Appendix I: A Dynamic Diffusion Model for GE Crops

Diffusion curves are based on the notion that the current adoption rate is a function of the ultimate adoption level and the current adoption level:

$$dZ(t)/dt = f\,(K, Z, t) \qquad (1)$$

where Z is the proportion of the total population that have adopted the innovation at time t, K is the ceiling value or longrun upper limit on adoption, and $dZ(t)/dt$ is the rate of diffusion at time t. Both K and Z are often expressed as a percentage of adopting units (usually percent of firms, although in agriculture the percentage often refers to acreage under adoption, e.g., Knudson, 1991). As Griliches observes, the choice of functional form for the diffusion curve is somewhat arbitrary. The logistic function is often used to represent the S-shaped (sigmoid) diffusion process for agricultural innovations for its relative simplicity (Griliches, 1957; Jarvis, 1981; Knudson, 1991; Karshenas and Stoneman, 1992). Other S-shaped functions used include the cumulative normal and the Gompertz model (Dixon, 1980). However, as Mahajan and Peterson (1985, p. 10) observe, any unimodal distribution function will generate a (cumulative) S-shaped curve.

It is common to assume that the rate of diffusion $dZ(t)/dt$ is proportional to the difference K-Z. In this case, one obtains the so-called "fundamental diffusion model" (Mahajan and Peterson, 1985, p. 13):

$$dZ(t)/dt = g(t)\ [K- Z(\ t)] \qquad (2)$$

where $g(t)$ is called the coefficient of diffusion. Clearly, in this model, as the adoption level increases and gets closer to the ceiling K, the diffusion rate decreases. If $g(t)$ is assumed to be constant, the resulting model is called the "external diffusion" model. If $g(t)= \phi\, Z(t)$ the model is referred to as the "internal influence" model (Mahajan and Peterson, 1985, pp. 17-20), also known as the "contagion" or "epidemic" model in biology (Jaffe et al., 2000, p. 18) in which the innovation spreads as a disease It is common to use the internal influence model in agricultural innovations. In this case, (2) explicitly becomes:

$$dZ(t)/dt = \phi\, Z(t)\ \ [K- Z(\ t)] \qquad (3)$$

Integrating (3), we obtain the logistic,

$$Z = K/[1+e^{(-a-\phi\, t)}] \qquad (4)$$

Making a log-linear (or logit) algebraic transformation of the adoption equation, we obtain $ln[Z/(K\text{-}Z)] = a + \phi\, t$ (Griliches, 1957), where the slope parameter ϕ is known as the natural rate of diffusion, rate of acceptance of the innovation, or rate coefficient (Griliches, 1957), as it measures the rate at which adoption Z increases with time. The parameter a is a constant of integration related to the extent of adoption at time 0, since at $t=0$, $a = ln[Z/(K\text{-}Z)]$. The ceiling K is the longrun upper limit on adoption. Technically, the diffusion rate $dZ(t)/dt$ approaches to zero as Z approaches to K (from equation 3). Also, K is the limit of Z as time tends toward infinity (equation 4). The logistic curve is symmetric around the inflection point (corresponding to the maximum adoption rate) at 50 percent of the ceiling level. The Gompertz model is similarly obtained from equation (3) simply by substituting the log of K and log of $Z(t)$ for the two terms in braces and integrating (Mahajan and Peterson, 1985, pp. 19-20).

Static and Dynamic Models. Static diffusion models, following the terminology of Knudson (1991), are growth models that represent the adoption path, expressing the percentage of adopters as a function of time. Such static models do not contain any other exogenous or endogenous factors. Two other characteristics of such models suggest their unsuitability for the type of innovations we are considering. First, they have a predefined point of maximum adoption as a share of the total population. Second, adoption must always increase over time until it converges to this maximum.

Knudson (1991) identifies the six basic assumptions of static diffusion models: (1) an individual either adopts or does not adopt; (2) there is a fixed, finite ceiling K; (3) the rate coefficient of diffusion is fixed over time; (4) the innovation is not modified once introduced, and its diffusion is independent from the diffusion of other innovations; (5) one adoption is permitted per adopting unit and this decision cannot be rescinded; and (6) a social system's geographical boundaries stay constant over the diffusion process. While many models have been used to study the diffusion of industrial innovations (Mahajan and Peterson, 1985, p. 30), for the case of agricultural innovations, the most common model is the static logistic.

The static logistic is represented by equation (4) assuming that N and K are constant (independent of t). In this case, the logit transformation of the adoption equation $ln[Z/(K-Z)] = a + \phi t$ allows the use of linear regression analysis (Griliches, 1957). The main advantages of the static logistic are its ease of use and its wide applicability. It is also useful for forecasting because it requires no extra exogenous variables. But its usefulness is limited since the parameters that determine the diffusion path are fixed over time.

Unlike static diffusion models, dynamic diffusion models allow the parameters of diffusion that determine the diffusion path (e.g., ϕ, K) to change over time. Dynamic diffusion methods relax some of the assumptions of static diffusion models by allowing for disadoption and variations in the rate of acceptance (slope), and helping directly identify the variables significant to the adoption of an innovation.

In practice, two variations of dynamic models are often considered: the variable-ceiling logistic and the variable-slope logistic models. The variable-ceiling logistic defines the ceiling level (maximum rate of adoption) as a function of a vector $S(t)$ of exogenous factors believed to influence adoption (Jarvis, 1981; Knudson, 1991). Two drawbacks of the variable-ceiling logistic model are that there is no guarantee that the ceiling will stay at theoretically justifiable levels, or that the equation will even converge when the data are extremely nonlinear. The second version of the dynamic logistic model is the variable-slope logistic model, obtained by allowing the adoption rate, rather than the maximum number of adopters, to vary as a function of exogenous factors like price, education, and so forth (Jarvis, 1981; Karshenas and Stonemann, 1992). This method has several advantages. In this model, the rate of acceptance (slope) can vary and even be negative, given the movement of the exogenous factors. It also allows the direct use of outside influences on adoption, and ceiling levels can be set at a theoretically justifiable level (e.g., 100 percent or lower). This model is easier to estimate and does not have the problems of the variable-ceiling logistic model for estimations using non-loglinear data (e.g., nonconvergence, unacceptable results such as *K* higher than 100 percent).

Dynamic Model for the Diffusion of GE Crops. The diffusion of GE crops is modeled with a variable-slope logistic. According to Griliches (1957), the slope, or rate of diffusion, is largely a demand or "acceptance" variable and differences in the slope are "interpreted as differences in the rate of adjustment of demand to a new equilibrium, and will be explained by variables operating in the demand side rather than by variables operating in the supply side." For this reason, and to specify a parsimonious model, the slope N of the logistic is set equal to a function of two sets of variables (***R, S***) that denote demand conditions for GM crops. Thus we have: $\phi = \phi_0 + \boldsymbol{\phi_1}'\boldsymbol{R} + \boldsymbol{\phi_2}'\boldsymbol{S}$. Substituting the variable slope in (4), we obtain:

$$Z = K / \{1+e^{[-a-(\phi_0 + \boldsymbol{\phi_1}' R + \boldsymbol{\phi_2}' \mathbf{S})] t}\} \qquad (5)$$

Making the logit transformation and adding a vector of regional dummy variables (***D***) to account for regional differences in technology (fixed effects, as we are using panel data) associated, for example with the initial availability as well as the initial degree of promotion of the technology, and appending the error term ε, we arrive at the estimating equation:

$$ln\,[Z/(K - Z)] = a + (\phi_0 + \boldsymbol{\phi_1}'\,\mathbf{R} + \boldsymbol{\phi_2}'\,\mathbf{S})\,t + \gamma'\,\boldsymbol{D} + \varepsilon = a + \phi_0\,t + \boldsymbol{\phi_1}'\,\boldsymbol{R}\,t + \boldsymbol{\phi_2}'\,\boldsymbol{S}\,t + \gamma'\,\boldsymbol{D} + \varepsilon \qquad (6)$$

The first set of variables (vector ***R***) attempts to capture consumer preferences and/or concerns about GE products. These concerns are reflected in "market events" including, for example, labeling regulations for foods adopted by the European Union (EU), proposals of mandatory labeling of genetically engineered foods by other countries such as Japan and Korea, announcements by UK food processors and supermarkets of plans to phase out use of biotech ingredients from their products, plans by some U.S. food processors (Heinz, Gerber, Frito-Lay) and several Japanese brewers to stop using biotech ingredients in some of their products. Appendix table 1.1 shows a summary of selected market events extracted from Dohlman, Hall, and Somwaru (2000).

Given the large number of components of the vector of "market events" that impacted the demand of GE crop products in recent years, and to conserve degrees of freedom, we specify a proxy that captures most of the information contained in the vector ***R*** of market events. The proxy selected is an index of stock prices of agricultural biotechnology firms. Such an index was developed by Dohlman, Hall, and Somwaru (2000), who show empirically the effect of market events on equity values of agricultural biotechnology firms and justify their findings by the efficient markets/rational-expectations hypothesis, which "asserts that security prices immediately reflect all available information." Moreover, an earlier study by Bjornson (1998) had shown that stock valuations of leading agricultural seed and biotechnology firms were increasingly being driven by the development of bioengineered crops. An additional advantage of the stock-price index selected as proxy for market events is that market events are incorporated into stock prices as soon as they occur but translate into farmers' plantings/adoption decisions once a year. In this context, the stock-price index assumes the role of leading indicator of demand conditions (for example, an import ban that occurs in November will be incorporated in the stock prices immediately, but will only translate into planted acreages/adoption in the next year).

The second type of demand variable, ***S***, is related to farmers' (marginal) cost decisions and depends on whether the technology provides insect resistance or herbicide tolerance. Since Bt crops replace chemical insecticides to control *Lepidopteran* insects, we use the average insecticide price as an explanatory variable for the rate of diffusion of Bt crops. Similarly, since most of the herbicide-tolerant crops imply the substitution of glyphosate for other herbicides, we include the price ratio of glyphosate to other herbicides as an explanatory variable for the rate of diffusion of herbicide-tolerant crops.

Regarding the effect of ***R***, we expect that an increase in the biotech stock price index (which reflects all known market events and consumer views about the agrobiotech products, thus acting as a leading indicator of the demand for those GE products) will foretell an increase in the demand of genetically engineered crops. Consequently, the R term is expected to have a positive coefficient. Regarding the crop-specific effects of S, an increase in insecticide price is expected to lead to an increase in the incentive for adoption of insect-resistant crops, other factors constant. Similarly, an increase in the price of glyphosate relative to the price of other herbicides is expected to lead to a reduction in the use of glyphosate-tolerant crops.

Ceilings. We specify ceilings for the adoption of different genetically engineered crops by considering likely limitations to demand from either farm production considerations or market restrictions. The base-case ceiling values for Bt crops are computed by considering infestation levels and refugia requirements. For Bt corn, the ceiling is calculated from past infestation levels of corn fields by the European corn borer (ECB), i.e., the percent of the corn acres infested with the European corn borer (at a treatable level) relative to the planted corn acreage. Appendix table 1.2 shows a summary of the results for major States for the 1997 crop year. The ceiling is computed by reducing the infested acreage by the refugia requirements. A 20-percent refugia, which is the figure most commonly recommended, was used in this study (Henderson, 1999; EPA, 1999). Similarly, for Bt cotton, the ceiling is obtained from a 3-year average of recent infestation levels of cotton fields, i.e., the percentage of the cotton acres infested by the bollworm, budworm, and pink bollworm. The results are shown in appendix table 1.3. This ceiling is also reduced by the refugia requirements. Alternative scenarios are obtained assuming infestation levels 30 percent higher and lower than the base case (past infestations).

For the case of herbicide-tolerant crops, a ceiling computed from weed infestation levels is not likely to be binding, since most acreage is potentially susceptible to infestation. For this reason, ceilings in these cases are based on other considerations. For the diffusion of herbicide-tolerant soybeans, the ceilings are computed based on potential demand restrictions in the export market. As soybean exports have represented around 35 percent of U.S. production in recent years (appendix table 1.4), we examined various scenarios considering different percentages of U.S. exports for which GE soybeans remained eligible. In one extreme case, it was assumed that all U.S. soybean exports would be of conventional crops. The other extreme case assumed no restrictions in exports of GE soybeans. Intermediate cases of export reductions of GE soybeans were also examined. As food safety and consumer concerns in the export market are not restrictive for herbicide-tolerant cotton, we follow Rogers (1983) and use a ceiling of 90-percent adoption. A 70-percent ceiling is used to examine the sensitivity of the results to the ceiling specification. Demand restrictions in the export market are not considered for Bt cotton, since consumer concerns do not extend to cotton.[1]

To summarize, the estimation of the dynamic logit regression (for the base cases) is based in the following ceiling specifications: the ceiling for the diffusion of Bt corn is computed from the ECB infestation level adjusted by refugia requirements; the ceiling for the diffusion of Bt cotton is obtained from the infestation level of bollworms and budworms, adjusted by refugia requirements; the ceiling for herbicide-tolerant soybeans is calculated assuming no exports of GE soybeans. Finally, the ceiling for the diffusion of herbicide-tolerant cotton is set at 90 percent. We re-estimate each regression for a set of alternative ceiling values.

Data and Estimation. Adoption data for 1996-98 are obtained from the ARMS surveys, conducted through onsite interviews by the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture. More recent data are obtained from two other NASS surveys: the Objective Yield Survey (OYS) and the June Agricultural Survey. The OYS was used to obtain adoption data for 1999 (USDA, NASS, 1999c). The June Survey provided adoption data for 2000 (USDA, NASS, 2000b). The crops included in the surveys are corn, soybeans, and upland cotton. A summary of these data sources is presented in box 1 (pp. 5-7). To define regional dummies, this analysis uses the new set of eight farm resource regions, recently constructed by ERS, depicting geographic specialization in production of U.S. farm commodities.

To estimate the expected prices of chemical inputs (glyphosate, other herbicides, insecticides), we use the actual prices paid lagged 1 year, obtained from USDA, NASS (2000a, c, d). The stock price index of ag biotech firms is calculated by constructing an equally weighted portfolio of the following agricultural biotech firms (or their predecessors or successors): Pharmacia, Aventis, Astra-Zeneca, Novartis, Dupont, Dow, Delta and Pine Land, Hoecsht, Hoecsht Schering AgrEvo, Astra, Mycogen, Dekalb, and Pioneer Hi-Bred. (Dohlman, Hall, and Somwaru).[2] The index is deflated by the S&P 500 index and lagged 1 year.

Maximum likelihood methods are used to estimate the regressions. Time is defined as the calendar year minus 1995. Weighted least squares estimation techniques are used to correct for heteroscedasticity because data were aggregated (States, regions). The dynamic logit model was estimated under several scenarios of ceilings for each crop/technology using data for the period 1996-2000. Comparing the scenarios provides a measure of the sensitivity of the results to the precise ceiling specification.

Results. The results of the dynamic logit parameter estimates for Bt corn, Bt cotton, and herbicide-tolerant soybeans and cotton are presented in appendix table 1.5 for the base cases. The fit of the dynamic logistic model

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[1] We do not consider export restrictions for Bt corn, because any such restrictions will be less binding than those implied by actual ECB susceptibility and/or infestation levels (compare appendix table 1.2 regarding corn borer infestations to appendix table 1.4 regarding the importance of corn exports).

[2] For some multiproduct firms (Monsanto, Aventis, Dupont), GE seeds are only a portion of their business and their stock prices may not be a very effective proxy for expectations in the market of GE seeds. For this reason, we have included a portfolio of 12 firms, several of which are seed and ag biotech firms (e.g, Delta and Pine Land, Pioneer, Mycogen, Dekalb), and we have given each firm the same weight regardless of its size. Moreover, even large multiproduct firms experienced stock price changes stemming from events in the GE demand (e.g., see article in the *New York Times*, Jan. 25, 2001, part 7: "..with the stock in the doldrums because of its struggles with agricultural biotechnology, Monsanto..."). And many firms are severing agricultural biotech activities from their other businesses (e.g., Monsanto IPO from Pharmacia).

appears to be good. For the base cases, the adjusted R-square ranges from 0.80 to 0.96. Overall, the dynamic diffusion model appears to fit reasonably well for Bt crops. Further, the significance of nontime exogenous variables in both equations suggests that the use of a dynamic specification rather than a static specification is warranted. In particular, the coefficients of the relevant market variables have the expected sign for Bt corn and Bt cotton. For both Bt crops (appendix table 1.5), the diffusion rate is positively and significantly related to the biotech stock price index, corroborating that biotech stock prices do capture relevant agricultural market information and serve as a leading indicator of the acceptance/demand of biotech products. The rate of diffusion is also positively related to the price index of chemical insecticides, suggesting that as insecticide prices rise the incentive to adopt the (substitute) Bt crops increases. The price of insecticide is only significant, however, for Bt cotton.

The lack of significance of insecticide price for the adoption of Bt corn may be understood by noting that, in the absence of Bt corn, the European corn borer (ECB) is only partially controlled using chemical insecticides. The economics of insecticide use to control ECB are often unfavorable, and timely application is difficult. For these reasons, farmers often accept some yield losses rather than incur the expense of chemical insecticides to treat the ECB and, therefore, do not view insecticides as a substitute for Bt corn adoption.

Contrary to our expectation, the adoption of herbicide-tolerant crops is positively and significantly related to the price ratio of glyphosate to other herbicides (appendix table 1.5). This sign may have resulted from the many advantages of herbicide-tolerant soybeans perceived by growers, which rapidly increased their adoption of herbicide tolerant soybeans between 1995 and 1998 despite glyphosate prices rising from about $54 to more than $56 per pound. This resulted in a positive correlation between glyphosate prices and adoption. Soybean growers continued increasing adoption while the glyphosate prices declined in 1999 and 2000 (glyphosate went off-patent in 2000), but this price decrease only affects the last year of data (2000) because we use expected (lagged) input prices in the model. For this reason, the effect of the negative correlation between prices and adoption in 2000 was weaker than that of the positive correlation of the previous 4 years, giving an overall positive sign.

For the herbicide-tolerant crops, the biotech stock price index is not significantly related to adoption, indicating that planting decisions regarding these crops are not correlated with events driven by consumer general concerns about genetically engineered crops. This, in turn, may be due to the fact that the majority of market concerns captured in the stock price index are related to Bt corn (e.g., appendix table 1.1), and in general, most media coverage is related to Bt corn. Moreover, despite that corn and soybean growers are essentially the same people, planting decisions for Bt corn and herbicide-tolerant soybeans may differ due to differences in the risk-return profiles of the two GE crops, relative to conventional varieties (Alexander, Fernandez-Cornejo, and Goodhue, 2000b). In particular, the production advantages of herbicide-tolerant soybeans may outweigh any market risk due to consumer concerns about genetically engineered crops. For Bt corn, on the other hand, production benefits are not so large relative to market risk. These results are supported by findings from focus groups and a survey about planting decisions among Iowa corn-soybean farmers reported by Alexander, Fernandez-Cornejo, and Goodhue (2000a). Both the focus groups and the survey indicated that, unlike the case of Bt corn, planting decisions of most soybean farmers are not influenced by concerns about using GE crops.

Appendix table 1.1—Selected market events correlated with the index of ag biotech firms

Event	Date
◆ Press release details journal article finding that useful predatory insects could be harmed by Bt corn	08/21/98
◆ EU labeling regulation 1139/98 enters into force	08/31/98
◆ French court places injunction on growing/marketing of Bt corn	09/25/98
◆ Greece bans import and sale of biotech rapeseed	10/02/98
◆ Report that biotech corn cross-pollinated adjacent field of conventional corn released	10/12/98
◆ UK supermarket ASDA asks suppliers not to use biotech corn or soybean ingredients in store brand products	10/13/98
◆ French court upholds ban on 3 strains of Novartis Bt corn	12/11/98
◆ Unilever UK, the Tesco supermarket chain, and Nestle UK announce plans to phase out use of biotech ingredients from their products	04/27/99
◆ EU to freeze approval process for biotech corn developed by Pioneer; Commission states that already approved products developed by Monsanto and Novartis could be affected	05/20/99
◆ Journal *Nature* publishes report that pollen from Bt corn can harm monarch butterflies	05/20/99
◆ Brazilian court upholds ban on biotech soybeans	08/16/99
◆ Korean minister announces plans for labeling foods with biotech ingredients	11/22/99

Source: Dohlman, Hall, and Somwaru (2000).

Appendix table 1. 2— Infestation of corn fields at a treatable level by the European corn borer, 1997 crop year

State/region	Infested area Ha[1]	Planted acres[2]	Percent acreage infested
	---------- *Thousands*	----------	*Percent*
Heartland			
Illinois	50.0	11,200	
Indiana	140.9	6,000	
Iowa	2,840.9	12,200	
Minnesota	913.6	3,600	
Missouri	56.8	7,000	
Nebraska	1,400.0	2,950	
Ohio	58.0	9,000	
	5,460.2	51,950	25.96
Northern Crescent			
Michigan	40.9	2,600	
Pennsylvania	68.2	1,070	
Wisconsin	124.1	3,800	
	233.2	7,470	7.71
Prairie Gateway			
Kansas	454.5	2,600	43.8
Other			
Kentucky	34.5	1,150	
North Carolina	54.5	870	
North Dakota	77.3	590	
	166.3	2,610	15.70
All major States	6,314.2	64,630	24.13

[1] From Pike (1999).
[2] USDA, NASS (1999c).

Appendix table 1.3—Infestation of cotton fields by bollworm, budworm, and pink bollworm, 1996-98

Pest/year	Acres infested[1]	Acres infested[2]	Percentage of acreage infested
	---------- *Thousands* ----------		*Percent*
Boll/budworms			
1996	10,249	15,024	68.22
1997	10,590	13,766	76.93
1998	9,052	13,653	66.30
Pink bollworm			
1996	486	15,024	3.23
1997	484	13,766	3.52
1998	304	13,653	2.23
All[3]			
1996	10,735	15,024	71.45
1997	11,074	13,766	80.44
1998	9,356	13,653	68.53
3-year average			73.47

[1] From Williams et al. (1997, 1998, 1999).
[2] USDA, NASS (1999c).
[3] Assuming no overlap

Appendix table 1.4—Total exports as a percent of U.S. production

Crop/item	1995/96	1996/97	1997/98	1998/99
Corn				
Production, *mil. bushels*	7.400	9.233	9.207	9.759
Exports, *mil. bushels*	2.228	1.797	1.504	1.981
Percent	30.1	19.5	16.3	20.3
Soybeans				
Production, *mil. bushels*	2.177	2.380	2.689	2.741
Exports, *mil. bushels*	0.851	0.882	0.873	0.801
Percent	39.1	37.1	32.5	29.2

Source: USDA, ERS, 2000b.

Appendix table 1.5—Dynamic logit parameter estimates

Variable	Parameter estimate	Standard error	t-Value	Pr > |t|
A. Bt corn, ceiling equal to ECB infestation adjusted by refugia requirements				
Intercept	2.20398	3.35249	0.66	0.5274
Time	-28.99758	16.79938	-1.73	0.1184
HEARTLAND	-0.87167	0.48001	-1.82	0.1028
NCRESCENT	-1.16932	0.71778	-1.63	0.1377
PGATEWAY	-2.88519	0.90590	-3.18	0.0111
PBindex*t	8.46688	3.01948	2.80	0.0206
PInsect*t	13.28019	8.81819	1.51	0.1633
Adjusted R-Squared	0.913			
B. Bt cotton, ceiling equal to infestation adjusted by refugia requirements				
Intercept	0.09120	0.54888	0.17	0.8722
Time	-7.46708	2.29334	-3.26	0.0116
MISSPORTAL	0.89482	0.33388	2.68	0.0279
SOUTHSEABOARD	0.93739	0.27486	3.41	0.0092
FRUITFULR	0.35130	0.33388	1.05	0.3235
Pbindex*t	0.59192	0.28320	2.09	0.0700
PInsect*t	4.82130	1.36198	3.54	0.0076
Adjusted R-Squared	0.799			
C. Herbicide-tolerant soybeans, ceiling calculated assuming no GE exports				
Intercept	-3.89182	0.46479	-8.37	<.0001
Time	-0.81329	0.26627	-3.05	0.0080
HEARTLAND	-0.07828	0.14632	-0.53	0.6005
MISSIPORTAL	0.20797	0.28968	0.72	0.4838
NCRESCENT	-0.36351	0.35074	-1.04	0.3164
PGATEWAY	0.59047	0.48103	1.23	0.2385
SOUTHSEABOARD	-0.64531	0.58688	-1.10	0.2889
EUPLANDS	0.87824	0.75083	1.17	0.2604
Pindex*t	-0.58520	0.62909	-0.93	0.3670
Pglytoherb*t	3.13419	1.21704	2.58	0.0211
Adjusted R-Squared	0.959			
D. Herbicide-tolerant cotton, ceiling equal to 90 percent				
Intercept	-17.48254	6.67041	-2.62	0.0278
Time	2.13720	1.10169	1.94	0.0843
MISSPORTAL	0.16209	0.27624	0.59	0.5718
SOUTHSEA	0.37307	0.26178	1.43	0.1879
Pbindex*t	-0.55928	0.65087	-0.86	0.4125
Pglytoherb*t	12.35018	6.19381	1.99	0.0773
Adjusted R-Squared	0.953			

Note:
TIME is the time in years, 1995=0.
HEARTLAND, NCRESCENT, PGATEWAY, MISSPORTAL, SOUTHSEABOARD, FRUITFULR, EUPLANDS represent dummy variables equal to one for the heartland region, northen crescent region, praire gateway, Missisippi portal, southern seaboard, fruitful rim, and uplands region, repectively.
PBINDEX is an index of ag biotechnology stock prices.
PINSECT is the insecticide price index.
PGLYPHERB is the price ratio of glyphosate to other herbicides.
PBINDEX_t is an interaction term equal to the product of PBINDEX and TIME.
PINSECT_t is an interaction term equal to the product of PINSECT and TIME.
PGLYPHERB_t is an interaction term equal to the product of PGLYPHHERB and TIME.