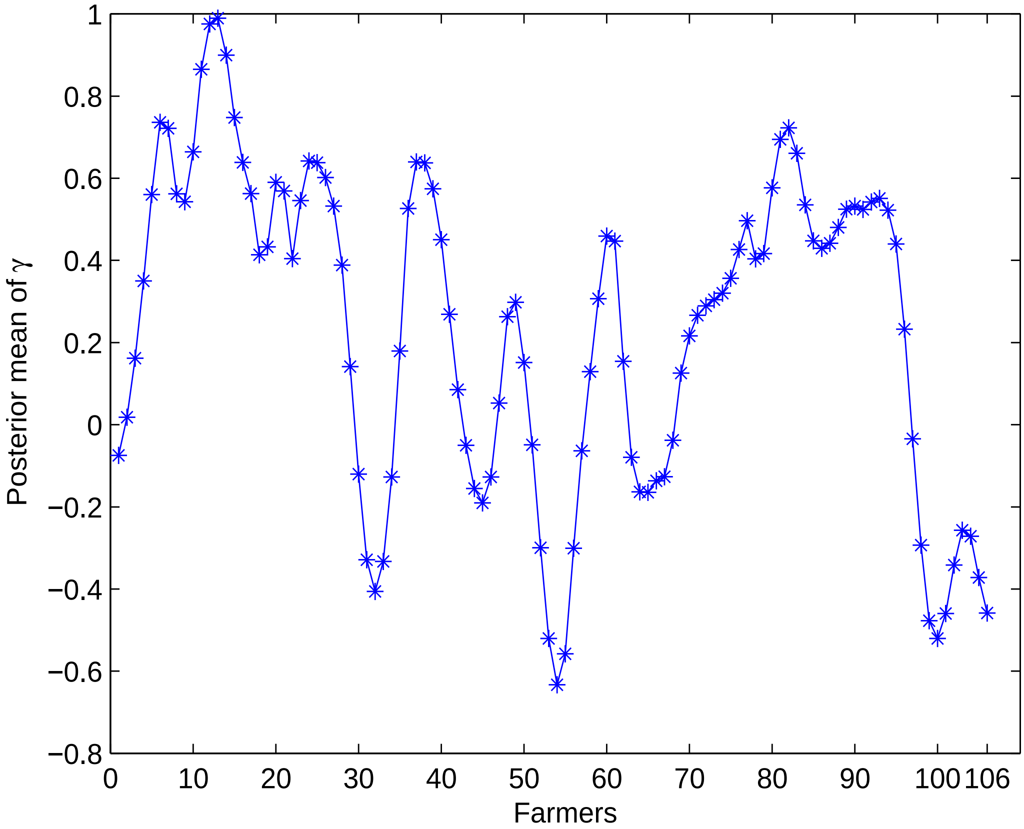

Figure 1: Posterior Means of Farmers' Habit Parameters