Potential Farmer Adoption of High Available Phosphorus Corn over a Three-year Period

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Corn containing high levels of available phosphorus (HAP) allows poultry to use more of the phosphorus they consume and could potentially reduce contamination of water from run-off. This study uses a conjoint analysis survey of Delmarva corn growers to model adoption of hypothetical HAP varieties over a three-year period. An optimal variety has a low technology fee and yield drag and a high harvest premium. Adoption of HAP corn increases during the period although growers' tolerance of technology fees and yield drags diminishes over time. Adoption is further affected by farm size, farmer age, and the portion of income from corn.

Key Words: chicken, conjoint analysis, corn, genetically modified, phosphorus pollution

Water pollution from agricultural sources is an environmental concern around the world. In the United States, according to the Environmental Protection Agency (EPA), agriculture was the leading source of impairment to rivers and streams; it accounted for approximately 38 percent of the pollutants and was the third leading source in lakes, ponds, and reservoirs (EPA 2004a). Among agricultural source pollutants, phosphorus is notable. Excess phosphorus (combined with nitrogen) can lead to heavy algal growth and eutrophication, thus reducing oxygen and causing fish kills. Some algal blooms, such as red tides, are directly toxic to aquatic ecosystems and to human beings. From an economic standpoint, nutrient-polluted waterbodies lead to losses of nearly $1 billion per year in the tourism industry (EPA 2012a) and millions are lost annually in the commercial fishing and shellfish industry because of low oxygen levels from algae blooms.

Agricultural sources of phosphorus pollution include manure and applications of artificial fertilizer. One of the greatest concerns is concentrated animal feedlot operations (CAFOs). They are of special concern because they tend to concentrate large amounts of nutrients in a small area because of the sheer volume of the operation, generating manure run-off and/or discharges to surface and ground waters. In 2004, EPA estimated that 53 percent of the U.S. population relied on ground water for drinking water (EPA 2004b). Thus, CAFOs' potential for contamination coupled with odor from manure has led to increased public complaints as the number of such facilities has grown.

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In Delaware and Maryland, which have large chicken-producing industries, at least 65 percent of the operations are considered CAFOs.[1] Using manure from these operations regionally as fertilizer could lead to agricultural fields being overfertilized, causing excess phosphorus from those fields to wind up in surface waters (Ribaudo et al. 2003).[2] Phosphorus was listed as the number one pollutant in terms of water-quality cases in Delaware and number seven in Maryland (EPA 2006), a situation that has led to regulations, including the Delaware Nutrient Management Law in 1999 (Delaware Department of Agriculture 2007) and similar legislation passed shortly thereafter in Maryland (University of Maryland 2006). These regulations restrict many procedures used in chicken production, such as applying fertilizer, planting of cover crops and vegetative buffer strips, and erosion control.

CAFOs also face increasing federal regulation by EPA to control phosphorus and nitrogen run-off (NASS 2007a, 2007b). One such regulation requires CAFOs to create certified nutrient management plans (NMPs). The plans establish a rate of manure application for each field, and producers are allowed to apply manure only if the rates of deposition of nitrogen and phosphorus meet the nutrient needs of current or proposed crops. Similarly, manure applications may be limited or even banned for fields that have a significant potential for phosphorus loss. In response, many farmers have adopted phosphorus-limiting nutrient planning programs. Instead of using readily available chicken manure, they have been applying more-expensive nitrogen-only sources of fertilizer (e.g., ammonia or urea). Meanwhile, the poultry industry has had to turn to relatively expensive manure disposal outlets.

While NMPs can be effective, they can also be expensive, ultimately requiring many farmers to seek help from the few financial assistance programs available. To reduce the cost of the NMPs, producers often substitute crops that have a greater tendency to produce run-off (Bonham, Bosch, and Pease 2006), which increases their use of phosphorus and allows them to use larger applications of manure. In some areas, farmers have increased their total number of crop acres in production and thus generated additional water pollution (Norwood and Chvosta 2005).

Due to the high costs and unintended consequences of current solutions, chicken producers are seeking ways to reduce the phosphorus content of chicken manure. The focus has been on corn fed to chickens since it is a primary component of chicken feed and a major source of phosphorus in manure. Much of the phosphorus in corn is in a form called phytic acid, or phytate, that chickens cannot digest. Hence, it ends up in the manure and farmers have to supplement the chickens' diet to meet their phosphorus needs. If the phosphorus in phytic acid could be digested, producers could reduce the amount of phosphorus in the manure and phosphorus supplementation of the diet. The current practice is to add an enzyme, phytase, to the diet to break down phytic acid into usable phosphorus; Smith et al. (2004) estimated that this reduced phosphorus in chicken manure by 10 percent.

A more effective and innovative approach would be to feed the chickens corn that provides a high level of available phosphorus (HAP). The corn can be either low in phytate or high in phytase (Raboy 2009). Either one could simplify diet

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[1] In the chicken industry, CAFOs consist of either 125,000 or more broilers or 30,000 broilers when the operation uses a liquid manure-handling system (Koelsch 2003).

[2] EPA (2012b) estimated that recoverable manure phosphorus exceeded crop production requirements in 485 of the 3,141 counties in the United States.

preparation and, ideally, reduce the producers' costs by decreasing the need for dietary supplements. Cost in particular has been noted as one of the main issues with the current approach, particularly in developing countries (Gao et al. 2012). Development of a HAP corn, however, has presented challenges (for a discussion, see Raboy (2009)). In an early effort, Raboy and Gerbasi (1996) developed a low phytate corn from a mutation that reduced the amount of phytic acid. When used as chicken feed, this variety of corn reduced the amount of dissolved phosphorus in the litter (Saylor et al. 2002, Smith et al. 2004) but also suffered from substantial yield drag and lacked other traits important to corn producers, such as disease resistance (Raboy et al. 2001). A more phytase-transgenic corn developed recently in China appears to have more potential (Gao et al. 2012). While genetic engineering techniques appear to offer the greatest potential (Swiatkiewicz and Arczewska-Wlosek 2011), work continues on several other methods of developing HAP corn.

The issue for this study then is identifying attributes that a HAP corn would need to have for farmers to adopt it. Unlike genetically modified (GM) varieties such as Bt corn that provide a direct benefit to the farmer in terms of pest resistance, HAP corn may involve extra costs, such as technology fees for GM versions and the possible need to segregate crops. Consequently, producers may need to receive a price premium to adopt HAP corn. Furthermore, since HAP corn is a new product, producers may be cautious about adopting it. Thus, the main objective was to examine the effect of the price of HAP technology, the degree of yield drag expected, and the amount of any harvest premium on adoption of HAP corn over a three-year period for corn producers on the Delmarva Peninsula, which consists of the entire state of Delaware, counties in Maryland between Chesapeake Bay and the Atlantic Ocean, and two counties in Virginia between the bay and the Atlantic that make up the peninsula's southern tip. In addition, the study analyzed the effect of demographic and farm characteristics on adoption. A secondary objective was to determine farmers' knowledge of and concerns about phosphorus and their attitudes toward GM crops.

Survey Design

A survey was mailed to approximately 2,000 farmers on the Delmarva Peninsula.[3] The survey was conducted in conjunction with the National Agricultural Statistics Service (NASS), which gave farmers a greater assurance of confidentiality and allowed access to NASS's detailed mailing list so that the survey could be sent primarily to corn growers.

Since low response rates are common for surveys of farmers, extra care was given in administering the survey. It was mailed in February 2007, before farmers would be busy in the fields, as Pennings, Irwin, and Good (2002) found that the time of year in which a survey is conducted is crucial to farmers' likelihood of participating. A dollar was enclosed with the survey as a token of appreciation, and several points of contact were used per Dillman (2000). Participants first received a postcard in late January announcing the survey. A week later, they received a packet in the mail that included the survey, a cover letter, a business-reply envelope, and the dollar incentive. One week later,

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[3] In designing the conjoint study and other aspects of the survey, a focus group that included Delaware farmers and Cooperative Extension personnel was conducted. A copy of the survey is available on request.

a reminder postcard was sent to participants who had not yet returned the survey. Given the approaching planting season, no further mailings were sent.

After undeliverable surveys and respondents who considered themselves as not qualified to participate were accounted for, the response rate was 38.91 percent (740 of 1,902). A comparison of the distribution of farm sizes in the survey to similar distributions from NASS records showed that larger farms were over-sampled, which is common. It was not possible to check the distributions of age and education level. The model incorporated demographic characteristics of farm size, education level, and farmer's age.

Conjoint Design

Bernard, Pesek, and Fan (2004a, 2004b) found that farmers readily responded when asked to identify the percentage of acres they would be planting with Roundup Ready® soybeans over a period of years. Consequently, it was decided to use a percent allocation approach for this analysis. This decision was supported by the idea that the choice-based conjoint analysis could then be presented in a format that closely reflected the process typically used by farmers when making planting decisions. To our knowledge, this is the first time that a choice-based conjoint study has used a percent allocation method to elicit farmer preferences for various crops.

The survey presented participants with various product profiles representing hypothetical HAP corn varieties, and the participants were asked to consider all other attributes of these HAP corn varieties to be identical to corn varieties they normally chose. Purchasing and pricing corn seeds are intricate processes because of the wide assortment of varieties available, which are differentiated by many agronomic characteristics and available with several value-added traits and technologies. Treating all of the other attributes as consistent with their previous selections simplified the scenarios presented.

Each corn profile consisted of three attributes—technology fee, yield drag, and price premium—at various levels, and participants were asked to estimate the percentage of corn acres they would be willing to plant to that HAP variety each year for three years, starting when it was first introduced. The HAP technology fee was chosen because many new varieties (especially GM varieties) are subject to a technology fee to recover the cost of its research and development. Yield drag is a common side effect of including a new trait and has been found for some experimental HAP varieties. Premiums can be used to provide an incentive for producers when customers want them to grow varieties that benefit the customer rather than the farmer. The number of years since being available in the market was included to assess adoption trends over time.

Since responses to the attributes were expected to be nonlinear, the survey presented three levels of each attribute to estimate quadratic effects. The fees for the HAP technology were $0, $15, and $30 per bag of seed and reflected typical technology fees according to a confidential industry source. The crop premiums were $0.00, $0.20, and $0.40 cents per bushel of corn. The values were based on premiums for value-added traits provided by the U.S. Grains Council (2002). The yield drags were 0.0, 2.5, and 5.0 percent and were based on previous work on HAP corn by Raboy and Gerbasi (1996) and Raboy et al. (2001).

Three years was a reasonable period over which to study adoption of a crop. Several years typically are needed since many producers are cautious and want to evaluate a new product's performance before deciding. Using more than three years would have resulted in a larger number of profiles than farmers would typically evaluate. The survey asked participants to assume that their expectations of a product were met each year to limit the analysis to adoption of an effective variety. This design allowed for assessment not just of feasible varieties of HAP corn but also of the ability to model the adoption path of each variety over three years.

In the model, interactions between several attributes were assumed since the impact of the costs and benefits could change over time: year and technology fee, year and premium, and year and yield drag. The D-optimal design (Atkinson and Donev 1992) generated eight profiles. To avoid respondent fatigue, the profiles were blocked into two sets of four profiles each for HAP fee, premium, and yield drag to be evaluated over the three-year period. The SAS OPTEX procedure was used to produce the final design (SAS 2011b). Table 1 presents the eight profiles and Figure 1 provides a sample profile and instructions as they appeared in the survey.

A GM attribute was not included since GM corn has already been widely adopted. According to the U.S. Department of Agriculture (USDA) Economic Research Service (ERS), approximately 70 percent of the corn planted in the United States in 2010 consisted of GM varieties (ERS 2011). GM crops have met with opposition from producers only when there has been significant concern that the product would be rejected in the market, which occurred with herbicide-resistant wheat and insect-resistant potatoes; use of those products was halted due to fear of consumer objections (Stokstad 2004). As a check, a survey question asked whether farmers preferred a non-GM HAP corn, preferred a GM HAP corn, or were indifferent; 58.99 percent of the respondents were indifferent, 30.22 percent preferred a GM HAP corn, and only 10.79 percent preferred a non-GM version.

Model

The farmer's percentage of acres devoted to HAP corn was modeled as a function of the design attributes, the demographic characteristics, and the interactions between them. The first and last of the categories were the primary elements of interest in determining how various types of farmers responded to the attributes. Since this approach created the potential for a large model, likelihood ratio tests were used to eliminate demographic characteristics and interactions for which farmer responses were found to be homogeneous.

Table 1. Seed Variety Profiles for the Conjoint Design

Profile	Block	Yield Drag (percent)	Premium (dollars per bushel)	Technology Fee (dollars per bag of seed)
1	1	0.0	0.20	30
2	1	2.5	0.40	0
3	1	2.5	0.20	15
4	1	5.0	0.00	15
5	2	0.0	0.00	0
6	2	0.0	0.40	15
7	2	2.5	0.00	30
8	2	5.0	0.20	0

16) Each of the HAP corn scenarios gives the additional cost per bag of seed, the expected yield drag, and the premium offered per bushel. For each, consider what percentage of your corn acreage you'd be willing to plant the first year HAP corn is available. Assuming each HAP variety met your expectations the previous year(s), please also estimate what percentage of your corn acreage you would plant HAP the second and third year it was available.

#1: Predicted Outcome of HAP Corn
The HAP trait is available at an additional cost of $30 per bag of seed in your usual corn variety without a yield drag. You are offered a premium of 20¢/bushel for HAP corn.

Percentage of corn acreage you'd plant HAP on

Year 1 ______%
Year 2 ______% } Assume HAP corn met your expectations previous year(s)
Year 3 ______%

Figure 1. Sample HAP Corn Profile with Instructions

Since percent of acreage planted with HAP corn was restricted between zero and one hundred for each profile, a two-limit Tobit model was necessary to account for the presence of both upper and lower censoring of the dependent variable. A larger issue was the potential for heteroskedasticity, which would lead to inefficient estimates in Tobit, probit, and similar models (Haefele and Loomis 2001). A model similar to the one in Bernard, Pesek, and Pan (2007) was therefore fitted to estimate the variance as a function of the attributes and demographic variables.

For the two-limit Tobit model, it is assumed that a latent variable y^* represents the farmer's potentially unobservable preference for a profile (Rosett and Nelson 1975). For example, a farmer might give a product with a highly undesirable attribute such as a high technology fee an internal negative value that can be observed only as 0 percent adoption of HAP corn. This type of latent variable is often used in rating-based conjoint analyses because predicting the rating is not particularly useful. Here, it is useful to predict the percentage of adoption of HAP corn.

The observed percent adopted, y, is related to y^* by

$$y_I = \begin{cases} \tau_L & \text{if } y_I^* \le \tau_L \\ y_I^* = \mathbf{x}_I\boldsymbol{\beta} + \varepsilon_I & \text{if } \tau_L < y_I^* < \tau_U. \\ \tau_U & \text{if } y_I^* \ge \tau_U \end{cases} \tag{1}$$

In this general form, τ_L is the lower limit (0 percent), τ_U is the upper limit (100 percent), $\mathbf{x}_I$ represents a vector of relevant independent variables, and $\boldsymbol{\beta}$ is a vector of coefficients. The error term ε_I is independent and normally distributed with mean zero and variance $\sigma^2(\exp(\mathbf{z}_I\boldsymbol{\gamma}))$ where $\mathbf{z}_I$ represents a second vector of relevant independent variables, $\boldsymbol{\gamma}$ is a second vector of coefficients, and σ^2 is the variance when $\mathbf{z}_i\boldsymbol{\gamma}$ is zero.

To predict the observed percent of acres planted, it is necessary to elaborate on the model. Following Long (1997), let

$$\phi(x) = (1 / \sqrt{2\pi})\exp(-x^2 / 2)$$

be the density of the standard normal distribution,

$$\Phi(x) = \int_{-\infty}^{x} \phi(t)dt$$

be its cumulative distribution function, $\mu = x\beta$ be the predicted latent variable, and $\sigma^2 = \exp(z\gamma)$ be the predicted variance. Furthermore, let $\delta_L = (\tau_L - \mu) / \sigma$ and $\delta_U = (\tau_U - \mu) / \sigma$ be the standardized upper and lower limits and

$$(2) \qquad f_T(x) = \begin{cases} 0 \text{ if } x \leq \tau_L \\ 1 / (\Phi(\tau_U) - \Phi(\tau_L))\ \phi((x - \mu) / \sigma) \text{ if } \tau_L < x < \tau_U \\ 0 \text{ if } x \geq \tau_U \end{cases}$$

be the density of the standard normal distribution truncated at τ_L and τ_U. It is known (Johnson and Kotz 1970) that

$$\mu_T = \mu + \sigma \frac{\phi(\delta_L) - \phi(\delta_U)}{\Phi(\tau_U) - \Phi(\tau_L)}$$

is the mean and that

$$\sigma_T^2 = \sigma^2 \left[1 + \frac{\delta_L\phi(\delta_L) - \delta_U\phi(\delta_U)}{\Phi(\tau_U) - \Phi(\tau_L)} - \left\{ \frac{\phi(\delta_L) - \phi(\delta_U)}{\Phi(\tau_U) - \Phi(\tau_L)} \right\}^2 \right]$$

is the variance of the truncated normal distribution, which is a stepping stone to the censored normal distribution defined by its cumulative distribution function:

$$(3) \qquad F_C(x) = \begin{cases} 0 \text{ if } x < \tau_L \\ \Phi((x - \mu) / \sigma) \text{ if } \tau_L \leq x < \tau_U. \\ 1 \text{ if } x \geq \tau_U \end{cases}$$

This distribution has a mass of $\Phi(\delta_L)$ at τ_L and of $\Phi(-\delta_U)$ at τ_U. If it is conditioned to the interval $\tau_L < x < \tau_U$, the truncated normal is obtained. The censored normal is the distribution of y. All of the values of the latent variable that fall at or below τ_L are concentrated at τ_L while all of the values of the latent variable that fall at or above the upper limit are concentrated at τ_U. To predict the percent of acres planted with HAP corn, the mean and variance of the censored variable are needed:

$$\mu_C = \tau_L \Phi(\delta_L) + \tau_U \Phi(-\delta_U) + \big(\Phi(\tau_U) - \Phi(\tau_L)\big)\mu_T$$

and

$$\sigma_C^2 = \big(\Phi(\tau_U) - \Phi(\tau_L)\big)\big(\sigma_T^2 + (\mu_T - \mu_C)^2\big) + \Phi(\delta_L)(\tau_L - \mu_C)^2 + \Phi(-\delta_U)(\tau_U - \mu_C)^2.$$

The formula for the mean is found in Long (1997) and a derivation of the variance formula is provided in an appendix available from the authors (a one-limit result is found Greene (2008)).

Hypotheses

A priori hypotheses were used to construct the initial variables of the vector **x**. With respect to the profile attributes, the HAP technology fee was expected to be negatively correlated with the percent of acres planted with HAP corn. Similarly, yield drag was treated as a cost and thus was expected to reduce the percent of acres of HAP corn planted. A premium for HAP corn was expected to be positively correlated with the percent of acres planted. Since the respondents were to assume that their expectations of each type of corn were met each year, percent of acres planted for each type of corn was expected to increase over time. The interactions between year and both fee and yield drag were expected to be negative while the interaction between year and premium was expected to be positive.

As previously mentioned, demographic characteristics of farm size, farmer age, and farmer education were included as variables in the model. Previous studies have shown that these characteristics can influence adoption decisions (e.g., Harper et al. 1990, Payne, Fernandez-Cornejo, and Daberkow 2003, Bernard, Pesek, and Fan 2004a, 2004b, Fernandez-Cornejo, Hendricks, and Mishra 2005) and that including the characteristics as variables can correct for potential selection bias (Dumouchel and Duncan 1983). Another variable included in the initial model was the percent of the farmer's income that came from corn production; it seemed likely that decisions about using HAP corn would be relatively unimportant for participants who grow little corn of any kind and quite significant for participants who grow mostly corn.[4] All of these variables could have affected the variance and were tested for inclusion in the model but no specific hypotheses were made regarding their signs.

Participants who had more than 4,000 acres, had less than 100 acres, and/or received 20 percent or less of their income from corn production were removed from the sample.[5] The final model was specified as

$$(4)\quad y_I^* = \beta_0 + \beta_1 Block_i + \beta_2 HAPfee_i + \beta_3 HAPfee_i^2 + \beta_4 Premium_i + \beta_5 Premium_i^2 + \beta_6 YieldDrag_i + \beta_7 YieldDrag_i^2 + \beta_8 Year_i + \beta_9 HAPfee_i \times Year_i$$

[4] Initially, concern about phosphorus pollution was included in the model since farmers who were relatively concerned about that kind of pollution might have a greater willingness to plant HAP corn. However, tests showed that this factor was not significant. Economic considerations likely tend to be more important to farmers than environmental concerns.

[5] The small number of large farms made effective estimates impossible, and the extremely small farms in terms of acres were unlikely to be economically relevant or important to the potential success of HAP corn, especially given the minute percentage of acreage they represented. While this means that interpretation of the results does not apply directly to the groups, it does apply to the vast majority of farms in the study area.

$$+ \beta_{10}Premium_i \times Year_i + \beta_{11}YieldDrag_i \times Year_i + \beta_{12}FarmSize_i$$
$$+ \beta_{13}HAPfee_i \times FarmSize_i + \beta_{14}HAPfee_i^2 \times FarmSize_i$$
$$+ \beta_{15}Premium_i \times FarmSize_i + \beta_{16}FarmSize_i^2 + \beta_{17}HAPfee_i \times FarmSize_i^2$$
$$+ \beta_{18}Age_i + \beta_{19}Year_i \times Age_i + \beta_{20}Age_i^2 + \beta_{21}SomeColl_i$$
$$+ \beta_{22}HAPfee_i \times SomeColl_i + \beta_{23}Premium_i \times SomeColl_i$$
$$+ \beta_{24}YieldDrag_i \times SomeColl_i + \beta_{25}CornIncome_i$$
$$+ \beta_{26}HAPfee_i \times CornIncome_i + \beta_{27}HAPfee_i \times CornIncome_i$$

with $\varepsilon_i \sim N\big(0, \sigma^2(\exp(z_i\gamma)\big)$ and where

$$\begin{aligned}(5)\quad z_i\gamma = {} & \gamma_1 HAPfee_i + \gamma_2 HAPfee_i^2 + \gamma_3 Premium_i + \gamma_4 Premium_i^2 + \gamma_5 Year_i \\ & + \gamma_6 FarmSize_i + \gamma_7 HAPfee_i \times FarmSize_i + \gamma_8 Premium_i \times FarmSize_i \\ & + \gamma_9 Premium_i \times Year_i \times FarmSize_i + \gamma_{10} FarmSize_i^2 \\ & + \gamma_{11} FarmSize_i + \gamma_{12} Age_i + \gamma_{13} HAPfee_i \times Age_i + \gamma_{14} HAPfee_i^2 \times Age_i \\ & + \gamma_{15} Premium_i \times Age_i + \gamma_{16} Premium_i^2 \times Age_i + \gamma_{17} Age_i^2 \\ & + \gamma_{18} HAPfee_i \times Age_i^2 + \gamma_{19} Premium_i \times Age_i^2 + \gamma_{20} Premium_i^2 \times Age_i^2 \\ & + \gamma_{21} SomeColl_i + \gamma_{22} Premium_i \times SomeColl_i + \gamma_{23} Premium_i^2 \times SomeColl_i \\ & + \gamma_{24} CornIncome_i + \gamma_{25} Premium_i \times CornIncome_i \\ & + \gamma_{26} CornIncome_i^2 + \gamma_{27} Premium_i \times CornIncome_i^2.\end{aligned}$$

Table 2 provides definitions of the variables, and ε_i is the error for the *i*th respondent. The errors are independent and normally distributed with mean zero and variance of $\sigma^2(\exp(z_i\gamma))$. The model was estimated using maximum likelihood with the QLIM procedure in SAS (SAS 2011a).[6]

Results and Discussion

Table 3 presents the coefficients of the mean portion of the model and Table 4 presents the coefficients for the variance portion of the model. The primary variables of interest—the interactions—are easier to interpret graphically and are presented in the figures. Each chart presents the result of holding a single model variable constant. These graphs and their implications are discussed.[7]

Estimates of Means

Figure 2 shows the results for the interaction of year and the technology fee; Figure 3 shows the results for the interaction of year and premium. The effect of the technology fee is negative as expected.[8] Note, though, that percent acres planted to HAP corn increases with time, which is consistent with participants assuming that their expectations were met and suggests that a tendency to

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[6] For the heteroskedastic Tobit regression, the log-likelihood function can have multiple local maxima. To help ensure that the true maximum was obtained, the analysis incorporated several convergence methods and the results were verified with LIMDEP (Greene 2002). Some scaling adjustments also had to be made to the variables to achieve convergence; all were converted back in the results.

[7] Each graph was created by holding other model variables constant.

[8] Since the result for the interaction between year and yield drag is nearly identical, the discussion applies to both.

Table 2. Description of Variables

Variable	Definition	Mean	Min.	Max.
Block	0 if respondents completed the first block of profiles; 1 if they completed the second	—	—	—
HAPfee	Fee for HAP technology added to the price for a bag of corn seed (in tens of dollars)	—	—	—
Premium	Premium farmers will receive for HAP corn in dollars per bushel	—	—	—
YieldDrag	Percent yield drag associated with the HAP corn seed variety	—	—	—
Year	Number of years since HAP corn became available starting with 1	—	—	—
FarmSize	Size of farm in thousand acres	0.64	0.00[a]	9.32
Age	Age in decades	5.7	2.6	8.7
SomeColl	0 if farmer's highest level of education is high school or less; 1 if level is at least some college	50 percent	—	—
CornIncome	Percent of farm income from corn[b]	34.83	10	90

[a] Less than 10 acres.
[b] The question asked for ranges (0–20, 21–40, etc.); these are mid-ranges.

be cautious about adopting a new technology can be overcome. In addition, the spread across years in the percent of acres planted to HAP corn declines as the technology fee increases. This is likely some form of boundary effect; when the price is high enough, HAP corn is no longer attractive regardless of its other attributes. As shown in Figure 3, the percent of acres planted increases with payment of a premium, as expected, and with year. Here, transformation from the latent variable to the percent of acres planted greatly diminishes the interaction.

The interaction of farm size with the technology fee in year 1 is shown in Figure 4. As expected, the overall percent of acres planted decreases as the technology fee increases. This effect is most extreme for the high fee, resulting in a relatively flat line that again suggests that a high fee creates a boundary that severely limits the potential for large-scale adoption of HAP corn. In the low-fee and no-fee situations, however, the differences in adoption across farm sizes are more pronounced. In general, then, percent adoption is greatest for the smallest and largest farms. Operators of small farms generally do not rely heavily on revenue from crops and thus may be more willing than operators of medium-sized farms to try new things. Large farms may have been able to grow so substantially because their operators were innovative and more willing to go to "the next big thing." These differences are most obvious for the no-fee case; the percent of acres for operators of the largest farms adopting is about 10 percent greater than the percent of acres for operators of small farms and about 30 percent greater than the percent acres for operators of medium-size farms.

Figure 5 shows the interaction of farm size and premium Once again, medium-sized farms are taking a more conservative approach to adoption. Also of interest is the relatively large gap between no-premium and low-premium compared to the size of the gap between the low and high premiums. This result suggests that receipt of a premium is the key issue for farmers while the amount of the premium plays a smaller role. The importance of a premium is most apparent for operators of small farms; in that case, there is a substantial gap in adoption between the no-premium and high-premium scenarios. The gap is smallest for the largest farms, suggesting that for this group it is not as crucial.

The results of the regressions for the demographic characteristics are shown in Tables 3 and 4. The interactions of education with fee and premium

Table 3. Coefficients for the Means Model

Parameter	Estimate	Std. Err.	t-Ratio	p-Value
Intercept	–16.31959	14.21756	–1.15	0.2510
Block	1.54413	1.83290	0.84	0.3995
HAPfee	**–2.85075**	0.68845	–4.14	< 0.0001
HAPfee^2	**0.07586**	0.02244	3.38	0.0007
Premium	**140.18057**	25.14704	5.57	< 0.0001
Premium^2	**–213.28774**	50.56751	–4.22	< 0.0001
YieldDrag	**–6.56710**	1.72120	–3.82	0.0001
YieldDrag^2	**1.00652**	0.30676	3.28	0.0010
Year	6.06173	4.63395	1.31	0.1908
HAPfee × Year	**–0.41596**	0.08000	–5.20	< 0.0001
Premium × Year	**29.38467**	5.84081	5.03	< 0.0001
YieldDrag × Year	**–3.71479**	0.49351	–7.53	< 0.0001
FarmSize	**–21.59917**	4.53266	–4.77	< 0.0001
HAPfee × FarmSize	**1.17935**	0.30194	3.91	< 0.0001
HAPfee^2 × FarmSize	**–0.02068**	0.00843	–2.45	0.0142
Premium × FarmSize	**–19.67591**	7.28790	–2.70	0.0069
FarmSize^2	**7.36037**	1.45318	5.07	< 0.0001
HAPfee × FarmSize^2	**–0.15524**	0.06858	–2.26	0.0236
Age	**1.34387**	0.43853	3.06	0.0022
Year × Age	**0.15111**	0.07424	2.04	0.0418
Age^2	**–0.01638**	0.00409	–4.00	< 0.0001
SomeColl	4.68749	4.17815	1.12	0.2619
HAPfee × SomeColl	**–0.56684**	0.13658	–4.15	< 0.0001
Premium × SomeColl	**42.00992**	11.27640	3.73	0.0002
YieldDrag × SomeColl	**–4.81052**	0.84440	–5.70	< 0.0001
CornIncome	0.00591	0.07628	0.08	0.9383
HAPfee × CornIncome	0.02470	0.01316	1.88	0.0605
HAPfee^2 × CornIncome	**–0.00089**	0.00044	–2.01	0.0442

Note: The estimated coefficients shown in bold are significant at the 5 percent level.

are relatively straightforward and again reflect the overall negative effect of higher technology fees on adoption of HAP corn. Farmers who attended college were willing to plant a greater share of their acres in HAP corn than farmers who had not. Again though, this difference gets smaller as the fee increases. The interaction of education and premium behaves as expected; those who attended college were willing to plant a higher percentage of HAP corn. Note, though, that the gap between those with some college and those with no college increases as the premium paid increases. An increase in the

Table 4. Coefficients for the Variance Model

Parameter	Estimate	Std. Err.	t-Ratio	p-Value
Sigma	379.95471	197.99549	1.92	0.0550
HAPfee	**–0.29229**	0.06497	–4.50	< 0.0001
HAPfee^2	0.00296	0.00177	1.68	0.0938
Premium	**–67.29022**	11.36024	–5.92	< 0.0001
Premium^2	**168.72839**	27.65278	6.10	< 0.0001
Year	**0.41837**	0.05441	7.69	< 0.0001
FarmSize	**–1.93706**	0.18025	–10.75	< 0.0001
HAPfee × FarmSize	**0.03645**	0.00909	4.01	< 0.0001
Premium × FarmSize	**–0.60981**	0.29157	–2.09	0.0365
Year × FarmSize	**0.11091**	0.04184	2.65	0.0080
FarmSize^2	**0.53514**	0.04944	10.82	< 0.0001
HAPfee × FarmSize^2	**–0.01387**	0.00287	–4.83	< 0.0001
Age	**–0.21779**	0.03516	–6.19	< 0.0001
HAPfee × Age	**0.00943**	0.00174	5.41	< 0.0001
HAPfee^2 × Age	**–0.00008**	0.00003	–2.50	0.0123
Premium × Age	**2.45326**	0.39085	6.28	< 0.0001
Premium^2 × Age	**–5.51219**	0.95908	–5.75	< 0.0001
Age^2	**0.00210**	0.00032	6.50	< 0.0001
HAPfee × Age^2	**–0.00007**	0.00001	–5.00	< 0.0001
Premium × Age^2	**–0.02032**	0.00341	–5.96	< 0.0001
Premium^2 × Age^2	**0.04370**	0.00828	5.28	< 0.0001
SomeColl	**0.86042**	0.11736	7.33	< 0.0001
Premium × SomeColl	1.73260	1.13778	1.52	0.1278
Premium^2 × SomeColl	**–6.66417**	2.63313	–2.53	0.0114
CornIncome	0.03257	0.01908	1.71	0.0877
Premium × CornIncome	**–0.25964**	0.07676	–3.38	0.0007
CornIncome^2	–0.00035	0.00020	–1.81	0.0696
Premium × CornIncome^2	**0.00291**	0.00079	3.69	0.0002

Note: The estimated coefficients shown in bold are significant at the 5 percent level.

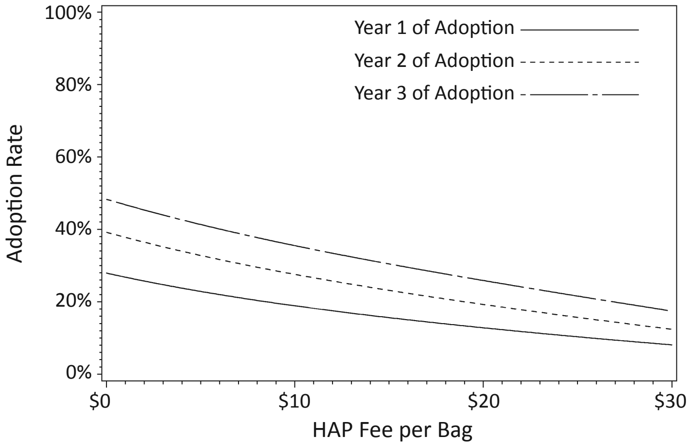

Figure 2. Percent Adoption by HAP Fee and Year since HAP Became Available

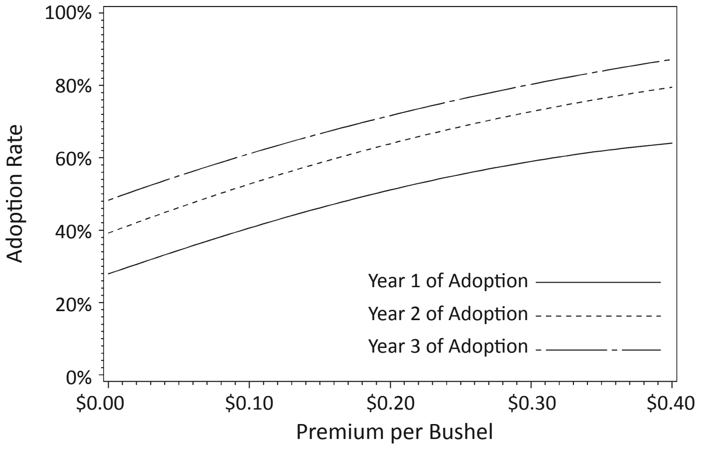

Figure 3. Percent Adoption by HAP Premium and Year since HAP Became Available

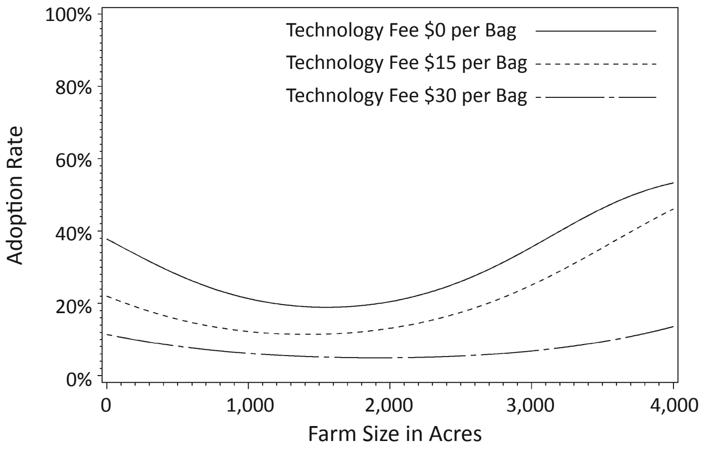

Figure 4. Percent Adoption by Farm Size and Technology Fee in Year 1

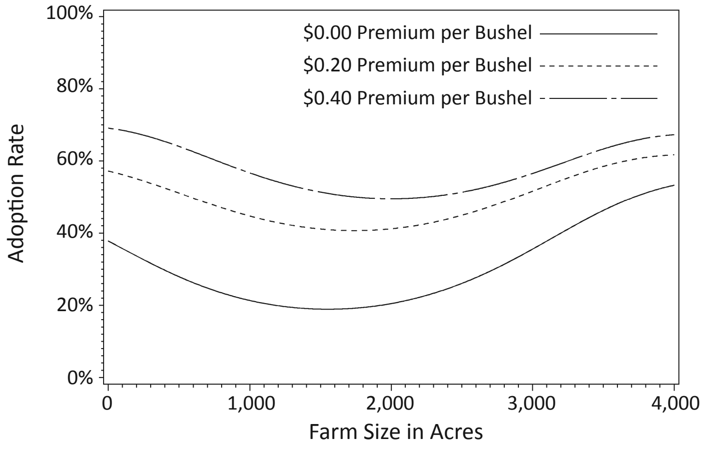

Figure 5. Percent Adoption by Farm Size and Technology Premium in Year 1

benefit provided by a premium may make an attractive product even more attractive.

The coefficients of interactions of fee with income from corn and year with farmer age are also significant. In the interaction between income from corn and the technology fee, the fee is far more important, but the rate of decrease in farmers' willingness to adopt is somewhat steeper for those who obtain only a small portion of their incomes from corn. For the interaction of year with the farmer's age, the percentage of adoption of HAP corn clearly increases over time regardless of age. However, the relationship between willingness to adopt and age changes over the three-year period. In the first year, adoption is highest for younger and older farmers. In the second year, there is not much difference by age, and in the third year, middle-aged farmers are the highest projected adopters. Thus, it appears that the middle age group was more conservative during the first year in adopting an unproven product but rapidly overcame that reticence when the product met expectations.

Estimation of Standard Deviations and Variance

Heteroskedasticity traditionally has been seen as a complication to be corrected for and then ignored. However, with a model that can predict the standard deviation, it is possible to consider its impact (see, for example, Bernard, Pesek, and Pan (2007) and Bernard and Bernard (2010)). A few results from this portion of the analysis are worth discussing. The first, interaction of the technology fee with farm size in the first year, is presented in Figure 6. Overall, the standard deviation decreases as the HAP fee increases, which is consistent with the previously mentioned concept of a boundary effect. At the high fee, most of the farmers viewed HAP corn unfavorably regardless of the size of their operations and consistently did not want to plant it. Regardless of the size of the technology fee, however, the greatest standard deviations were for those who had relatively small and relatively large farms. This suggests that operators of medium-sized farms were more consistent in their adoption decisions. Recall Figure 4, which showed that most operators of medium-sized farms did not adopt regardless of the amount of the fee.

The interaction of premium with farm size shows the same pattern of larger standard deviations for large and small farms. The standard deviations are always smallest when the premium is highest so it seems clear that farmers generally lean toward adoption. However, for operators of farms of up to 2,500 acres, the standard deviation is greater for the low premium than for no premium. It is expected that lack of a premium will, in many cases, lead to a fairly consistent decision not to adopt HAP corn; a small premium could generate the most varied reactions from farmers.

Figure 7 illustrates the interaction of year and farm size. In the first year, mid-size farms are far less volatile than large and small farms. The same is true in the second and third years but is far less pronounced. The interaction of fee and farmer age in the first year again shows that variance decreases as the HAP technology fee increases and supports the idea that conservative middle-aged farmers consistently fail to adopt HAP corn while the responses of younger and older farmers are less uniform.

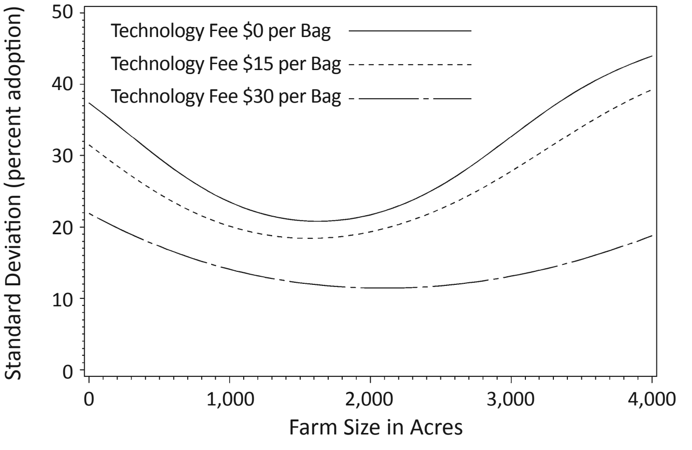

Figure 6. Standard Deviation by Farm Size and HAP Fee for Year 1 of HAP Availability

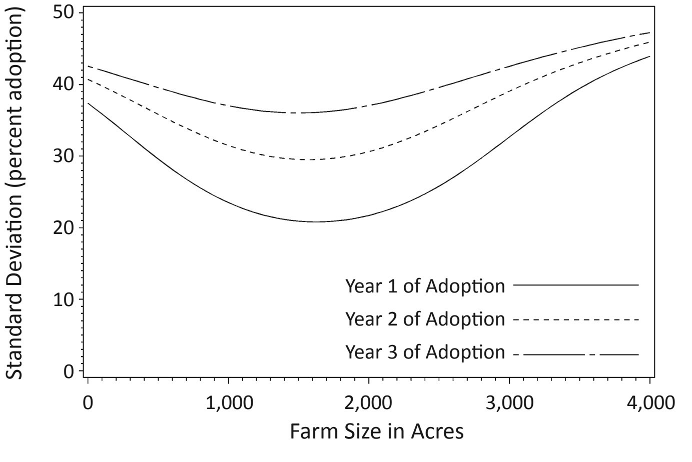

Figure 7. Standard Deviation by Farm Size and Year since HAP Became Available

The remaining significant interactions are farmer age, farmer education, and farm income from corn with premium. Unfortunately, none of the resulting standard deviations and variances has an obvious interpretation, pointing to how little is yet known about modeling complex variances. For the interaction of age and premium, high-premium is always lower than no-premium and both are higher at younger and older farmers, but middle-premium starts low and crosses both. The interaction of age and premium is the most difficult to understand. The standard deviation is always smaller for the high-premium, which would be consistent with a high premium making it desirable to plant HAP corn. Younger and older farmers show more variability than the ones in the middle. It is a reasonable expectation that the standard deviation for the low premium would be in between no-premium and high-premium. Instead, its standard deviation is lower than both for younger farmers but higher than both for middle-aged and older farmers.

The results for the interaction of premium and education are less startling. There is a larger standard deviation for college-educated farmers than for farmers without college education. The variance for less-educated farmers is relatively level, but for college-educated farmers, the variance rises to a peak of about $0.15 per bushel and then declines, and the range of variation is narrow at around 12 percent. The greater volatility seen for college-educated farmers may stem from their having read and heard more about HAP corn, but the information does not lead them to uniform conclusions. Lastly, in the interaction of premium and farm income from corn, the curve for the low premium crosses the curves for the high premium and no premium, a potential indicator that the intermediate value can at times produce greater uncertainty in decisions about adopting HAP corn.

Conclusions

This study modeled farmers' potential adoption of HAP corn using a unique approach in which the data collected represent actual shares of acres farmers were willing to plant to HAP corn over a three-year period given a range of hypothetical scenarios. The results indicate that the typical Delmarva farmer's preferred HAP corn variety requires no more than a small technology fee and causes only modest yield drag and for which there is a readily accessible market that offers a high premium per bushel sold. The results also suggest that corn growers are likely to become less tolerant of high technology fees and yield drags as time progresses. This finding is reasonable since new technologies tend to improve over time and become less expensive. The results indicate that adoption of HAP corn will increase over time unless it leads to financial losses for producers.

The study shows that certain groups of farmers will likely have a high overall willingness to purchase HAP corn. Those with higher levels of education may be more sensitive to potential negative aspects of HAP corn, such as technology fees and reductions in yield. Operators of relatively large farms may be more skeptical about the value of the product, at least initially. Marketing efforts that provide the results of research on HAP corn could alleviate such concerns and encourage adoption.

It is apparent that the success of HAP corn depends on incorporation of other popular value-added traits such as YieldGard Corn Borer and Roundup Ready. The average Delmarva corn farmer is not opposed to GM versions of HAP corn and may actually prefer them as a way to reap the benefits of HAP without having to give up other beneficial agronomic characteristics.

Naturally, other issues beyond the scope of this study factor into market adoption of HAP corn. Ideally, adoption would require no specialized management approaches, such as on-farm storage and field segregation, but that may not be possible since HAP corn is a nutritionally beneficial product. The need for field segregation would likely deter many farmers from adopting HAP corn unless markets offered very large premiums. Delmarva grain handlers would be wise to develop an efficient way to segregate corn that would not greatly inconvenience farmers. That effort might require handlers to update their processing equipment, purchase additional storage bins, and/or dedicate certain locations or days to accepting HAP corn at handling facilities.

Another important factor is the reaction of broiler companies, which are the peninsula's major buyers of grains. Corn producers could be compelled to adopt HAP corn if the broiler industry pushes for it. The industry's acceptance is likely to be shaped, at least in part, by consumers. Bernard, Pesek, and Gupta (2011), for example, found a high potential for consumer acceptance of chicken raised on HAP corn. There was less consumer enthusiasm for a GM version of HAP corn, but the study demonstrated that the environmentally friendly aspects of HAP could be used in marketing efforts. Use of a product with an environmental benefit also could increase the social acceptability of CAFOs and provide another reason for the industry to explore HAP corn diets as a way of dealing with the issue of phosphorus pollution more seriously.

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