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Diffusion of Bt Cotton and Insecticide Use

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Paper prepared for Presentation at the:
Western Agricultural Economics Association
Annual Meeting, June 30-July 2, 2004
Honolulu, Hawaii

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Abstract

This study estimated a dynamic logistic model to explain the diffusion Bt cotton in the United States. Regional differences in the speed and extent of Bt cotton adoption were explained by differences in availability of Bt seed adapted to local conditions, potential seed supplier profits, and economic variables affecting grower gains from adoption. The study also estimated the impact of Bt cotton on insecticide use, controlling for differences in pest infestations and prices and correcting for the endogeneity of the Bt adoption decision. Bt cotton significantly reduced insecticide applications to control target pests – cotton bollworm, tobacco budworm, and pink bollworm. Bt cotton has led to an overall reduction in these applications per total US cotton acres, ranging from 0.5 in 1996 to 1.8 in 2003. Reductions in applications per infested acres ranged from 0.67 to 2.3.

1. Introduction

Plants genetically modified to express a gene extracted from Bacillus thuringiensis (Bt) – a soil bacterium – produce a protein toxic to budworms, bollworms and pink bollworms. Use of Bt cotton can reduce yield losses from these pests and reduce the need for pesticides. In 1995, the year before the commercial introduction of Bt cotton, nearly two-thirds of U.S. cotton acreage was treated for these pests at a cost of $373 million (Frisvold and Tronstad). In that year, bollworms and budworms reduced US cotton yields 4% (over a quarter of a billion dollars) even though growers' made an average of four insecticide applications those pests (Williams).

This study has two main objectives. First, it examines the role of economic factors in the diffusion of Bt cotton. This is done by estimating a dynamic logistic diffusion model using time series – cross section data for 27 state and sub-state regions in the United States. The dynamic diffusion model is an extension of the classic static diffusion model used by Griliches in his pioneering work on the spread of hybrid corn (Griliches. 1957, 1960). In the dynamic specification, diffusion parameters are not fixed, but modeled explicitly as functions of economic variables that can vary across space and time. The approach taken here is similar to that of earlier work (Jarvis; Knudson; Gruber and Verboven; Fernandez-Cornejo et al.).

The study's second objective is to estimate the impact of Bt cotton adoption on insecticide use. Several studies suggest that Bt cotton significantly reduces insecticide use (Carlson, et al.; Fernandez-Cornejo and McBride 2000; 2002; Gianessi, et al.; Huang, et al.; Ismael, et al.; Marra, 2001; Marra et al.; Pray et al.; Qaim et al.; Qaim and Zilberman; Thirtle et al). Yet, the overall impacts of Bt cotton are still hotly debated (Benbrook 2001, 2003; Wolfenbarger and Phifer). In a recent exchange in the journal *Science*, Wolfenbarger and Phifer call for, "[c]arefully designed experiments . . . to ascertain what effect individual transgenic crops have on agrochemical use, independent of other important variables." Carpenter responds, "[al]though precisely measuring changes in pesticide use attributable solely to the adoption of GM crops remains a challenge, it is survey, not experimental, data that will address this question." Multivariate regression analysis is used to control for changes in cotton prices and insecticide application costs, as well as state participation in boll weevil eradication programs. The analysis also controls for differences in the extent of pest infestations over space and time and tests for potential endogeneity of the Bt adoption variable.

The paper is divided into six remaining sections. Section 2 discusses the general specification of a dynamic innovation diffusion model. Section 3 discusses the econometric specification. Section 4 presents estimation results. Section 5 specifies the econometric insecticide use equation, while Section 6 reports estimation results. Section 7 concludes by summarizing main findings.

2. Static and Dynamic Diffusion Models

Before proceeding, a brief word on terminology is in order. The term "dynamic" diffusion model may sound redundant because diffusion refers to the aggregate spread of technology over space and time, itself a dynamic process. Static models estimate diffusion paths as functions of constant diffusion parameters (Griliches; Mansfield; Santarelli, E. and S. D'Altri). Dynamic models, rather than treating diffusion parameters as scalar constants, directly estimate them as functions of time-varying exogenous variables. It is specifying diffusion parameters as functions that vary across time (and space) that make modern diffusion models dynamic.

The static logistic diffusion is of the form

(1) $$P = K / [\,1 + e^{-a-bt}\,]$$

where P measures the proportion of the innovation that is adopted. This can be expressed either as the percent of producers adopting the innovation or as the percent of acreage where the innovation is applied. The term K is the adoption ceiling, representing the maximum rate of adoption in long-run equilibrium. The term t is a time trend, while a and b are scalar constants. As time passes (t gets large), adoption increases at first an increasing, then decreasing rate. This produces the classic *S*-shaped diffusion curve. Griliches (1960) noted that this specification,

> "[a]llows us to summarize large bodies of data on the basis of three major characteristics (parameters) of a diffusion pattern: the date of beginning (origin), relative speed (slope), and final level (ceiling) (p. 275)"

Griliches was interested in answering three basic questions. Why did some areas begin using hybrid corn before others? Why did hybrid corn spread faster in some areas in others? Why did some areas reach higher adoption ceilings than others? He related regional differences to differences in the origin (a), speed (b), and ceiling (K).

He characterized a – the origin parameter – as capturing the date of availability of hybrid corn and depending on the supply of suitable seed. He hypothesized that seed suppliers would focus seed development and marketing in areas where they could make the most profits. These would be in larger markets, ones where gains from adoption were larger, or both. Another factor was whether experiment stations had developed new seed lines well adapted to local conditions.

While a was discussed in terms of supply-side factors, b measured the rate of acceptance of the new seed varieties by producers. The speed of adoption (b) should increase with the profit advantage of the new technology. Differences in the adoption ceiling K could be explained by differences in the average profit gain from adoption and that, except for marginal production areas, a common fixed ceiling would perform quite well.

He acknowledged, though, that the ceiling would not be static, but would change with changes in market conditions, overall corn acreage and availability of other new technologies.

To test these hypotheses, he assumed values for K and transformed equation (1) to

$$ln\ [P_{it}\ /\ (K_i - P_{it})] = a + bt + u_{it} \qquad (2)$$

where u_{it} is an error term, K_i values are pre-specified, and a and b can be estimated through linear regression. The dependent variable is the natural log of the ratio of actual to potential adopting acres in time t. Griliches estimated different diffusion curves for different regions and then looked at the correlations between the different estimated *b*s and economic variables. Mansfield estimated separate diffusion curves for different innovations, obtaining different estimates of b. He then regressed estimated values of b on profitability of the innovation and initial capital cost. As hypothesized, he found that the estimated *b*s were positively related to profitability and negatively to costs.

Dixon later raised questions about the restrictions implicit in a logistic function. The logistic model imposes an *S*-shaped symmetric diffusion trend with a maximum diffusion rate at the point where the actual adoption rate reaches 50% of the potential adoption rate. Other functional forms with *S*-shaped properties have different inflection points. Re-estimating Griliches data, Dixon found that a Gompertz model (which assumes an inflection point at 37%) performed better than the logistic.

A more fundamental question, however, is not which fixed diffusion path to specify (say logistic versus Gompertz) but rather, why specify a fixed diffusion path at all? If one believes that diffusion parameters depend on economic variables, why not explicitly model them as such? If the speed of adoption parameter b is a function of variables, $\boldsymbol{Z}$, such that $b = b(\boldsymbol{Z})$, then leaving them out of the original regression equation can lead to omitted variables bias.
The general specification of a dynamic logistic function would be

$$P_{it} = K(\boldsymbol{W})\ /\ [\ 1 + e^{-a(\boldsymbol{X})\ - b(\boldsymbol{Z})\ t}\ ] \qquad (3)$$

where the adoption ceiling, origin, and speed of adoption are functions of vectors of exogenous variables $\boldsymbol{W}$, $\boldsymbol{X}$, and $\boldsymbol{Z}$. Because $K = K(\boldsymbol{W})$, (3) cannot be transformed into a function that is linear in parameters. Equation (3) requires estimation through some type of non-linear technique. Gruber and Verboven (2001) estimate equation (3) in their study of diffusion of mobile telecommunications services in the European Union using non-linear least squares. Other studies have estimated dynamic diffusion models using special cases of equation (3). In a study of diffusion of improved pastures in Uruguay, Jarvis specified K and b as functions of cattle prices. Knudson estimated a model of diffusion of semi dwarf wheat varieties where K depended on prices of grain, seed, and fertilizer.

A slightly less general specification is

$$(4) \qquad P_{it} = K_i / [\, 1 + e^{-a(\boldsymbol{X}) \; - b(\boldsymbol{Z})\, t} \,]$$

Equation (5) can be linearized to

$$(5) \quad ln\, [P_{it} \; / \; (K_i - P_{it}\,)] = a_0 + a_1X_1 + \ldots + a_nX_n + \; b_0\, t + b_1Z_1\, t + \ldots \; + b_mZ_m\, t + \; u_{it}$$

Fernandez-Cornejo et al. (2002) estimate this type of model using nonsample information to specify K, allowing them to linearize their model in a study of biotechnology diffusion. They also specify b as a function of agricultural chemical prices and an index of biotechnology stock prices (to capture effects of consumer concerns over biotechnology). The origin, a, varies by major farm resource regions.

3. Econometric Specification and Data

For this study, equation (5) was estimated, where Pit is the percent of cotton acreage planted to Bt cotton in one of 27 state or sub-state regions in years 1996 to 2003. The regions were Alabama-Central, Alabama-North, Alabama-South, Arizona, Arkansas-Northeast, Arkansas-Southeast, California, Florida, Georgia, Louisiana, Mississippi Delta, Mississippi Hills, Missouri, New Mexico, North Carolina, Oklahoma, South Carolina, Tennessee, Texas-Coastal Bend, Texas-Far West, Texas-High Plains, Texas-Lower Rio Grande Valley, Texas-North Central (N. Blacklands), Texas-North Rolling Plains, Texas-South Central (S. Blacklands), Texas-Southern Rolling Plains, and Virginia. Data on adoption rates come from the Cotton Crop Loss Database, supported by the National Cotton Council and maintained at Mississippi State University (Williams). This is not the only source of Bt cotton adoption data. The USDA, Agricultural Marketing Service, publishes an annual *Cotton Varieties Planted* report, which provides estimates of the percent of acreage planted to different seed varieties by state. The USDA, National Agricultural Statistics Service publishes an annual *Acreage* report that began reporting Bt cotton adoption rates for selected major cotton producing states, beginning in 2000. USDA's Economic Research Service also reports adoption rates for Bt cotton for more aggregate regions from the Agricultural Resource Management Study (ARMS) surveys. All of these sources provide slightly different estimates of adoption rates. The *Cotton Crop Loss* data provides the most years of coverage (1996-2003), combined with observations at a sub-state level.

Following Griliches' (1960) verbal discussion, the $\boldsymbol{X}$ variables in $a(\boldsymbol{X})$ are specified as supply-side variables. The first, *PARENT* is the percent of acres planted to the recurrent parent varieties of the first commercially available Bt cotton varieties – Deltapine's NuCotn 33B and NuCotn 35B in 1995. The recurrent parents of these varieties are Deltapine 5415 and 5690. More widespread adoption of recurrent parent lines implies that these lines are well adapted to local growing conditions. *PARENT* is meant to capture the extent to which the new Bt varieties, first available in 1995, were adapted to local conditions. Data come from *Cotton Varieties Planted* (USDA, AMS). Griliches also hypothesized that seed suppliers would target areas for development and marketing where profits from adoption would be greatest. This is captured by the variable *HISTLOSS*, which is the historic cost per region of yield losses and pest control expenditures for cotton bollworm, tobacco budworm, and pink bollworm, the main target pests of Bt cotton. The *Cotton Crop Loss* database reports estimated yield damage and pest control costs, by pest, year and region. *HISTLOSS* is the average annual loss plus control costs per region from 1991-5 in 2000 dollars. It is in regions where *HISTLOSS* is largest that gains from Bt cotton would be largest and the surplus to be extracted by a monopolist seed developer (Monsanto) would be greatest.

Finally, *CA* is a dummy variable for California. Until, 1999, California's San Joaquin Valley (SJV) maintained the One-Variety Law, which effectively prohibited use of Bt cotton. In the 1920s, the scientists at the University of California and USDA, along with growers proposed that if everyone in the SJV grew the same, high quality cotton variety, they could better market California cotton (Marsh). In 1925, the California Legislature enacted the One-Variety Law, allowing that only one Acala variety selected as the standard could be grown in the SJV. In response to grower demand for short-season cotton varieties, the One-Variety Law was repealed in 1999. In this case, the supply constraint on seed availability was institutionally sanctioned. The *CA* variable may also pick up the effects of California's Pink Bollworm Program for the SJV. Begun in 1967, the program's goal is to prevent pink bollworm (PBW) from becoming established in the cotton growing areas of the San Joaquin Valley. The program uses trapping, sterile release, crop destruction, and occasional pheromone treatments (CDFA). Pink bollworm and cotton bollworm are more of a problem in California's Imperial Valley (Marsh, Williams)

The ***Z*** variables in *b*(***Z***) are those that influence the rate of acceptance of Bt cotton. The first, *FEE* is the per acre technology fee charged as a price premium for Bt cottonseed. This fee declined over time and varies across states, from $32 per acre in Arizona to about $19 per acre in North Carolina. The second *LAGLOSS* is bales lost per acre from budworm, bollworm and pink bollworm in a region in the previous year. Growers with greater yield losses in the previous year may expect more of a profit advantage from adopting Bt cotton. Conversely, if pest pressure declines, the specification allows for de-adoption. *APPCOST* is the per acre cost of one insecticide treatment for the target pests. Bt cotton substitutes for conventional insecticide applications. *BWEP* is the percent of a region's acreage that is participating in a boll weevil eradication program. Boll weevil sprays can kill predators of bollworms and bollworms. For this reason, growers in *BWEP* areas are advised to plant Bt cotton to control for secondary outbreaks of bollworms and bollworms (Gianessi et al.; Karner et al.; Hardee et al., Lambert; Lentz, et al.) The variables *FEE*, *LAGLOSS, APPCOST,* and *BWEP* all come from the Cotton Crop Loss database.

The effective price variable, *PRICE*, is the lagged price received per pound by farmers in the state for upland cotton plus the loan deficiency (and market gain) payments received per pound. The cotton price dropped significantly from 1996 to 2003, while loan deficiency and market gain payments sheltered producers from much of the price decline, the effective price of cotton declined over the study period. One would expect that the profitability of Bt cotton and the speed of acceptance would be positively related to price. Data for price received comes from *Agricultural Prices* (USDA, NASS), while loan deficiency and market gain payment data come from the Price Support Division of USDA's Farm Services Agency. The final *Z* variable is *PERHAR*, the percent of planted acres that are harvested in a state. This is an average over the previous 10 years. Data comes from USDA *Historical Data*. A lower value for *PERHAR* implies a greater rate of crop failure and abandonment. One might expect slower adoption in areas with higher rates of crop failure from drought, floods, or hail. The Bt technology fee must be paid up front, while the gain of adoption will be more uncertain in marginal production areas.

In areas with more chance of crop failure, it may also be more difficult to judge how well a new seed variety is performing. It is hypothesized that a lower value of *PERHAR* will reduce the rate of Bt cotton acceptance.

Finally, to estimate equation (5) using linear methods, one must specify values for the adoption ceiling *K*.[1] To slow the development of resistance to Bt cotton the Environmental Protection Agency requires that Bt cotton adopters plant refuges of non-Bt cotton to maintain a population of susceptible pests. There are different refuge options, but the smallest legal refuge is 5 percent of Bt acreage. The specification reported in this paper sets $K = 0.95$ for all regions.[2]

4. Diffusion model results and discussion

4.1. Static and dynamic model results

Table 1 provides descriptive statistics for variables used in diffusion model estimation. Table 2 compares regression results under both static and dynamic specifications. Under the static specification, $a = a_0$ and $b = b_0$, while the other terms $a_1 \ldots a_n$ and $b_1 \ldots b_m$ are restricted to equal zero. The dynamic model provides a better fit to the data than the static model, with an adjusted R-squared of 0.5210 versus only 0.1197 for the static model. All the *X* and *Z* variables except insecticide application costs are significant at least the 5 percent level and all variables have the expected signs. The hypothesis that the coefficients on the supply-side variables *PARENT*, *HISTLOSS* and *CA* is strongly rejected, with an F-statistic [3, 205] = 34.96. Results are consistent with Griliches' hypothesis that differences in adoption rates can be explained by availability of locally adapted seed. The positive and significant coefficient for *PARENT*

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[1] With nonlinear regression, one can have an estimated $K(\boldsymbol{W})$ below actual adoption rates. This implicitly assumes that *K* is not an absolute ceiling. For more discussion of implications of specification of K in a classical and Bayesian setting, see Bewley and Griffiths.

[2] Alternative specifications based on historic percentages of acres infested or requiring treatments did not perform better than the assumption of a common $K = 0.95$ and are omitted to save space. The specification $K = 0.95$ did perform better than $K = 1.0$.

suggests that adoption, particularly early adoption, is positively associated with prior adoption of the recurrent parents of the first Bt cotton varieties. We interpret this as a measure of how well early Bt cotton varieties were adapted to local production conditions. The negative coefficient for CA also is consistent with the delay in availability of seed varieties in California.

The positive, significant coefficient for *HISTLOSS* is also consistent with Griliches' hypothesis that potential seed supplier sales revenues are important. The variable *HISTLOSS* measures the average historic, economic losses in a region from target pest damage and control costs. It approximates the total potential surplus that a monopolist seed supplier could extract in a given region.

Turning to the rate of acceptance variables, the econometric evidence suggests that implementation of Boll Weevil Eradication Programs (BWEPs) has sped adoption of Bt cotton. This is consistent with anecdotal reports from a number of states (Gianessi et al.; Karner et al.; Hardee et al., Lambert; Lentz, et al.). In addition, the rate of acceptance was greater when yield damage from target pests were greater in the previous year (*tLAGLOSS* positive). The rate of acceptance was also greater in areas where crop loss / abandonment have been relatively lower historically (where *tPERHAR* is high). As noted above Bt cotton requires additional sunk costs, which may be harder to recoup in areas with greater crop loss.

Differences in the rate of diffusion may also be explained by changes in relative prices. The rate of adoption declines as the price of Bt cotton rises (*tFEE* negative), while it is increasing in the effective price of cotton (*tPRICE* positive). The effective price includes coupled commodity program and is meant to capture realized per-pound revenues from cotton, lagged one year. Again, results are consistent with Griliches's hypothesis that higher output prices induce greater adoption. This result is also consistent with earlier diffusion studies by Jarvis and by Knudson. The variable *APPCOST* is the per acre cost of applying conventional insecticides. Bt cotton is meant to substitute for insecticides.

The coefficient is positive, as one would expect, but not statistically significant. The hypothesis that the coefficients on the demand variables *tBWEP, tLAGLOSS, tFEE, tAPPCOST, tPRICE, tPERHAR,* is strongly rejected, with an F-statistic [6, 205] = 8.83.

4.2. Fixed effects vs. supply-side effects

Given that we have time series – cross section (TSCS) data, there might be some other regional heterogeneity, not captured by the supply-side (***X***) and demand-side variables (***Z***) variables. A standard approach to address this is to relax the assumption that each region has the same intercept.

(6) $ln\,[P_{it} \,/\, (K_i - P_{it})] = a_i + a_1 X_1 + \ldots + a_n X_n + \; b_0 t + b_1 Z_1 t + \ldots \; + b_m Z_m t + \; u_{it}$

Equation (6) allows each region to have its own intercept, a_i. Hsaio (1986: 41-43) has shown that fixed, rather than random effects are appropriate for making inferences about the observed units. Random effect models are appropriate where observed units are samples from a larger population. Here, however, the regions themselves are of interest.

As Beck (2001) notes, including fixed effects "come at some cost (p. 285)" that require some modeling choices. The variable *CA* will be subsumed as part of the region variables. The other supply side variables, *PARENT and HISTLOSS*, however, do not vary over time. These will be collinear with the fixed effects and must be dropped from the model. One must choose between either time-invariant variables or fixed effects.

Table 3 presents the fixed-effects model (equation (6)) alongside the basic dynamic model (equation (5)). In the fixed effect model, the R-squared increases from 0.521 to 0.799. Based on an F-test, one rejects the hypothesis that all intercepts are equal. For the *Z* variables, *tBWEP*, *tFEE*, and *tPERHAR* all remain significant at the 1% level. The significance of *tLAGLOSS* declines to the 10% level, while the significance of *tPRICE* increases from the 5% level to the 1% level. The coefficients of the *Z* variables all decline (in absolute value).

Table 4 reports the separate intercepts for each region. The *a* coefficient in the logistic model acts to shift the initial level of adoption up or down in the first year of adoption ($t = 1$). It thus captures regions that had high (or low) rates of initial adoption. The more negative the number, the lower the initial adoption rate. Griliches (1960) observed that hybrid corn tended to diffuse along latitude lines first, then longitude lines later. For Bt cotton, a similar geographic pattern is discernible. Regions with the lowest values of *a* tend to be the higher latitude regions. The bulk of California's cotton production is in relatively higher latitude counties. Regions in Texas also tend to have lower *a* values. Of course, the fixed effect models cannot say *why* regions in higher latitudes or in Texas were later adopters. Griliches suggested that the spread of technologies might depend on adoption rates in bordering areas, particularly those bordering to the east or west. One possibility for future research might be to explicitly account for spatial lags in the diffusion model.

To summarize, variables related to farm-level profitability of Bt cotton adoption go a long way in explaining regional differences in the speed of technology diffusion. We also experimented with mutually exclusive sets of time-invariant supply-side variables and fixed effects. The fixed effect model provides a better fit to the data and suggests some geographic patterns to the diffusion process. The time-invariant variables, however, also were highly significant in the basic dynamic model. While their inclusion did not improve the fit of the model as much as the fixed effects, they provide more economically appealing interpretations.

5. Bt cotton and insecticide use

As noted above, there has been a great deal of controversy over whether or to what extent insect-tolerant crops such as Bt cotton or Bt corn reduce insecticide use. For example, in discussing the budworm bollworm complex (BBW), Benbrook (2001) states,

> " . . .in Alabama, another high *Bt*-cotton adoption state (62% acres planted), BBW insecticide applications almost doubled from 1997 to 2000," and also, "Some low-adoption *Bt*-cotton states have also markedly reduced BBW acre-treatments. Texas cotton (7% *Bt*-cotton), for example, was treated an average 1.3 times with BBW insecticides in 1995 and 0.65 times in 2000 - about a 50% drop."

There are (at least) two problems with making simple comparisons of means of state-level data, however. First, comparisons of means do not control for other factors, such as differences in changing pest pressure, presence of Boll Weevil Eradication Programs, or differences in prices that affect insecticide use. Second, regions are not randomly assigned to a treatment or control group as in a controlled experiment. Rather, areas with more pest pressure will adopt Bt cotton more readily. An unobserved variable –pest population – affects both decisions. In the context of measuring farm-level impacts of biotechnology adoption, this becomes a sample selection problem (Maddala), which has been addressed in micro-level studies (Fernandez-Cornejo and McBride (2000), (2002); Fernandez-Cornejo et al. (2002)). With regional data, the problem is a form of simultaneity bias, where Bt cotton adoption is a potentially endogenous regressor in a pesticide demand equation.

The following insecticide use model was estimated

(8) $$dSPRAY_{it} = \beta_0 + \beta_1\, dCOST_{it} + \beta_2\, dPRICE_{it} + \beta_3\, BWEP_{it} + \delta Bt_{it} + v_{it}$$

where v_{it} is the stochastic error term. Descriptive statistics for all are listed at the bottom of Table 1. Variable $dSPRAY_{it}$ is the change in applications per acre infested with bollworm, budworm, and pink bollworm from the 1991-5, pre-Bt cotton application rate. Our interest is explaining the change in insecticide applications from the 1991-5 (pre-Bt) base. Most areas have only bollworm / budworm pressure and the *Cotton Crop Loss* data makes no distinction between the two pests. California, Arizona, New Mexico, Texas – Far West, and occasionally Texas – High Plains also have pink bollworm. For these regions, a weighted average application per infested acre rate was derived. The *Cotton Crop Loss* database reports percent of acres infested by particular pests. Applications per total acres can differ simply because the extent of infestations can vary by year and by region. While we do not have a measure of pest population *per se*, we can make use of information about when and where that population is zero.

The variable $dCOST_{it}$ is the change in application costs per acre for bollworm, budworm, and pink bollworm between the given year and the 1991-5 average. On average, the cost of insecticide applications was higher from 1996-2003 than the 1991-5 average. Again, reduced insecticide use from 1996-2003 may be explained, in part, by the higher cost of insecticide applications. The variable $dPRICE_{it}$ is the change in the effective cotton price (defined as before) from the 1991-5 average. Even with loan deficiency and market gain payments, the effective price of cotton has fallen since the early-to-mid 1990s. So, one might observe reduced insecticide applications as a consequence of lower realized revenues from cotton production.

Noting the significant drop in insecticide applications for bollworm, budworm, and pink bollworm after 1995, Benbrook (2001) argues, "Two factors clearly account for this large reduction – the boll weevil eradication program and second, *Bt* cotton, especially in the western U.S." We test this hypothesis formally below. The variable $BWEP_{it}$ is the percent of a region's cotton acres newly enrolled in a Boll Weevil Eradication Program since 1995, while *Bt* is the proportion of cotton acres planted to Bt cotton. No Bt cotton was planted commercially before 1996.

The dependent variable $dSPRAY_{it}$ subtracts historical application rates from current rates, allowing us to use a region as its own control. Figure 1 illustrates why we might want to do this. In Figure 1, the units on the y-axis are insecticide applications, while the units on the x-axis are and Bt cotton adoption rates. The black rectangles (■) show a pairing of pre-Bt cotton insecticide applications with subsequent adoption rates. As shown, regions with more insecticide applications before Bt cotton's commercialization have higher adoption rates once Bt cotton becomes available. At the extreme, there is an observation at the origin with no adoption or applications. Fitting a line through this plot would yield line L_0, which shows a positive correlation between *past* pest pressure and *current* Bt cotton adoption. Now, suppose that after Bt cotton is introduced insecticide applications fall. This could arise because of Bt cotton, other factors, or both. The plot of *current* applications on *current* Bt adoption rates is shown by the black triangles (▲). As drawn, insecticide applications are lower post-adoption (except for the origin observation where there is no room to move). We are interested in how much of the drop in insecticide use (the vertical distance between points) is attributable to Bt cotton versus other factors, such as changes in prices. The vertical distances are $dSPRAY_{it}$. Note, however, that if one simply fits a line to the ▲, one gets line L_1, which shows a *positive* association between Bt cotton adoption and insecticide use! Indeed, in the database, the partial correlation between current Bt adoption and current insecticide applications is slightly positive (0.11).

6. Estimation Results

Equation (8) was estimated both using ordinary least squares (OLS) and with two-stage least squares (2SLS) to correct for endogeneity bias from the *Bt* variable (Table 5). The instrumental variables used in the 2SLS estimation include the variables used in the diffusion equation. In both specifications, the coefficient on *dCOST* is statistically significant and negative (as expected), suggesting that application rates are declining in application costs. The variable *dPRICE* has the wrong sign, suggesting a negative relationship between lagged effective cotton price and insecticide use. The coefficient is not statistically significant, however, so we fail to reject the hypothesis that applications are insensitive to changes in lagged output price. New boll weevil eradication programs (*BWEP*) do not appear to account for any changes in target pest applications. The coefficient is insignificant in both regressions.

The coefficient for *Bt* is negative and statistically significant under both specifications. The coefficient is -2.8861 in the OLS regression, but more negative, -3.9354, in the 2SLS specification. The Hausman test was applied by:

(1) regressing the variable *Bt* on the set of instrumental variables

(2) re-estimating equation (8) with the residuals from the first regression as an additional regression.

The test of exogeneity is a test of whether the coefficient for the residuals equals zero.

Table 5 shows that the null hypothesis of exogeneity of the Bt variable can be rejected at the 0.1% level. The results suggest that estimating insecticide use on Bt cotton adoption using OLS leads to a downward bias in the estimate of the impact of Bt cotton on insecticide use. The 2SLS coefficient of –3.9354 implies that if a region's adoption rate fell by 25 percentage points (e.g. from 75% to 50%) then the region would have one additional application per infested acres.

One can use the results to extrapolate impacts of Bt cotton adoption up to a national level. This is done by summing up $\delta Bt_{it} = -3.9354\, Bt_{it}$ by time and region. Figure 2 shows the impact of Bt cotton adoption on applications per infested acre and per total cotton acres. These reductions are only reductions in applications for the target pests – cotton bollworm, tobacco budworm, and pink bollworm. Results suggest Bt cotton adoption has led to an overall reduction in these applications per infested US cotton acres, ranging from 0.67 to 2.3. Reductions in applications per total acres ranged from 0.5 in 1996 to 1.8 in 2003. From 1996-98, Bt cotton adoption rates were still low, nationally. As adoption rates rose, however, the national-scale impacts grew more pronounced.

7. Conclusions

This study estimated a dynamic logistic diffusion function to examine how differences in the speed and rate adoption of Bt cotton throughout different parts of the United States. Economic variables affecting grower gains from adoption significantly influenced the rate of acceptance. Supply-side variables, such as initial availability of Bt seed adapted to local conditions and potential seed supplier profits, were also important. These latter variables were time invariant and could not be used with an alternative fixed effect model. The hypothesis of no fixed effects was rejected. The significance of demand-side grower acceptance variables were also significant in the fixed effect model.

The study also estimated the impact of Bt cotton on insecticide use, controlling for target pest infestations and prices and correcting for the endogeneity of the Bt adoption variable. Bt cotton adoption was found to be an endogenous regressor in an insecticide use equation. The coefficient measuring the effect of Bt cotton adoption on insecticide use had a downward bias relative to a two-stage least squares estimate.

Bt cotton significantly reduced insecticide applications to control target pests – cotton bollworm, tobacco budworm, and pink bollworm. The 2SLS coefficient estimate implies that if a region's adoption rate fell by 25 percentage points (e.g. from 75% to 50%) then the region would have one additional application per infested acres. Results suggest Bt cotton adoption has led to an overall reduction in these applications per total US cotton acres, ranging from 0.5 in 1996 to 1.8 in 2003. Reductions in applications per infested acres ranged from 0.67 to 2.3.

Table 1.
Descriptive statistics for (untransformed) variables used in regression estimations

Variable Name	Definition	Mean	S.D.
Bt	Proportion of acres planted to Bt cotton	0.365	0.292
PARENT	Proportion of acres planted to recurrent parents of first Bt varieties in 1995	0.101	0.148
HISTLOSS	Cost per region of damages and costs to control budworm, bollworm and pink bollworm; 1991-5 average (constant 2000) $ millions	14.775	15.121
BWEP	Proportion of region's acres in boll weevil eradication program	0.367	0.453
LAGLOSS	Bales lost per acre in previous year	0.055	0.109
FEE	Bt technology fee (constant 2000) $ / acre	27.307	7.9971
APPCOST	Cost of insecticide application for target pests (constant 2000) $ / acre	10.633	2.6467
PRICE	Effective price of cotton: prices received by farmers in state + loan deficiency and market gain payments (constant 2000) $ / pound	0.655	0.100
PERHAR	Harvested acres as a percent of planted acres (1986-1995 average)	0.940	0.047
dSPRAY	Target pest insecticide applications per infested acre in year *t* – 1991-5 average	-1.741	1.853
dCOST	Per acre cost of insecticide application for target pests in time *t* – 1991-5 average	0.485	3.367
dPRICE	Effective price of cotton in time *t* – 1991-5 average	-0.101	0.098

Table 2
Static and Dynamic Models for Bt Cotton, 1996-2003

	Static Model	Dynamic Model
***a* variables**		
Intercept	-3.2548	-3.9748
	(-8.03)*	(-8.04)*
PARENT		6.1449
		(5.39)*
HISTLOSS		0.0256
		(2.29)**
CA		-6.1425
		-6.89*
***b* variables**		
t	0.4415	-3.3190
	(5.50) *	-4.12*
tBWEP		0.3095
		4.21*
tLAGLOSS		1.6250
		3.05*
tFEE		-0.0175
		-3.34*
tAPPCOST		0.0136
		1.20
tPRICE		1.1708
		2.12**
tPERHAR		3.3047
		3.94*
R-squared	0.1197	0.5210
Log-Likelihood	-520.37	-450.00

* significant at 1% level; ** significant at 5% level; *** significant at 10% level

Table 3.
Bt Cotton Dynamic Diffusion Models
with Time-Invariant Regressors and with Fixed Effects

	Dynamic Model	**Dynamic Fixed-Effects Model**
***a* variables**		
Intercept	-3.9748	—[a]
	(-8.04)*	
PARENT	6.1449	
	(5.39)*	
HISTLOSS	0.0256	
	(2.29)**	
CA	-6.1425	
	(-6.89)*	
***b* variables**		
t	-3.3190	-1.6430
	(-4.12)*	(-2.65)*
tBWEP	0.3095	0.2786
	(4.21)*	(7.63)*
tLAGLOSS	1.6250	0.4372
	(3.05)*	(1.67)***
tFEE	-0.0175	-0.0123
	(-3.34)*	(-3.28)*
tAPPCOST	0.0136	-0.0013
	(1.20)	(-0.21)
tPRICE	1.1708	0.8510
	(2.12)**	(3.70)*
tPERHAR	3.3047	1.7327
	(3.94)*	(2.60)*
R-squared	0.5210	0.7990
Log-Likelihood	-450.000	-315.59

a. Group effects shown separately in Table 4.
* significant at 1% level; ** significant at 5% level; *** significant at 10% level

Table 4.
Intercepts from Fixed Effects Model

Region	Intercept
Alabama Central	-0.17
Arizona	-0.25
Alabama North	-0.30
Florida	-0.64
Alabama South	-0.85
Mississippi Hills	-1.02
South Carolina	-1.11
Georgia	-1.17
Louisiana	-1.37
Mississippi Delta	-1.51
Texas Southern Rolling Plains	-1.69
Arkansas Southeast	-1.82
Texas Far West	-2.36
North Carolina*	-2.54
Tennessee*	-2.70
Oklahoma	-2.94
New Mexico	-3.04
Texas Coastal Bend	-3.12
Texas South Central (S. Blacklands)	-3.18
Texas North Central (N. Blacklands)	-3.59
Arkansas Northeast*	-3.90
Virginia*	-4.46
Missouri*	-4.72
Texas North Rolling Plains	-5.50
Texas High Plains	-6.05
Texas Lower Rio Grande Valley	-6.21
California*	-8.79
Median	-2.54
Mean	-2.78

* denotes higher latitude cotton production area

Table 5.
Regression equations for factors affecting changes in insecticide applications for bollworm, budworm, and pink bollworm from 1991-95 base

OLS Regression

R-Square Adjusted: 0.2378

Variable	**Coefficient**	**Standard Error**	**t-ratio**	**P-value**
Constant	-0.75601	0.1991	-3.80	0.000
Bt	-2.8861	0.4042	-7.14	0.000
dCOST	-0.10889	0.0330	-3.29	0.001
dPRICE	-1.0222	1.219	-0.84	0.403
BWEP	0.05194	0.2515	0.21	0.837

Hausman endogeneity test for Bt cotton variable

Variable	**Coefficient**	**Standard Error**	**t-ratio**	**P-value**
Residual	2.8350	0.8161	3.474	0.001

2SLS Regression

R-Square Adjusted: 0.2135

Variable	**Coefficient**	**Standard Error**	**t-ratio**	**P-value**
Constant	-0.49905	0.2164	-2.306	0.022
Bt	-3.9354	0.5174	-7.606	0.000
dCOST	-0.09795	0.03375	-2.902	0.004
dPRICE	-1.9802	1.271	-1.558	0.121
BWEP	0.11886	0.2562	0.4638	0.643

Figure 1. Correlations between Bt cotton adoption, pre-adoption insecticide use, and post-adoption insecticide use

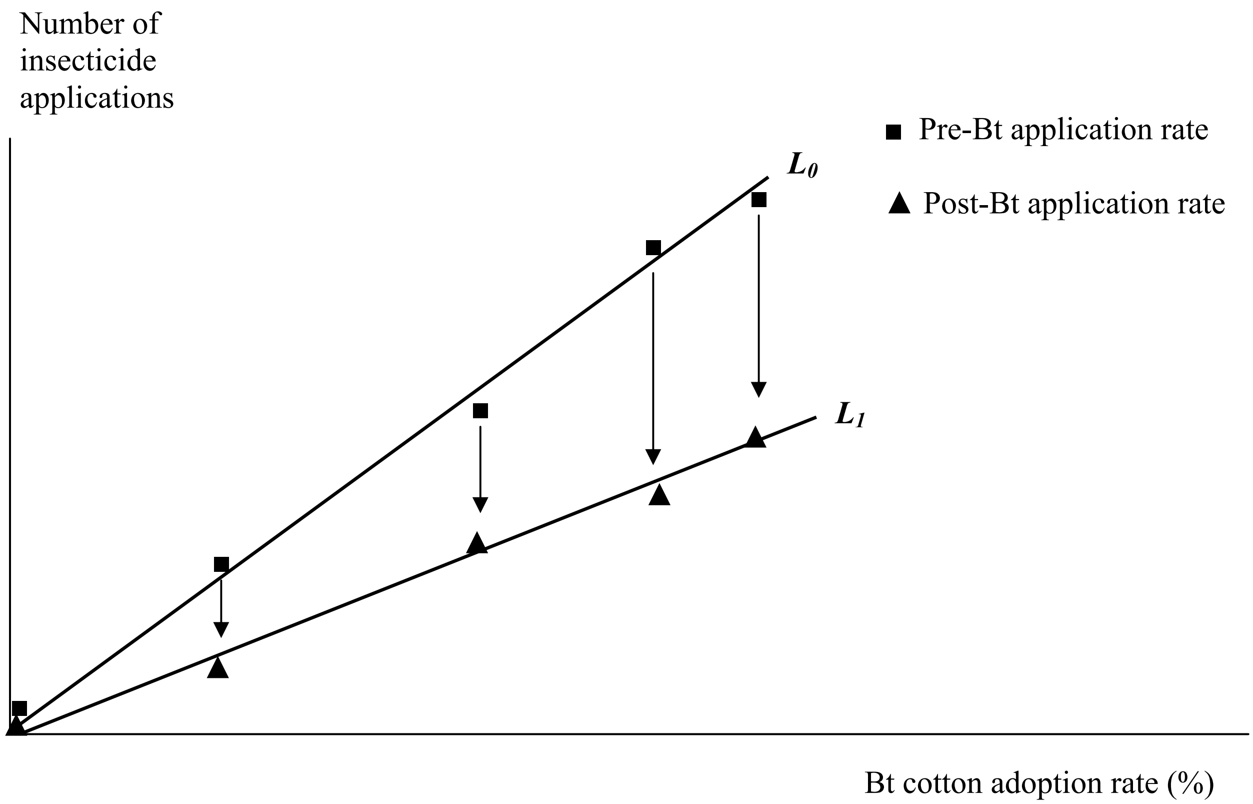
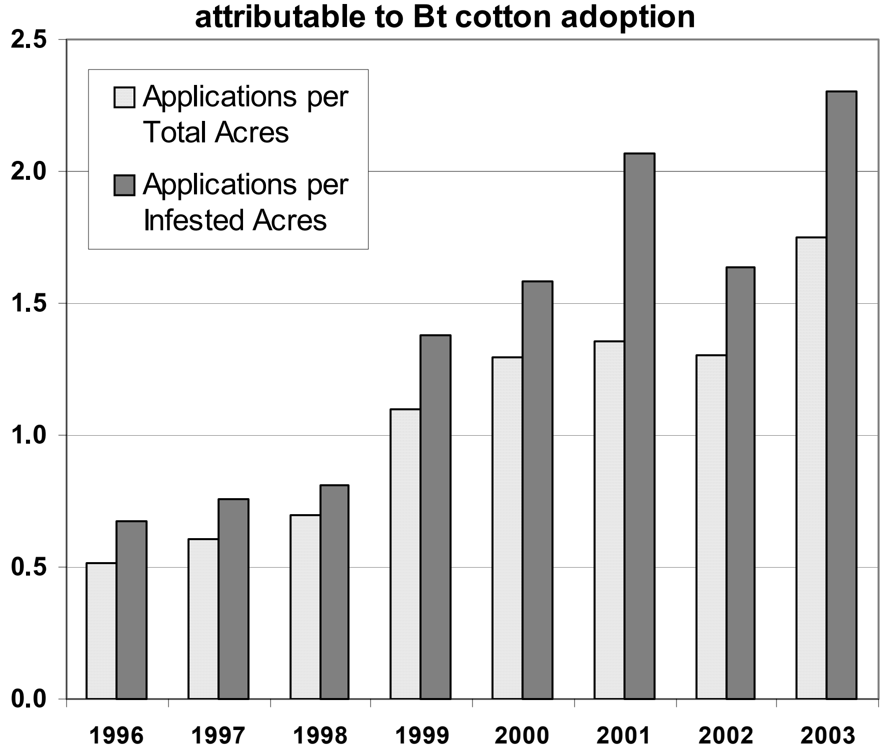


Figure 2.
Reductions US insecticide applications to control bollworm, budworm, and pink bollworm attributable to Bt cotton adoption



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