# Performance Results and Characteristics of Adopters of Genetically Engineered Soybeans in Delaware

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Genetically engineered (GE) soybeans first became available to farmers in 1996. Despite the common questions regarding any new crop technology, the new seeds were rapidly adopted. This study examines the characteristics of adopters, as well as yield and weed control cost changes, using survey results from Delaware farmers at the start of the 2000 season. Duration analysis reveals that earlier-adopting farmers had larger farms and tended to use computers for financial management, while regression analysis shows significantly lower weed control costs and, to a lesser extent, higher yields for GE soybeans.

***Key Words:*** GE soybeans, technology adoption

The first-generation crops created through genetic engineering were designed to incorporate traits beneficial to farmers. The two major lines of these crops featured either insect resistance or herbicide tolerance. Among the most successful was a soybean genetically engineered (GE) by the Monsanto Corporation to be resistant to the herbicide glyphosate. Sold under the brand name Roundup Ready, they became available in 1996, and were rapidly adopted. According to USDA figures, within four years, these GE soybeans accounted for over 50% of U.S. soybean acreage [U.S. Department of Agriculture/National Agricultural Statistics Service (USDA/NASS), 2000a].

Given this situation, the primary objective of this research was to determine what factors or characteristics have led farmers to adopt GE soybeans at different times. This was accomplished through the use of duration analysis. The secondary goal was to analyze the performance of GE soybeans in the field. Performance was judged in terms of two criteria: yield and weed control costs per acre. While the quick adoption alone would strongly suggest farmers approved of the GE soybeans, actual yield and cost changes could be difficult for individual farmers to judge due to differing conditions each season. These aspects were examined using regression analysis.

## Data

A mail survey of soybean farmers in Delaware was conducted to obtain the data for this study. The mailing list was compiled in three segments, one for each county in the state, provided by the respective offices of the University of Delaware's Cooperative Extension. Each list varied in the breadth of its audience, with the lists for New Castle, Kent, and Sussex counties providing addresses for soybean farmers, grain farmers, and all farmers. Extraneous entries were culled, leaving a final mailing list of 787 farmers.

The survey, cover letter, and a postage-paid return envelope were mailed at the end of March 2000. Timing was selected to reach farmers prior to the start of their busy spring planting season, but after they had made final decisions on their plantings for the year. This mailing was followed two weeks later

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by a postcard designed to be a reminder to nonrespondents or a thank-you for those who had responded. The survey yielded a 22.24% response rate, or 175 surveys. After removing 46 respondents who indicated they were not soybean farmers and 13 whose surveys were too incomplete for any analysis, 116 usable responses remained for analysis. While these remaining surveys still were not all fully complete, every available complete response was used for each model.

Table 1 contains a summary of the variables of interest, including the characteristics of respondents, and their means and standard deviations. An examination of the summary statistics shows the fewest respondents were young farmers under age 40 and those with graduate degrees, with most respondents being between 40 and 55 and possessing only a high school degree. The majority sold soybeans under contract, and the vast majority had adopted narrow row spacing. There was also great homogeneity in both sources and ranking of importance of sources of information regarding GE soybeans. Almost all farmers based their adoption decisions on information obtained from seed companies and cooperative extension offices, and far fewer on arguably more negative media sources.

Direct comparisons with official figures, however, did suggest the sample was skewed toward larger and perhaps better-managed farms. First, the survey's average of 30.3 bushels per acre in 1999 exceeded the USDA's estimate of 27 bushels for that year (USDA/NASS, 2000b). Second, the sample distribution was more heavily weighted toward large size farms than the *1997 Census of Agriculture* (USDA/NASS, 1998). This latter statement should be tempered by noting that more than 200 small farms had since ceased operation, and more farmers with operations of over 3,000 acres responded than were reported existing in the Census (Delaware Agricultural Statistics Service, 2000).

For each year GE soybeans were available, the survey additionally asked farmers if they had used them and, if so, what percentage of their soybean crop had been planted with the GE seeds. These figures are reported in table 2. A rapid rise in both of these percentages over the 1996–2000 time period is readily apparent, showing Delaware farmers adopting at a pace much more rapid than USDA national estimates. It took only five years from introduction for GE soybeans to become the Delaware farmers' dominant soybeans. Nevertheless, it should be noted that most farmers did not convert entirely to the GE version, but rather tended to plant both. Theoretically this practice could be viewed as evidence either of risk aversion or of learning-by-using on the part of the farmers (Sunding and Zilberman, 2001). In particular, this finding may reflect existence of doubt about both the costs and yield differences between the soybean versions. Comments on the survey indeed noted some uncertainty, and an interest by respondents in better identifying the differences.

## Background

Some background is useful in understanding the adoption of GE soybeans. First, farmers' handling of weeds had been changing even prior to the introduction of GE soybeans. One major set of tools which emerged in the 1980s were herbicides that could be used postemergence in soybean fields. While use of these selective postemergence herbicides required farmers to first scout for different weeds in their fields and then to identify and apply appropriate herbicides for each group, this gave farmers an important new option over mechanical cultivation. In turn, the use of postemergence herbicides led to two other trends in soybean farming: the adoption of conservation tillage and use of narrow row spacing (Carpenter and Gianessi, 1999).

During this time, use of the herbicide glyphosate—sold under the brand name Roundup—was increasing. Glyphosate was popular among farmers due to its ability to effectively control for both grasses and broad-leaf weeds, representing the majority of weeds that could be present in soybean fields (Bullock and Nitsi, 2000). Glyphosate also was a nonresidual herbicide, thus allowing planting of any crop in the field the next year, and was considered less harmful to the environment. However, since it was a nonselective herbicide and toxic to traditional soybeans, its usage in terms of timing was limited. It was in this context that GE soybeans appeared, with the advantage of allowing farmers to use glyphosate postemergence. Given its wide-ranging abilities, farmers no longer would need to use the scouting-and-selecting method.

Having soybeans able to withstand applications of Roundup gave farmers access to an herbicide easier to use, and less expensive, than available substitutes. Carpenter and Gianessi (1999) believe it was the ease of using primarily Roundup for weed control that made GE soybeans especially appealing to farmers and led to their rapid adoption. While the simplicity of weed control is important, it remained

**Table 1. Definitions and Means of the Primary Survey Variables by Category**

| Category / Variable Name | Definition | Mean | Standard Deviation |
|---|---|---|---|
| **Labeling Opinion:** | | | |
| *Support* | 1 if farmer supports labeling foods containing GE ingredients | 0.449 | 0.499 |
| *Indifferent* | 1 if farmer is indifferent to labeling foods containing GE ingredients | 0.163 | 0.371 |
| [base reference] | Farmer does not support labeling foods containing GE ingredients | 0.388 | 0.483 |
| **Information Sources:** | | | |
| *InfoCoop* | 1 if information from cooperative extension is important in adoption decision | 0.983 | 0.129 |
| *InfoSeed* | 1 if information from seed companies is important in adoption decision | 0.966 | 0.183 |
| *InfoMedia* | 1 if information from media sources is important in adoption decision | 0.389 | 0.490 |
| **Farmer Characteristics:** | | | |
| *Age* | Farmer's age, in years | 52.272 | 12.652 |
| Education: | | | |
| *HiSchool* | 1 if farmer's maximum education is high school | 0.578 | 0.496 |
| *College* | 1 if farmer's maximum education is a college degree | 0.273 | 0.446 |
| *Graduate* | 1 if farmer's maximum education is a post-graduate degree | 0.062 | 0.242 |
| [base reference] | Farmer's maximum education is less than high school | 0.086 | 0.280 |
| **Farm Characteristics:** | | | |
| *Acres* | Size of farm (100s of acres) | 6.69 | 9.71 |
| *GESoybeans* | Percent of soybean acres planted to GE in 1999 | 56.92 | 23.72 |
| *Yields* | Farm soybean yields, bushels per acre in 1999 | 30.32 | 8.77 |
| *Costs* | Farm soybean weed control costs, $ per acre in 1999 | 21.63 | 9.79 |
| *SoyInc* | Percent of farm income from soybeans | 34.80 | 14.85 |
| *Computer* | 1 if farmer uses computer for farm financial management | 0.471 | 0.502 |
| *Storage* | 1 if grain storage capability exists on farm | 0.312 | 0.468 |
| *Contract* | 1 if farmer sells soybeans under contract | 0.637 | 0.491 |
| *Narrow* | 1 if farmer uses narrow row spacing; = 0 if wide row spacing is used; = 0.5 if a mixture is used | 0.853 | 0.456 |
| County: | | | |
| *Kent* | 1 if farm is located in Kent County | 0.510 | 0.417 |
| *Sussex* | 1 if farm is located in Sussex County | 0.365 | 0.401 |
| [base reference] | New Castle County | 0.125 | 0.272 |

**Table 2. Farmers' Usage of GE Soybeans**

| | GE Soybean Usage | |
|---|---|---|
| Year | % of Farms | % of Acreage |
| 1996 | 6.3 | 2.3 |
| 1997 | 29.5 | 14.2 |
| 1998 | 58.1 | 40.4 |
| 1999 | 72.1 | 68.0 |
| 2000 | 86.8 | 77.4 |

to be seen how the soybeans would perform on the farm. The two issues of concern were whether weed control costs would significantly decrease, and what changes, if any, would occur in yields.

Yields were examined in a number of early field trials. The results were inconsistent, leading to debate over the performance of GE soybeans compared to traditional varieties. Initially there were concerns about the existence of a "yield drag" with GE soybeans. Reporting on field experiments, Elmore et al. (2001) showed GE soybeans yielded from 5% to 10% less than other varieties. About half of this difference appeared to exist only in comparison to the highest yielding soybean varieties, which were not the same base from which GE soybeans had been engineered. Despite this consideration, however, there still remained an approximately 5% lower yield compared with sister lines.

In contrast to the above study, others observed either no differences in yields or superior yields from GE soybeans. In the former category, Delannay et al. (1995) found no decrease in yields even after applying Roundup at a level twice that considered necessary for weed control. Most remaining studies, highlighted in Fernandez-Cornejo, Klotz-Ingram, and Jans (2002), appear to suggest higher yields from

GE soybeans. Roberts, Pendergrass, and Hayes (1999), while conducting an economic analysis of returns from GE soybeans, found them to have a higher return which the authors attributed to both better yields and lower herbicide costs. However, beyond these controlled field experiments, there was little evidence on yield comparisons from actual farmer experience. To date, the major study using farmer survey data (Fernandez-Cornejo, Klotz-Ingram, and Jans, 2002) did show a slight but significant increase in yields with GE soybeans.

For weed control costs, questions regarding both the amounts of Roundup that would be used on a farm, and any changes in its price from increased demand, have made this issue more difficult. Part of the cost equation involves the question of the amount of herbicides needed. The adoption of GE soybeans naturally increased the use of glyphosate. One reason weed control costs may not be significantly lower for adopters would be the effect of this demand shift on market prices. With the potential lowered demand for other herbicides, a corresponding price decrease would not be unexpected. Bullock and Nitsi (2000) found that the costs of using other herbicide programs did decrease after the appearance of GE soybeans.

The Bullock and Nitsi (2000) study, using survey data from eight Midwestern states, further concluded that for the average farm in 1999, using GE soybeans was more expensive than using traditional varieties. Estimated costs were lower until the technology fee for GE seeds was factored in, leading to a deficit of $2.18 per acre. Farms using no-till and GE soybeans also lagged behind traditional seeds by $1.94 per acre. As noted by Bullock and Nitsi, due to herbicide price changes and adoption of GE soybeans, overall production costs were down across the Midwest. These figures, however, came from information on weeds present on farmer fields, not on reported costs from farmers.

The largest undertaking to analyze farmer experiences with GE soybeans was the special version of the USDA's 1997 Agricultural Resource Management Study (ARMS). This survey was sent to soybean producers in 17 states in four geographic areas: Lake States, Delta, Northern Plains, and the Corn Belt. Using ARMS data, McBride and Brooks (2000) examined adoption percentages for both GE soybeans and cotton, and compared yields, costs, and cultural practices between GE and non-GE seed varieties. They found yields from GE soybeans to be significantly higher than other seed varieties in three of the four geographic regions. These results were limited, however, in that no other factors were controlled for in the analysis.

The comparison of the above results to this study would expand the areas considered since, while accounting for 93% of total U.S. acreage, the ARMS survey did not include Delaware or any other state with a similar profile. Soybeans are an important crop in the state of Delaware. For nearly three decades they have been the state's largest crop, with acreage increasing each year. The end use for the majority of these soybeans has been as feed for the Delmarva Peninsula's poultry industry—a fact which appears to have insulated Delaware farmers from some uncertainties over consumer demand that may have affected adoption patterns and characteristics in other regions of the United States (Bernard, Pesek, and Fan, 2004). This dynamic additionally makes Delaware a good candidate for the analysis of adoption and performance; extraneous factors likely present elsewhere did not appear to meaningfully influence the farmer survey respondents participating in our study.

### Hypotheses

The theoretical framework used for generating hypotheses explaining the adoption process was based primarily on the work of Rogers (2003). Rogers is known for defining five categories of adopters: innovators, early adopters, early and late majority, and laggards. Within this framework, variations in timing in the adoption process can be explained by characteristics of the farms and farmers themselves. The components of these factors believed to be related to earlier adoption have been categorized as communication, socioeconomic, and personality.

Beginning with the communication category, those with greater knowledge of innovations and exposure to media are expected to adopt earliest. The most basic issue here is the role of information, which, as noted by Klotz, Saha, and Butler (1995) and Marra, Hubbell, and Carlson (2001), can play a crucial role in timing of adoption. To begin, it is expected that certain farmers may have earlier knowledge, and thus an added opportunity to adopt first. However, as suggested by the descriptive statistics from the current survey (see table 1), very little differences in information appear across the sample. This could be partly due to the small size of the state, where information likely spreads rapidly. Additionally, farmers' increasing Internet usage should help increase both the speed and extent of the distribution of information (Hopkins and Morehart, 2001). Consequently, after consideration of theory and evidence, the role of information was assumed to have little effect on the adoption decision.

Farm and farmer characteristics play the major role within the socioeconomic category. For the former, those with higher acreage, operations possessing grain storage capabilities, and those considering soybeans their primary business should be among the earliest adopters. It was therefore hypothesized that all three characteristics would be positively related to adoption time. Additionally, selling soybeans under contract was considered an important characteristic. It has been included as a variable in previous studies and is believed likely to have an effect on farmer planting decisions. However, no hypothesis was formed regarding the sign of the effect. For farmer characteristics, those most receptive and able to accurately process the chances of success of GE soybeans should be those who are more highly educated. Age could also play a role, with younger farmers adopting earlier, although as noted by Rogers (2003), past empirical studies have yielded inconsistent results.

Within the personality category, factors such as attitudes toward change and toward science should influence adoption time. These factors were captured in the survey in two ways. First, it was determined which farmers were already using advanced technologies. Advanced technologies were considered broadly to be either the use of narrow row spacing or the farmer's use of computers. The former also suggests the farmer is receptive to following the current trends, and perhaps views GE soybeans as an extension of these. For the latter technology, rather than simply identifying whether a farmer owns a computer, it was hypothesized that those individuals who used a computer for the financial operation of the farm would be the most comfortable adopting new technologies early. The second personality factor was associated with farmers' attitudes about GE foods. Some farmers could be opposed to the technology for reasons other than its performance; these individuals should be identifiable by their support for labeling of GE foods. Thus, support for labeling was hypothesized to have a negative effect on timing of adoption.

Consideration of variations in the yield and weed control costs models were also made in the context of differences across farms and farmers. For the latter, human capital variables were included in farmer age and education. Both were expected to affect farmers' ability to make the best use of the technology. Following standard convention, it was hypothesized that older and more highly educated farmers would be able to obtain the greatest performance from their soybeans, regardless of version.

Considering farm differences, a key preexisting trend was the use of narrow row spacing, made possible with the development of postemergence herbicides (Carpenter and Gianessi, 1999), and this trend would be expected to expand with the adoption of GE soybeans. The narrower the spacing, the more difficult it should be for weeds to compete with the soybeans (Roberts, Pendergrass, and Hayes, 1999), while correspondingly, an increase in yields would be anticipated simply because more rows per acre are planted.

Farm size was the other major farm variable hypothesized to affect yields and weed control costs. Large farm size was expected to have a negative effect on costs, from both the potential for economies of scale and as a proxy for better farm management practices. Larger farms were also anticipated to have higher yields, although as Fernandez-Cornejo, Daberkow, and McBride (2001) noted, this could be the result of this trait being a surrogate for many other factors. The technology itself should be scale-neutral, and farm size should mostly capture differences in management practices and abilities.

Other farm conditions, such as different weather patterns, extent of weed problems, and soil conditions, could carry over into both yields and costs.[1] An attempt was made to control for all these variations by the inclusion of county dummies within the model. Because of its highly built-up, urban characteristics, New Castle County was hypothesized to have inferior performance associated with both yields and costs, while Sussex, the most rural county, was expected to show the best performance.

## Empirical Models

### *Adoption Decision Model*

The major objective of the Delaware farmer survey was to determine what factors or characteristics have led farmers to adopt at different times. Duration analysis, a methodology that has been used

[1] As noted by a reviewer, fertilizer and other inputs may also have some influence on yields and costs. However, no other input information was collected in the survey. It was believed, though, that any bias from missing variables would likely be small.

extensively to study "spells," such as spells of unemployment, was selected to meet this objective. Here, spells of non-adoption are considered. Duration analysis has been applied recently to the adoption of organic horticultural technology (Burton, Rigby, and Young, 2003), and adoption of natural resource-conserving agricultural technology (Fuglie and Kascak, 2001). Although used in econometric studies since at least 1972, Burton, Rigby, and Young (2003, p. 31) noted, "The dearth of applications to agricultural adoption is rather surprising as the great advantage of Duration Analysis is that it deals with both cross-section and time series data." Because this method is relatively new to agricultural adoption studies, we include a short introduction here.[2]

If a spell, such as a spell of non-adoption of GE soybeans, occurs, let 0 be the beginning of the spell (here, 0 stands for 1996, the year GE soybeans became available). Assume the time of adopting, ending the spell of non-adoption, is a stochastic event as indicated by a random variable $T$ with density $f(t)$, so that

$$\Pr(T \leq t) = \int_0^t f(s)\, ds$$

is the probability of adopting before time $t$. Let $S(t) = \Pr(T > t) = 1 - \Pr(T \leq t)$ be the probability that adoption occurs after time $t$. For modeling purposes, an auxiliary quantity called the "hazard function" is used,[3] defined as:

$$(1)\quad \lambda(t) = \lim_{\Delta t \to 0^+} \frac{\Pr(t \leq T < T + \Delta t \mid T \geq t)}{\Delta t} = \frac{f(t)}{S(t)}.$$

Roughly, the hazard function is the rate at which the events of interest (adoption) occur, given that they have not occurred up until time $t$. The tail probability $S(t)$, called the "survival function," can be expressed in terms of the hazard function as:

$$S(t) = \exp\left(-\int_0^t \lambda(s)\, ds\right).$$

To incorporate covariates, which may be time dependent, into the hazard function, the hazard function is assumed to be a baseline hazard function $\lambda_0(t)$ times a function $q(\mathbf{X}(t), \boldsymbol{\beta})$, i.e., $\lambda(t) = \lambda_0(t) q(\mathbf{X}(t), \boldsymbol{\beta})$. It is common to take $q(\mathbf{X}(t), \boldsymbol{\beta}) = \exp(\mathbf{X}(t)\boldsymbol{\beta})$. The baseline hazard function may be modeled as parametric, i.e., $\lambda_0(t) = \lambda_0(t, \theta)$ [see Burton, Rigby, and Young (2003) for examples]. However, since it is often difficult to determine an appropriate choice of probability distribution, the semi-parametric model of Cox is frequently used. In this model, the baseline hazard function is modeled nonparametrically but the covariates are modeled parametrically. Thus, the Cox model gives the hazard function for an individual $i$ as $\lambda_i(t) = \lambda_0(t)\exp(\mathbf{X}_i(t)\boldsymbol{\beta})$, where $\lambda_0(t)$ is an unspecified baseline hazard function of time, $\mathbf{X}_i(t)$ is a $\{1 \times p\}$ vector of covariates at time $t$, and $\boldsymbol{\beta}$ is a $\{p \times 1\}$ vector of coefficients. The coefficient vector $\boldsymbol{\beta}$ and the baseline hazard function $\lambda_0(t)$ are estimated using a partial likelihood method.[4]

For modeling adoption of GE soybeans, the following form for $\mathbf{X}_i\boldsymbol{\beta}$ is proposed:

$$\begin{aligned}(2)\quad \mathbf{X}_i\boldsymbol{\beta} = {} & \beta_1 Support_i + \beta_2 Indifferent_i + \beta_3 Acres_i \\ & + \beta_4 SoyInc_i + \beta_5 Age_i + \beta_6 Age_i^2 \\ & + \beta_7 HiSchool_i + \beta_8 College_i \\ & + \beta_9 Graduate_i + \beta_{10} Computer_i \\ & + \beta_{11} Storage_i + \beta_{12} Contract_i \\ & + \beta_{13} Narrow_i,\end{aligned}$$

where the terms, following the previously stated hypotheses, are as defined in table 1. Note that there is no intercept in the Cox model; its role is played by the baseline hazard function.

In order to estimate the Cox model, the treatment of ties must be considered. The model was developed for continuous events. However, it is common for events to occur simultaneously (to be tied). Since farmers may make the decision to plant GM soybeans at any time of the year but only the year of the decision is given, times in our study are only accurate to within a year, and thus ties will occur. When this is the case, the Cox model is estimated with the exact method.[5]

It is customary when interpreting econometric models to concentrate on the structural information provided by the coefficients. Like the more familiar logistic regression model, the interpretation of the

[2] For more information on duration analysis, interested readers are referred to the following sources: Burton, Rigby, and Young (2003); Greene (2000); Therneau and Grambsch (2000); and Allison (1995).

[3] Duration analysis originated in the insurance industry where a spell was being alive and the end of the spell was death—hence the name hazard function. It is also called the force of mortality. In our application, it could be called the force of adoption.

[4] An important feature of duration analysis is its ability to use incomplete data. In our study, the information that a farmer has not adopted GE soybeans up until 2000 is used to estimate the model. Such data are called "censored."

[5] Here, the term "exact" refers to the nature of the estimation procedure and not to the timing of the adoption decision. If decisions did occur at precise time points, a method of estimation called "discrete" would be used.

coefficients is not as straightforward as with the ordinary least squares model. If two individuals have fixed covariate vectors $\mathbf{X}_i$ and $\mathbf{X}_j$ (not dependent on $t$), then the hazard ratio is defined as:

$$(3) \qquad \frac{\lambda_i(t)}{\lambda_j(t)} = \frac{\lambda_0(t)\exp(\mathbf{X}_i\boldsymbol{\beta})}{\lambda_0(t)\exp(\mathbf{X}_j\boldsymbol{\beta})}.$$

The hazard ratio of a change of $\Delta x_j$ in the $j$th covariate (assuming a linear functional form and no interactions with the $j$th covariate) is $\exp(\beta_j \Delta x_j)$, and does not depend on time or the values of the other covariates.[6] Thus, a hazard ratio of one means that there will be no change in the rate of adoption (of those who have not adopted up until time $t$), while a hazard ratio of less than one indicates the rate of adoption will decrease, and a hazard ratio greater than one indicates the rate of adoption will increase.

The effect of the change on the survival probability (the probability of continuing to use conventional soybeans) can also be given. The current survival function changes from $S_c(t)$ to $S_c(t)^{\exp(\beta_j \Delta x_j)}$. If the coefficient $\beta_j$ is one, the survival function is unchanged. If it is less than one, the survival function will increase (recall that $0 \le S_c(t) \le 1$), and so the probability of continuing to use conventional seed up until time $t$ will increase. If $\beta_j$ is greater than one, the survival function decreases and the probability of continuing to use conventional seed up until time $t$ will decrease. The change in the survival function is greatest when it is close to one-half, and least when it is close to zero or one.[7]

### *Yields and Weed Control Costs*

Constructing the yield and weed control cost model equations was straightforward. As discussed above, the models use the same independent variables. To begin, the costs model was formulated as:

$$\begin{aligned}(4) \quad Costs_i = {} & \beta_0 + \beta_1 GESoybeans_i + \beta_2 Acres_i \\ & + \beta_3 Narrow_i + \beta_4 Kent_i + \beta_5 Sussex_i \\ & + \beta_6 Age_i + \beta_7 Age_i^2 + \beta_8 HiSchool_i \\ & + \beta_9 College_i + \beta_{10} Graduate_i + \varepsilon_i.\end{aligned}$$

While weed control costs were important, the change in yield from GE products will greatly influence farmers' decisions on continued use. The yields model was similarly constructed as follows:

$$\begin{aligned}(5) \quad Yields_i = {} & \beta_0 + \beta_1 GESoybeans_i + \beta_2 Acres_i \\ & + \beta_3 Narrow_i + \beta_4 Kent_i + \beta_5 Sussex_i \\ & + \beta_6 Age_i + \beta_7 Age_i^2 + \beta_8 HiSchool_i \\ & + \beta_9 College_i + \beta_{10} Graduate_i + \varepsilon_i.\end{aligned}$$

For both models in equations (4) and (5), the variables are again as defined in table 1. Note that only one question each was asked for both weed control cost and yield numbers. Thus, for the large number of farmers who planted both GE and non-GE soybeans, separate cost and yield information was not collected. This missing information was accounted for by including the percentage of total soybean acreage devoted to GE soybeans in each model.

As specified, however, there existed the potential for selection bias in the models. The concern stems from the possibility that unobserved factors within the error terms may also affect the farmer's adoption decision, implying *GESoybeans* would be endogenous in the models. Because this theoretical concern suggests potentially serious consequences for the analysis of results, the first step was to determine the appropriate methodology for estimating the above models [equations (4) and (5)]. Ordinary least squares would be most efficient only if adoption was exogenous; otherwise, a two-stage least squares procedure would be required.

The adoption variable, *GESoybeans*, was tested for endogeneity in each model using the procedure outlined in Wooldridge (2003). This involved a two-stage process by which *GESoybeans* was first estimated as a function of the structural variables in (4) and (5), and instrumental variables selected from the earlier duration analysis. For the second stage, the residuals were included as explanatory variables in the yield and cost models and tested for significance. While significance on these coefficients would indicate *GESoybeans* was endogenous, the resulting $p$-values were 0.4406 for the yields model and 0.5159 for the costs model. Consequently, given the lack of evidence of endogeneity in either model, each was estimated using ordinary least squares.

## Results and Discussion

### *Adoption Decision Model*

The adoption decision model results, based on 104 observations, are reported in table 3. As observed from this table, the only significant effects at the 5%

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[6] The lack of dependence of the hazard ratio on the values of the other covariates is analogous to the lack of dependence of the odds ratio on the values of the other covariates in logistic regression.

[7] This is analogous to the impact of the odds ratio on the probability of an event in logistic regression.

**Table 3. Results from Proportional Hazards Model for Adoption Process**

| | | | | 95% Confidence Limits for Hazard Ratio | |
|---|---|---|---|---|---|
| Effect | Estimate | *p*-Value | Hazard Ratio | Lower Limit | Upper Limit |
| Support labeling | !0.0198 | 0.9458 | 0.980 | 0.553 | 1.737 |
| Indifferent to labeling | 0.3085 | 0.3814 | 1.361 | 0.682 | 2.716 |
| Farm Size (100s of acres) | 0.0422 | 0.0041 | 1.043 | 1.013 | 1.074 |
| Soybean income (%) | 0.0099 | 0.1293 | 1.010 | 0.997 | 1.023 |
| Age | !0.0228 | 0.7618 | 0.977 | 0.843 | 1.133 |
| Age squared | 0.0002 | 0.7507 | 1.000 | 0.999 | 1.002 |
| High School | 0.5225 | 0.3905 | 1.686 | 0.512 | 5.559 |
| College | 0.8962 | 0.1931 | 2.450 | 0.635 | 9.449 |
| Graduate | 0.3780 | 0.6211 | 1.459 | 0.326 | 6.532 |
| Computer used for farm finances | 0.8685 | 0.0072 | 2.383 | 1.265 | 4.491 |
| Grain storage capability | !0.1480 | 0.6056 | 0.862 | 0.492 | 1.512 |
| Contract sales of soybeans | !0.0181 | 0.9583 | 0.982 | 0.499 | 1.933 |
| Narrow row spacing | 0.5364 | 0.3876 | 1.710 | 0.506 | 5.774 |

*Note:* Number of observations = 104.

level were farm size and use of a computer for finances. Consistent with expectations, both of these factors increase the probability of early adoption. However, the other farm operation and technology use variables were not found to be significant. For technology, the use measure of narrow row spacing did not affect speed of adoption. We believe this result likely stemmed from the fact that nearly all farmers in the sample had already adopted this technique, and therefore the variable *Narrow* was not as good an indicator of the use of new technologies as anticipated. Of the two remaining operations variables, soybean income and grain storage capability, the insignificance of the former at even the 10% level was the greater surprise. At the same time, however, it should be noted that the wide confidence intervals for the hazard ratios of many of the covariates suggest this study cannot rule out an effect of these or the remaining covariates on farmers' adoption process.

Examining the results of the adoption decision model for the human capital variables, neither age nor education was significant (table 3). The non-significance of *Age* was less surprising, given inconsistent findings of its significance across various previous adoption studies, as discussed earlier. The result for education, however, was more unexpected, but the likely reason for the consistency of adoption across our survey sample was the homogeneity in the sources of information used by farmers in making their planting decisions. This common information probably alleviated one or both of these traditionally examined quantifiers of adopters.

The final variables which had been expected to capture any of the controversial aspects of GE soybeans were those indicating individual farmers' attitudes toward labeling. Again, neither the *Support* nor *Indifferent* labeling variables were found to be significant. While it appears Delaware farmers do have differing opinions on the issue of labeling, this has not been an important factor with respect to when or if to adopt. It could be that the adoption decision was made before the labeling issue gained prominence, or perhaps the farmers do not perceive the labeling issue as actually affecting their markets. This second possibility would be in accord with recent findings reported by Bernard, Pesek, and Fan (2004).

As previously noted, there are few earlier studies with which to directly compare the results of this analysis. Nevertheless, comparing our results to those of Fernandez-Cornejo, Klotz-Ingram, and Jans (2002) reveals some mixed findings. There was agreement on farm size—perhaps the most consistently found determinant of technology adoption across studies—and on the lack of significance of use of contracts. For the education variable included in both models, however, our study did not find the significance reported in theirs. The uniform nature of the information noted here perhaps was not the case elsewhere, leading to this divergent result. This and the rapid nature of adoption, whereby the majority of farmers were quickly using GE soybeans,

**Table 4. Regression Results from Yield and Weed Control Costs Models**

| | Yield Model | | Weed Control Costs Model | |
|---|---|---|---|---|
| Variable | Estimate | *p*-Value | Estimate | *p*-Value |
| Intercept | 24.5994 | 0.031 | 32.5408 | 0.015 |
| | (11.2439) | | (13.0312) | |
| *GESoybeans* | 0.0342 | 0.066 | !0.0524 | 0.020 |
| | (0.0184) | | (0.0221) | |
| *Acres* | 0.0909 | 0.319 | !0.3086 | 0.005 |
| | (0.0907) | | (0.1060) | |
| *Narrow* | 3.4761 | 0.286 | 3.2605 | 0.402 |
| | (3.2413) | | (3.8657) | |
| *Kent* | 4.9018 | 0.029 | !2.0016 | 0.457 |
| | (2.2133) | | (2.6789) | |
| *Sussex* | !3.4036 | 0.147 | 2.1014 | 0.452 |
| | (2.3249) | | (2.7795) | |
| *Age* | !0.1879 | 0.635 | !0.4102 | 0.378 |
| | (0.3941) | | (0.4629) | |
| *Age*$^2$ | 0.0020 | 0.580 | 0.0032 | 0.460 |
| | (0.0036) | | (0.0043) | |
| *HiSchool* | 8.7840 | 0.004 | 6.0679 | 0.085 |
| | (3.0030) | | (3.4824) | |
| *College* | 9.3959 | 0.005 | 2.4922 | 0.512 |
| | (3.2752) | | (3.7784) | |
| *Graduate* | 4.8144 | 0.276 | 3.0306 | 0.557 |
| | (4.3980) | | (5.1385) | |
| $R^2$ | 0.2124 | | 0.2985 | |
| *F*-Statistic | 2.56 | 0.008 | 3.28 | 0.001 |
| Sample | 106 | | 88 | |

*Note:* Values in parentheses are standard errors.

may also account for one other similarity between the two studies: a lack of variables that were significant. These two elements may have weakened the importance of variables often found to be significant in studies of adoption of other technologies.

### *Yields and Weed Control Costs*

The results for both the yield and weed control costs regressions are presented in table 4. Both models were examined for heteroskedasticity and severe multicollinearity and were not found to suffer from either problem. Examining yields first, the primary variable of interest—the percentage of acres planted to GE soybeans—was significant only at the 10% level. As shown by the coefficient for *GESoybeans*, for each additional 1% of soybean field turned over to GE, an increase of approximately 0.03 bushels per acre could be expected. Extrapolating from this value, a farmer planting all GE soybeans would be expected to achieve a yield of three more bushels per acre than a farmer not using the technology. This finding appears consistent with the early field trials which had suggested slight improvements in yields.

With regard to the human capital variables, two of the education dummy variables—*HiSchool* and *College*—were significant at the 1% level. These results revealed that farmers with high school or college education had substantially higher yields than those without a high school degree. The remaining significant variable was the dummy for Kent County, where yields were higher than those in the base New Castle County. While this result was expected, the lack of significance for Sussex County, hypothesized to be the most productive, was not.

For the remainder of the variables, the lack of significance for farm size (*Acres*), partly also a proxy for farm management, and narrow row spacing (*Narrow*) were also initial surprises. The *Acres* coefficient did, however, conform to the notion that the GE technology should be scale-neutral. Narrow row spacing, which intuitively would seem to imply higher yields per acre, was likely not significant simply due to the fact that the vast majority of farmers had adopted this technique. Finally, the relatively low $R^2$ value (0.2124) suggested a number of factors explaining the variation in yields were not captured in the model.

Turning to the results of the weed control costs model presented in table 4, the percentage of soy acreage to GE soybeans was significant, with the expected negative sign, at the 5% level. Here, the coefficient suggests an extra percentage to the GE variety reduces control costs by about 5¢. This translates into a savings of approximately $5 per acre for a farm planting only GE soybeans. In contrast to the yields model, farm size (*Acres*) was significant, with the expected negative sign. Regardless of the use of GE soybeans, economies of scale would be expected with the larger farms, as is confirmed by the model's findings. High school education was significant at the 10% level, with an unexpected positive sign. Neither the county dummies nor narrow row spacing were found to influence weed control costs. As with the yield model result, where *Narrow* also had been strongly hypothesized to be significant, the lack of significance of this variable in the weed control costs model was the most surprising. Again, however, this finding may simply be explained by farmers' prior adoption and use of narrow row spacing.

## Conclusion

While findings from earlier studies based mostly on controlled field experiments showed questionable benefits from adopting GE soybeans, survey results from adopting Delaware farmers revealed higher yield and lower weed control costs. Some of the differences in these findings are likely the result of the fact that adopters tend to be larger scale, better managed farms—aspects not captured by field experiments. Indeed, farm size was shown to be one of only two variables significant in the diffusion process. The other significant variable, use of a computer for farm management, further reinforces the hypothesis that better managed farms adopt more readily and benefit more from the change. Thus the adoption of the new GE crop technologies, despite their apparent scale-neutrality, may advance the agricultural treadmill process toward fewer and larger farms.

Some limitations of the study should also be noted, however. Because the survey respondents represented only a small region of the country, the results may certainly vary in the major soybean-producing regions. Also, the slight bias in responses toward larger farms may overstate the adoption of and success with GE soybeans. Yet, despite these concerns, the results presented here provide an important contribution to the literature, especially given the significance of this crop and the limited work conducted to date examining its adoption and performance in the field.

Finally, while the results reported here are positive, it should be cautioned that a future limitation of the technology may be the emergence of glyphosate-resistant weeds. Powles et al. (1998) first discovered resistant weeds in Australia after long-term continuous use of the herbicide. Since the time of this survey in 2000, these concerns have spread to Delaware, as researchers have identified a resistant horseweed (VanGessel, 2001). Given the current high usage of glyphosate, this could be of paramount concern. Farmers will need to monitor this development. The problem may eventually overcome the cost savings, suggesting an avenue for future research. The success of the product may limit its life span.

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