Is Hedging a Habit? Hedging Ratio Determination of Cotton Producers

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We examine the role that habit plays when producers determine their hedge ratio. Data were collected from U.S. cotton growers in which they indicated their hedging position in 2001 and 2002 as well as their perceived profitability, land ownership structure, and income. To account for heterogeneity, a generalized mixture regression model is used to identify the influence of the determinants of the hedge ratio. Our results identified two segments. In the smaller segment, consisting of 35% of the producers, habit did not affect the hedge ratio; instead, land ownership and perceived profitability were most influential. In the larger segment, consisting of 65% of the producers, the hedge ratio was solely driven by habit. The results show the important role of habit formation in understanding producers' employed hedge ratio, confirm the importance of heterogeneity, and strengthen the relationship between financial structure and market-risk mitigating behavior.

Key Words: cotton producers, habit, hedge ratios, mixture models

How do farmers choose the amount of their anticipated production to hedge? The literature has paid attention to what the "optimal" hedge ratio is, but not whether farmers have the same motivation or optimization problem as we academics assume. In this paper, we utilize farm-level data to analyze producers' hedging decisions in hopes of uncovering the drivers behind the observed behavior. We use a mixture model approach that allows for heterogeneity in those decision-making processes, whereby all farmers need not share the same motivation in their hedging decisions. If extension educators are to design effective programs for producers related to hedging, they must understand how producers are currently making their hedging decisions.

The factors influencing producers' hedging behavior have been the focus of considerable recent research. Most studies have investigated the initial decision concerning whether or not the producer hedges (Pennings and Leuthold, 2000). Less attention has been devoted to the hedge ratio producers employ and the

factors which influence that hedge ratio. (There is a substantial literature on opti-mal hedge ratios, but not on what hedge ratios producers actually apply.) Further, the procedure used by producers to arrive at their hedging position is largely unknown.

Here, we focus on the factors that influence producers' hedge ratios. Particular attention is paid to habit, a factor which has received attention by economists when examining the choice behavior of consumers (Blanciforti and Green, 1983; Dynan, 2000; Holt and Goodwin, 1997; Pollack, 1970; Starmer, 2000), but not in studying risk management. By "habit," we refer to decisions based on previous behavior rather than current economic conditions.[1] We hypothesize that habit is an important driver of producers' employed hedge ratios. In addition, following Collins (1997), who argued that hedging is motivated by a desire to avoid finan-cial failure and not by a desire to avoid price risk, we expect the farm's financial structure also influences the hedge ratio employed.

To test these notions, we use data from a survey of Georgia cotton producers, in which (among other influences) habit and financial structure can influence producers' choices of hedge ratios. Producers were asked to indicate their pre-harvest hedging position in 2002 and 2001. The data include information on the producer's self-perceived profitability, land ownership structure, income, and basic demographics. In addition, each producer was asked to indicate how (s)he chooses the hedge ratio (e.g., by habit, marketing consultant's recommendation, talking to other producers, conducting an analysis of the market, or a combination of these strategies). The unique data allow for an investigation into different hedging decision processes of producers and possible identification of hetero-geneous factors influencing those decisions.

As shown by Pennings and Garcia (2004), factors associated with hedging have a differential effect on behavior of firms. In their work, they use a generalized mixture regression model which simultaneously classifies firms into segments on the basis of the relationship between hedging and its determinants, and estimates the influence of the determinants on hedging practices for each segment identified. We apply this modeling framework to farm-level data to both model producers' hedging decisions and allow for heterogeneity in those decision-making processes.

The results confirm Heckman's (2001) notion that decision makers may respond differently to the same economic stimuli, which in our context translates into the determinants of hedging affecting the employed hedge ratio differentially across producers. We identify two segments of producers. In the smaller segment, consisting of 35% of the producers, habit does not drive the hedge ratio employed. In this segment, supporting Collins' (1997) assertion that hedging is related to the equity structure of the farm, the land ownership structure is an

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[1] In this paper, we use the term "habit" to refer to observed behavior which does not match that predicted by a single-period optimization framework. In the consumption literature, habit is the common term; on the production side, the term "persistence" is sometimes employed. Here, sub-optimal behavior can reflect farmers who just do the same thing every year or can be the result of a multi-period optimization with either adjustment costs of some type or imperfect future forecasts.

important driver of the hedge ratio, along with the perceived profitability of the farm. In the larger segment, consisting of 65% of the producers, the hedge ratio is solely driven by habit.

The remainder of the paper is organized as follows. We first review some background material on hedging and describe precisely what is implied by the term "habit" in our context. We then provide a conceptual framework of our model of heterogeneous types of hedging decisions by farmers and the statistical model. The next section gives a discussion of the data employed in our application, followed by a section devoted to the results of the application. The paper ends with an overview of our conclusions and suggested focal areas for future research.

A Conceptual Model of Hedging Behavior Incorporating Farmer Heterogeneity

Background and Motivation

In the agricultural economics and finance literature, extensive research has been conducted on the factors that drive hedging behavior. Behavioral studies have investigated the effects of producer risk characteristics, structure of the production process, and information sources and availability on hedging. Here, we do not review all the factors that have been identified to influence hedging behavior. The combined works of Froot, Scharfstein, and Stein (1993), Nance, Smith, and Smithson (1993), Mian (1996), Tufano (1996), Géczy, Minton, and Schrand (1997), Lee and Hoyt (1997), Koski and Pontiff (1999), Pennings and Garcia (2004), and Graham and Rogers (2002) provide a discussion of these factors in the financial literature. Similarly, in the agricultural economics literature, the factors associated with hedging are addressed by Asplund, Foster, and Stout (1989), Goodwin and Schroeder (1994), Pennings and Leuthold (2000), Shapiro and Brorsen (1988), and Turvey and Baker (1990).

In this study, we focus primarily on two factors that have received less attention in an empirical setting: habit and the equity structure of the farm. Apart from the limited understanding of how habit and equity structure affect hedging, we focus on these factors because of their intuitive appeal in explaining dynamic behavior. The effect of habit formation on economic decision making has been identified in a variety of meaningful contexts. Further, the importance of the financial structure of the firm, particularly in a dynamic decision context, suggests it should be included in any assessment of behavior over time.

Habit formation has been studied extensively in consumer demand. In this context, habit refers to the notion that current utility depends on current expenditures and on a stock formed by lagged expenditures (Pollak, 1970; Pope, Green, and Eales, 1980; Dynan, 2000). In production, the existence of lagged responses is often explained by adjustment costs whereby firms do not change output immediately in response to shocks to their environment (Dorfman and Heien, 1989; Vigfusson, 2004). In a finance context, Constantinides (1990) uses habit

formation to provide an explanation for the equity premium puzzle, and argues that the evidence for persistence suggests it should be embedded in many economic analyses to provide a richer understanding of dynamic behavior. Clearly, an implication of habit formation is that decision makers adjust to shocks slowly. In this paper, we assess habit formation by examining the extent to which hedging behavior closely reflects past hedging behavior.

Prior behavioral studies of farmer hedging have investigated the effects of producer risk characteristics, structure of the production process, and information sources and availability on hedging. Here we investigate the effect of habit on a producer's hedge ratio (i.e., the proportion of an expected crop that has its associated price risk offset by the sale of futures contracts to establish a forward price), focusing on habit and the equity structure of the farm. We posit that habit formation will mean a slow adjustment by producers to changes in prices which impact the "optimal" amount hedged. In effect, habit may imply that factors commonly associated with hedging in the literature, such as risk perceptions (Pennings and Wansink, 2004), have only limited and indirect influence. We hypothesize that for some producers, habit plays a dominant role in arriving at their hedge ratios, and for these producers, many of the other factors identified in the literature to explain hedging behavior may not be relevant. An explanation for the importance of habit in the hedging decision may lie in the costs of establishing and adjusting market positions or could reflect farmers having expectations of harvest price that adapt slowly from year to year.

Despite the availability of information, hedging is often perceived to be a complex and costly activity (Pennings and Leuthold, 2000). For some producers who do not use futures contracts, this may imply that perceived costs are unacceptably high, negating any risk-reducing benefits associated with the hedge. For other producers who use futures contracts, once an acceptable level of risk management has been achieved, change requires not only transaction costs, but implicit costs associated with monitoring the market, and assessing the relative attractiveness of alternative market positions. For producers, these costs may limit their willingness to initiate and change their market positions, leading to a structure where previous positions—habit—affect current market positions.

Collins (1997) has argued that "hedging is motivated by a desire to avoid financial failure, rather than a desire to reduce income variability, and that differences in cost structure, profitability, and financial structure are what affect the likelihood of failure and hence cause the differences in hedging choices" (p. 498). This suggests producers with highly profitable enterprises that are less susceptible to financial failure will be less likely to use futures contracts for hedging purposes. In a similar vein, Turvey and Baker (1990) found that producers who are in a high debt position are more likely to use price risk management instruments. Here, we expect the structure of land ownership, as measured by the proportion of owned to total acres farmed, will provide a relevant measure of the producer's financial situation. We also include perceived farm profitability and farm income, as these factors may bear on the ability of the producer to avoid failure and hence affect

hedging. It is important to note the financial situation of a producer may not change dramatically over a given time period, suggesting it may be difficult to disentangle the effects of habit and financial pressure.

Finally, we incorporate a factor—the use of market advisory services—which may reduce some of the implicit costs of monitoring and assessing alternative market positions and hence mitigate a habit-hedging relationship. Pennings and Leuthold (2000) and Pennings and Garcia (2004) have demonstrated the importance of a farmer's decision-making unit on hedging decisions. In effect, producers are often influenced by the perceptions of those around them regarding the effectiveness of marketing instruments. In this case, we conjecture that producers who make use of a market advisory service will be more likely to change their market positions over time.

We note two related factors excluded from our model: crop insurance and government programs. Crop insurance is a complementary risk management tool and, depending on how farmers insured their crops, may play a role in influencing their hedging decisions. Cotton prices were low in both years in our study (averaging 33 cents per pound in 2001 and 47 in 2002). While the change in market price across years looks large enough to potentially change hedging strategies, in 2001 and most of 2002, the price stayed below the loan rate. Both of these factors might have some effect on keeping hedging strategies constant and could be ascribed in our model to habit. Given the minimal variability in prices and crop insurance program offerings within the state, we cannot address this issue further.

Heterogeneity and Our Model

Heterogeneity, the notion that individuals respond differently to the same economic stimuli, can have profound consequences for the interpretation of empirical evidence and hence for understanding revealed behavior (Heckman, 2001). In the hedging literature, the role of heterogeneity has been recognized by segmenting producers based on some observable variables such as farm size or age (e.g., Pennings and Leuthold, 2000). While accounting for heterogeneity using observable segmentation criteria may be helpful, this assumes producers within such segments behave in a similar way—which may not necessarily be the case. Behavior is the outcome of the producer's decision process. Hence, heterogeneity in behavior is driven by the heterogeneity in decision-making processes. We hypothesize that the decision-making process is reflected in the relationship between hedging and its determinants, and we take heterogeneity into account by segmenting producers based on that relationship using the procedure proposed by Pennings and Garcia (2004). This mixture model procedure classifies producers into segments based on whether they *respond* in a similar manner to the determinants of hedging behavior.

In our empirical analysis, these determinants are assumed to be: income, perceived profitability, hedge ratio in previous year (reflecting habit), proportion

of owned acres to total farmed acres (reflecting the producer's equity position), and use of consultants. Specifically, we seek to explain observed hedging decisions by regressing them against the above variables. This makes theoretical sense if those included regressors are important variables in the optimization problems being solved by the individual farmers when they make their hedging decisions. While each segment of farmers is therefore assumed to have similar or identical objective functions, objective functions should be expected to vary across segments.

The finance and agricultural economics literature discussed earlier suggest perceived farm profitability and farm income both influence the hedge ratio, often due to their effect on the perceived riskiness of the farm operation. We also have Collins' (1997) contention that hedgers are motivated by their desire to avoid financial failure. If we seek to measure a farmer's perception of financial failure (i.e., what is the probability my farm business could fail?) or the perceived riskiness of the farm, we need observable variables likely to be correlated with these unobserved subjective probabilities. We choose producer income, self-reported profitability of the farm business, and the producer's land ownership structure measured by the proportion of owned acres to total farmed acres as proxies for the farmer's perception of the probabilities of financial failure and operational risk. If these variables do indeed enter into the farmer's optimization problem as state variables (or correlate with something that does, such as the mentioned probabilities), then these variables should be correlated with producers' hedge ratios and be found significant in our regression model.

Further, based on the findings of Pennings et al. (2004), who showed that market advisory services influence producers' market behavior and producers using market advisory services tend to hedge more, we hypothesize that a farmer's use of such information sources can influence the hedge ratio employed by that farmer. Therefore, the use of consultants is also included in our mixture model as a potential explainer of observed hedging behavior.

Within a segment, the *influence* of these determinants on hedging is the same, while hedging is dependent on the *level* of these determinants. Operationally, estimation is based on the notion that each segment has a different econometric structure, which is estimated with the observations having the highest probability of conforming to that structure. In an economic context, the mixture method is attractive, because it separates producers into segments, so that within each segment the responses of its members to the determinants of hedging are similar.

Statistical Model

To address heterogeneity, we group producers based on the relationship between hedging behavior and its determinants, using a modeling procedure first proposed by DeSarbo and Cron (1988) and Wedel and DeSarbo (1995), and extended by Pennings and Garcia (2004) and Pennings, Garcia, and Irwin (2004). The mixture model groups producers so that the determinants of hedging have a similar

influence (i.e., the estimated regression coefficients) on behavior. Thus the procedure permits the determinants of hedging behavior to have a different influence on hedging for each group identified. The generalized mixture model framework allows us to simultaneously investigate the relationship between economic behavior and a set of variables for each unobserved group in the population, and at the same time identify these groups.

Mixture models assume a sample of observations arises from a number of underlying populations of unknown proportions; i.e., each data point is drawn from one of a set of distributions rather than all observations coming from the same data-generating process. A specific form is specified for each of the density functions, and the mixture model approach decomposes the sample into its components (separating observations into groups whose members all come from the same distribution).

Assume the measures on hedging [e.g., the dependent variable(s), which in our case is the employed hedge ratio] are indexed by $k = 1, ..., K$ for $j = 1, ..., J$ market participants. (In the empirical study which follows, hedging behavior is measured by a single variable, and hence $K = 1$.) The measurements are denoted by y_{jk}. We assume the market participants come from a population which is composed of a mixture of G unobserved groups, with relative sizes $\pi_1, ..., \pi_G$, where

$$\pi_g > 0 \quad \text{and} \quad \sum_{g=1}^{G} \pi_g = 1.$$

The distribution of y_{jk}, given that market participant j comes from group g, is from the exponential family of distributions and is denoted as $f_{jk|g}(y_{jk})$.[2] Given group g, the expectation of y_{jk} is denoted as ϑ_{gjk}. Within groups, these expectations are modeled as a function of the set of P ($p = 1, ..., P$) explanatory variables and the associated parameters β_{pg} in group g:

$$(1) \qquad\qquad\qquad L(\vartheta_{gjk}) = \sum_{p=1}^{P} x_{jkp}\beta_{pg},$$

where $L(\cdot)$ is the link function which links the expectations of the measurements to the explanatory variables. Within each identified group, β_{pg} is the same; however, across groups, it differs. The linear predictor is thus the linear combination of the explanatory variables and the set of parameters to be estimated. The linear predictor is in turn related to the mean of the distribution, μ_{gk}, through a link function $L(\cdot)$ whereby in group g:

$$(2) \qquad\qquad\qquad L(\vartheta_{gjk}) = L(\mu_{gjk}).$$

Thus, for each group, a linear model is formulated with a specification of the distribution of the variable (within the exponential family), a linear predictor ϑ_{gjk}, and a function $L(\cdot)$ that links the linear predictor to the expectation of the

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[2] The exponential family includes the normal, binomial, Poisson, and gamma distributions.

distribution. Since we assume the dependent variable in our application (the employed hedge ratio measured as the sum of the underlying value of hedged positions in relation to annual sales) is normally distributed, the canonical link is the identity $\vartheta_{gjk} = \mu_{gjk}$. By combining equations (1) and (2), the standard linear regression model within groups arises.

Then, the unconditional probability density function of an observation y_{jk} is given by:

$$(3) \qquad\qquad f_j(y_{jk} \mid \Phi) = \sum_{g=1}^{G} \pi_g f_{j\mid g}(y_{jk} \mid \boldsymbol{\beta}_g),$$

where $\boldsymbol{\beta}_g$ is a vector of the β_{pg}, and the likelihood for Φ is:

$$(4) \qquad\qquad L(\Phi; \mathbf{y}) = \prod_{j=1}^{J} f_j(\mathbf{y}_j \mid \Phi),$$

where $\mathbf{y}_j$ is the observation vector $\mathbf{y}$ of market participant j, and π_g is the relative group size. An estimate of Φ, the set of parameters that identifies the groups to which the market participants belong and the regression functions within groups, is obtained by maximizing the likelihood function (4) with respect to Φ subject to

$$\pi_g > 0 \quad \text{and} \quad \sum_{g=1}^{G} \pi_g = 1.$$

The parameters of the mixture model can be estimated using the method of moments or maximum likelihood (Hasselblad, 1969; Quandt and Ramsey, 1978; Basford and McLachlan, 1985). Since maximum likelihood has been shown to be superior for the estimation of the mixture, we use this method to estimate the parameters of the model in (4) (cf., Fryer and Robertson, 1972; Wedel and DeSarbo, 1995).

The likelihood function is maximized using the iterative expectation-maximization (EM) algorithm (Redner and Walker, 1984; Titterington, 1990). The two iterative steps to our EM algorithm are to take an expectation to decide which segment each observation is in and then to find the parameter values that maximize the likelihood function subject to the just-chosen segments. The expectation step involves calculating the posterior membership probabilities according to Bayes' rule and the current parameter estimates of Φ and substituting them into the likelihood. When the iterative solutions converge (i.e., stop changing), we have arrived at the solution. [See Wedel and Kamakura (1998) for the derivation of the EM algorithm.]

The actual number of groups is unknown and must be inferred from the data. We use Bozdogan's (1987) consistent Akaike's information criterion (CAIC) to determine the number of groups. The CAIC is defined as:

$$(5) \qquad\qquad CAIC = -2\ln L + (P * G + G - 1)(\ln(J) + 1),$$

where P is the number of explanatory variables, G is the number of groups, and J is the number of market participants. The number of groups that best represents the data is determined when the CAIC reaches a minimum.

For any set of groups, an entropy statistic (E_g) can be calculated to assess whether the groups are well separated (therefore, well defined). E_g is defined as:

$$(6) \qquad E_g = 1 - \sum_{j=1}^{J} \sum_{g=1}^{G} - \alpha_{gj} \ln(\alpha_{gj}) / J,$$

where α_{gj} is the posterior probability that market participant j comes from latent group g. The posterior probability can be calculated for each observation vector $\mathbf{y}_j$ with an estimate of Φ [e.g., equation (4)] by means of Bayes' theorem and is given by:

$$(7) \qquad \alpha_{gj}(\mathbf{y}_j, \Phi) = \frac{\pi_g \prod_{k=1}^{K} f_{jk|g}(y_{jk} \mid \boldsymbol{\beta}_g)}{\sum_{g=1}^{G} \pi_g \prod_{k=1}^{K} f_{jk|g}(y_{jk} \mid \boldsymbol{\beta}_g)}.$$

The entropy statistic E_g in (6) is a relative measure, bounded between 0 and 1, and describes the degree of separation in the estimated posterior probabilities. E_g values close to 1 indicate the posterior probabilities of the respondents belonging to specific groups are close to either 0 or 1; the groups are well defined. E_g values close to 0 indicate that the groups are not well defined.

Data

Data were collected by a mail survey of large-scale farmland owners in Georgia. We defined large-scale farmers by requiring a minimum of 300 owned acres. This requirement assured responses from farmers with enough production to make the futures markets easily accessible without worrying about the size of contracts. The survey was pretested on a sample of 252 farmland owners. Fifty-three usable surveys were returned and no serious problems were discovered in the survey design. The survey was then mailed to 1,250 farmland owners (again with the minimum of 300 acres owned) throughout the state of Georgia, using a random sample drawn by the Georgia Agricultural Statistics Service. The total population of such farms was estimated at about 9,100 in 2002, so the survey was mailed to a fairly large proportion of the targeted population. The original mailing was in May 2003, followed by a second mailing to increase the response rate. In the end, 497 surveys were completed and returned. Forty-two surveys were excluded from the sample as the producer no longer met the sample qualifications. This reduced the effective sample to 1,208, giving a final response rate of 41.1%.

The survey collected basic demographic information, along with information on the commodities produced, the acres owned and rented, future expectations related to expansion and profitability of the farm, and data on hedge ratios for several

commodities. No follow-up was performed after the second mailing, but sample means of demographic variables in the survey for the 497 respondents were compared to state averages from past mandatory surveys of Georgia cotton farmers by the Georgia Agricultural Statistics Service and no significant deviations were found. Hence, the survey responses do not appear to suffer from any important nonresponse or selection bias.

Here we focus on the largest sample of responses on hedging, which was for cotton, an important commodity in Georgia. We use only those producers from whom we had information on all the variables of the conceptual model. A total of 72 producers met that criterion.

The hedging ratios used for the dependent variable and the lagged hedging variable (to measure habit effects) are the percentage of cotton crop hedged in 2002 and 2001, respectively. Farmers were simply asked to report on the survey "the percent of your estimated production that you hedged in each year." Thus, this is pre-harvest hedging, as opposed to post-harvest, storage-related hedging. Zeros were included as valid responses; blanks in one year were treated as zero hedging, but blanks in both years were treated as a nonresponse. Explanatory variables created from the survey were as follows. Producer income is reported as being in one of a list of provided ranges (shown in table 1). The perceived profitability of a farm, as self-reported by the survey respondent, was coded as 1 = losing money, 2 = breaking even, and 3 = profitable. Use of consultants is a dummy variable equal to 1 if consultants were used. Finally, proportion of owned land is simply owned acres divided by total acres farmed. Summary statistics for these variables are reported in table 1.

For our sample, the average producer's age was 50.8 years, and on average, 78% of the land farmed was owned by the producer. Producers had an average hedge ratio of 43.8% in 2002 and 40.8% in 2001. The statistics on the hedge ratios reveal that producers in our sample are relatively more involved in hedging than producers studied in previous investigations (e.g., USDA/Economic Research Service, 1996; Anderson and Mapp, 1996). Table 1 reconfirms the important role played by consultants in producers' marketing decisions (Pennings et al., 2004).

Results

An Aggregate Model

We first estimated a model imposing homogeneity (i.e., only one segment of producers; $G = 1$). The hedge ratio employed in 2002 is the dependent variable and the producers' income, perceived profitability of the farm, hedge ratio in 2001, use of consultants, and the proportion of owned acres to total farmed acres are the independent variables. The results are presented in table 2.

Table 1. Sample Descriptive Statistics of Georgia Cotton Growers ($N = 72$)

Description	Mean	Median	Std. Deviation
Proportion of owned acres to total farmed acres	0.78	0.54	0.92
Hedge ratio in 2002	43.8%	50.0%	37.5%
Hedge ratio in 2001	40.8%	34.0%	35.8%
	Use	Do Not Use	
Use of consultants	65.3%	34.7%	
	Profitable	Breaking Even	Losing Money
Perceived profitability of farm	58.3%	34.7%	7.0%
Percentage of producers in income class	< $15,000 0%	$15,000–$30,000 9.7%	$30,000–$45,000 16.7%
	$45,000–$60,000 16.7%	$60,000–$75,000 12.5%	$75,000–$90,000 13.9%
	$90,000–$120,000 8.3%	> $120,000 22.2%	

Table 2. Explaining Employed Hedge Ratio in 2002: Aggregate Regression Model Estimates

Variable	Regression Coefficient	Standard Error
Producer income	0.001	0.015
Perceived profitability of farm	−0.054	0.047
Hedge ratio in 2001	0.801*	0.073
Proportion of owned acres to total farmed acres	0.051	0.028
Use of consultants	0.057	0.055
Intercept	0.108	0.135

Log likelihood = 7.405
CAIC = 22.127
$R^2 = 0.397$

Note: An asterisk (*) denotes $p < 0.05$.

The aggregate model has an R^2 of 0.397, which is quite good for cross-section data and such a small number of regressors. Table 2 shows that only the hedge ratio in the previous year is significantly related to the employed hedge ratio. Given that the hedge ratios in 2001 and 2002 are in the same units, complete habit formation in choosing a hedge ratio would yield a coefficient of 1.0 on the 2001 hedge ratio. The actual result is an estimated coefficient of 0.8, slightly less than 1.0 but still quite large, indicating the producers' hedge decisions are mainly driven by habit with a small amount determined by unknown or random factors.

Mixture Model Results

To examine if the influence of the independent variables in our model differs across groups of producers, we next estimated the mixture model, allowing different segments of producers. To calculate the number of segments in our data, models were estimated for different numbers of segments with the optimal number of segments estimated using a model fit criterion. We estimated models with up to five segments ($G = 1$ to $G = 5$), and used the minimum CAIC statistic to select G. Note that as the number of segments increases, the total number of model parameters increases, so fit is expected to increase with G; however, the CAIC statistic includes a penalty for the number of parameters in order to discourage overfitting. The log likelihoods, corresponding CAIC, and the entropy E_g and R^2 statistics for these five specifications are listed in table 3. Based on the minimum CAIC statistic, we selected $G = 2$ as the appropriate number of segments. This solution has the second highest E_g statistic, which measures how confidently the model classifies observations into categories (E_g when $G = 3$ is slightly higher). The E_g value of 0.82 indicates the mixture components are well separated or defined, i.e., the posteriors are close to 1 or 0. Table 4 presents the estimated coefficients for this two-segment solution.

The results of the two-segment solution demonstrate the existence of multiple producer segments with different relationships between hedging behavior and its determinants. In segment 1 ($g = 1$), which contains 35.5% of the producers, perceived profitability and proportion of owned acres to total farmed acres are driving the hedge ratio employed. This finding confirms Collins' (1997) assertion that hedging is driven by the farm equity structure for at least a significant segment of producers. If the proportion of owned acres to total farmed acres increases, the hedge ratio decreases.

Further, we find a positive relationship between perceived profitability and the percentage hedged. This result may sound counterintuitive, as one might argue that nonprofitable producers would have a lower risk tolerance and hence would hedge more. However, this result may represent a differentiation between commercial and hobby farmers. Also, the result matches a finding reported in Harwood et al. (1999, p. 59) that producers in the highest income class are the most likely to use forward contracting and all other forms of risk management. Interestingly, in this segment, habit plays virtually no role. These findings contrast with those for the second segment, consisting of 64.5% of the producers. Hedging behavior is solely driven by habit, with its estimated coefficient not differing statistically from 1 and all other coefficients not differing from 0. These results confirm that the influence of the drivers of hedging is different across producers and suggest a large proportion of cotton producers determine their hedge ratio completely by habit. Also, note that the estimated parameters in table 4 when compared to the results reported in table 2 show the aggregate model clearly suffers from aggregation bias. Imposing homogeneity—forcing similar parameters for all producers—leads to biased estimates not equal to a weighted average

Table 3. Fit Statistics of the Mixture Models for the Segments *G* = 1 to *G* = 5

Segments *G*	Log Likelihood	CAIC	E_g	R^2
1	7.405	22.126	—	0.397
2	69.624	−90.099	0.819	0.694
3	81.318	−41.273	0.838	0.914
4	88.408	−13.239	0.581	0.975
5	97.634	10.521	0.786	0.989

Notes: CAIC is the consistent Akaike's information criterion; E_g is the entropy statistic.

Table 4. Mixture Regression Results for the Two-Segment Model

	Segment	
Variable	*g* = 1	*g* = 2
Producer income	−0.043	−0.001
	(0.033)	(0.003)
Perceived profitability of farm	0.300*	−0.009
	(0.117)	(0.008)
Hedge ratio in 2001	0.271	0.965*
	(0.214)	(0.097)
Proportion of owned acres to total farmed acres	−0.254*	−0.000
	(0.075)	(0.005)
Use of consultants	−0.131	0.006
	(0.124)	(0.011)
Intercept	−0.268	0.015
	(0.255)	(0.023)
Relative segment size π	0.355	0.645
Hedge ratio in 2002	45.2%	43.1%

Note: An asterisk (*) denotes $p < 0.05$.

of the coefficients in the mixture model and also masks the significance of nonhabit determinants of hedging behavior.

Finally, at the bottom of table 4, note the hedge ratios employed in 2002 are nearly identical across the two segments. This finding suggests that the difference uncovered is truly habit, not something else such as different risk-aversion levels. While extremely high or low risk aversion could produce hedge ratios that were consistent across years (at values either near 0 or 1), such risk-aversion differences cannot produce moderate hedge ratios as exemplified by those seen here.

To gain further insight into the process used by producers to arrive at their hedge ratio, we profiled the two segments with respect to the producers' self-reported methods of forming a hedging strategy. Table 5 reports the results.

Table 5. Comparison Statistics for the Two Segments

	Segment	
Description	$g = 1$	$g = 2$
Producer's Method of Choosing Hedge Ratio: [a]		
Habit	8.3%	0.0%
Market consultant's recommendation	12.5%	37.5%
Talking to other producers	4.2%	10.4%
Doing my own analysis of the market	54.2%	33.3%
Change in Hedge Ratios:		
Average hedge ratio in 2001	35.95%	43.21%
Average absolute change in hedge ratio, 2002–2001 [b]	33.66%	11.68%
Producer Characteristics (segment average):		
Income class	5.75	4.90
Profitability class	2.54	2.50
Acres owned	1,396.9	1,087.2
Acres farmed	2,129.6	1,807.1
Acres owned / acres farmed	0.731	0.802

[a] Percentages for producers' methods of choosing hedge ratios do not sum to 100% because of non-respondents to this question. Multiple responses were also allowed.

[b] The average absolute change in hedge ratio is significantly different between the two segments using a t-test for differences in the mean ($p = 0.000$).

As observed from table 5, producers in segment 1 claim to conduct their own analysis. This is congruent with the fact that in this segment habit does not play a role, but instead the producers' perceived profitability of the operation and the producers' equity structure drive their hedge decisions. Interestingly, in segment 2, the segment in which habit as reflected in the previous year's hedge ratio almost exclusively drives hedging behavior, producers indicate they mostly use consultants and their own analysis to arrive at their hedge ratio instead of habit. Either consultants recommended the same hedge strategy in both years or these producers are deluding themselves. Market conditions were fairly different in 2001 and 2002, so the consultant recommendations are unlikely to have remained constant, meaning it is most likely producers are reticent to admit they just repeat what they did last year. Thus, segment 2 producers are hedging based on habit (as shown in table 4), but do not want to admit to such nonoptimal behavior. It is also possible that when these producers "do their own analysis," their analysis tends to lead them to the same hedging strategy each year. Table 5 also shows that producers differ with respect to the extent to which they change their hedge ratio during the period 2001–2002. Producers in segment 1 changed their hedging ratios (in terms of absolute changes) significantly more (33.66% versus 11.68%) than producers in segment 2, both in statistical (by a t-test) and economic senses. This finding validates the result that the hedging ratio in segment 2 is driven by

habit. In terms of some standard farm characteristics, the two segments are quite similar, confirming it is hedging behavior that is being used to separate our segments, not some other variable in the model.

Conclusions

The results of this study reject the assumption of homogeneity, i.e., the assumption that the influence of the factors driving the hedge ratio is similar for all producers. The generalized mixture regression model identifies two segments. For producers within each segment, the *influence* of the determinants on hedging behavior is the same, and the hedge ratio employed is dependent on the level of the determinants.

In the first segment, consisting of 35% of the sample, the previous year's hedge ratio does not drive the current hedge ratio employed. Instead, the producer's equity structure as reflected in the producer's land ownership plays an important role in choosing the hedge ratio, confirming Collins' (1997) hypothesis. In addition, the producer's perceived profitability has a large impact on the chosen hedge ratio, with producers who consider themselves profitable having higher hedge ratios. In the second segment, consisting of 65% of our sample, this year's hedge ratio is determined almost completely by last year's hedge ratio, i.e., by habit. Other factors, such as income, land ownership structure, and perceived profitability, do not drive the employed hedge ratio. This result confirms the important role of habit formation in understanding producers' employed hedge ratio.

Curiously, the observed hedge ratio does not differ significantly between the two segments. Consequently, investigating differences in hedge ratios employed would not reveal these differences in the hedging motivation of producers. While different factors influenced their decisions, on average, the two segments of producers arrived at the same proportion of the crop hedged.

Several questions emerge from our findings that need to be addressed in future research. Why does a large group of producers rely on habit, implying their hedge ratio changes extremely slowly over time? One of the reasons may be that hedging is perceived as a complex activity (e.g., Pennings and Leuthold, 2000) and that the costs associated with using sophisticated methods are too high for producers. Interestingly, our results indicate that while a large group of producers rely on habit, the producers in this group do not want to acknowledge it. When asked directly about the procedure they use to arrive at the hedge ratio, these producers did not list habit among the methods used.

Future research examining the cost of arriving at a hedge ratio and the role of habit is warranted. In addition, future research may assess the relationship between the obtained hedging effectiveness and the hedging strategy used to arrive at the hedge ratio. In the context of this study, this would mean comparing the actual hedging effectiveness between segments 1 and 2. Finally, the finding of a positive relationship between perceived income and hedging in segment 1 raises an interesting question: Is the hedge ratio driving perceived profitability or vice

versa? Only a longitudinal panel research design can answer this question. Such a research design would permit an investigation of how changes in perceived income and in hedge ratio change are related dynamically.

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