Journal of Agricultural and Resource Economics 30(2):268–284

The Economics of Testing for Biotech Grain: Application to StarLink Corn

Demcey Johnson and William Lin

StarLink corn, a variety not approved for human use, disrupted the marketing system in 2000 because of inadvertent commingling. This paper provides an overview of the economics of testing grain for biotech content. What are the risks facing buyers and sellers, and how are these influenced by testing protocols? How do market premiums and discounts, testing costs, and prior beliefs affect the incentives to test? A conceptual model is developed in which sellers choose whether to pre-test grain prior to shipment. Through simulation analysis, we illustrate the impact of market premiums and other variables on testing incentives and buyer risk.

Key words: biotechnology, grain marketing, quality risk, StarLink, testing

Introduction

The emergence of markets for non-biotech grains has created demand for grain testing and stimulated development of new testing methods. Buyers who wish to avoid biotech grain can make use of commercially available diagnostic tests. These allow detection of specified transgenic events (DNA or protein) in grain samples with levels of accuracy that have been verified by USDA's Grain Inspection, Packers, and Stockyards Administration (GIPSA). While statistical aspects of grain testing have been examined previously (see, e.g., Remund et al., 2001), there is relatively little literature on the economic incentives and risks associated with testing for biotech content.[1] This study places testing within an economic context. What is the economic value of information gained through testing? What are the tradeoffs between testing costs, accuracy, and risks to buyers and sellers? How are risks affected by testing protocols, market premiums and discounts, and agents' beliefs about the true concentration of biotech content? The conceptual model is applied to testing for StarLink corn, a biotech variety not approved for food use that became inadvertently commingled with other corn supplies in 2000, leading to product recalls and the disruption of U.S. corn exports.[2]

Demcey Johnson and William Lin are economists with the Market and Trade Economics Division, Economic Research Service, U.S. Department of Agriculture, Washington, DC. The authors thank the editor and two anonymous reviewers for helpful suggestions. We are also grateful to Mike Price, Gerald Plato, and David Skully for their comments on an earlier version. Remaining errors are the authors' responsibility. The views expressed in this paper are those of the authors and not those of the U.S. Department of Agriculture.

Review coordinated by DeeVon Bailey.

[1] Wilson and Dahl (2002) provide one of the few published analyses on the economics of testing for biotech content. Using simulation methods, they evaluate the optimal location for testing within the grain marketing system after the (hypothetical) commercialization of a biotech wheat variety.

[2] See Lin, Price, and Allen (2003) for analysis of the market and trade impacts of StarLink. Sjerven (2001) provides additional background on industry adjustments in the year after the first detection of StarLink protein in food products.

The paper begins with a review of statistical concepts and a summary of recent test results for StarLink. We then discuss testing within a Bayesian framework, and present a conceptual model in which sellers can make a strategic choice about whether to test grain prior to shipment. Incentives for testing and implications for buyer risks are investigated in a simulation exercise. The paper concludes with a short discussion of results.

Testing for Presence of Biotech Kernels

In the following discussion, we assume that the buyer's acceptance of a shipment is contingent on a test indicating zero (or a very low concentration of) biotech kernels. Tests for the presence of biotech kernels involve the binomial distribution.[3] Let n denote the number of kernels in a random sample, and let g denote the *true* concentration of biotech kernels (in a grain lot from which the sample is drawn). The probability of *exactly* "x" biotech kernels in a random sample is designated by:

$$b(x; n, g) = \binom{n}{x} g^x (1 - g)^{n-x} \quad \text{(pdf of binomial distribution).} \tag{1}$$

The probability of *no more than* "x" biotech kernels in a random sample is given by:

$$B(x; n, g) = \sum_{k=0}^{x} b(k; n, g) \quad \text{(binomial cdf).} \tag{2}$$

A *qualitative* test—the type most often used by grain traders—establishes the presence or absence of biotech kernels. (Quantitative tests, which estimate the proportion of biotech kernels in a sample, are much more costly and time consuming.) For a qualitative test, $x = 0$ and the chance of acceptance is $B(0; n,g)$. The chance that grain will be rejected due to presence of biotech kernels is $1 - B(0; n,g)$. Figure 1 shows the relationship between chance of acceptance and sample size based on a single sample plan.

A single large sample serves the buyer's interest well if the buyer is willing to accept a low concentration of biotech kernels, but not a high concentration. However, under a single sample plan, the risk of rejecting lots that are actually acceptable is greater for the seller with a larger sample size. Decreasing the sample size would lower this risk. Hence, increasing the sample size in a single qualitative test may not serve the best interests of both the buyer and the seller.

An alternative is to implement a multiple sample plan. Suppose there are m independent samples, each with n kernels. The buyer agrees to accept the grain if there are no more than r positive test results ($0 \le r < m$). In this case, the probability of acceptance is:

$$B(r; m, q) = \sum_{k=0}^{r} b(k; m, q), \tag{3}$$

where q is the probability of rejecting one sample,

$$q = 1 - B(0; n, g). \tag{4}$$

---

[3] Our discussion is focused on sampling error. However, as noted in the USDA/GIPSA (2000) web briefing, "Sampling for the Detection of Biotech Grain," there are other potential sources of measurement error, including sample preparation and analytical method.

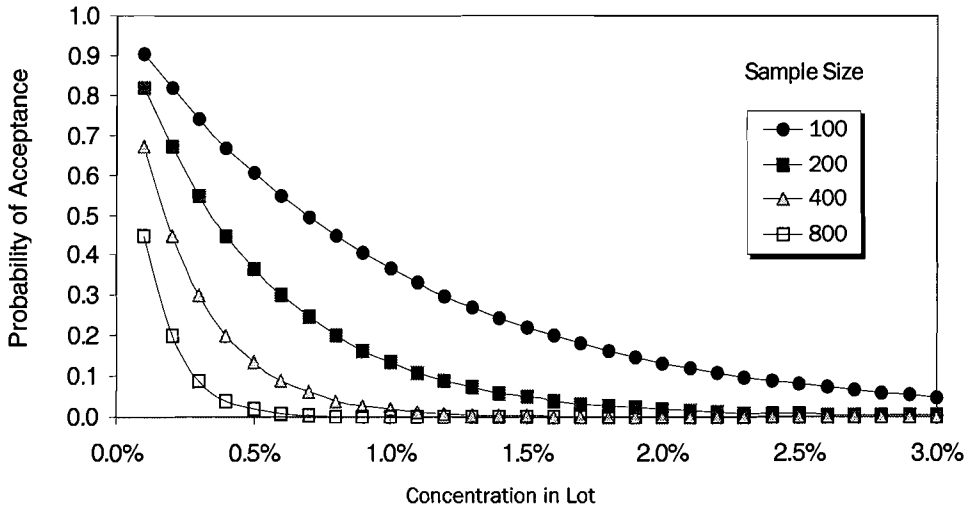

Figure 1. Impact of sample size on probability of acceptance

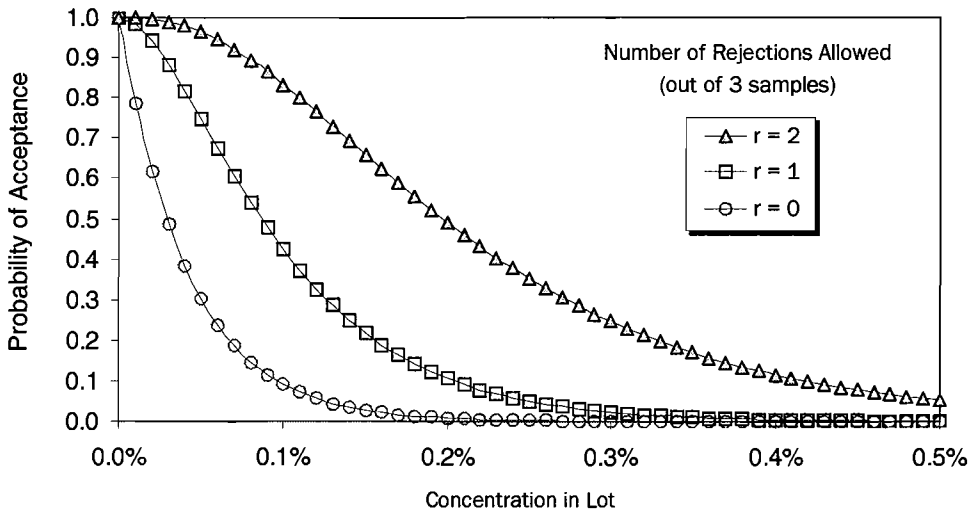

Figure 2. Probability of acceptance under multiple sample protocol for corn exports

Application to StarLink

For export shipments to Japan, the official testing protocol for StarLink (developed by USDA/GIPSA in consultation with Japanese authorities in November 2000) involves three corn subsamples ($m = 3$) of 800 kernels each. This plan is based on sampling and testing recommendations of GIPSA and the Food and Drug Administration, but it also reflects the limitations of production and handling processes and current testing technology. At present, the detection sensitivity reaches 0.125% (1 StarLink kernel in 800) for most test kits.

Figure 2 shows the chance of accepting grain for alternate values of r. Setting $r = 0$ allows none of the three samples to indicate presence of StarLink. Less stringent requirements ($r = 1$, or $r = 2$) expose the buyer to more risk, as shown in table 1. When no positive results are allowed ($r = 0$), the buyer has 99% confidence that the actual StarLink concentration (g) does not exceed 0.19%.[4] Put another way, the chance that the concentration exceeds 0.19% is no more than 1%. For a chosen confidence level, the maximum concentration rises as the requirement becomes less stringent. When $r = 3$, the maximum concentration jumps to 100%. When all three samples are allowed to test positive, no direct inference can be made about the concentration of StarLink. This is because the probability of rejection is zero regardless of the concentration level.

These calculations require no prior information about the distribution of StarLink in corn being tested. For a chosen confidence level, the maximum concentration level provides a worst-case assessment of buyer risk. The maximum concentration level may be substantially higher than the *expected* concentration of StarLink kernels, given available information from actual test results. To illustrate this distinction, we use information presented in table 2 to derive an estimate of the mean StarLink level in corn tested over the period January 12, 2003 through January 10, 2004. The overall probability of a sample testing positive was

$$(5) \qquad q = \frac{\textit{total number of positives}}{\textit{total number of samples}} = \frac{138*(1) + 40*(2) + 61*(3)}{17{,}973} = 0.007437.$$

The value of g that solves[5]

$$(6) \qquad 1 - B(0; 800, g) = 0.007437$$

provides an estimate of the underlying concentration of StarLink kernels. Using this procedure, we estimate the concentration at about 0.00093% in the corn tested. This is substantially less than concentration levels reported in table 1, which reflect no prior information about the distribution of StarLink. For perspective, estimated StarLink concentration levels were about 10-fold higher in the 2000 crop year, based on GIPSA test results (Freese, 2004).[6]

---

[4] For the 99% confidence level, the maximum concentration is the value of g that solves $B(r; m, q) = 0.01$, where q is the probability of rejection for an individual sample, $q = 1 - B(0; n, g)$. This may be represented graphically in figure 2 by drawing a horizontal line at prob = 0.01; the maximum concentration is determined by the intersection of this line with an acceptance curve.

[5] This can be done using SOLVER in an Excel spreadsheet.

[6] It should be emphasized that samples submitted to GIPSA for StarLink testing are not from randomly selected lots. Tests are conducted at the request of the applicant.

Table 1. Maximum StarLink Concentrations Based on $n = 800$ and $m = 3$

r: Allowed Number of Positive Test Results	Maximum Concentration (%), by Confidence Level		
	99% Confidence	90% Confidence	50% Confidence
0	0.19	0.10	0.03
1	0.35	0.20	0.09
2	0.71	0.42	0.20
3	100.0	100.0	100.0

Table 2. Frequency of Test Results During January 12, 2003 and January 10, 2004

Number of Subsamples Testing Positive (out of 3)	Number of Tests	Share of Total %
0	17,734	98.670
1	138	0.768
2	40	0.223
3	61	0.339
Total:	17,973	100.000

Source: Robert Lijewski, USDA/GIPSA (2004).
Notes: Table data are based on the testing protocol for StarLink in export shipments ($m = 3$, $n = 800$). Test results reported by the Federal Grain Inspection Service and official agencies.

Risks to Buyers and Sellers: A Bayesian Perspective

As outlined above, the chance of accepting a shipment of grain is conditional on g, the proportion of biotech (or StarLink) kernels in the population from which the sample is drawn. We now consider a situation in which g is unknown, but buyers or sellers of grain have prior beliefs that can be represented by probability distributions. Beliefs may be modified (updated) on the basis of test results.

Assume that a buyer has a tolerance level for presence of biotech kernels (which may be arbitrarily close to zero), and that grain is tested before purchase. Based on the test result, the grain will be either accepted or rejected by the buyer. The seller does not have perfect information about the content of biotech kernels, but can assign probabilities to a grain shipment having high or low levels (relative to the buyer's tolerance). Let $P(H)$ denote the (subjective) probability of a high level, and $P(L)$ the probability of a low level. Probabilities that the buyer's test will indicate "accept" or "reject" are denoted $P(A)$ and $P(R)$, respectively. Outcomes can be represented as follows:

		Test Result		
		Accept (A)	Reject (R)	Marginal
Biotech Concentration	Low (L)	$P(L, A)$	$P(L, R)$	$P(L)$
	High (H)	$P(H, A)$	$P(H, R)$	$P(H)$
	Marginal	$P(A)$	$P(R)$	1.0

Joint probabilities are shown within the box. For example, $P(L, A)$ is the joint probability of a low concentration and acceptance, and $P(L, R)$ is the joint probability of low concentration and rejection. Marginal probabilities sum to one, and joint probabilities sum to marginal probabilities.

Conditional probabilities are defined via Bayes' rule. For example, the conditional probability of H, given A, is denoted by:

$$P(H \mid A) = P(H, A)/P(A). \tag{7}$$

This represents the *buyer's risk*—the risk that grain has a high concentration of biotech content despite a favorable test result. *Seller's risk* can be interpreted in different ways. From the seller's perspective, risk could be represented by $P(R)$, the probability of a rejected shipment (irrespective of the actual concentration), particularly if costs are incurred as a result of the rejection. Another interpretation[7] views seller's risk as the conditional probability of rejection given low concentration:

$$P(R \mid L) = P(L, R)/P(L). \tag{8}$$

In that case, the test has led to the wrong conclusion, e.g., because of sampling error. Buyer and seller risk (in either form) will reflect the testing protocol, the buyer's tolerance, and prior beliefs about the distribution of biotech kernels.

Testing and the Value of Information

From the buyer's perspective, the value of information gained from a test could be represented by:

$$V = K * \left[P(H) - P(H \mid A)\right], \tag{9}$$

where K is the (possibly subjective) unit value of avoiding high levels of biotech kernels, and the expression in brackets is the reduction in buyer risk associated with testing. If the value of information exceeds the unit cost of the test, then testing prior to purchase makes economic sense for the buyer.

Now consider the incentives for sellers. Under what conditions will sellers test grain for biotech content? To explore this question, we construct an example in which market premiums and discounts play a role, along with testing costs. Assume that a seller can deliver grain to one of two markets. The first is a premium market (where sales are conditional on test results), and the second is a reserve market (where tests are not conducted). Grain shipped to the premium market is tested by the buyer. If biotech kernels are not detected, the buyer accepts the grain and the seller earns a premium, Y ($/mt). If the grain is rejected due to biotech content, it must be re-routed to another location where it incurs a known discount, D.[8] Alternatively, the seller could avoid

---

[7] This is the interpretation given by USDA/GIPSA (2000) in its web briefing, "Sampling for the Detection of Biotech Grains" (p. 7).

[8] This is a simplification. In international trade, rejection by one importer may lead to alternate options for the seller: a discount negotiated with the original buyer, possibly with labeling requirements; arranging a sale to another company at the same port; or re-routing to another port with additional shipping costs. Thus, discounts may be uncertain.

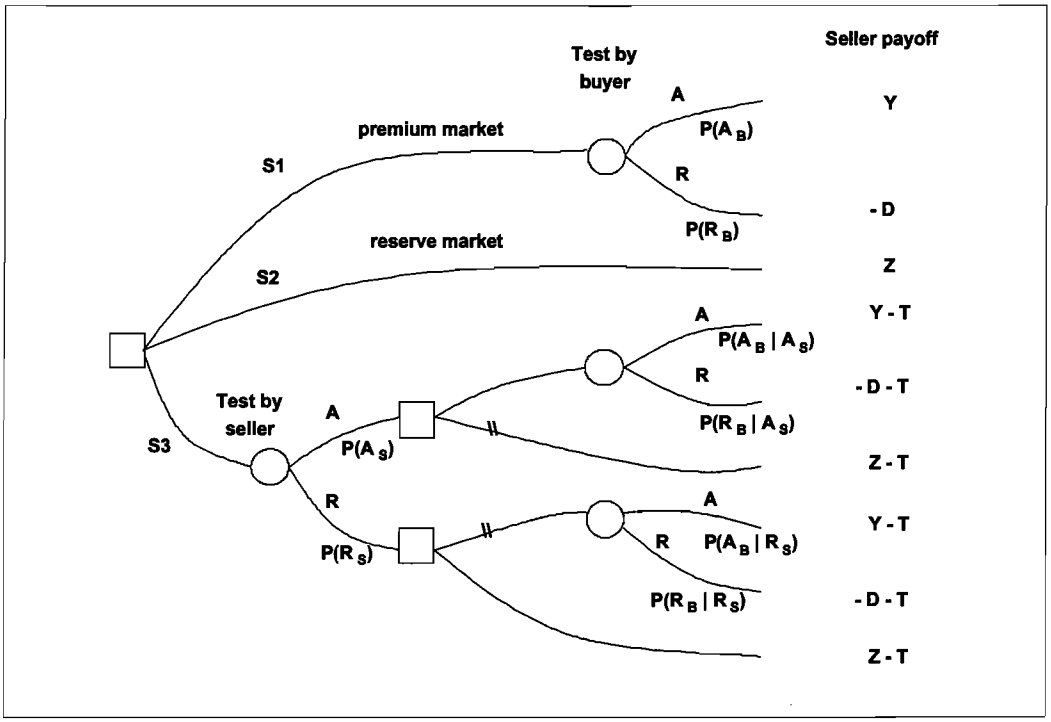

Figure 3. Seller's problem as a decision tree

testing by bypassing the premium market and shipping directly to alternate buyers, where the grain earns a reserve price, Z. Before deciding where to ship the grain, the seller could conduct his/her own test, at cost T (\$/mt), to gain information about odds of buyer acceptance in the premium market. Figure 3 provides a decision tree of the seller's problem, with chance nodes represented by circles and decision nodes by squares.

For plausible parameter values there are three seller strategies to consider.[9] Strategy S1 is to ship directly to the premium market without pre-testing. Strategy S2 is to bypass the premium market and ship to the reserve market. Strategy S3 involves a test prior to shipping, for which the seller incurs a testing cost. If the result is favorable (indicating no biotech content, or "accept"), the grain is shipped to the premium market; otherwise it is shipped to the reserve market. Under S3, the probability of acceptance in the premium market is $P(AB \mid AS)$. That is, the probability of buyer acceptance is conditioned by the first test result (known to the seller only). Expected payoffs for the three seller strategies are presented in table 3.

Also shown in table 3 is the buyer risk in the premium market. (This is not applicable when the premium market is bypassed, as in S2.) The buyer's risk is actually lower under S3, i.e.,

$$P(H \mid A_B, A_S) < P(H \mid A_B), \tag{10}$$

[9] We assume $Y > Z$, etc. In the tree diagram (figure 3), dominated strategies are indicated by double backslashes (\\ ). For example, it would make no sense for the seller to test grain and, if the test result were favorable, ship to the reserve market where price is lower.

Table 3. Expected Payoffs and Buyer Risks Under Different Strategies

Seller Strategy	Seller's Expected Payoff	Buyer Risk
S1	$P(A_B)*Y - P(R_B)*D$	$P(H \mid A_B)$
S2	Z	Not Applicable
S3	$P(A_S)[P(A_B \mid A_S)*Y - P(R_B \mid A_S)*D] + P(R_S)*Z - T$	$P(H \mid A_B, A_S)$

Definitions:

S1 = Seller ships grain to premium market without pre-testing
S2 = Seller ships grain to reserve market where testing is not required
S3 = Seller tests grain before deciding where to ship
A_S = "Accept" indicated by seller's test prior to shipment
A_B = "Accept" indicated by buyer's test upon delivery to premium market
R_S = "Reject" indicated by seller's test prior to shipment
R_B = "Reject" indicated by buyer's test upon delivery to premium market
Y = Premium for grain accepted in premium market ($/mt)
D = Discount applied if grain is rejected in premium market ($/mt)
Z = Price received in reserve market where grain is not tested ($/mt)
T = Testing cost incurred by seller for pre-test ($/mt)

because under this strategy the grain has been tested twice and probabilities of "high" levels of biotech kernels are reduced accordingly. This hinges on our assumption that parameters of the underlying probability distribution are not known with certainty, so that successive test results can lead to revision of (subjective) risk assessments.

Pre-testing by the seller (S3) works to the advantage of the buyer in the premium market by lowering risk. However, the seller's optimal strategy depends on multiple factors, including the premium offered by the buyer (Y), the discount if grain is rejected (D), the reservation price (Z), and the testing cost (T) and testing protocol. Pre-testing is not always optimal from the seller's perspective.

Figures 4 and 5 illustrate how the premium (Y) could affect seller payoffs, holding other parameters fixed. In each figure, crossover points are marked where returns are equalized across strategies. Thus, payoffs for strategies S1 and S2 are equalized at $Y = b$, payoffs for S1 and S3 are equalized at $Y = a$, and payoffs for S2 and S3 are equalized at $Y = c$. Slopes are given by the derivative of the seller's expected payoff (table 3) with respect to Y. The payoff for S2 is independent of the premium, and hence has zero slope. Buyer risks are also represented in figures 4 and 5. When S1 is the dominant strategy (lying above S2 and S3), the buyer's risk is higher, as discussed earlier.

In figure 4 there is a range of premiums ($c \leq Y \leq a$) for which strategy S3 (pre-testing) is optimal. Below that range, strategy S2 is optimal, and above it strategy S1 is optimal. When the premium is too low ($Y < c$), the seller bypasses the premium market. When it is too high ($a < Y$), the seller maximizes expected return by shipping to the premium market without pre-testing.[10] Figure 5 illustrates a different situation—one in which no

[10] This follows from the specification of the seller's problem. Note that in figure 4, the line for S1 is more steeply sloped than that for S3. Slopes are given by $\partial\pi_1/\partial Y = P(A_B)$ for S1, and $\partial\pi_3/\partial Y = P(A_S)P(A_B \mid A_S) = P(A_S, A_B)$ for S3, where π denotes the seller's expected payoff. Since $P(A_B) = P(A_S, A_B) + P(R_S, A_B)$ and all probabilities are positive, it is certain that $\partial\pi_1/\partial Y = P(A_B) > P(A_S, A_B) = \partial\pi_3/\partial Y$. The implication is that, for sufficiently high premiums (greater than "a" in figure 4), holding other parameters fixed, S1 will have a higher expected payoff than S3. Another explanation may be more intuitive. Under strategy S1, the seller attaches probability $P(A_B)$ to grain earning a premium. Under strategy S3, a smaller probability, $P(A_S, A_B)$, applies. The difference is $P(R_S, A_B)$: the probability that test results might conflict in a way favorable to the seller's interest. By pursuing S1, the seller avoids diverting grain (based on a pre-test) the buyer would accept.

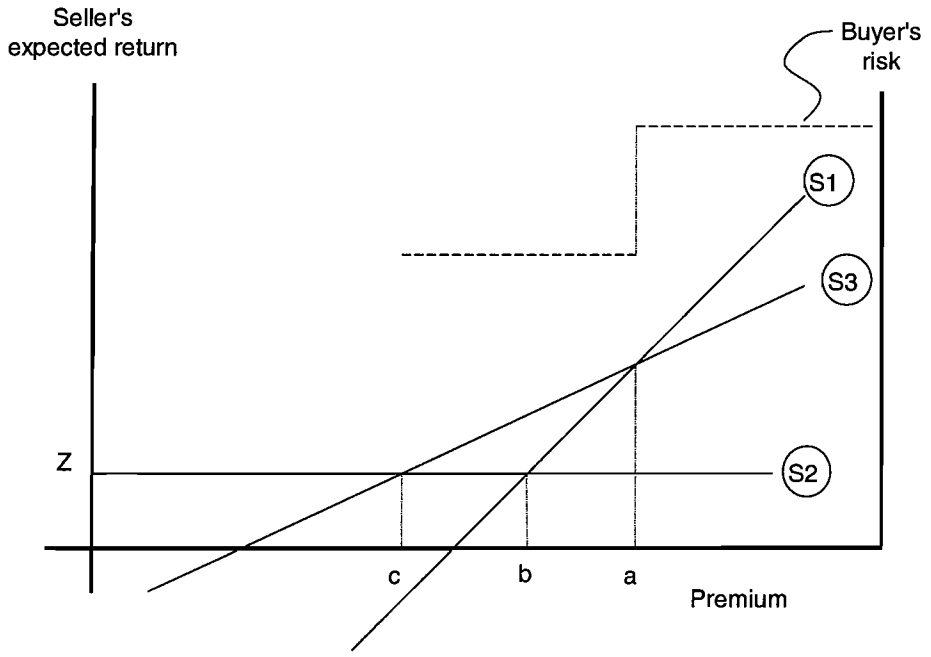

Figure 4. Seller returns as function of premium, version 1

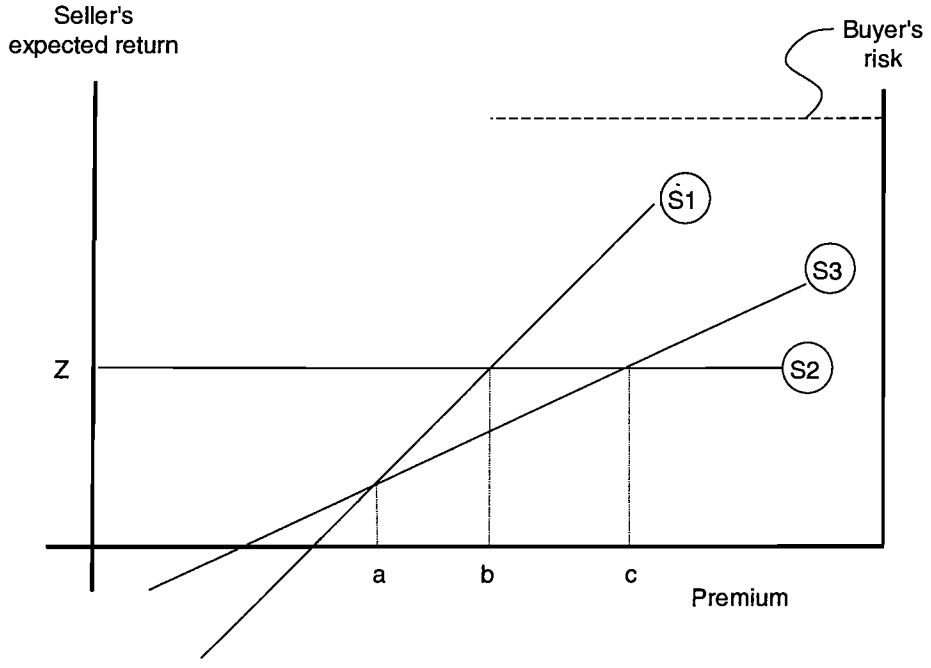

Figure 5. Seller returns as function of premium, version 2

premium can induce pre-testing by the seller. This would occur if testing costs were prohibitively high, for example. Note that crossover points are now in a different order ($a < b < c$), relative to figure 4.

Seller strategies carry different implications for buyer risks. However, the buyer and seller do not share the same information. They may have different prior beliefs about the distribution of biotech kernels, and results from the seller's own tests (prior to shipment) are private information. There are aspects of a principal-agent problem in this situation. The principal (buyer) cannot observe whether the agent (seller) has tested grain prior to shipment, and hence does not have equally good information about the risk of high concentration. The buyer influences the incentives for pre-testing through the choice of premium (and testing protocol), but must consider two factors. If the buyer's premium is too low, the seller will be driven to an alternative market (participation constraint). If the premium is too high, the seller will participate without pre-testing, exposing the buyer to higher risk (incentive compatibility constraint).[11] In the next section, the tradeoff between participation and buyer risk will be explored in a simulation analysis.

Testing for Starlink: A Simulation Analysis

The following analysis uses simulation to represent a universe of potential grain sellers, each with different prior information and opportunity costs. The likely concentration of StarLink kernels (as perceived by potential sellers) is represented by a Weibull distribution.[12] This distribution is characterized by two parameters: β, the shape parameter, and θ, the scale parameter. Choosing $\beta = 0.4$ and $\theta = 3 \times 10^{-6}$ produces a distribution that is broadly consistent with StarLink test results for the January 12, 2003–January 10, 2004 period.[13] However, in the simulation presented here, we consider a range of values for the scale parameter. This is meant to reflect differences in the prior beliefs of sellers, with smaller values of θ representing more refined information about the concentration of StarLink in grain available for sale. In the simulation, 500 values of θ are drawn from a uniform distribution,[14] $\theta \sim UNIF(3 \times 10^{-6}, 3 \times 10^{-5})$.

Sellers may also differ in terms of their reservation price (opportunity cost). It seems plausible that sellers with more refined information (lower value of θ) would have a higher reservation price—e.g., to ensure recovery of higher costs associated with quality management. For this reason, we assume Z, the seller's reservation price, is a random variable that is negatively correlated with θ. For convenience, we assume Z has a uniform distribution, $Z \sim UNIF(0, 10)$. The assumed correlation coefficient is -0.5. Other

---

[11] See Gardner (1995, pp. 271–298) for discussion of principal-agent problems using game theory.

[12] The Weibull distribution was chosen for illustrative purposes. It can assume a variety of shapes and is bound below by zero. As noted by Bain and Engelhardt (1992, pp. 116–117), its probability density function (pdf) has the form:

$$f(x; \theta, \beta) = \frac{\beta}{\theta^{\beta}} x^{\beta-1} e^{-(x/\theta)^{\beta}}, \quad x > 0,$$

with $\beta > 0$ and $\theta > 0$; and its cumulative distribution function (cdf) is given by:

$$F(x; \theta, \beta) = 1 - e^{-(x/\theta)^{\beta}}, \quad x > 0.$$

[13] These parameter values were chosen to be consistent with an expected concentration level of $E(x) = 0.001\%$. The implied cumulative probability of StarLink concentrations less than 0.01% is 0.983, which is reasonably close to the percentage of samples testing negative for StarLink over the January 2003–January 2004 period (table 2).

[14] The choice of uniform distribution is ad hoc. As noted by a reviewer, a plausible alternative assumption is that this distribution is bimodal, with one group possessing refined information and another having diffuse priors.

parameters are fixed. They include T, the unit testing cost (\$/mt), and D, the unit cost associated with rejected shipments (\$/mt). Initially we assume $T = 0$ and $D = \$25$. The buyer is assumed to apply the standard testing procedure for export shipments (3 samples of 800 kernels each), and the threshold between "low" and "high" concentrations is 0.01%.[15]

The simulation is implemented in an Excel spreadsheet using @Risk software. For each drawing of the random variables (θ, Z), the spreadsheet calculates the range of buyer premiums that would support different seller strategies, as illustrated in figures 4 and 5.[16] Risks to buyers are also calculated based on the seller's prior information and (when applicable) test results.[17]

Simulation results are summarized in figures 6–8. Each figure shows results for three different testing protocols, of which "A0" is the most stringent (allowing none of the three test samples to be positive for StarLink), and "A2" the least (allowing two samples to test positive). Figure 6 shows how the number of sellers varies with the size of the premium.[18] For each testing protocol, higher premiums induce a larger share of potential sellers to ship to the premium market where testing is required. For the most stringent protocol, a \$10 premium attracts about 40% of potential sellers; participation rates are substantially higher for less stringent protocols. Participation is complete (100%) for all protocols when the premium reaches \$20.[19]

Of the sellers who ship to the premium market, not all choose to test grain prior to shipment. As shown by figure 7, the share of sellers who pre-test is highest under the most stringent testing protocol. The share of sellers who pre-test declines with higher premium levels, so that under all protocols there is insufficient incentive for pre-testing when the premium reaches \$25. The decline in pre-testing is not intuitively obvious, but is consistent with earlier indications (table 3, figures 4 and 5) that a non-pre-testing strategy will come to dominate at higher premium levels.

Figure 8 shows the combined impact of seller participation rates and testing decisions on buyer risk. In principle, higher premiums (over a given range) can lead to higher or lower levels of buyer risk, depending on the relative importance of these factors. Under the most stringent protocol (A0), average buyer risks increase with the premium. However, under the least stringent protocol (A2), buyer risk falls slightly (for premiums between \$5 and \$10) before stabilizing. This modest decline in buyer risk is due to expanded participation of sellers.

---

[15] This is equivalent to 1 kernel in 10,000, which is the limit of detection for currently approved test kits.

[16] For each realization, this entails calculation of the crossover points (premiums) at which expected seller payoffs are equalized. If $c < b < a$ (as in figure 4), strategy S2 dominates for premiums less than c; S3 dominates for premiums between c and b; and S1 dominates for premiums greater than a. Buyer risks also differ in these ranges. If $a < b < c$ (as in figure 5), strategy S2 dominates for premiums less than b; strategy S1 dominates for premiums greater than b; and strategy S3 is never optimal.

[17] Conditional probabilities are calculated with discrete approximations. For example, the chance of acceptance given "low" levels of StarLink (relative to buyer's tolerance) is given by:

$$P(A \mid L) \approx \sum_{j=1}^{k} \left[F(j*h + c) - F((j-1)*h + c) \right] * B(r; 3, q),$$

where $q = 1 - B(0; 800, j*h)$. In this calculation, the range of "low" concentration is divided into k equal increments of length h, and c is a lower bound arbitrarily close to zero (e.g., $c = 0.00001$). $F(j)$ is the Weibull cdf. Calculations of $P(A \mid H)$ are similar. Given conditional probabilities, other relevant probabilities are derived via Bayes' rule and adding-up properties.

[18] In figure 6, "participation rate" represents the share of sellers who sell to the premium market.

[19] Actual premiums paid by buyers for StarLink-free corn might differ, depending on end use. For food-use corn, Japanese buyers presently are willing to pay \$8 to \$10 per metric ton premium for non-biotech corn that is produced, handled, and distributed under identity preservation to avoid potential StarLink commingling. This premium level does not apply to feed-use corn. However, the U.S.-Japan testing protocol for StarLink applies to both food- and feed-use corn.

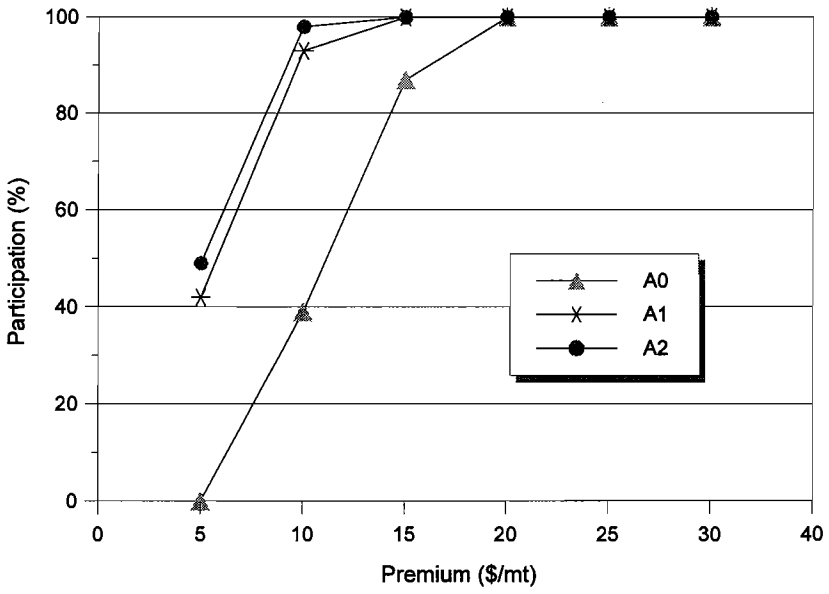

Figure 6. Impact of premium on rate of seller participation

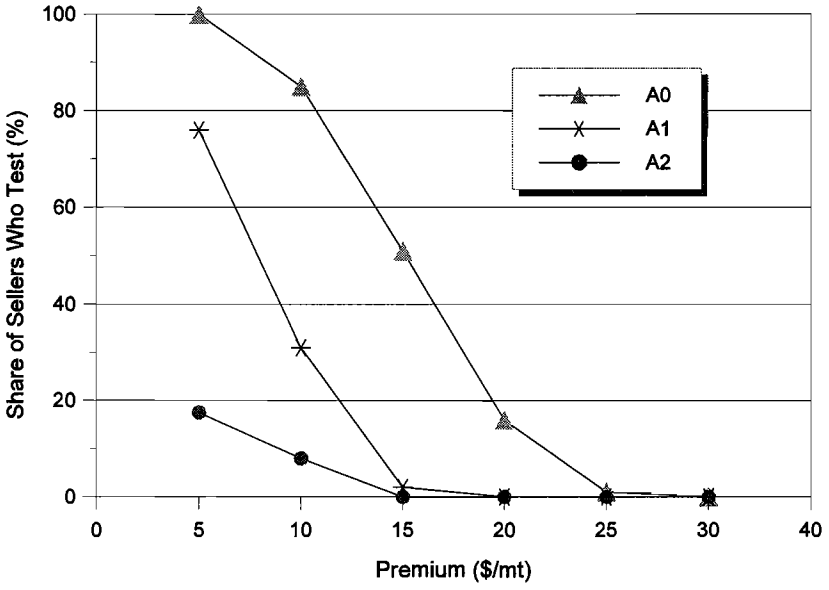

Figure 7. Impact of premium on testing by sellers prior to shipment

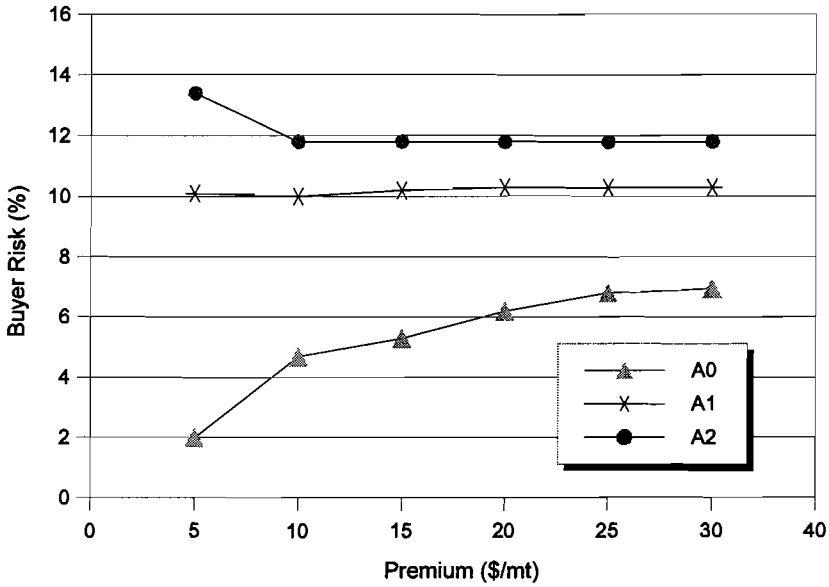

Figure 8. Impact of premium on risks to buyers

A More Accurate Test for StarLink: Impact of Lot Size and Testing Cost

For comparison, a simulation was conducted using a different testing protocol—one based on a single sample of 10,000 kernels. This represents the most sensitive of commercially available tests for StarLink. Previously, we assumed testing costs were zero, which is in line with the use of the lateral flow strip test, a protein-based method that is stipulated in the U.S. and Japan StarLink testing protocol. The more sensitive micro-titer well test kit can detect 1 StarLink kernel in 10,000, but this testing procedure costs more and takes 2–4 hours to complete. The retail cost is around $195 to $200, and the cost charged by private laboratories varies from $35 to $100 per test. A more typical range is between $45 and $75 per test (Kendall, 2004).

The size of the corn lot also affects the per-unit cost. Typical lot size varies from about 800 bushels (20.3 metric tons) for a truckload, to 3,570 bushels (100 short tons) for a hopper car, and 50,000–55,000 bushels (1,330 metric tons) for a barge. Thus, test cost per metric ton ranges from $3.33 for truck to $0.74 for hopper car and $0.05 for barge.

Simulation results are shown in figures 9–11. Impacts of the premium on the share of sellers who ship to the premium market, share of sellers who test prior to shipment, and buyer risk vary by lot size. Sellers have little or no incentive to ship to the premium market when the premium falls below $20 per metric ton (figure 9). Participation rises as the premium exceeds $20/mt, but varies by lot size. The rate of participation is highest for barge-size lots, as the test cost is spread over a much larger grain volume. Participation is lowest when testing is done by truckload.

Sellers find little incentive to pre-test for the presence of StarLink corn in their shipments if the buyer's premium falls below $15 per metric ton, given positive testing costs (figure 10). However, there is interest in pre-testing for barge and hopper car shipments if the premium exceeds $15 or $20 per metric ton. The hike is particularly stiff for barge

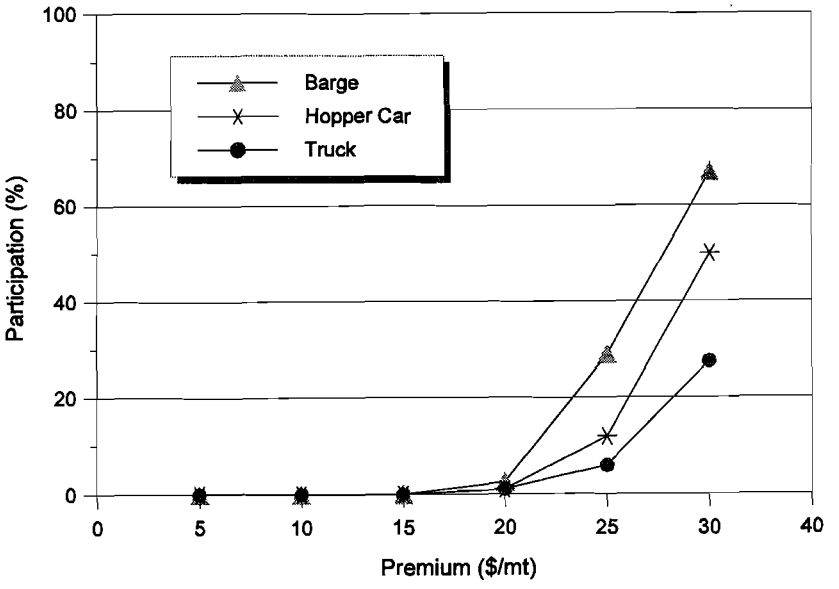

Figure 9. Impact of premium on rate of seller participation by lot size

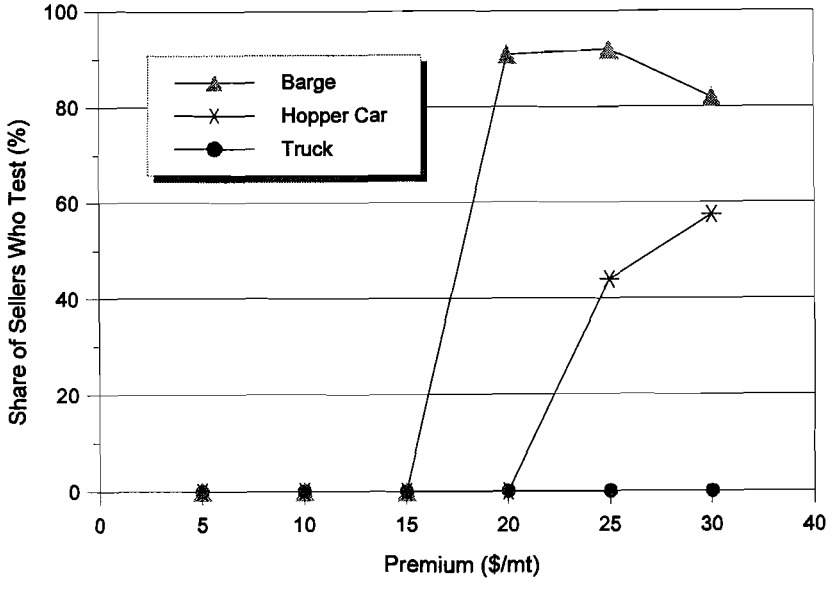

Figure 10. Impact of premium on pre-testing by sellers by lot size

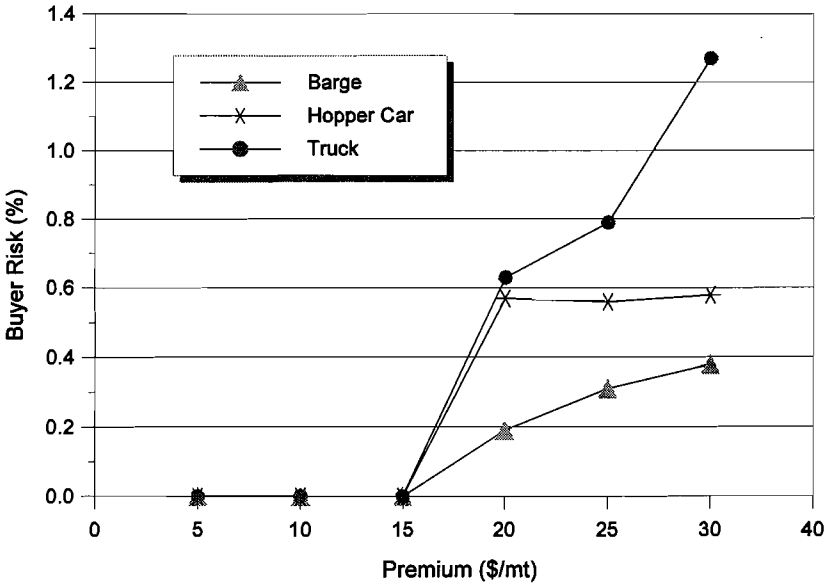

Figure 11. Impact of premium on buyer risk by lot size

shipment—over 90% of the sellers pre-test for the presence of StarLink when the premium exceeds $20/mt. Sellers have no incentive to pre-test for truck shipment even when the premium reaches $30/mt, due to high per-unit testing costs.

Buyer risk is inversely related to the share of sellers who pre-test for the presence of StarLink kernels, for reasons indicated earlier [equation (10)]. Relationships between premiums and buyer risk (by lot size) are shown in figure 11. In the case of truck shipments, higher per-unit testing costs discourage the sellers from pre-testing. In that case, the positive relationship between the premium and buyer risk is due entirely to participation effects. For hopper car and barge shipments, changes in buyer risk (at higher premium levels) are due to a combination of participation effects and changes in sellers' testing strategies. In general, barge shipments expose the buyer to the lowest risk of high StarLink concentration.

Concluding Remarks

Tests for the presence of biotech grain expose buyers and sellers to new risks. In combination with premiums and discounts, these risks can be an important aspect of procurement and marketing decisions. Buyers who wish to exclude biotech grains can influence their risk through their choice of testing protocol (e.g., sample size, single vs. multiple sample plans). Buyer risk is also influenced by the size of the price premium offered for non-biotech purchases. Higher premiums can actually add to buyer risk, either because of participation effects (adverse selection of sellers) or because of reduced incentives for seller pre-testing. Risks facing sellers must be viewed in the context of marketing alternatives. Incentives for sellers to test grain prior to shipment depend on a number of factors: applicable premiums and discounts, testing costs, and prior beliefs about the concentration of biotech kernels.

Simulation analysis provides a flexible means for investigating these effects—particularly when there is uncertainty about underlying distributions. In our experiments, simulation was used to represent a universe of potential sellers, each with different prior beliefs and opportunity costs. Ceteris paribus, sellers with more refined information about the "true" concentration of biotech kernels have less incentive to test grain prior to shipment. Pre-testing is more advantageous when priors are diffuse.

Estimated concentrations of StarLink in tested corn (based on results collected by official agencies) are now substantially lower than in 2000, when contamination of processed foods was first reported. However, testing protocols remain in effect for export shipments to Japan, and some domestic manufacturers maintain more stringent tests. Commercial test kits can now promise detection of one StarLink kernel in 10,000, but at a cost that limits their appeal for bulk grain handlers. This points to the inherent difficulty of satisfying a "zero-tolerance" standard for unapproved biotech events.

An emerging issue is whether, and under what conditions, the interests of buyers and sellers are well served by a reliance on testing. An alternative approach involves identification and certification of suppliers who meet stringent quality-assurance criteria: when buyers have high confidence in a supplier, extensive testing (with its costs and risks) may be obviated. The Process Verification Program (PVP) now offered by GIPSA is intended to facilitate marketing of value-enhanced commodities, including non-biotech grains, by providing independent, third-party verification that suppliers meet internationally recognized standards for quality management. Simulation analysis, like that presented here, could provide insights into the expected payoffs from participating in such programs.

Some limitations of the analysis should be mentioned. Although we alluded to some agency aspects, the analysis falls short of a fully integrated model of buyer-seller interactions. To extend it in the direction of a principal-agent model would require formal specification of the buyer's objectives and constraints. Currently, the analysis does not make explicit assumptions about the buyer's risk aversion.[20] A risk-averse utility function (or the inclusion of chance constraints[21] in a cost-minimization problem) might provide some of the necessary structure. The analysis presents a rather simplified view of the seller's decision environment, ignoring the temporal nature of the grain market, the importance of repeat business, and the reputation effects that might be associated with rejected shipments. Incorporating these factors would surely require a multi-period model (e.g., dynamic games). Finally, we have not captured the complexity of grain procurement, storage, and shipping logistics—or the diverse ways in which biotech grain can be introduced into a product stream through adventitious commingling.

[*Received August 2004; final revision received May 2005.*]

[20] However, we assume the seller to be risk neutral—i.e., model results are driven by the seller's maximization of expected profit.

[21] See Wilson and Preszler (1992) for an application of chance-constrained programming to an importer's wheat purchase decision.

References

Bain, L. J., and M. Engelhardt. *Introduction to Probability and Mathematical Statistics.* Belmont, CA: Duxbury Press, 1992.

Freese, L. D. Observations on StarLink test results. Personal communication, USDA/GIPSA, Kansas City, MO, March 25, 2004.

Gardner, R. *Games for Business and Economics.* New York: John Wiley and Sons, 1995.

Kendall, D. C. StarLink testing information. Personal communication, USDA/GIPSA, Kansas City, MO, April 8, 2004.

Lijewski, R. S. StarLink data. Personal communication, USDA/GIPSA, Washington, DC, February 5, 2004.

Lin, W., G. K. Price, and E. W. Allen. "StarLink: Impacts on the U.S. Corn Market and World Trade." *Agribus.: An Internat. J.* 19,4(2003):473–488.

Remund, K. M., D. A. Dixon, D. L. Wright, and L. R. Holden. "Statistical Considerations in Seed Purity Testing for Transgenic Traits." *Seed Sci. Res.* 11(2001):101–119.

Sjerven, J. "StarLink Recedes as a Threat, Not as a Burden." *Milling and Baking News* (27 November 2001), pp. 1, 26, 28, and 30.

U.S. Department of Agriculture, Grain Inspection, Packers, and Stockyards Administration. "Process Verification Service." Directive No. 9180.79, January 31, 2005. Online. Available at http://151.121.3.117/reference-library/directives/9180-79.pdf.

———. "Sampling for the Detection of Biotech Grains." USDA/GIPSA, Washington, DC, October 2000. Online. Available at http://www.usda.gov/gipsa/biotech/sample2.htm.

Wilson , W., and B. Dahl. "Costs and Risks of Testing and Segregating GM Wheat." Agribus. and Appl. Econ. Rep. No. 501, Dept. of Agribus. and Appl. Econ., North Dakota State University, Fargo, October 2002. [Forthcoming, *Review of Agricultural Economics*, Summer 2005.]

Wilson, W., and T. Preszler. "End-Use Performance Uncertainty and Competition in International Wheat Markets." *Amer. J. Agr. Econ.* 74(1992):556–563.