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

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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 4 years on four crops, we examine the role of habit, demographics, farm characteristics, and information sources on the hedging decisions made by 57 different farmers. We find that the role of habit varies widely and that estimation of a single habit effect suffers from aggregation bias. Thus, modeling farmer-level heterogeneity in the examination of habit and hedging is crucial.

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

JEL Classifications: C11, Q12, Q14

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 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. A recent paper by Pannell et al. (2008) points to factors such as other risk management tools (e.g., diversification), price expectations, and low to moderate farmer risk aversion as fully explaining the level of observed hedging activity. Also investigating the variation in observed hedging behavior, Dorfman, Pennings, and Garcia (2005) and Pennings and Garcia (2004) 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 article, 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 four crops hedged over a 4-year period. In our model, we want to incorporate habit effects through use of lagged hedge ratios that we have data on as a result of our rare panel data set. Habit effects have been considered in many areas of economics, particularly in the demand literature

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(Blanciforti and Green, 1983; Holt and Goodwin, 1997; Pope, Green, and Eales, 1980). 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 article 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 semiparametric 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 semiparametric coefficient 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. Because our panel data of farmers does not have a natural ordering, we use Bayesian model averaging to form a robust estimator that avoids having to choose a single ordering over which we impose the coefficient smoothing.

Thus, this article contributes to the literature by expanding the explanation of farmers' hedging decisions beyond market conditions. Additional factors explaining hedging decisions include information sources, attitude toward technology adoption, farmer characteristics, and the role of habit. This broader look at hedging, particularly the rare chance to use farm-level panel data, allows us to search for heterogeneity in the role of habit and to include other determinants of the farmer's decision-making process. This article is the first to produce farmer-specific estimates of the habit effect in hedging. Combining this innovation with the other insights provided by our model, these results add significantly to the literature seeking to explain individual hedging decisions.

The remainder of this article 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 57 distinct farmers, each growing one or more of the four crops studied: corn, soybeans, wheat, and cotton. Information was also collected on basic demographic traits, farm characteristics, information sources for farm management decisions, computer use, 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. The survey was mailed to a sample of farmers who owned at least 300 acres of land, so these farmers are all medium- to large-scale farmers. Georgia Agricultural Statistics Service constructed the sample and mailed the surveys. These data on all such Georgia farmers and the responses received confirm that in basic demographics and farm characteristics we have a representative sample. Hedging questions were asked for the four crops for the years 1999–2002. The hedge ratio variable is self-reported by farmers as "the percent of your crop hedged" with responses given for each year and for as many of the four crops covered as the farmer grew or for which the farmer responded.

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 four 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 in which a single farmer could represent up to 12 observations (four crops, 3 years [2000–2002]). After removing observations with missing variables on the desired set of explanatory variables we were left with 250 observations. Observations on corn were 22.4% of the sample, soybeans 9.6%, wheat 20.8%, and cotton the remaining 47.2%.

Explanatory variables to include in the model, other than lagged hedge ratio, include: education-level dummies, income range dummies, percent of income from farming dummies, years of farming experience, number of commodities produced, attitude toward technology adoption dummies (early, mid, or late adopter), profitability of the farm dummies (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 and seed store. Some basic statistics on the variables are displayed in Table 1.

A Model with Smooth Spatial and Response Characteristics

In this article, we wish to explain hedging decisions based on a range of explanatory variables, but with particular emphasis on the role of habit. We measure the role of habit by the parameter on the lagged hedge ratio, which will enter 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:

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

where x_{it} 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 semiparametric estimator 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. Because there is no natural way to order the farmers (such as time), any ordering chosen will be somewhat arbitrary. To avoid the choice of z_i having an undue influence on our empirical results, we allow for uncertainty over the correct ordering. Five different orderings were considered, each based on a composite variable created by summing four standardized exogenous variables to create a z_i. Bayesian model averaging is then used to form posterior estimates with the uncertainty over the ordering integrated out (Dorfman and Lastrapes, 1996).[1] Note that although 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

To demonstrate the smoothing methodology, it is easier to work with all the observations stacked into matrices and to ignore the model averaging for now. Thus, rewrite the model in Equation (1) as:

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

[1] When performing smoothing across observation-specific parameters, the order of the observations is clearly very important. In cross-sectional data such as we have in this application, there is no natural order to the observations in the data set. The obvious approach is to order the observations by the order of an exogenous variable or set of such variables. We follow this practice here by sorting the observations according to the value of a composite sorting index variable created by summing the normalized values of four of our model regressors.

Table 1. Summary Statistics

	Mean	Minimum	Maximum	Standard Deviation
Hedge ratio	55.152	0	100	33.504
Hedge ratio in previous year	56.072	0	100	32.097
Education				
Some high school	0.064	0	1	0.245
High school graduate	0.204	0	1	0.404
Some college	0.260	0	1	0.439
College graduate	0.336	0	1	0.473
Master's degree	0.088	0	1	0.284
Ph.D.	0.048	0	1	0.214
Income				
<$30K	0.076	0	1	0.265
$30K–$60K	0.408	0	1	0.492
$60K–$90K	0.208	0	1	0.407
$90K–$120K	0.132	0	1	0.339
>$120K	0.176	0	1	0.382
Percent of income from farming				
<25%	0.088	0	1	0.284
25–50%	0.076	0	1	0.265
50–75%	0.276	0	1	0.448
>75%	0.560	0	1	0.497
Years of experience	27.512	5	56	10.286
Commodity mix	4.428	2	20	3.120
Technology adoption				
Early	0.388	0	1	0.488
Average	0.540	0	1	0.499
Late	0.060	0	1	0.238
Information sources				
Consultants	0.628	0	1	0.484
Extension	0.968	0	1	0.176
Magazine	0.840	0	1	0.367
Internet	0.372	0	1	0.484
Field trial	0.692	0	1	0.463
Feed store	0.404	0	1	0.492
Profitability				
Money making	0.504	0	1	0.501
Breakeven	0.452	0	1	0.499
Money-losing	0.044	0	1	0.205
Proportion of owned acres to total farmed acres	0.882	0	6	1.172

Note: Summary statistics are computed using all 250 observations. Thus, all the variables for a farmer are counted as many times as the number of observations on that farmer.

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 nonsquare 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 semiparametric habit coefficients.

To accomplish the smoothing of the nonparametric functions, one must first define what is meant by "smooth." In this article, we use the definition that smooth means coefficient changes from farmer to farmer are relatively constant, meaning that the farmer-specific coefficients lie roughly on a line after the observations have been ordered by the variable z_i to create an ordering where imposing some structure on the varying coefficients makes some sense. Smoothing can also be used to make observation-specific coefficients be approximately equal to a constant or to make the coefficients lie roughly on a quadratic equation. Our chosen smoothing pattern of coefficients being roughly on a line is accomplished by smoothing on second differences, whereas the two alternatives just mentioned would have smoothing based on first and third differences, respectively.

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

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

D is an $(n_f \times n_f)$ second differencing matrix. Because second differencing requires us to have two free parameters, we do not impose the same smoothing on the first and last γ_i parameters with this approach. This is accomplished in D by the ones on the main diagonal in the top left and bottom right corners. This smoothing matrix is similar but not identical to those used in Koop and Poirier (2004) and Koop and Tobias (2006). The difference in smoothing matrices is the result of variations in handling the initial conditions. We allow the first and last observations to be free of smoothing, whereas Koop and Tobias (2006) leave the first two observations free. This presentation is more straightforward and in keeping with the traditional formulas used in Bayesian estimation.

To write the idea of smooth coefficients mathematically, define the smoothing matrix, $\widehat{D}$ which contains the $n_f - 2$ middle rows of D; that is, all but the first and last row. This matrix allows us to write mathematically the smoothness desired as the linear approximate restriction

$$\widehat{D}\gamma \approx 0. \tag{4}$$

This equation imposes $n_f - 2$ approximate restrictions on the n_f parameters in γ and no restriction on the parameters in β. More specifically, the restrictions take the form $(\gamma_{i+1} - \gamma_i) \approx (\gamma_i - \gamma_{i-1})$, for $i = 2, \ldots, n_f - 1$.

If the restrictions in Equation (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 Equation (4) through a Bayesian prior with a nonzero prior variance, we will allow the nonparametric function represented by the vector γ to vary from such a line but not be completely unfettered. Thus, the model will allow the effect of $h_{i,t-1}$ to vary as z_i changes but in a gradual, more continuous way than without the smoothness prior.

The simplest way to implement such a procedure is to rewrite the model in Equation (2) as:

$$\begin{aligned} h &= X\beta + H(D^{-1}D)\gamma + \varepsilon = [X \;\; HD^{-1}]\begin{bmatrix} \beta \\ D\gamma \end{bmatrix} \\ &= W^*\lambda^* + \varepsilon. \end{aligned} \tag{5}$$

Treating W^* as a data matrix, the model in Equation (5) is a standard linear model and given a prior distribution for λ^* the derivation of the posterior distribution is straightforward.

A Bayesian Prior Distribution

We need priors for λ^* and for σ_ε^2. If we use the natural conjugate prior, this model can actually be examined analytically. We have no strong prior beliefs about any of the structural parameters in β, so an essentially uninformative prior for β seems reasonable. For $D\gamma$ we need an informative prior that imposes the smoothing prior with the desired amount of smoothing. We assume a normal-Gamma prior of the form (Koop, 2003):

$$p(\lambda^*, \sigma_\varepsilon^{-2}) \sim NG(m_o, V_o, s_o^{-2}, v_o). \tag{6}$$

The prior mean of the regression model parameters, m_o, is set to a vector of zeros because we do not claim to have specific prior information on the β parameters and a prior mean of zero is essential on the differenced parameters (implying no expected change between $(\gamma_i - \gamma_{i-1})$ and $(\gamma_{i+1} - \gamma_i)$). 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. Because there are four classes of parameters in λ^* (smoothed, structural, initial condition, and mean rate of change for γ), it is appropriate to specify this matrix in four parts:

$$(7)\qquad V_o = \begin{bmatrix} \tau_1 I_k & 0 & 0 & 0 \\ 0 & \tau_2 & 0 & 0 \\ 0 & 0 & \tau_3 I_{n_f-2} & 0 \\ 0 & 0 & 0 & \tau_4 \end{bmatrix}.$$

This partition of the prior variance allows for the researcher to place a loose prior on the structural parameters in β by setting τ_1 to a relatively large scalar (in our application $\tau_1 = 1{,}000$). In turn, τ_3 controls how smooth the changes in the parameter on the lagged hedge ratio are to be; smaller values of τ_3 lead to smoother nonparametric functions. In the extreme, as τ_3 goes to zero, all farmer-specific habit effects will fall exactly on a line. In our application, τ_3 is set to 0.0001 to introduce a definite smoothing of γ. Finally, τ_2 and τ_4 control the priors on the initial conditions of the smoothed γ_i's. Tightening these priors will tend to move the mean value of γ_i closer to zero and to make the line nearer to horizontal (that is, in the extreme as τ_2 and τ_4 approach zero, the γ_i would vary around zero with no trend). In our application, τ_2 and τ_4 are set to 0.01.

The Gamma prior on the error variance term is a standard one. Common choices of values for s_o^{-2} are on the order of 0.1 or 0.01 or even zero. The degree of freedom hyperparameter v_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 $v_o = 0$, so we have an uninformative prior on the variance of the model errors, which means s_o^{-2} need not be specified. 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:

$$(8)\qquad p(\lambda^*, \sigma_\varepsilon^{-2}) \sim NG(m_p, V_p, s_p^{-2}, v_p),$$

where

$$(9)\qquad V_p = (V_o^{-1} + W^{*\prime} w^*)^{-1},$$

$$(10)\qquad v_p = v_o + n,$$

$$(11)\qquad m_p = V_p(V_o^{-1} m_o + W^{*\prime} h),$$

and

$$(12)\qquad s_p^2 = v_p^{-1}\big(v_o s_o^2 + (h - W^* m_p)'(h - W^* m_p) + (m_o - m_p)' V_o^{-1}(m_o - m_p)\big).$$

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. In fact, the posterior mean of γ is simply given by:

$$(13)\qquad \gamma_p = D^{-1} R m_p = D^{-1} R V_p (V_o^{-1} m_o + W^{*\prime} h),$$

where R is an $n_f \times (k + n_f)$ matrix that pulls out habit parameters from λ^*,

$$(14)\qquad R = \begin{bmatrix} 0 & I_{n_f} \end{bmatrix}.$$

A similar transformation of the posterior variance matrix V_p can yield the posterior variance matrix of the recovered γ. 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 $A\lambda$. A common point estimator based on these posterior distributions is the posterior mean. So point estimates can be obtained from Equations (11) for β and (13) for γ.

Handling a Dynamic Panel Model

Our model of habit in hedging is based on lagged hedging levels affecting the current decision on hedging. Thus, we have a lagged dependent variable on the right-hand side of our regression equation. Given that our data are in the form of panel data (multiple observations on each individual farmer), the lagged dependent variable causes a serious econometric issue. In such a framework, the lagged dependent variable is equivalent to current endogenous variables on the right-hand side in a simultaneous equations framework. The manner of addressing the issue is the same; instrumental variables estimation (IVE) can be used to address the endogeneity problem caused by the lagged hedging variable.

To create an instrumental variable estimator for the lagged hedge ratio, we use as instruments data on farmers' age, crop dummies, and the individual farmer dummies. The R^2 for this regression is 0.70, which is good for an instrumental step because you do not want the R^2 to be too high or too low. The fitted estimates for the lagged hedge ratios are then used in the Bayesian smooth coefficient model as regressors in the place of the actual lagged hedge ratios. Furthermore, to test the validity of our instruments, we compared the marginal likelihood ratios from our models with the fitted lagged hedge ratio with the one from a model excluding the latter and found that the marginal likelihood increases by a factor of 10^6 when fitted lagged hedge ratio is included.

Bayesian Model Averaging

To allow for uncertainty over the ordering to impose on the data set before performing the smoothing, we introduce an ordering index to our model using superscripted (j) to represent one of the $j = 1, \ldots, 5$ possible orderings considered. Thus, the model in stacked matrix form becomes

$$
\begin{aligned}
h^{(j)} &= X^{(j)}\beta^{(j)} + H^{(j)}\gamma^{(j)} + \varepsilon^{(j)} \\
&= W^{(j)}\lambda^{(j)} + \varepsilon^{(j)},
\end{aligned} \tag{15}
$$

where the index is placed on the data matrices to reflect that the order of the rows would be changed by the ordering and on the parameter vectors because once the smoothing is imposed, different orderings produce different posterior distributions.

Now, introduce the apparatus for handling model specification uncertainty. Begin with a discrete prior weight on each model:

$$
p\left(M^{(j)}\right) = \mu_j, \quad \sum_{j=1}^{M} \mu_j = 1. \tag{16}
$$

These weights can be uninformative ($\mu_j = \frac{1}{M}, \forall j$) or can be weighted to display a preference for certain models. We choose to be uninformative about ordering and choose equal prior weights in this article. Next, using the posterior distribution shown in Equation (8), derive the marginal likelihood function by integrating out the ordering uncertainty to leave a conditional likelihood for each model:

$$
p(h^{(j)}|M^{(j)}) = c^{(j)} \left[\frac{|V_p^{(j)}|}{|V_o^{(j)}|}\right]^{\frac{1}{2}} \left(\nu_p^{(j)} s_p^{2(j)}\right)^{-\frac{\nu_p^{(j)}}{2}}, \tag{17}
$$

where $c^{(j)}$ is a normalizing constant. See Koop (2003) for more details. Combining Equations (16) and (17) allows one to derive the posterior probability of each model:

$$
\begin{aligned}
p(M^{(j)}|h^{(j)}) &\propto \mu_j \left[\frac{|V_p^{(j)}|}{|V_o^{(j)}|}\right]^{\frac{1}{2}} \left(\nu_p^{(j)} s_p^{2(j)}\right)^{-\frac{\nu_p^{(j)}}{2}} \\
&= \mu_j p(h^{(j)}|M^{(j)}), \quad j = 1, \ldots, M.
\end{aligned} \tag{18}
$$

Normalizing the values in Equation (18) by dividing each value by the sum across all M models will ensure that the posterior model probabilities will sum to unity. Denote these normalized posterior probabilities by:

$$
\omega^{(j)} = \frac{\mu_j p(h^{(j)}|M^{(j)})}{\sum_{j=1}^{M} \mu_j p(h^{(j)}|M^{(j)})}, \quad j = 1, \ldots, M. \tag{19}
$$

Given the normalized posterior model probabilities, the next step is to derive the marginal posterior distribution by removing the conditioning on the ordering. This is done by integrating over the five models creating a single posterior distribution for the regression parameters that are a weighted average of the posteriors for each data ordering. Thus, the full marginal posterior distribution of the regression parameters, λ, accounting for all the orderings considered, is a mixture distribution, in this case, a mixture of t-distributions where the mixing weights are the posterior probabilities of each model from Equation (19). In this particular case, the posterior mean of the mixture distribution is simply the weighted average of the individual posterior means from the five different orderings with the weights being the normalized posterior model probabilities from Equation (19).

Econometric Results and Implications

For comparison purposes and as a starting point, we also estimated the model in Equation (1) with a constant parameter γ by IVE (to handle the dynamic panel data problem). The results of this estimation are shown in Table 2. We find that a total of 10 parameters is statistically significant (at a 0.10 level), including the γ parameter on the lagged hedge ratio. The IVE estimate of γ is 0.991 with a *t*-ratio of 12.93, implying that habit almost completely determines a farmer's hedging decision. Other statistically significant variables are the farmer's income level, the percent of income from farming, the attitude toward technology adoption, the use of the Internet as an information source, and the perceived profitability of the farm operation. The model has an R^2 of 0.486, which is quite acceptable considering the nature of the panel data (small T, medium N).

Our composite variables $z_i^{(j)}$ which are used to sort the farmers for the purposes of the smoothing are formed from four variables chosen from a set of seven possible variables: education, income, percent of income from farming, number of commodities produced, attitude toward technology adoption, profitability of the farm, and the ratio of acres owned to acres farmed. Dorfman, Pennings, and Garcia (2005) found that percent of 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 because diversification of products is another form of risk management. Education level and attitude toward technology adoption are included as likely indicators of willingness to use hedging. Each of the variables was scaled to have a mean of one and then summed to create our composite sorting index variable. The five orderings are based on the following sets of variables to form each composite $z_i^{(j)}$ {education, number of commodities produced, attitude toward technology adoption, ratio of acres owned to acres farmed}, {income level, percent income from farming, profitability, ratio of acres owned to acres farmed}, {percent income from farming, number of commodities produced, profitability, ratio of acres owned to acres farmed}, {income, number of commodities produced, profitability,

Table 2. Instrumental Variable Estimation Results

	Regression Coefficient	*t* Values
Intercept	4.807	0.299
Education		
High school graduate	–3.586	–0.243
Some college	11.828	0.780
College graduate	–3.888	–0.246
Master's degree	16.568	0.810
Ph.D.	19.092	0.875
Income		
\$30K–\$60K	–21.317	–2.237
\$60K–\$90K	–30.230	–2.768
\$90K–\$120K	–26.123	–2.486
>\$120K	–28.914	–2.450
Percent of income from farming		
25–50%	–22.391	–2.015
50–75%	–25.310	–2.438
>75%	–14.035	–1.514
Years of experience	5.004	0.709
Commodity mix	0.079	0.098
Technology adoption		
Average	9.532	1.692
Late	–8.644	–0.504
Information sources		
Consultants	9.148	1.545
Extension	24.554	1.505
Magazine	–1.239	–0.147
Internet	8.377	1.735
Field trial	–5.216	–0.905
Feed store	–3.291	–0.702
Profitability		
Breakeven	–14.010	–2.658
Money-losing	–5.131	–0.358
Proportion of owned acres to total farmed acres	1.503	0.673
Hedge ratio in previous year	0.991	12.931
R^2	0.486	
Adjusted R^2	0.423	

ratio of acres owned to acres farmed}, and {education, income, profitability, ratio of acres owned to acres farmed}. The posterior model probabilities show two models dominating with 13% of the posterior probability on the fourth ordering and 86% on the fifth ordering (using the previous $z_i^{(j)}$ variable listings). The other three orderings essentially drop out of the results based on Bayesian model averaging because combined they only have 1% of the posterior weight. We present results for both model averaging and the ordering with the highest posterior model probability.

The results of the smooth coefficient model estimation are shown in Tables 3 and 4. Table 3 contains summary measures and statistics on the 57 farmer-specific, model-averaged and ordering-specific, smoothed estimates of γ_i, whereas Table 4 contains the Bayesian posterior means and standard deviations for the structural (nonsmoothed) parameters of the model.

Allowing the habit parameter to vary by farmer while being smoothed by our Bayesian estimator to remove some of the effect of noise appears to have worked reasonably well. Table 3 shows that 49 of the 57 farmer-specific, model-averaged habit parameters lie in the expected range of (0, 1) with 37 within (0.5, 1.0). Thus, for the majority of our farmers, habit plays a sizeable role in their hedging decisions. Negative habit parameters imply odd behavior, perhaps reacting to perceived bad outcomes from the previous year's hedging. Thus, we are pleased that none of the estimated habit parameters are negative. Eight of the model-averaged γ_i exceed 1 (see Figure 1A), which is important, because that implies nonstationarity. Nonstationarity is not desirable because it implies hedge ratios exceeding

Table 3. Habit Parameter Statistics

	Model Averaging	Highest Odds Model
	Number of Observations (out of 57)	Number of Observations (out of 57)
$\gamma_i > 0$	57	57
$\gamma_i < 0$	0	0
$\gamma_i > 1$	8	10
$0.5 < \gamma_i < 1$	37	34

one eventually, which turns hedging into speculation. This is certainly admissible behavior (some farmers surely do so), but we do not believe that many farmers should fall into that category. Many of the model-averaged γ_i's are estimated very precisely with 48 having 90% highest posterior density regions (HPDRs, the Bayesian equivalent to confidence intervals) that do not include zero and 51 having 80% HPDRs that do not cover zero. Because the marginal posterior distributions of the γ_i are in the form of the Student's *t* distribution, having a 90% HPDR that does not include zero is equivalent to that particular γ_i having a 95% posterior probability of being positive. Thus, for the vast majority of farmers in our sample, habit plays at least some role in their hedging decisions.

As an additional result of allowing sample variation in the habit parameter, it is worth noting that of the 57 smoothed farmer-specific, model-averaged γ_i's, 36 of them have at least a 90% posterior probability of being either greater or smaller than the constant coefficient estimate of 0.991. That is, 63% of the farmers have habit effects with high posterior probabilities of being 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 0.726 and the median of the posterior means is 0.653. Both of these values are quite different than the constant coefficient estimate suggesting that not only is there considerable variation in these parameters if it is allowed, but that constraining it introduces some aggregation bias.

Table 3 shows that the habit parameters obtained from the model with the highest posterior probability have similar characteristics as the ones obtained from model averaging. All habit parameters are positive and 47 of the 57 farmer-specific habit parameters lie in the (0, 1) range and 34 in (0.5, 1.0) range. As can also be seen in Figure 1B, 10 of the habit parameters exceed one. Furthermore, 34 of them have at least a 90% posterior probability of being either greater or smaller than the IVE estimate.

Table 4 shows that including farmer-specific habit effects greatly improved the model fit with the model-averaged R^2 now equal to 0.622 when taken at the posterior means of the

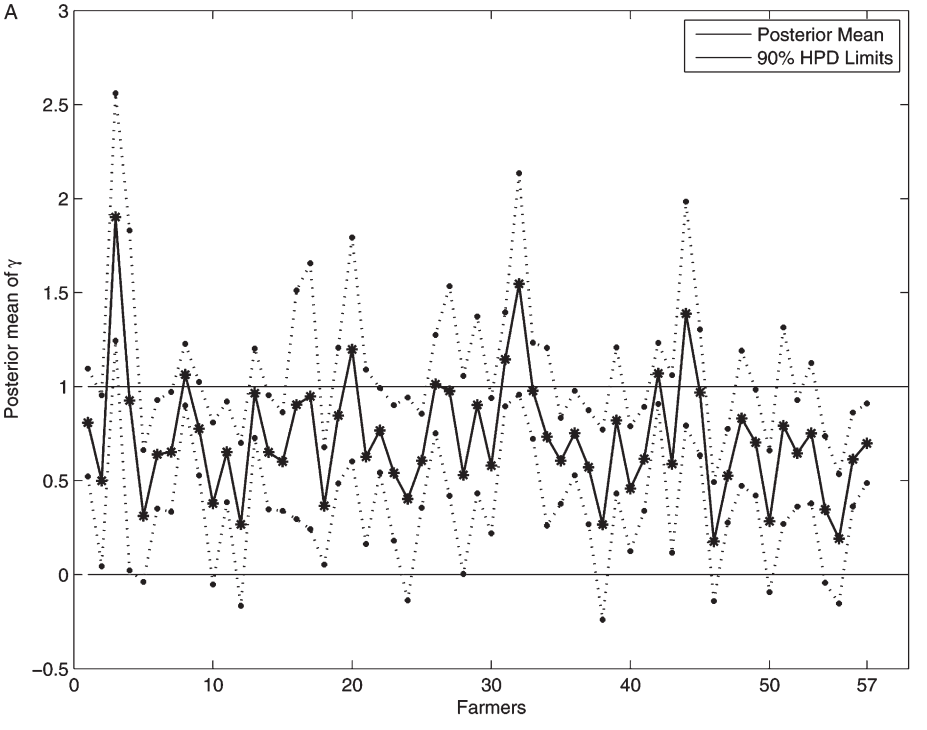
Table 4. Bayesian Smoothing Results

	Model Averaging		Highest Odds Model	
	Posterior Mean	Posterior Standard Deviation	Posterior Mean	Posterior Standard Deviation
Intercept	–12.240	22.815	–14.636	23.281
Education				
High school graduate	18.607	16.186	23.169	16.509
Some college	37.064	16.664	41.954	16.975
College graduate	29.872	17.939	35.241	18.364
Master's degree	32.879	20.435	37.811	20.712
Ph.D.	40.672	33.881	39.867	34.866
Income				
\$30K–\$60K	8.680	12.025	9.522	12.088
\$60K–\$90K	0.022	12.380	1.343	12.237
\$90K–\$120K	12.003	13.108	13.035	13.100
>\$120K	14.722	14.183	16.677	14.208
Percent of income from farming				
25–50%	1.023	12.742	4.145	12.697
50–75%	–13.267	11.233	–12.147	10.998
>75%	–18.452	9.906	–17.731	9.743
Years of experience	5.348	8.674	3.771	8.632
Commodity mix	1.290	0.875	1.392	0.838
Technology adoption				
Average	–3.717	5.926	–4.708	5.867
Late	–15.716	16.281	–14.321	16.109
Information sources				
Consultants	1.422	7.215	0.701	7.151
Extension	–9.678	19.313	–14.692	19.902
Magazine	–1.515	9.416	1.419	9.435
Internet	10.500	4.848	10.277	4.831
Field trial	0.881	5.691	0.469	5.695
Feed store	–1.454	5.180	–1.850	5.182
Profitability				
Breakeven	–0.614	6.240	–0.438	6.361
Money-losing	–6.618	17.821	–7.217	18.442
Proportion of owned acres to total farmed acres	0.841	3.662	0.898	3.675
R^2	0.622		0.712	
Adjusted R^2	0.434		0.567	

Note: R^2 is measured at posterior means.

parameter distributions. This is a very large improvement from the 0.486 of the IVE estimates with a single habit parameter. The improvement does not all come from the additional parameters that the farmer-specific effects allow, because the adjusted R^2 also rises from 0.423 to 0.434. The improvement in model fit is greater when we consider the model with the highest posterior probability. The R^2 and adjusted R^2 increase to 0.712 and 0.567, respectively.

Table 4 reveals that allowing for some sample variation in the habit parameter across farmers has not particularly improved the estimation of the remaining, constant parameters. The model averaging results have four parameters with 90% HPDRs that do not include zero, whereas the



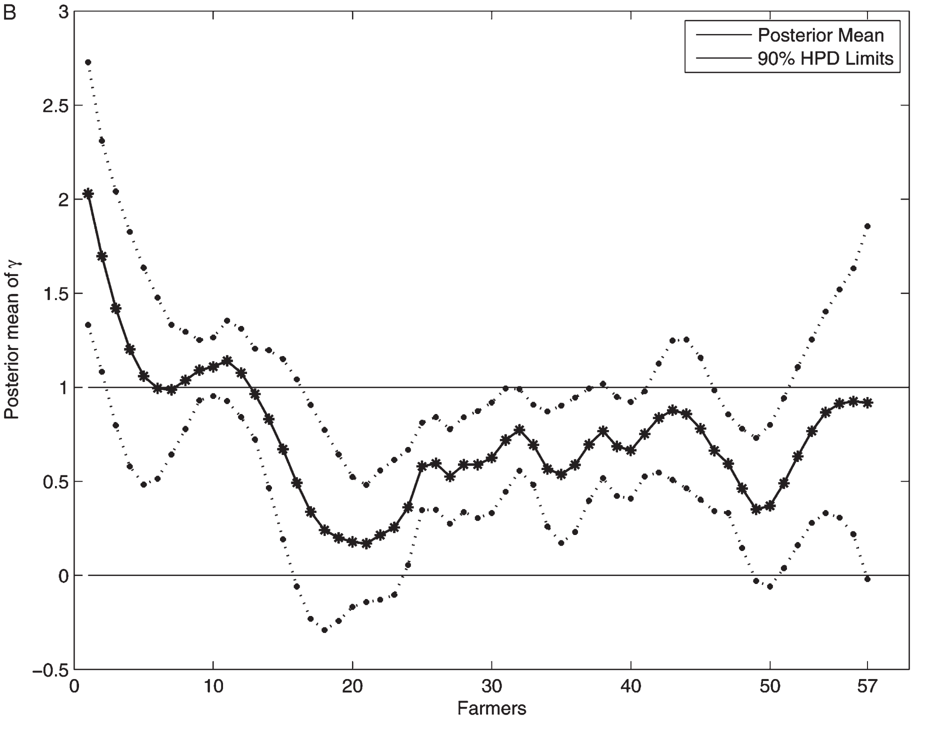


Figure 1. Posterior Means of Farmers' Habit Parameters (A) Model Averaging (B) Highest Odds Model

highest odds model has six such parameters. This is less than the nine statistically significant parameters in the IVE model when you do not count the habit parameter. The new results have high posterior probabilities for education variables. However, none of the income variables, technology adoption variables, and profitability variables shows strong posterior support for a particular sign.

The education-level dummy variables show that (compared with the base of not graduating from high school) education tends to lead to more hedging. However, the effect changes as education continues. That is, a college graduate would hedge more than a high school graduate but less than a farmer with some college education. Farmers who earn more than 75% of their income from farming are found to hedge less than farmers who earn less than 25% of their income from farming by an average of 18% of the crop, which is a large change in hedging behavior. Commodity mix variable from the highest odd model shows that farmers who grow more variety of commodities hedge more.

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 only one of the six information sources has posterior probability of having a clearly signed effect on hedge ratios that exceed 95% (the Internet) with expected change in hedge ratios of 10.5% (in amount of crop hedged, not as a percent of the mean hedge ratio). This is very economically significant amount by which to influence hedge ratios.

Overall, we get less empirical support for structural variables in the Bayesian smooth coefficient models. However, we believe that the IVE results with a single habit parameter are less appealing as a result of a particular dichotomy. The single habit parameter is highly significant with a value very close to unity, implying that habit fully explains hedging decisions. Yet, we find nine other significant structural variables. We think that this result is contradictory and the Bayesian results are more dependable.

Conclusions

This article used a panel data set of Georgia farmers to investigate the role of a variety of factors on the hedging decisions of farmers on four major crops: corn, soybeans, wheat, and cotton. Furthermore, 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 almost all farmers but that the heterogeneity of the habit effect is enormous. Even with a Bayesian smoothing prior in place on the 57 farmer-specific habit effect parameters, the parameters vary greatly in magnitude within the range of approximately (0.2, 1.9). Across the sample, the median model-averaged habit effect is 0.726, which differs considerably from the estimate derived from a simple constant coefficient model of 0.991. Models without allowances for heterogeneity would therefore suffer from aggregation bias and could lead to incorrect policy decisions.

The results provide some interesting insights into the effect of farmer characteristics on hedging decisions. As educational attainment increases, farmers hedge more of their crops. In general, farmers who derive the highest percentage of income from farming hedge less. This last result might be surprising because those farmers are the most dependent on farm income for total household income, but perhaps as more full-time farmers, they feel capable of tracking the commodity markets and selling at the optimal time. Finally, the use of the Internet as an information source has some sizeable effect on hedging decisions.

Overall, the results confirmed those in Dorfman, Pennings, and Garcia (2005) that habit effects are important but are heterogeneous across farmers. The other factors that influence hedging decisions do not seem to be consistent across models and are dominated by the habit effects. The overwhelming percentage of farmers with high posterior probabilities of habit effects may explain why extension faculty has a difficult time convincing farmers to hedge more. Our results suggest if they are persistent enough, eventually they will succeed.

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