The Illusion of Control, Cognitive Dissonance and Farmer Perception of GM Crops

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Abstract

We examine the correlation between farmers' beliefs and practices regarding GM crops with yield shocks from the previous year the crop was grown. Farmers who may have had poor yields due to weather, were more likely to change adoption decisions. Yields marginally affect farmers' beliefs regarding the EU ban on GMO's, or the adverse environmental affects of GM crops. This behavior is consistent with many known psychological biases.

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"It must be indicative of something, besides the redistribution of wealth. List of possible explanations. One: I'm willing it. Inside where nothing shows, I'm the essence of a man spinning double-headed coins, and betting against himself in private atonement for an unremembered past." – Guildenstern in *Rosencrantz and Guildenstern are Dead,* by Tom Stoppard after 89 consecutive coin tosses resulting in heads.

The adoption of new technologies has been most often modeled as a function of some combination of profitability, risk preferences, information and human capital constraints. When new technologies become available, there is often little or even conflicting information on the explicit trade-offs involved in adoption. This was the case in the late 1990s and early 2000s, as farmers began considering the use of genetically modified (GM) crops for the purpose of pest damage control. Although Bt corn and cotton were touted for increases in average yield and lower pest control costs, this information was coupled with news of consumer fears, and warnings that the European Union and others would not import GM crops. Further, concerns over environmental externalities were highly publicized.

Amid conflicting information, it is easy to understand why farmers might take on different adoption strategies. Fernandez-Cornejo finds that few variables besides location have strong predictive power in explaining the use of Bt corn by US farmers in this time period. Geographic patterns of adoption behavior also appear somewhat idiosyncratic. In an atmosphere of confusion and ill-defined incentives, it seems only natural that less rational decision-making may be prevalent. In this paper, we explore the evidence that farmers were unable to mentally separate the affects of general adverse weather conditions and the specific use of GM vs. non-GM crops on yields. Further, we examine the phenomenon of cognitive dissonance in deciding to adopt or dis-adopt GM crops. After taking account of various factors in production, and the probability of having previously adopted, we find negative yield shocks experienced in a county in previous years cause subsequent adoption of Bt cotton and perhaps corn. This finding may indicate false attribution due to hindsight biases and the illusion of control, as individuals assume their poor performance was somehow due to poor choices rather than uncontrollable events (these yield shocks appear weather related and show no autocorrelation). In addition, we find some evidence supporting the notion that previous years' yield shocks are correlated with the perception of environmental and export problems with Bt crops. This may suggest cognitive dissonance, or seeking to rationalize one's choices by altering beliefs regarding the relative sizes of benefits and costs.

In the following section we briefly outline the literature regarding technology adoption as it relates to Bt corn and cotton in the US. We also describe the experimental literature detailing the effects of hindsight bias, the illusion of control, and cognitive dissonance. We then describe the data to be used in estimation and our methods. In the following section we present results and discussion regarding the use of Bt corn and cotton.

Rational versus Irrational Adoption

From its inception, the economic literature has acknowledged the large role played by information in technology adoption. Rogers defined adoption as a mental process beginning when an individual first hears of a technology, which eventually leads to use of the technology. Schultz describes periods of disequilibrium that may exist when market players are beginning to understand a new technology. During this period of disequilibrium, a lack of information on newer technologies leads to experimentation, and eventually to a new equilibrium. Although many acknowledge that a lack of information leads to inefficiencies, the literature has focused mainly on inefficiencies due to uninformed but rational actions. In their review of the technology adoption literature, Feder, Just and Zilberman note that adoption is almost exclusively modeled as the result of expected utility of profit maximization. O'Mara modeled the information gathering of farmers as a Bayesian process, whereby they use the information from their own and neighbor's yields to update their prior beliefs about the technology. O'Mara's work has inspired many similar studies examining the spread of information regarding new technologies and the influence on adoption.

More specifically, the adoption of Bt corn and cotton in the US has been widespread and well publicized. USDA has found significant variability in adoption across states. Fernandez-Cornejo and McBride specifically examine the effects of producer attributes on the adoption of Bt corn and cotton, as well as several other GM crops. Although few attributes were statistically significant, education and farm size appear to positively affect the adoption of Bt corn. Growth of adoption of a new technology (diffusion) is usually continuous for such a new technology; in this case, however, adoption rates dipped slightly in the early 2000s. In 1999 the European Union (EU) began a moratorium on the import of nearly all genetically modified corn varieties. This ban on GM corn led to a marked decline in US corn exports to the EU. Prior to the ban, the US had averaged nearly $300 million in corn exports to EU, compared to $70 million annually for the previous three years. Following the EU ban on GM crops, the percent of US corn farmers using Bt fell from near 30% to less than 20%. Alexander, Fernandez-Cornejo and Goodhue use focus group responses from 1999 and 2000 to analyze farmer opinions and information regarding the use of GM crops. They find that many farmers worry about the possibilities of marketing genetically modified crops given the consumer furor in the EU and rising consumer issues in the US. There are wide differences in opinions on whether the higher average yields and lower pesticide costs are worth the added expense. Interestingly, some farmers view Bt varieties as a form of insurance. Their responses appear to reflect a lack of clear information, as in the disequilibrium Schultz suggests.

Psychology and Expectations

In the opening act of *Rosencrantz and Guildestern are Dead* (Stoppard) Guildenstern repeatedly flips a coin, resulting each time in a draw of heads. Guildenstern begins to believe the singular occurrence must be the result of fate, or his own subconscious will. Psychologists and behavioral economists have consistently found humans to be poor processors of information. When presented with new information, there are several systematic and known biases that shape the use of this information for decision-making. In the case of Bt corn and cotton, with very little information regarding future profitability, psychological biases may have become more influential in farmer adoption decisions.

Particularly notable biases are those that arise when individuals try to infer causation from seemingly correlated events. In an early study on the psychology of correlation and causation, Kahneman and Tversky found an illusion of causation associated with reversion to a mean. In his study of Israeli flight trainers, Kahneman and Tversky tried to assess the effectiveness of rewards (punishments) given after particularly good (bad) flights. It was the common view among flight trainers that punishments were more effective than rewards because pilots did better on average after receiving punishment, but worse on average after receiving rewards. Kahneman and Tversky found no correlation between the punishments/rewards and pilot performance. Rather, the pattern of behavior was observed because punishments (rewards) were only given after exceptionally bad (good) performance. The probability of exceptional performances is smaller than that of an average performance. Hence random outcomes had been misinterpreted as the effect of trainer actions. Subsequent studies delineated this phenomenon into two separate behavioral biases: illusion of correlation, and illusion of control.

Illusion of correlation occurs when individuals perceive uncorrelated events to be correlated. Gilovich, Vallone and Tversky found this to be common among basketball fans (and subsequent studies have found it among bettors). In what they called the hot hand bias, individuals perceive basketball shots to be correlated over time, with players going on streaks. However, statistical analysis of shooting data provides little evidence of positive autocorrelation in shooting accuracy. (Although, there appears to be slight *negative* autocorrelation.) Similar phenomena have been observed in many other settings. In general, individuals expect a series of uncorrelated draws (like the flipping of a unbiased coin) to alternate, which would actually be consistent with negative correlation. When data reflect the length of streaks that are natural in an uncorrelated series, people mistake the streaks for evidence of correlation. In general, individuals appear to read too much into happenstance occurrences, trying to find deterministic explanations for random events.

Tversky and Kahneman call this belief in the law of small numbers, or, an irrational belief that small samples must reflect properties of the larger population. Grether explored this phenomenon using economic experiments and found that individuals place too much emphasis on the most recent information when making economic decisions, a form of representativeness bias.

Illusion of control occurs when individuals misinterpret the degree of control they have over situations and outcomes. For example, it has been observed that individuals throw dice harder when desiring larger numbers, but softer when desiring smaller numbers (Henslin). Langer found evidence of the illusion of control by allowing subjects to bet on the outcome of dice rolls. Some subjects were permitted to bet on the outcome before the roll of the dice and others bet after the dice were rolled, but before the outcome was revealed. Those betting before the roll made larger bets than those betting after the roll. It is theorized that those who bet more believed they had a greater influence on the outcome because the roll had not yet taken place. The illusion of control appears to be linked with several attributes of the random situation. Langer cites several of these cues that, when trivially linked to random outcomes, lead to an illusion of control:

- Competition – payoffs are dependent on others' outcomes
- Choice – the random process is preceded by some (possibly trivial) choice
- Active involvement – participation in generating the random outcome
- Response familiarity – familiarity with the types of outcomes

As illusion of correlation and illusion of control combined to blur the effects of flight trainers, control and correlation may also be misinterpreted by farmers making technology adoption decisions. Farmers face uncertainty on many levels. Some of this uncertainty is correlated across geographic areas, while some shocks are farm specific. By examining the effects of local and transitory regional supply shocks on subsequent individual decisions, we detect adoption patterns that may be attributable to illusions of correlation and control.

Cognitive Dissonance

Another well-documented psychological phenomenon is cognitive dissonance. Once having made an irreversible decision, such as this year's planting, individuals are often faced with evidence that their decision may not have been the best. In this case, researchers have found that individuals have a tendency to find or invent new reasoning for making their decisions ex post (Festinger). This phenomenon may be related to confirmation bias (Wason). Given a certain set of beliefs, individuals selectively look for information that confirms prior beliefs and selectively disregard information that contradicts prior beliefs. Thus, information that conflicts with one's past decisions may be discounted. Information that corroborates one's beliefs will not be subject to the same scrutiny. In the context of GM crops, this may lead those who have decided that increased yields from Bt cotton and corn are not worth the added price, to inflate their beliefs in problems with the international markets, or environmental problems.

Few studies have examined the information processing biases of farmers. Still, some results bear mention. Roberts and Key find that US farmers react heavily to previous year's yield shocks. This reaction is highly suggestive of a representativeness bias. More evidence is found by Glauber and Collins, who find that crop insurance rolls increase dramatically the year after a bad yield shock. Together these studies suggest that illusions of correlation and control may entail real consequences in US farming. Lybbert, Barrett, McPeak and Luseno find that pastoral farmers in Ethiopia display an optimism bias in responding to weather forecasts. In all, the evidence of psychological biases among farmers is anecdotal, but consistent with the findings from behavioral finance and experimental economics.

Data and Methods

In the years 1998 through 2001 for corn, and 1997 through 2000 for cotton, the Phase II of Agricultural Resource Management Survey (ARMS) asked producers if GM seed varieties had been used in the current and previous years on sampled fields. These data were combined with county-level yield shocks estimated from publicly available county summaries at the USDA National Agricultural Statistics Service. The yield shocks are computed as residuals from a non-parametrically estimated yield trend estimated separately for each county using 30 years of data.[1] If yield shocks affecting all farms in a neighborhood cause adoption decisions to change, this may reflect that illusion of correlation or illusion of control is influencing adoption decisions. That is, farmers may misconstrue the cause of the yield shock, or the independent nature of yield shocks more generally, associating them with the use or non-use of Bt. Thus we test for the effect of past yield shocks as a cause of subsequent use of Bt.

Table 1 shows the number of Bt and non-Bt farmers in each quartile of the yield shock experienced two years prior to the current year. We examine the shock two years prior to planting because on a large majority of corn and cotton fields, the crop is rotated with a crop besides corn or cotton, so the shock two-years prior is more likely to be the farmer's most recent experience on the sampled field. The quartiles were calculated using the distribution of all shocks from all years, with each shock measured as a proportion of

[1] The non-parametric procedure we used is called "loess", short for "local polynomial regression." This procedure estimates the trend level at each time point using only points near the estimated point and weighting points closer to the estimated point more heavily. The procedure also uses a re-weighting procedure for robustness. The key decision in this procedure is a decision regarding the share of points considered local to each estimated point. We chose a different share of points for each county using an adapted AIC criterion (Hurvich and Simonoff 1998). The yield trends are near linear in most counties and the yield shocks (the residuals) display no autocorrelation.

predicted yield. From Table 1, the percent of adopters was 16.82% for corn for the entire sample period, and 31.43% for cotton.

Examination of adoption is complicated by the fact that the majority of farmers use some form of crop rotation. In this case, for example, a shock may be experienced in year one when non-Bt corn is used, some other crop may be grown in year two, and the farmer reacts by growing Bt corn in year three. In either case, reacting to previous yield shocks could be viewed similarly to insurance behavior following disasters. Several have documented increases in insurance coverage following disasters despite stable probabilities of disaster (Camerer). In this case, Bt may be perceived as an insurance policy shielding against lower yields. When general yield shocks hit, this may lead to greater use of Bt despite the general nature of the shocks.

Because ARMS includes only two years of seed-variety decisions, it is impossible to determine the seed previously used in rotation. For this purpose, we divide our sample into two sub-samples, single-croppers and crop switchers. Among single-croppers, we can directly test for the effect of negative shocks on adoption decisions. Alternatively, by using a control for probability of previous adoption, we can examine the effects of yield shocks in crop rotation. As a primary control, we use a spatial indicator of location (latitude and longitude), as location seems to be the best explanatory variable of Bt use.

In the 2001 ARMS, corn farmers choosing not to use Bt seed varieties were asked the primary reason for their decision. They were given the following choices: (1) Did not expect to have enough corn borers to justify the costs of Bt corn, (2) Concerned about finding a market for Bt corn, (3) This field was used as refuge in 2001, (4) Concerned about the environmental impact of Bt corn, (5) None of the above. Because of the unique timing of the 2001 ARMS survey and the novel question regarding farmer's rationale for non-adoption ofBt corn, we are provided a unique opportunity to learn about belief formation among farmers. Prevailing economic theory supposes that rational individuals base beliefs regarding any particular variable, on stimuli, cues, and information that relates directly or indirectly to the process that generates it. These beliefs may be updated differently based on the information, cues or stimuli individuals experience and their ability to understand them. A rational individual's beliefs are supposed to be independent of any stimuli not related to the generating process.

In the case of US corn farmers, yield shocks, due largely to local weather conditions, bear no apparent connection to the trade environment. So, we should expect prior yield shocks to be unrelated to citing reasons (2) or (4). More explicitly, if farmers who experienced better-than-average weather in 1998 and 1999 were less likely to use traditional varieties due to a fear of the EU ban than those experiencing less exceptional weather in those years, then farmers beliefs likely display a pattern of cognitive dissonance. Because they may be questioning their original reasoning (low prior year yields) they may have begun to focus on other potential reasons to use traditional seed.

Cognitive Dissonance in Bt Corn

Table 2 displays the number of switching farmers citing each reason for non-adoption by yield quartile from two years prior. There were too few disadopters among single-croppers to allow for statistical inference (20 altogether). A statistical test for the hypothesis that there is no correlation between yield shocks and responses (Hogg and Craig, p. 300) produces a chi-square statistic that rejects the hypothesis of no correlation at any reasonable level of significance. More specifically, we can test the hypothesis that having a negative yield shock is correlated with citing (2) or (4). This test also rejects (at the 0.01

level), supporting the notion that a significantly greater number who experienced poor yield shocks, now expect environmental or market problems to make Bt corn unprofitable.

This provides some (modest) evidence consistent with cognitive dissonance in adoption decisions. Those who had particularly bad weather in the years preceding the ban, who had also used Bt corn, may have unduly ascribed their bad fortune to the use of Bt, producing a negative association. Then, when given information about the impending trade restrictions and environmental problems that could negatively affect their benefit from the use of Bt, these farmers may have given undue weight to these problems in their decision-making.

Regression Analysis

To examine these hypotheses more deeply, we use a two-step empirical procedure. In the first step, we predict the likelihood of adopting Bt varieties of corn and cotton seed using location, past yield shocks, and other covariates. In the second step, we examine how the likelihood of adoption and past yield shocks relate to farmers' stated reasons for not adopting. Specifically, the second step examines the likelihood farmers who did not adopt Bt cotton chose one of the two non-production-related reasons for this decision, either trade or environment concerns (alternatives (2) or (4), as described above).

For both steps, we use a non-parametric generalized additive model (GAM). A GAM, an non-parametric adaptation of the generalized linear model, is a flexible model that relates smooth functions of covariates to any random dependent variable belonging to the exponential family of distribution. For our model, we use the binomial logit to relate our covariates to the probability of Bt adoption. Specifically, for the first step we assume the adoption decision on field i is tied to a latent variable Y_i that scales the utility of adopting Bt varieties relative to the utility of using non-Bt seed varieties.

$$(1)\quad Y_i = \alpha + s_1(LONG, LAT) + s_2(ACRES) + s_3(FIELD) + s_4(SHOCK.1) + s_5(SHOCK.2) + d_1 I_i(YEAR_i = 1999) + d_2 I_i(YEAR_i = 2000) + d_3 I_i(YEAR_i = 2001) + \varepsilon_i ,$$

Where LONG and LAT are the longitude and latitude of the field location, ACRES is the farm-wide total number of acres planted to corn, FIELD is the number of acres in the field sampled, SHOCK.1 and SHOCK.2 are the county yield shocks from the previous two years, I_i(YEAR = *X*) is an indicator variable for the year the field was sampled (equal to 1 if the year is *X* and zero otherize), d_1, d_2, and d_3 are fixed, unknown parameters, $s_1()$,$s_2()$, and $s_3()$, are smooth non-parametric functions, and ε_i an error that encapsulates unobserved factors influencing adoption.

We use LAT, LONG, FIELD, ACRES, and YEAR as our primary covariates because previous research suggests that these are variables are among the strongest predictors of adoption (USDA-ERS). For most of our observations, we do not have information on operator or other farm characteristics that are often included in adoption equations. Rather than restrict our sample to the single year for these data are available, we elected to include all observations from four years and use fewer explanatory variables. We made this choice for several reasons. First, in previous studies farm-operator characteristics, though statistically significant in some circumstances, were weak predictors of adoption. Second, the spatial variables should pick up many unobservable variables. Third, and most importantly, with only a single year of data the yield shocks may be confounded by the spatial surface or other factors that vary spatially, so it was important to use several years of adoption data. Fourth, because the weather-induced yield shocks vary widely and unpredictably from year-to-year, they should be uncorrelated with any factors excluded from our model, so their omission should not bias our regression.

For the second step, we consider farmers not adopting Bt corn in 2001 and examine their rationale for not doing so. For this second step, we only examine corn farmers in 2001 because this is the only instance a question was asked regarding the reasoning non-adoptors. We assume a farmer's non-production-related rationale for not adopting Bt corn (reason (2) or (4), as cited above) is tied to a latent variable Z_i, where

$$(2) \qquad Z_i = \beta + f_1(LONG, LAT) + f_2(ACRES) + f_3(FIELD) + f_1(Prob\ [Y_i > 0]) + f_2(SHOCK.2) + f_3(SHOCK.2 * Prob\ [Y_i > 0]) + \eta_i ,$$

the variables *LONG*, *LAT*, *ACRES*, *FIELD*, and Y_i are defined as described above, SHOCK.2 is the county-wide yield shock from two years prior (1999), and η_i is the error that encapsulates unobserved factors. We assume both Y_i and Z_i have a logistic distribution such that

$$Prob\ [Y_i > 0] = \exp(Y_i) / (1 + \exp(Y_i))$$

and

$$Prob\ [Z_i > 0] = \exp(Z_i) / (1 + \exp(Z_i)).$$

The smooth terms in this two-step model are estimated using penalized regression splines with smoothing parameters selected by an unbiased risk estimator (UBRE). For a general overview of these methods, see Wood (2001) and Wood and Augustin (2002). To estimate the model we used a regression package "mgcv," written by Wood, for the statistical software R. This statistical software and package are available for free (see http://www.r-project.org/).

Summaries of estimates of equation (1) for corn and cotton are reported in tables 3 and 4, respectively; a summary of estimates for equation (2) for corn is reported in table 5 (no data is available to estimate equation 2 for cotton). The summary tables report estimates and standard errors of the fixed coefficients, equivalent degrees of freedom, and overall statistical significance of the smooth terms, and the percent deviance explained, a measure of overall fit akin to the R^2 measure in continuous-response models.

In figures 1, 2, and 3 we present plots of the estimated smooth functions together with standard error bands (plus and minus two standard errors at each point). These plots illustrate the marginal effects of the covariates. The hash lines on the bottom of each plot show where the data lie. The vertical axis on these plots is the latent variable (*Y* in figure 1 and *Z* in figure 2), holding all other covariates at their population medians.

The two-dimensional spatial terms are plotted below the one-dimensional terms using contour maps that overlay maps of the United States. For these plots, the predicted latent variables have been transformed into the predicted probability. For example, Figure 3-B displays contour lines for the estimated probability of claiming non-production-related rationale for *not* adopting Bt Corn (either alternative (2) or (4), as described above). The points on the map show the locations of the sampled fields. The contour lines show the estimated probability that the operator chose (2) or (4), holding all other explanatory variables equal to the population median and the year equal to 2001. The map shows a valley in the interior of the country (low probability) and three high plateaus over the northern plans, central Texas, the east. The estimated probability is above 0.8 on the plateaus and below 0.2 in the valley. Note that this map holds all other explanatory variables constant.

The earlier statistical tests show a correlation between negative yield shocks and the citing of environmental or marketing concerns. By itself, this provides some evidence of cognitive dissonance among the farmers that decided not to use Bt corn. After having decided to not adopt, possibly due to a bad previous experience, these farmers may have inflated their concerns about EU's trade ban or environmental concerns to justify their decisions ex-post. The statistics fail, however, to take account of other factors that may cause these beliefs. For example, it may be that these beliefs are a result of the way media portrayed these possibilities in the particular areas where bad yield shocks had occurred. In fact the regression raises some doubt about whether this is the case. Here using a spatial map as a control for previous disposition is a problem because this map may completely represent local yield shocks from a single year (in this case 1999). Hence, there may be a problem with multicolinearity. In fact, the regression reported in table 5 shows the yield shocks to be insignificant, but positively related to citing non-production related reasons for not using Bt corn. While this result does not rule out the existence of cognitive dissonance, it provides little support for the hypothesis. More powerful tests would be possible if more years of data regarding farmers' reasons for non-adoption were available. With more years of data, there would be less multicolinearity between the shocks and location.

The map in figure 3-B raises other questions as to correlation with weather. Here there appears to be a big split between central corn growing states (such as Iowa and Illinois) where production problems were cited as the primary reason not to use Bt, and more urban states (Ohio, Pennsylvania, North Carolina) where environmental and trade restrictions were the primary concern. In fact, this map appears to display the exact inverse of the map in Figure 2, which displays the marginal effect of location on the probability of adoption. In other words, farmers were much more likely to react to problems with the environment or trade if they are located in an area where there is a low concentration of production. If farm operators were more prone to believe in trade problem or environmental problems in areas that happened to have negative supply shocks in 1999, our results may have been caused by spurious correlation.

More detail can be obtained by examining the longer series of adoption decisions among cotton and corn farmers as related to previous weather shocks. By using the entire panel of data from the first stage, we can more fully take advantage of the spatial map as a control and compare to idiosyncratic yield shocks. The results for cotton are stark. In table 4 we see that after controlling for spatial effects, yield shocks from two years previous has a significant effect on adoption decisions, while previous years yield has only a marginal effect. Moreover, the graph in figure 2 suggests that this is a negative relationship. Thus, a farmer, after experiencing a bad year, is more likely to adopt Bt cotton in the next year cotton is planted on the field. This provides some evidence to counter the rational model of adoption for several reasons. First, it appears the idiosyncratic yield shock has somehow provided new information to the farmer, when yields are the result of a nearly stable distribution (our shocks display no autocorrelation). In this case, the farmer may display representativeness bias, placing too much weight on new observations, and underweighting previous experience. This is consistent with the notion that Bt seeds are viewed as insurance, as this behavior has been repeatedly observed in insurance markets.

Secondly, since these yield shocks are not autocorrelated, and primarily related to weather, it is puzzling that farmers would react by adopting Bt. This suggests that farmers suppose that they can change their fortunes by altering production decisions that are unrelated to their poor performance. It would be difficult to reconcile this behavior with a sound understanding of the mechanisms that affect the performance of Bt cotton. These biases are confirmed in our examination of mono-croppers.

In examining the results for Bt corn, we find some evidence of the representativeness effect, although table 3 shows that effect of yield hsocks it is not significant. Though we cannot rule out the same effect, it is interesting that the effect is not as strong with the larger sample corn provides. While cotton is grown in a few, widely dispersed areas, it is spatially concentrated where it is grown. Corn, on the other hand is grown throughout the US, by a much larger number of farmers. This is perhaps evidence of the more effective information distribution mechanism for corn farmers. It may be that irrational effects are the result of confusion and misinformation arising more often for more localized or specialized crops. Even without significant effects for corn, these results paint a consistent story that some portion of adoption is based on trying to overcome uncontrollable and chance events.

Conclusion

Adoption of new innovations occurs almost exclusively in the absence of complete information regarding costs and benefits. Perhaps this environment of confusion and contradictions provides a perfect environment for subjective, and less than rational, reasoning. Although our results provide some evidence of representativeness and the illusion of control, we find weak evidence of cognitive dissonance among those considering the use of Bt crops.

The evidence of representativeness and control biases is somewhat stronger in the case of US cotton than corn. This may be a result of better extension and education efforts regarding the use of Bt corn. Corn is a major crop grown on nearly all farm land in a large number of contiguous states. Alternatively, cotton production is concentrated in a few widely dispersed areas. One possibility is that strong behavioral effects are most likely to be found among more isolated producers, where superior information may not travel as fast, or be as widely published. Further research to document the contribution of heuristics and behavioral effects to the diffusion of new technologies may lead to greater insight into ways to help farmers correct these biases. Improved understanding of these effects can help eliminate informational deficiencies and aid rational adoption decisions. Only with an understanding of the heuristics and biases involved in changing production technologies can we hope to overcome ungrounded perceptions about new technologies.

References

Alexander, C., J. Fernandez-Cornejo, and R. Goodhue. “Iowa Producers’ Adoption of Bio-engineered Varieties.” *Journal of Agricultural and Resource Economics* 28(3): 580-595.

Camerer, Colin. (1995). “Individual Decision Making.” in John H. Kagel and Alvin E. Roth (eds.) *The Handbook of Experimental Economics.* Princeton, NJ: Princeton University Press, 1995.

Feder, G. R.E. Just and D. Zilberman “Adoption of Agricultural Innovations in Developing Countries: A Survey.” *Economic Development and Cultural Change* 34 (1985): 255 – 298.

Fernandez-Cornejo, J. and W. McBride. “Adoption of Bioengineered Crops.” USDA, ERS, Agricultural Economic Report No. 810, 2002.

Festinger, L. *A Theory of Cognitive Dissonance,* Evanston, Ill.: Row Peterson, 1957.

Gilovich, T., R. Vallone, and A. Tversky "The hot hand in basketball: On the misperception of random sequences," *Cognitive Psychology*, 17 (1985): 295-314.

Glauber, J W., and K J. Collins. “Risk Management and the Role of the Federal Government,” in R. Just and R. Pope, eds., *A Comprehensive Assessment of the Role of Risk in U.S. Agriculture,* Boston: Kluwer Academic Publishers, 2002, pp. 469-488.

Grether, D.M. “Bayes Rule as a Descriptive Model: The Representativeness Heuristic.” *Quarterly Journal of Economic* 95(1980): 537 – 557.

Henslin, J. M. “Craps and magic.” *American Journal of Sociology*, 73 (1967):, 316-330.

Hogg, R.V. and A.T. Craig, *Introduction to Mathematical Statistics* 5th ed. Englewood Cliffs, NJ: Prentice Hall, 1995

Hurvich, C. M., and Simonoff, J. S. (1998), "Smoothing Parameter Selection in Nonparametric Regression Using an Improved Akaike Information Criterion" *Journal of the Royal Statistical Society B*, 60, 271 -293.

Kahneman, D. and A. Tversky. "On the Psychology of Prediction." *Psychological Review* 80 (1973): 237 – 251.

Langer, E. "The Illusion of Control." In Kahneman, D., P. Slovic and A. Tversky (eds.),
Judgment under Uncertainty: Heuristics and Biases. New York: Cambridge University Press, 1982, pp. 231 – 238.

Lybbert, T. C. B. Barrett, J. G. McPeak and W. K. Luseno, "Bayesian Herders: Optimistic Updating of Rainfall Beliefs in Response to External Forecasts." Department of Applied Economics and Management, Cornell University, Working Paper, 2004.

Rogers, E. *Diffusion of Innovations*. Iowa Stat Agricultural Experiment Station Report no. 18. Ames: Iowa State University, 1957.

Roberts, M.J. and N. Key "Does Liquidity Matter to Agricultural Production? How Transitory Yield Shocks Influence Subsequent Plantings." In Just. R. E. and R.D. Poper (eds.) *A Comprehensive Analysis of the Role of Risk in US Agriculture*. New York: Kluwer Academic Press, 2002, pp.

SAS Manual LOESS

Schultz, T.W. "The Value of the Ability to Deal with Disequilibrium." *Journal of Economic Literature* 13 (1975): 827 – 46.

Stoppard, T. *Rosencrantz and Guildenstern are Dead*, New York: Grove Press, 1991.

Tversky, A. and D. Khaneman, "Belief in the law of small numbers," *Psychological Bulletin*, 76 (1971): 105 – 110.

USDA, “Adoption of Genetically Engineered Crops in the U.S.” ERS website: http://ers.usda.gov/Data/BiotechCrops/ , November 12, 2003.

Wason, P.C., “Reasoning About a Rule.” *Quaterly Journal of Experimental Psychology*. 20 (1968): 273 – 281.

Wood (2001) mgcv:GAMs and Generalized Ridge Regression for R. R News 1(2):20-25.

Wood and Augustin (2002) GAMs with integrated model selection using penalized regression splines and applications to environmental modelling. Ecological Modelling 157:157-177

Table 1. Number in Sample Using Bt and Non-Bt Seed by Yield Shock Quartile

	Yield Shock Quartile			
	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
		Corn		
Bt	255	538	444	489
Non-Bt	1726	2611	2074	2123
		Cotton		
Bt	359	359	527	503
Non-Bt	1145	722	802	1144

Source: Authors' calculations based on data from USDA Production Practices surveys (1997-2000 for cotton and 1998-2001 for corn).

Table 2. Reasons for Nonadoption (Crop Rotation)

	Two Years Previous Yields			
Reason Cited	First Quartile	Second Quartile	Third Quartile	Fourth Quartile
(1) Borers	216	221	224	204
(2) Market	46	74	65	38
(3) Refuge	8	7	11	13
(4) Environment	28	11	19	18
(5) Other	270	251	245	295

Farmers were asked which of five reasons most accurately describes why they did not adopt. They were given the following choices:

(1) Did not expect to have enough corn borers to justify the costs of Bt corn
(2) Concerned about finding a market for Bt corn
(3) This field was used as refuge in 2001
(4) Concerned about the environmental impact of Bt corn
(5) None of the above

Table 3. Regression Results : Liklihood of Bt Corn Adoption.

First Stage Regression: Estimating the Probability of Adoption

Binomial logit: dependent variable, BT = 1 if Bt corn planted, 0 if conventional seed

Model:

$$Y_i = \alpha + s_1(LONG, LAT) + s_2(ACRES) + s_3(FIELD) + s_4(SHOCK.1) + s_5(SHOCK.2) +$$
$$d_1 I_i(YEAR_i = 1999) + d_2 I_i(YEAR_i = 2000) + d_3 I_i\ (YEAR_i = 2001) + \varepsilon_i$$

Parametric Coefficients	Estimate	Standard Error	t-ratio
Intercept (α)	-2.015	0.064	-31.25
d_1	0.249	0.087	2.86
d_2	0.048	0.086	0.55
d_3	0.334	0.081	4.14

Smooth Terms	Equivalent Degrees of Freedom	Chi-squared statistic	p-value
$s_1(LAT, LONG)$	26.7	491.6	< 2.22e-16
$s_2(ACRES)$	6.97	62.36	3.84e-11
$s_3(FIELD)$	2.80	20.932	7.16e-05
$s_4(SHOCK.1)$	2.1	1.4273	0.51356
$s_5(SHOCK.2)$	1.313	0.95263	0.42979

N = 10,121 Deviance Explained: 10.6%

Table 4. Regression Results : Liklihood of Bt Cotton Adoption.

First Stage Regression: Estimating the Probability of Adoption

Binomial logit: dependent variable, BT = 1 if Bt corn planted, 0 if conventional seed

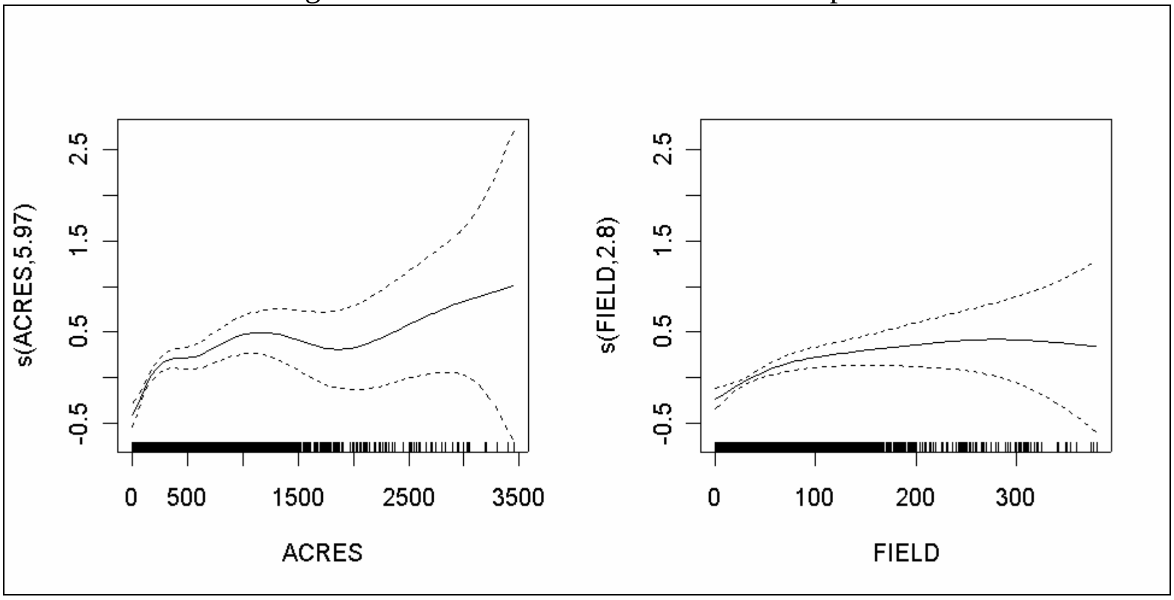
Model:

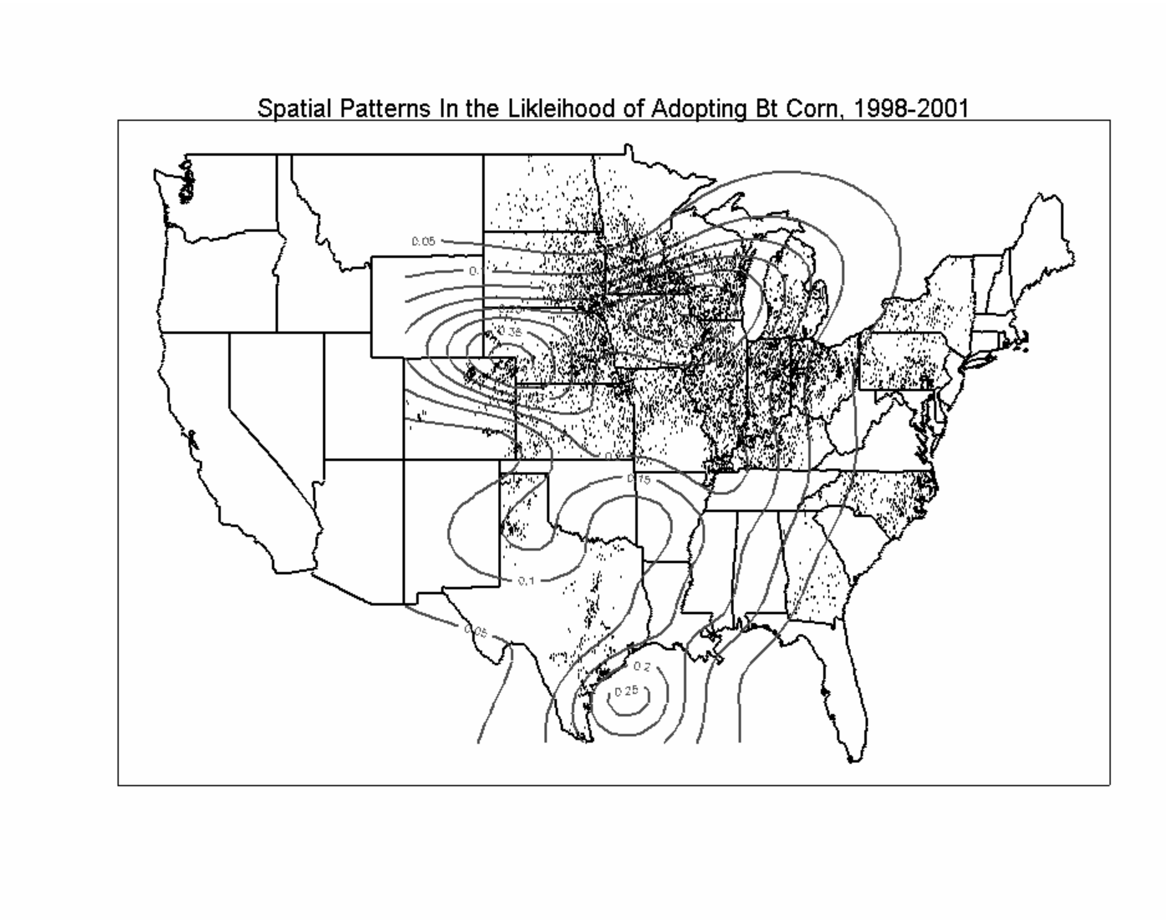
$$Y_i = \alpha + s_1(LONG, LAT) + s_2(ACRES) + s_3(FIELD) + s_4(SHOCK.1) + s_5(SHOCK.2)$$
$$+ d_1 I_i(YEAR_i = 1998) + d_2 I_i(YEAR_i = 1999) + d_3 I_i(YEAR_i = 2000) + \varepsilon_i$$

Parametric Coefficients	Estimate	Standard Error	t-ratio
Intercept (α)	-2.171	0.112	-19.35
d_1	0.863	0.139	6.194
d_2	0.996	0.141	7.083
d_3	1.490	0.124	12.01
Smooth Terms	**Equivalent Degrees of Freedom**	**Chi-squared statistic**	**p-value**
$s_1(LAT, LONG)$	28.06	911.97	< 2.22e-16
$s_2(ACRES)$	1.05	9.576	0.002
$s_3(FIELD)$	1.72	5.765	0.042
$s_4(SHOCK.1)$	1	2.492	0.114
$s_5(SHOCK.2)$	8.541	20.372	0.012

N = 5,238 Deviance Explained: 25.8%

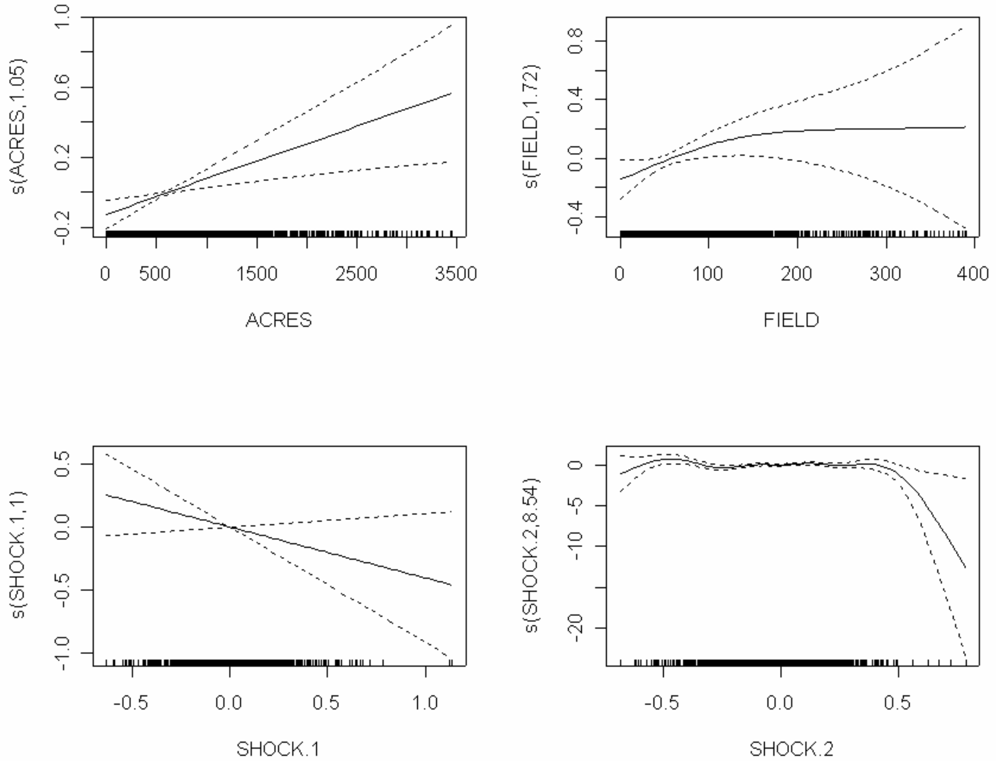
Figure 1 Estimated Terms for Bt Corn Adoption





Note: Red contour lines display estimated probability of adoption (see results reported in table 3) holding continuous covariates besides location (latitude and longitude) equal to population median and the year equal to 2001.

Figure 2 Estimated Terms for Bt Cotton Adoption



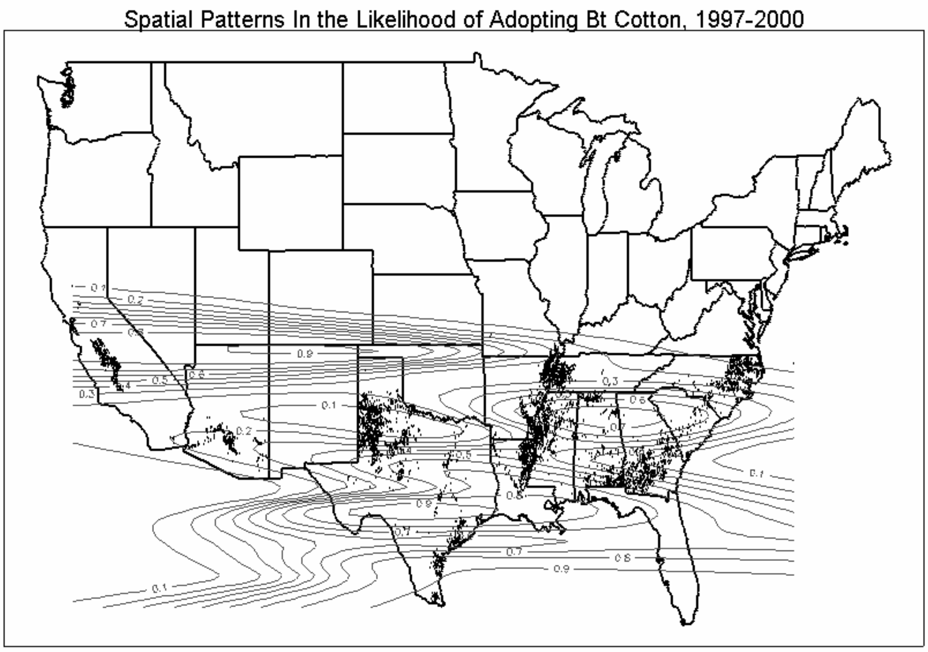


Table 5. Regression Results: Liklihood of Non-Production Influences

Second Stage Regression: Estimating the Probability of Non-production-related reason for NOT adopting BT Corn

Binomial logit: dependent variable = 1 if (alternative 2 or 4), 0 otherwise

Model:

$$Z_i = \beta + f_1(LONG, LAT) + f_2(ACRES) + f_3(FIELD) + f_4(Prob\,[Y_i > 0]) + f_5(SHOCK) + f_6(SHOCK{*}\,Prob\,[Y_i > 0]) + \varepsilon_i\ ,$$

Parametric Coefficients	Estimate	Standard Error	t-ratio
Intercept (β)	-5.335	0.38	-14.04
Smooth Terms	**Equivalent Degrees of Freedom**	**Chi-squared statistic**	**p-value**
$f_1(LONG, LAT)$	29	77.06	3.09e-06
$f_2(ACRES)$	8.018	48.69	7.44e-08
$f_3(FIELD)$	3.424	44.84	1.90e-09
$f_4(Prob\,[Y_i > 0])$	8.541	62.04	3.34e-10
$f_5(SHOCK)$	1	0.053	0.8177
$f_6(SHOCK{*}\,Prob\,[Y_i > 0])$	1	0.034	0.8535

N = 2315 Deviance Explained: 29.5%

Figure 3-One-Dimensional Smooth Terms from Table 5

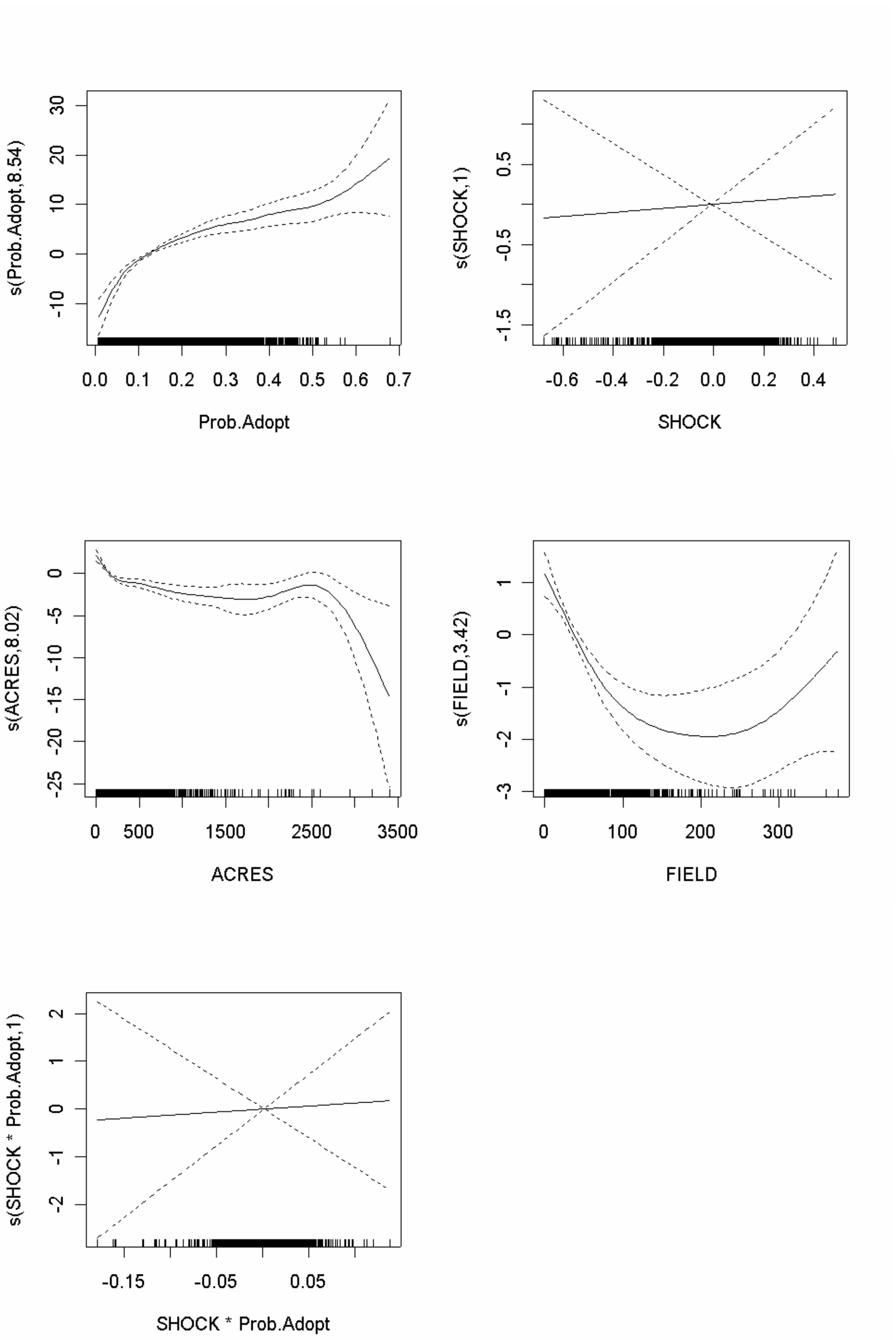
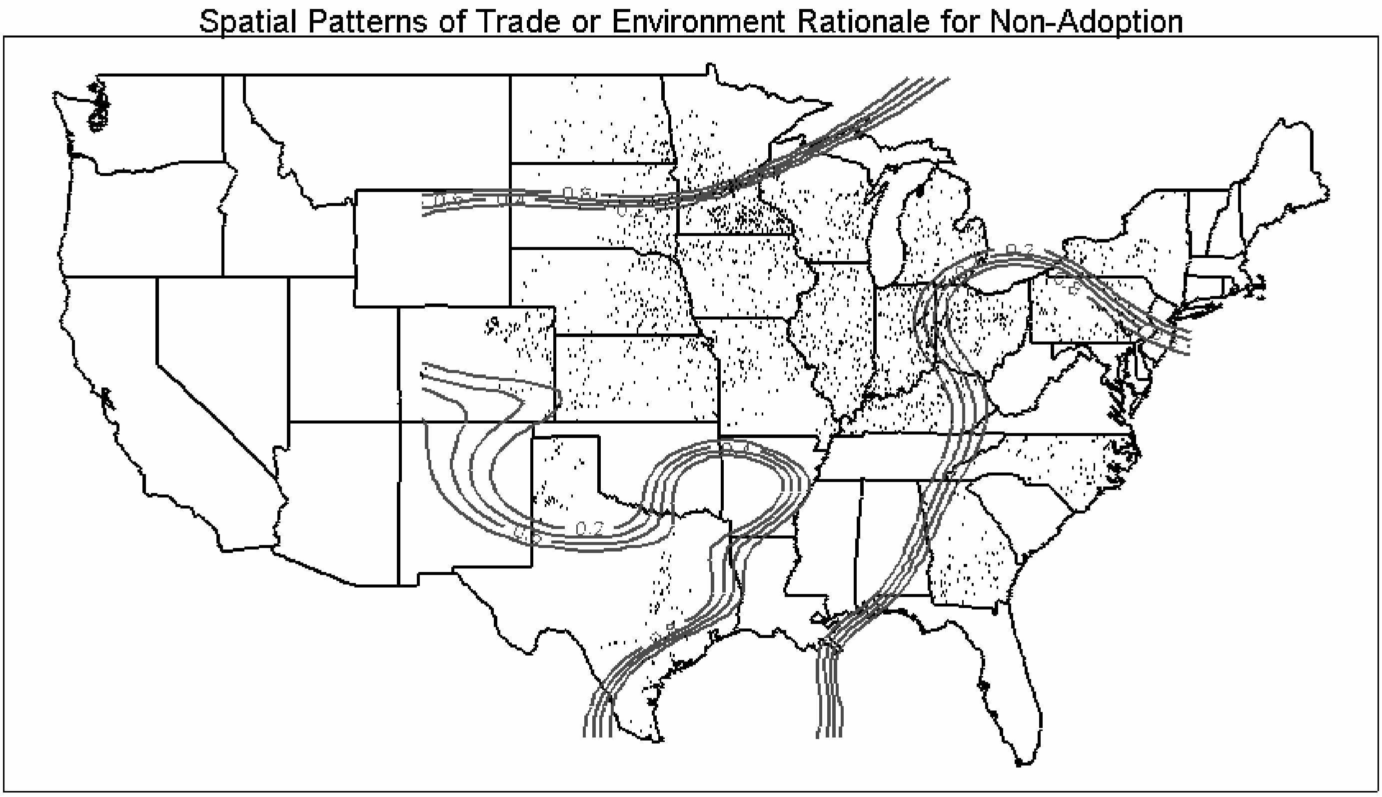


Figure 3-B. Non-Adoption Due to Trade or Environment.



NOTES: This map displays contour lines for the estimated probability of claiming non-production-related rationale for *not* adopting Bt Corn. More specifically, for fields planted with a non-Bt variety of corn, farmers were asked which of five reasons most accurately describes why they did not adopt. They were given the following choices:

(1) Did not expect to have enough corn borers to justify the costs of Bt corn
(2) Concerned about finding a market for Bt corn
(3) This field was used as refuge in 2001
(4) Concerned about the environmental impact of Bt corn
(5) None of the above

The points on the map show the locations of the sampled fields. The contour lines show the estimated probability that the operator chose (2) or (4), holding all other explanatory variables equal to the population median and the year equal to 2001. The map shows a valley in the interior of the country (low probability) and three high plateaus over the northern plans, central Texas, the east. The estimated probability is above 0.8 on the plateaus and below 0.2 in the valley.