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Socio-economic Impacts of Bt Cotton Adoption in India: Evidence from Panel Data

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Several empirical studies have evaluated the farm-level and aggregate impacts of transgenic crops in developed and developing countries, however there is extensive opposition in the wider public. In particular, concerns have been raised about the performance of transgenic crops in developing counties in terms of their environmental, health, and social effects. This study addresses some of these research gaps by analyzing the effects of insect-resistant transgenic cotton in India, building on several years of data. The results indicate that Bt technology is very successful in India. Adopting farmers have realized significant benefits through pesticide reductions, higher effective yields, and higher profits. Even though the diffusion of Bt was a learning process for farmers in the beginning, aggregate adoption has increased steadily and reached more than 80% of India's total cotton area by 2008. A random-effects probit adoption model shows that Bt technology is scale-neutral. Therefore, the common notion that transgenic crops are only suitable for rich and large-scale farmers is not confirmed under Indian conditions. However, farmers with more formal education and those with better knowledge and information about the technology are more likely to be among the early adopters, underlining that structural constraints need to be overcome. The estimation results confirm yield- and profit-enhancing impacts of Bt cotton. These findings confirm and extend previous studies on Bt cotton impacts in India and other developing countries, building on a unique dataset.

Key words: Bt cotton, transgenic crops, pesticides, adoption, yield, farm income, panel data.

Introduction

A high degree of politicization occurred in India both prior to the official release, as well as after the introduction of Bt cotton, for commercial cultivation. The technology was projected during the initial phase of introduction to be a cutting-edge technology by the proponents, while the opponents had labeled the technology as a complete failure in India. Indeed, Bt cotton technology has altered the organizational structure of the entire cotton sector in India, which is now the second-largest cotton exporter in the world. Bt cotton technology has now been commercially available for long enough that the technology is arguably mature, especially given its long pre-commercialization debate.

The article utilizes five years of biennial panel data from major cotton-growing regions in India to analyze patterns and dynamics of Bt cotton adoption. Using Bt cotton panel data in an Indian context is apparently the first study of its kind. Most empirical studies to date have viewed Bt cotton adoption in India at a single point of time and have ignored the time-scaling effect on adoption. The study presented in this article aims to analyze and explore the factors that led to widespread acceptance and adoption of Bt cotton by Indian farmers as well as the technology's agronomic and economic impacts through the exploration of panel-data techniques. Numerous empirical studies have shown that farmers benefit considerably from adopting GM technology in terms of reductions in pesticide use and higher effective yields (Bennett, Kambhapati, Morse, & Ismael, 2006; Crost, Shankar, Bennett, & Morse, 2007; Morse, Bennett, & Ismael, 2006; Pray, Huang, Hu, & Rozelle, 2002; Qaim, Subramanian, Naik, & Zilberman, 2006) and, in particular, Bt cotton for Indian farmers (e.g., Bennett et al., 2006; Crost et al., 2007; Gandhi & Namboodiri, 2006; Kathage & Qaim, 2012; Kouser & Qaim, 2011; Krishna & Qaim, 2012; Qaim et al., 2006; Qaim & Zilberman, 2003; Subramanian & Qaim, 2009). Nevertheless, there are concerns about the sustainability of effects over time since most empirical evidences have emerged based on the short-term farm-level benefits; therefore, uncertainty prevails over their long-term implications (Fukuda-Parr, 2007; Qaim & Heidhues, 2005). Besides, the net production and profitability effects brought about by the technology over traditional technology—particularly for the resource-poor and small farmers in developing country agriculture—have scarcely been studied so far.

Furthermore, the net production and profitability effects brought about by the technology that usually determines advantage of technology adoption over traditional technology—particularly for the resource-poor and small farmers in a developing country's agriculture—have gained limited attention. While there has been a great amount written on yield effects of Bt crops, only a few studies have focused on the methodological problem of self selectivity in addressing the technology's productivity and profitability (e.g., Crost et al., 2007; Foltz & Chang, 2002; Moser & Barrett, 2006). Such dynamics of diffusion raise questions about previous Bt studies. Most studies have shown Bt adopters significantly gain from the adoption and that these adopters have the characteristics typically associated with early adopters of any technology, but these differences may be due more to the timing of measurement than anything specific about the technology. Thus, the estimated effects might be a result of the moment when the analysis took place rather than the attributes of Bt technology. The major benefit of panel-data econometrics is that of having multiple observations on the same units, which allows one to control for certain unobserved characteristics of individuals.

Study Area

Though numerous studies carried out at different points in time have assessed the early adoption and ongoing Bt cotton adoption in India, the present study is based on biennial panel data over a period of five years. Use of such panel data of five years to analyze Bt cotton cultivation in India is apparently the first of its kind; most previous studies to date have viewed Bt cotton adoption in India at a single point in time, thus ignoring the effect of time scaling on adoption. Also, empirical evidence on the sustainability of effects brought out by Bt technology over non-Bt technology has not been depicted sufficiently by studies due to the unavailability of household-level panel data (Moser & Barrett, 2006). Few recent studies (e.g., Barham, Foltz, Jackson-Smith, & Moon, 2004; Crost et al., 2007; Foltz & Chang, 2002; Foster & Rosenzweig, 1995) have highlighted the importance of panel data in uncovering these subtle dynamics of learning, strategic behavior, and coordination among producers. Hence, this study tries to add to the growing body of literature on adoption impacts of Bt cotton in India based on evidence generated with the help of advanced panel-data methodologies.

Table 1. Distribution of sample size in study area.

State	District	2002-03	2004-05	2006-07
	Aurangabad	36	41	42
	Beed	32	32	36
	Parbhani	37	41	41
Maharashtra		105	114	119
	Haveri	36	40	43
	Raichur	32	42	44
	Belgaum	35	35	44
Karnataka		103	117	131
	Guntur	35	37	41
	Warangal	35	36	42
	Kareemnagar	32	37	43
Andhra Pradesh		102	110	126
Tamil Nadu	Coimbatore	31	35	31
Total sample		**341**	**376**	**407**

Data Collection

An interview-based survey of cotton farmers was undertaken in three rounds with two years in-between each round, beginning in 2002—first year of Bt cotton commercialization in India. The survey and research work funded by the German Research Foundation (DFG) aimed at representing the overall cotton scenario in central and southern India. Farmers were sampled out from major cotton-growing areas in the states of Maharashtra, Karnataka, Andhra Pradesh, and Tamil Nadu, which are all situated in the central and southern regions of India. The list of farmers who purchased and cultivated Bt cotton in the first season of Bt cotton introduction was utilized to create a random sample; this created a sample of farmers across 58 villages spread throughout 10 districts in Maharashtra, Karnataka, Andhra Pradesh, and Tamil Nadu (Table 1). These states represent more than 50% of overall cotton cultivation in India and are the major zones affected by bollworm infestation. In addition, the absence of assured irrigation for cotton crops in these parts of the country make the region more vulnerable to low productivity as opposed to northern regions. The northern zone had the highest productivity in the country due to assured irrigation facilities for the cotton crop coupled with inter-crop cultivation of cotton and wheat combinations, which lessens bollworm infestation more than in other regions (Alam, 2004). As a result, most of the cotton improvement programs in the country were concentrated on hybrid development to boost productivity in the severely bollworm-infested central and southern regions.

The first round of interviews were carried out in 2002-03 with the cotton farmers to record their experiences in the first year of Bt cotton cultivation in India. In total, 341 farmers were selected through a stratified random sampling procedure. Since the proportion of Bt adopters was very small in the first season, they were purposely over-sampled using complete customer lists of Bt seed sales for random selection. Hence, two representative sub-samples were generated—one from the population of official Bt adopters and the other from the population of non-adopters. The farmers were interviewed on several aspects of cotton cultivation, including input use and output details. Furthermore, data were collected on general farm, household, and contextual characteristics. The details of Bt and non-Bt plots were separately recorded from those having both the plots. So the number of plot observations is somewhat larger than the number of farmers in the sample. Hence, a total of 434 plot observations (133 Bt and 301 non-Bt) were recorded to be more than the farm observations, which could be used for the comparison of plots individually.

The second round of the survey was carried out two years later in 2004-05 during which total Bt cotton area was steadily increasing, and the third round took place two years later in 2006-07. In the second round (2004-05), 318 farmers from the original sample (93%) were interviewed. A total of 376 farmers with 465 plots were interviewed of which 165 plots were cultivated with Bt cotton and 300 with conventional cotton. During the third round in 2006, in which I was personally involved, a total of 407 farmers with 373 cotton plots (317 Bt and 56 non-Bt) were contacted. In this round we managed to interview 289 farmers (85%) from the original sample. In both the second and third rounds, we attempted to interview all farmers from the first round. However, several farmers from the first round had migrated, passed away, or could not be met for other reasons. Yet, additional samples were taken from both the conventional and Bt cotton categories in order to maintain and slightly increase the overall sample and its randomness.

Analytical Approach

Random-effects Probit Model of Adoption

Given that technology adoption is a dynamic process, it cannot be analyzed keeping time as a constant. But most previous studies of Bt cotton adoption in India have been based on static models using cross-sectional data. While they can provide important insights into the adoption process, this method can also be misleading by producing biased coefficient estimates if the adoption process is not yet complete (Besley & Case, 1993; Cameron, 1999; Lindner, 1987). The bias results from ignoring the dynamic effects of learning and the inability to control for unobserved household heterogeneity. A cross-sectional sample of non-adopters would include both potential future adopters and those who will never adopt, yet these two populations would be treated the same in a static study. Similarly, recent adopters who may not yet be sure of the technology's benefits are treated the same as long-time adopters who have much experience and may be more likely to continue with the technology (Moser & Barrett, 2006). Hence, the factors of adoption pointed out in the previous literature could be due to the timing of measurement than anything specific about the technology. Panel data could potentially overcome this limitation of cross-sectional data. Cross-sectional estimates of Bt adoption may also suffer from omitted variable bias, which could be managed by taking repeated observations of the same unit; this is provided only by the panel-data structure to control for the missing variables (Barham et al., 2004). Besley and Case (1993), Foster and Rosenzweig (1995), Cameron (1999), Conley and Udry (2000), Barham et al. (2004), Moser and Barrett (2006), and Crost et al. (2007) have all explored panel data in recent studies of learning and technology adoption.

Binary choice models (probit or logit) have frequently been used to analyze discrete choices to use (or not) a particular technique. Moser and Barrett (2006) note that controlling for household fixed effects is impossible in these models unless all farmers in the dataset are observed both as non-adopters (0) and adopters (1). This problem is lessened by the random-effects estimator, which is potentially a very important estimator due to the large number of analyses that involve survey datasets of either cross-sectional or longitudinal form and the frequency with which the dependent variable is only measured by a dichotomous response (Guilkey & Murphy, 1993). Hence, a random-effects probit model is applied in the present study to model the adoption of Bt cotton in India. The model is specified as,

$$Y_{it} = \beta X_{it} + (q_i + \mu_i) + \upsilon_{it}\,, \tag{1}$$

where there are K regressors, including a constant. We explicitly include an intercept so that we can make the assumption that the unobserved effect, μ_i , has zero mean (without loss of generality). The component q_i is the random heterogeneity specific to the i^{th} observation and is constant through time. We would usually allow for time dummies among the explanatory variables as well. In using a fixed-effects model, the goal is to eliminate μ_i because it is thought to be correlated with one or more of the explanatory variables. Suppose we think μ_i is uncorrelated with each explanatory variable in all time periods; then, using a transformation to eliminate μ_i results in inefficient estimators. The above equation becomes a random-effects model when we assume that the unobserved effect μ_i is uncorrelated with each explanatory variable:

$$\text{Cov}\,(X_{itn}\,,\,\mu_i) = 0,\; t = 1,2,\,\ldots,T;\; n = 1,2,\,\ldots\,k. \tag{2}$$

In fact, the ideal random-effects assumptions include all of the fixed-effects assumptions plus the additional requirement that μ_i is independent of all explanatory variables in all time periods. It is important to see that, if we believe that μ_i is uncorrelated with the explanatory variables, the β_j can be consistently estimated by using a single cross section: there is no need for panel data at all. But using a single cross section disregards much useful information in the other time periods (Wooldridge, 2006).

The standard probit model is usually modeled as a choice between adopting the Bt cotton or not adopting. Farmers make their decision by choosing the alternative that maximizes their perceived utility (Fernandez-Cornejo, Beach, & Huang, 1994). The index function that estimates farmers' Bt cotton adoption is

$$\text{Bt}_i^* = Z'_i\,\gamma + u_i\,, \tag{3}$$

where Bt is a dummy for the use of Bt cotton and Bt_i^* is an unobservable index variable denoting the difference between the utility of using Bt cotton (U_{i1}) and the utility of not using Bt cotton (U_{i0}). If $\text{Bt}_i^* = U_{i1} - U_{i0} > 0$, then the individual farmer *i* will use Bt cotton. The term $Z'_i\,\gamma$ provides an estimate of $U_{i1} - U_{i0}$ using farm characteristics (Z_i) as explanatory variables, while u_i is an error term unobserved by the researcher and assumed to be normally distributed $u_i \sim N\,(0,1)$. The model can then be estimated with a standard probit log-likelihood function.

Fixed-effects Regression Model

Previous studies of Bt cotton in India have casually discussed the productivity effects using both on-field experimental farms and on-farm samples (e.g., Bennett et al., 2006; Qaim et al., 2006; Qaim & Zilberman, 2003). A number of on-farm studies used data from a single year or two subsequent years, most of which do not address the problem of endogeneity of explanatory variables. An important source of bias in such estimates, endogeneity overestimates the yield response from Bt cotton usage. The study addresses this weakness in the literature by trying to confirm the yield effect found in a representative panel sample of cotton producers from India, which potentially overcomes the endogeneity problem. In order to provide the extent to which such a self-selection bias can affect GM technology productivity estimates, the estimates from the fixed-effects model are compared with an uncorrected model (pooled model) that ignores individual farmer heterogeneity.

The problem of endogeneity arises when one of the elements in the explanatory variable X_{it} is correlated with error component model u_{it}. Or, all the elements of X_{it} are exogenous in the population model, but data are missing on an element of X_i, and the reason data are missing might be systematically related to u_i (Wooldridge, 2002). Generally, endogeneity issues in productivity estimates arise when one or more of the explanatory variables are also choice variables for the farmers, where a similar calculation of the expected yield and profitability of those choices might also be a part of the farmers' decision-making calculus (Barham et al., 2004). Specifically with respect to adoption of Bt crops, the problem is that if the adoption is endogenously determined, a correlation exists between the Bt variables and the error term, violating one of the model's basic assumptions. This bias—also known as self-selectivity—exists when farmer or household unobservables determine whether to adopt, leading to biased estimates of the effects of the technology. Hence, the estimated high productivity or profitability effects could be due to self-selection by the farmers rather than anything specific about the technology. Thus, the frequent finding of a technological productivity in Bt adoption might be a result of the unobservable farmers' inherent characteristic to adopt the technology more eagerly than their peers rather than to attributes of Bt technology.

Panel data provide a straightforward way to resolve the endogeneity problem associated with other endogenous variables and their influence on the adoption of the technology in question. The major challenge of this panel methodology is to control the impact of unobserved heterogeneity that is provided by the fixed-effects model. In the fixed-effects model, the heterogeneity represented by μ_i is unobserved but correlated with X_{it}, hence the least squares estimator of β is biased and inconsistent as a consequence of an omitted variable. While in the random-effects model the unobserved individual heterogeneity is assumed to be uncorrelated with the included variables. The fixed-effects model is an appropriate specification if we are focusing on a specific set of *N* firms, and our inference is restricted to the behavior of these sets of firms. In this case, the μ_i are assumed to be fixed parameters to be estimated and the remainder disturbances stochastic, with υ_{it} independent and identically distributed. The fixed-effects model allows for endogeneity of all the regressors with the individual effects. In order to account for the individual heterogeneity, we assume the intercept varies for each included variable but still assume that the slope coefficients are constant across time. Hence, the model takes the form

$$Y_{it} = \beta_{1i} + \beta_2 X_{2it} + \beta_3 X_{3it} + \mu_i + \upsilon_{it} , \quad (4)$$

where Y_{it} is output/profit per acre of farm *i* in season *t* as the case may be, X_{it} includes input levels per acre and household characteristics of farm *i* in season *t*, μ_i denotes the unobservable individual-specific effect, and υ_{it} the remainder disturbance. The variable μ_i captures all unobserved, time-constant factors that affect Y_{it}. The fact that μ_i has no '*t*' subscript indicates that it does not change over time. Generically, μ_i is called an unobserved effect. The model is called an unobserved-effects model or a fixed-effects model. In applications, μ_i is also referred to as unobserved heterogeneity or individual heterogeneity and so on. The error υ_{it} is often called the idiosyncratic error, or time-varying error, because it represents unobserved factors that change over time and affect Y_{it}. These are very much like the errors in a straight time-series regression equation.

Such a model is known as a fixed-effects (regression) model (FEM) due to the fact that, although the intercept may differ across individuals, each individual's intercept does not vary over time (or time invariant). This model is a classical regression model, so no new results are needed to analyze it. The FEM assumes that the (slope) coefficients of the regressors do not vary across individuals or over time. The use of FEMs to control for unobserved heterogeneity is widespread. Recent studies exploring panel-data methodologies in estimating productivity effects have employed fixed-effects approaches as a way to overcome the problem of self-selectivity. Recent impact studies using fixed-effects panel-data approaches include Foltz and Chang (2002); Barrett, Moser, McHugh, and Barison (2004); and Crost et al. (2007).

Results

Major Cotton Hybrids

This section presents an overview of major cotton hybrids being cultivated by farmers in the sample and provides a comparison of the yield levels of different hybrids. The mean yield per acre of different cotton hybrids from our sample is shown in Table 2. As already presented, only three Bt cotton hybrids from Monsanto-Mahyco Biotech India Private Ltd. (MMBL) were approved for cultivation in the first year of commercial release. Among the three available Bt hybrids, MECH-162 was widely grown by the farmers (accounting for 84% of the sample), while the MECH-184 hybrid yielded better than the other even though it was cultivated in much smaller proportions. Among non-Bt, Bunny was the most popular hybrid preferred by most of the respondents. The yield from Bunny was higher than other hybrids in recent years (2006-07), however the Brahma hybrid yielded the highest overall (obtained in 2004-05) There was a 34% net increase in cotton yield levels due to Bt cotton hybrids.

In 2004-05 there were four official hybrids available for commercial cultivation. Among them, Rasi was the most preferred hybrid, as it was more highly productive than any other hybrid. As with non-Bt hybrids, the same trend is observed as in the previous season, while yield levels improved among all the hybrids. By 2006-07, there was a wide variety of Bt hybrids available, of which Bunny hybrid with a Bt strain became more popular than any other hybrid. As farmers knew about Bunny non-Bt hybrid, most farmers also started cultivating the Bt form of Bunny. Within the Bt hybrids, Mallika was found to be higher yielding than all other hybrids. As the prevalence of other Bt hybrids increased, the MECH hybrids became less preferred by the farmers. In 2006-07, Bunny was the most preferred non-Bt hybrid, the area of which was shrinking drastically.

Table 2. Yield comparison of cotton hybrids.[a]

	2002-03		2004-05		2006-07	
Hybrid	**% obs**	**Mean (SD)**	**% of obs**	**Mean (SD)**	**% of obs**	**Mean (SD)**
MECH-162	84	609 (381)	20	738 (289)	6	582 (275)
MECH-184	14	840 (315)	12	704 (348)	--	--
MECH-120	--	--	15	646 (261)	3	685 (433)
Rasi-222	--	--	39	797 (314)	18	858 (340)
Brahma	--	--	--	--	6	917 (338)
Bunny	--	--	--	--	33	817 (378)
Mallika	--	--	--	--	15	1,009 (284)
All others	2	1,417 (144)	14	738 (48)	18	808 (347)
Total Bt	100	659 (394)	100	743 (328)	100	842 (356)
Non-Bt cotton						
Bunny	41	553 (337)	39	564 (296)	41	662 (321)
Brahma	12	597 (450)	10	655 (273)	--	--
All others	47	423 (171)	50	548 (284)	59	555 (340)
Total non-Bt	100	491 (336)	100	551 (292)	100	590 (335)

[a] Yield (kg/acre) at the farm level expressed in terms of raw cotton (seed cotton), including lint and seed.
Source: Sadashivappa (2009)

Farm-level Effects of Bt Cotton in India

In the next step, the farm-level effects of Bt cotton cultivation in India based on the sample results are analyzed. These results are based on the plot observations of cotton farmers, which include details on cotton cultivation with input use and output details. In all three rounds of the survey, data were collected at the plot level, and farmers who cultivated both Bt and non-Bt cotton were interviewed with the same questionnaire. Hence, the number of plot observations is somewhat larger than the number of farmers in the sample—the particulars of which are presented later in this article. Though the sample contains a few observations of farmers who have used illegal Bt seeds, most Bt adopters had used official seeds. In India, Bt cotton has yielded two major agronomic effects over the years—pesticide reducing and yield enhancing. First, the pesticide-reducing effect of Bt cotton is presented.

Insecticide-reducing Effect of Bt Cotton. In all three seasons surveyed, the number of insecticide sprays and insecticide amounts used were significantly lower on Bt than on non-Bt plots. The exact reductions vary from year to year, which is partly due to seasonal variations in pest pressure. The number of sprays has reduced over the years from 4.18 sprays in 2002-03 to 3.29 sprays in 2006-07 (Figure 1). For the same periods, non-Bt cotton needed two extra sprays when compared to Bt cotton to achieve the existing reasonable yield levels. In 2002-03 and 2004-05, insecticide quantities on Bt plots were reduced by approximately 50%. This is consistent with other studies for India (Bennett et al., 2006; Gandhi & Namboodiri, 2006). Though sprayed two times more than Bt cotton, the yield levels of non-Bt plots remain below average levels.

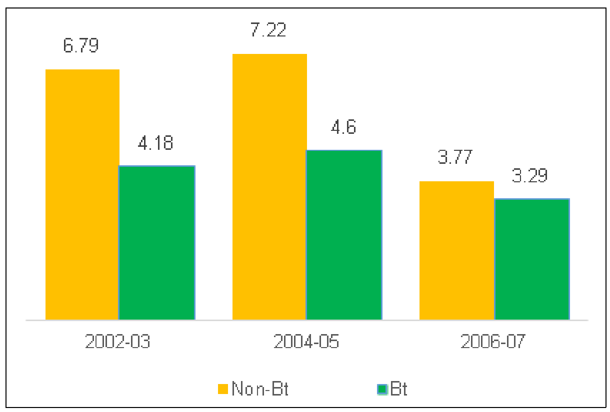

Figure 1. Number of sprays on cotton plots.

In 2006-07, average reductions were only 21%. Yet, this lower reduction is not due to increases in insecticide sprays on Bt plots, as one might expect when Bt resistance would emerge or secondary pests would gain in importance. On the contrary, sprays on Bt plots were further reduced, but sprays on non-Bt plots were reduced as well. This might be due to self-selection of farmers: by 2006-07, farmers who used to apply a lot of

Table 3. Crop enterprise budgets (Rs./acre).

	2002-03 Mean (SD)			2004-05 Mean (SD)			2006-07 Mean (SD)		
	Bt (n=133)		Non-Bt (n=301)	Bt (n=165)		Non-Bt (n=300)	Bt (n=317)		Non-Bt (n=56)
Output price (Rs./kg)	20.65 (1.96)		20.93 (2.26)	18.63 (2.74)		18.30 (3.17)	19.94 (1.72)	*	20.35 (2.92)
Seed cost	1,573 (196)	***	490 (286)	1,624 (548)	***	527 (240)	803 (245)	***	479 (207)
Insecticide cost	1,258 (1,469)	***	2,128 (1,748)	1,573 (1,633)	***	2,413 (1,835)	1,173 (1,738)		1,139 (1,233)
Fertilizer cost	1,883 (1,199)	***	1,658 (1,073)	1,882 (1,180)	**	1,665 (1,286)	1,953 (2,997)		1,466 (869)
Manure cost	722 (834)	**	590 (729)	314 (785)		257 (813)	904 (1,917)		651 (1,584)
Labor and custom operations cost	1,721 (1,310)	***	1,406 (1,080)	1,878 (1,094)		1,766 (1,020)	2,769 (2,062)		2,728 (2,163)
Harvesting cost	1,198 (1,339)	***	847 (822)	1,581 (747)	***	1,172 (676)	1,833 (836)	***	1,339 (829)
Other cost	85 (179)		104 (218)	66 (399)		124 (1,471)	225 (909)	**	20 (69)
Total variable cost	8,441 (3,452)	***	7,224 (3,337)	8,919 (3,422)	***	7,924 (3,682)	9,662 (5,778)	**	7,822 (3,963)
Gross revenue	13,735 (8,425)	***	10,357 (7,290)	13,841 (6,321)	***	10,077 (5,270)	1,6783 (7,542)	***	12,003 (7,726)
Profit	5,294 (8,117)	***	3,133 (6,774)	4,922 (6,291)	***	2,152 (5,477)	7,121 (7,655)	***	4,181 (7,563)

, **, * Mean values are significantly different from those on non-Bt plots at the 10%, 5%, and 1% level, respectively.*
47 Indian Rupees (Rs.) ~ US $1; Source: Sadashivappa and Qaim (2009a)

insecticide in non-Bt cotton had adopted Bt technology, so that the sample of non-adopters then mostly consisted of farmers who spray little anyway—either because of lower pest problems or because of lack of awareness. Moreover, due to the wide dissemination of Bt cotton over the past 2-3 years, there seems to be an overall decline in the populations of Bt target pests, especially the American bollworm (Khadi, Rao, & Singh, 2007). This can be interpreted as a positive externality of Bt technology for non-adopting farmers. (It could potentially even lead to a free-rider problem, including technology disadoption among some, although the relatively low Bt seed prices observed today might prevent this from happening.)

Figure 2 depicts that the amount of active ingredient usage per acre has also been very high in non-Bt cotton, which was twice the amount used on Bt cotton in 2002-03 and 2004-05 seasons and has been reducing in the recent years. The amount applied remained similar for non-Bt plots across the two seasons and has decreased drastically by 63% in the 2006-07 season. Pesticide usage both in terms of number of sprays and active ingredient usage (kg/acre) have shown a declining trend with the increased coverage of Bt cotton and have reached almost similar levels for both Bt and non-Bt plots in 2006 season. The usage of pesticide decreased to just more than 1 kg/acre for both the plots, while the reduction was significant with respect to non-Bt cotton.

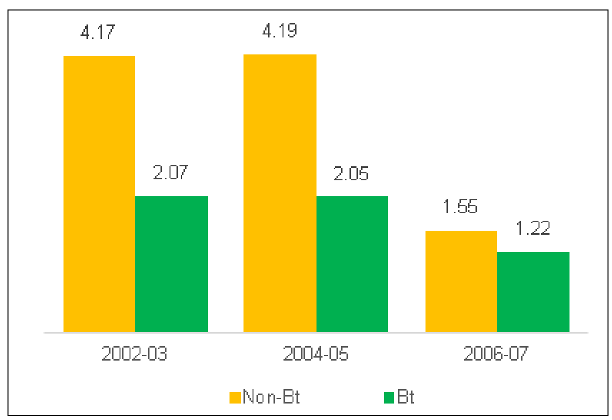

Figure 2. Mean insecticide usage (kg/acre).

Yield-enhancing Effect of Bt Cotton. Apart from insecticide reductions, a major effect of Bt cotton in India is a

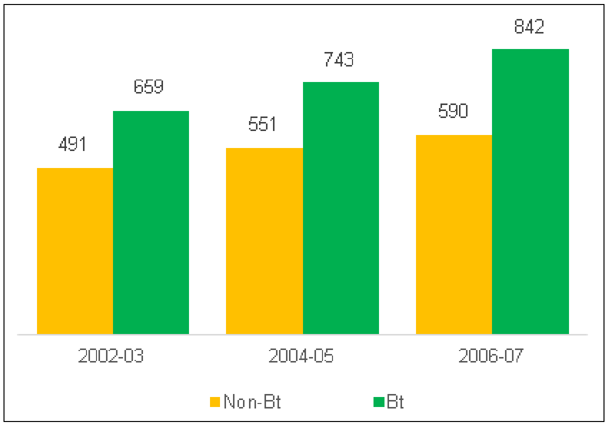

Figure 3. Mean yield levels (kg/acre).

significant yield advantage due to lower crop losses, as previously predicted by Qaim and Zilberman (2003). The overall yield levels have been increasing over the years, while the rate of growth for Bt has been far higher than the non-Bt plots. Over the years, average yields were 30-40% higher on Bt than on non-Bt plots (Figure 3), which is due to more effective pest control and thus a reduction in crop damage. Moreover, differences over the years are largely due to variability in pest pressure.

Crop Enterprise Budgets

Based on the survey data, economic performance of Bt cotton at the plot level is shown in Table 3. The economics of per-acre cotton cultivation provide a clear distinction of the benefits for Bt cotton farmers. Here, a plot-wise cost structure of cotton cultivation for both the plots is provided. Seed costs were the major cost component during 2002-03 and 2004-05 but declined in 2006-07 due to government interventions in the market forces. Conventional or non-Bt cotton farmers had to bear a higher share of the total cost of production on insecticides, which has reduced in the recent years; this is a positive externality of Bt cotton. Fertilizers were the major cost component for Bt cotton in the first years of its introduction. Labor and operational costs have dominated the cost structure of cotton cultivation in the recent years. Though the Bt cotton growers spend higher amounts on variables costs, the returns in turn have been significantly higher.

Over the years the net revenue from Bt cotton have been higher and the difference between revenues of Bt and non-Bt cotton has grown steadily (Table 3). The cost structure has been decreasing while profit margin has been increasing continuously over the years. Higher yields and crop revenues are also the main reason for the significant gains in cotton profits. Profit differences between Bt and non-Bt cotton even increased over time, from Rs. 2,161 (US $49.23) per acre in 2002-03 to Rs. 2,940 (US $66.97) in 2006-07. These are large benefits for cotton-producing households in India, many of whom live near or below the poverty line.

Table 4. Comparative advantage of Bt over non-Bt cotton.

	2002-03	2004-05	2006-07	Average
Insecticide use	-50%	-51%	-21%	-41%
Yield	+34%	+35%	+43%	+37%
Seed cost	+221%	+208%	+68%	+166%
Total variable cost	+17%	+11%	+24%	+17%
Gross revenue	+33%	+37%	+40%	+37%
Profit	+69%	+129%	+70%	+89%

Source: Sadashivappa and Qaim (2009b)

In summary, the farmers cultivating Bt cotton have realized insecticide reduction as well as profit enhancement benefits from Bt cotton cultivation (Table 4). The reduction in insecticide sprays and application has led to a 41% decline in overall insecticide use, while there has been a 37% gain in yield levels over the years. The seed cost margin has been declining over the years, and the difference in the seed prices was offset by higher yield levels. Though Bt cotton farmers spend 17% higher than the non-Bt farmers, they realize profit gains to the tune of 89% from Bt cotton. Hence, Bt cotton has been benefiting farmers agronomically in terms of high yields as well as economically by way of higher net returns in addition to reduced pesticide applications.

Panel Dataset

The analyses are based on a balanced panel of 282 observations from each survey round, which brings the total observations to 846. The rest of the panel observations outside the balanced panel are not considered for this analysis. Hence, from the three survey rounds, 846 usable panel farmer observations were included in the analysis. The number of Bt adopters in the sample has constantly increased in the sample over the years. In cases where farmers contained more than one cotton plot, the dataset was comprised of information only from the major cotton plot of the farmer—the dataset includes only one observation per farm. For Bt adopters, the Bt cotton plot was considered as the major plot. Hence, the final dataset was made up of observations from 435 Bt adopters and 411 non-Bt adopters.

Adoption of Bt Cotton—Random-effects Probit Model

Explanatory Variables. The explanatory variables considered for the analysis are presented in Table 5. Explanatory variables are included based on the review of previous adoption studies. These variables are farm-specific and farmer-specific variables in addition to year and regional-specific variables. These farm and farmer variables have been basic and significant determinants of technology adoption in developing countries. The farm-specific variables include the farm size, rotation, soil quality, and irrigation. Farm size has been an integral part of the explanatory variables in most of the adoption studies. Feder, Just, and Zilberman (1985) emphasized the significance of farm size and provided the relationship of farm size to the rate of adoption by citing various empirical studies. The farm size in this study is measured as the number of acres of farmland owned by the farmer. The variable rotation is included as a dummy, which states whether the farmers followed crop rotation. This rotational practice is viewed as one of the major characteristics of an innovative and efficient farmer. Soil is described as a dummy variable for black soil, which is highly suitable for cotton cultivation. The variable irrigation is a dummy variable, which implies whether the plot is irrigated or a rain-fed plot.

The farmer-specific variables include education, cotton experience, credit and information constraints, and per-capita expenditure. Education is defined as the number of years of schooling of the respondent farmer. Formal education is assumed to play an important role in adoption decision, and better-educated farmers are supposed to adopt the technology quickly due to their access to better information sources than their peers and may be able to apply innovations more efficiently (Lele & Makki, 1997; Lin, 1991). Years of farming experience might have an influence on the adoption decision. The usual presumption is that early adopters tend to be the more experienced farmers, and this presumption has been confirmed by previous adoption models (Thirtle, Beyers, Imael, & Piesse, 2003).

Many recent studies have emphasized the importance of proper access to credit and information as major elements in the adoption process (e.g., Feder & O'Mara, 1981). Differential access to capital is often cited as a factor in differential rates of adoption. Hence, a credit constraint dummy is defined, which is based on the farmers' access to loans from the bank or credit from informal sources. Access to information is expected to play a significant role in the adoption process; this has been highlighted in recent literature by many empirical studies (e.g., Matuschke, Mishra, & Qaim, 2006). In our survey we asked farmers about their source of information on the innovations of cotton and if they have proper access to such information. Accordingly, an information constraint dummy is defined, which is based on the farmers' access to information on Bt cotton. In addition, large-scale and better-income farmers are usually thought to better bear the uncertainties and costs associated with innovations. As a result, annual household

Table 5. Adoption of Bt cotton: Random-effects model.

Variable and description	Probit model of adoption	
Constant	-0.109 (0.375)	
Farm size (Acres owned by the farmer)	0.009 (0.010)	
Rotation (Dummy: 1=follows crop rotation, 0=otherwise)	0.153 (0.135)	
Soil (Dummy: 1=black soil, 0=otherwise)	0.421 (0.220)	*
Irrigation (Dummy: 1=irrigated, 0=otherwise)	0.958 (0.236)	***
Education (Years of schooling)	0.022 (0.013)	*
Cotton experience (Years of experience)	0.006 (0.006)	
Credit constraint (Dummy: 1=constraint, 0=otherwise)	0.089 (0.130)	
Information constraint (Dummy: 1=constraint, 0=otherwise)	-0.669 (0.163)	***
Expenditure (Per-capita annual food and nonfood expenditure [Rs.])	-1.040E-05 (1.710E-05)	
Year 2002 [a]	-1.619 (0.385)	***
Year 2004 [a]	-0.835 (0.328)	**
Year 2002 farm-size interaction	0.005 (0.012)	
Year 2004 farm-size interaction	-0.004 (0.011)	
Year 2002 irrgation interaction	-0.359 (0.290)	
Year 2004 irrgation interaction	-0.620 (0.289)	**
Year 2002 soil interaction	-0.242 (0.311)	
Year 2004 soil interaction	-0.293 (0.286)	
Year 2002 expenditure interaction	4.010E-05 (1.970E-05)	*
Year 2004 expenditure interaction	1.120E-05 (1.740E-05)	
Maharashtra (State dummy [b])	0.101 (0.231)	
Karnataka (State dummy [b])	0.114 (0.229)	
Andhra Pradesh (State dummy [b])	-0.111 (0.226)	
Regression statistics (Log likelihood)	-473.20	
Wald Chi-square	143.16	***

Note: Figures in parentheses are standard errors
****, **, * significant at 1%, 5%, and 10%, respectively*
[a] The reference variable for the year dummies is Year 2006.
[b] The reference variable for the state dummies is Tamil Nadu.

expenditure on food and non-food items is used as a proxy for income in the regression analysis that reflects the farmers' standard of living. In addition, year and state dummy variables are included to capture the time-specific and regional effects, respectively. Also, interaction terms between year and a few explanatory variables are included to examine the importance of variables in a specific year.

Regression Results. The estimates of the adoption model for Bt cotton is presented in Table 5. The coefficients represent the expected changes in utility index if explanatory variables changes one unit. From the coefficients in the model it is observed that though the farm-specific variables have the expected signs and direction, they do not have more significant influence on the adoption of Bt cotton in India. The presumption that large farmers with higher acreage tend to adopt Bt cotton turns out to be insignificant for Indian cotton farmer. Hence, irrespective of land ownership, the technology is being adopted by farmers of all farm sizes. In a similar manner, following a crop rotation does not necessarily increase the adoption of Bt cotton. Crop rotation taken as a proxy for a characteristic feature of efficient farmers does not significantly influence the adoption decision of Bt cotton. Black soil—which has a high soil quality—has a significant influence on adoption of Bt cotton. Black soils are the ideal soil for cultivation of cotton, and its availability in the region improves the probability of Bt cotton adoption. Availability of irrigation facilities improves the probability of adopting Bt cotton technology significantly. However, irrigation availability became irrelevant for Bt cotton adoption in 2004 as indicated by the interaction term in the year 2004. But the availability of which has significantly improved the probability of Bt cotton adoption as a whole, as indicated by high significance of the irrigation variable. Hence, Bt cotton technology has proved itself to be a scale-neutral technology in India that does not merely depend on the availability of ideal farm characteristics. This emphasizes the fact that the technology could also be well adopted in less favorable agronomic conditions.

Among the farmer-specific variables, only educational status seems to significantly improve the probability of adoption of Bt cotton technology. However, cotton experience does matter in the adoption of Bt technology in a positive direction, but the influence was not observed to be significant. Better-educated and highly-experienced farmers are more likely to adopt Bt cotton technology in India. It is natural that better-educated farmers are well aware of the technological aspects and have always been early adopters of the technology, as also is the case with experienced farmers. But access to credit has no significant influence on the adoption of Bt cotton. This could be due to the prevalence of informal credit systems in India. Most of the farmers in India prefer informal credit sources for agricultural purposes. Hence, credit is not a major constraint for adoption of the Bt technology in India.

On the other hand, information availability on the technology seems to have a higher influence on the adoption decision in India. Access to information on the technology is one of the major pre-requisites for adoption of a technology. Large numbers of studies have emphasized the importance of proper access to information as facilitating elements in the adoption process. Similarly adoption studies on India have derived similar results that reinforce the importance of information constraints under the Indian context (e.g., Matuschke et al., 2006). Annual per-capita expenditures taken as a proxy for farmers' living standard also has no significant influence on adoption decision. This is opposed to the fact that only better-off farmers are able to adopt innovative technologies. Rather, it signifies that the technology is being adopted by all sections of farmers irrespective of their standard of living; this signifies the overall appealing nature of the technology. The interaction term between year and expenditure indicates that although the variable had some influence over the first year, it had no influence in the later years of adoption. It is also a well-known fact that the new technologies are adopted initially by better-off farmers with a better income status (Feder et al., 1985). But as the technology became widely available, it was adopted by farmers of all income levels. Hence, the technology is affordable not only by large farmers but also small and marginal farmers. Due to this, adoption of Bt cotton in India has increased to more than 80% over a period of six years since its introduction.

The year dummies are negative and highly significant, which shows the existence of a time-specific effect on the adoption rates of Bt cotton in India. The technology faced huge criticism from opponents during the initial years of its commercialization, and this is partially why technology became popular among farmers in an undesired way. But as the technology spread widely, more farmers realized the real benefit of the technology and adopted in recent years. It signifies that the technology has matured over the years, and more farmers have come to appreciate the technology as the years have gone by. The state dummies Maharashtra and Andhra

Table 6. Estimated coefficients of the production function.

Variable and description	Pooled model		Fixed-effects model	
Constant	75.38 (71.79)		55.60 (46.82)	
Bt adoption (Dummy)	164.49 (24.91)	***	118.77 (28.66)	***
Insecticide (Amount of insecticide [kg/acre])	3.67 (5.21)		7.36 (5.72)	
Insecticide squared	-0.11 (0.08)		-0.11 (0.08)	
Rotation (Dummy: 1=follows crop rotation, 0=otherwise	25.39 (26.13)		23.74 (29.33)	
Season length	3.50 (0.55)	***	4.69 (0.65)	***
Season length squared	-0.01 (1.88E-03)	***	-0.01 (2.17E-03)	***
Soil (Dummy: 1=black soil, 0=otherwise)	-16.40 (23.90)		-65.94 (31.82)	**
Fertilizer cost (Cost of fertilizer [kg/acre])	0.04 (0.01)	***	4.48E-03 (0.01)	
Fertilizer cost squared	-6.53E-07 (2.47E-07)	***	5.78E-08 (2.89E-07)	
Irrigation (Dummy: 1=irrigated, 0=otherwise)	175.89 (21.91)	***	149.84 (27.92)	***
Labor (Days of hired and household labor)	0.25 (0.10)	**	0.29 (0.10)	***
Labor squared	-1.81E-05 (8.43E-06)	**	-2.32E-05 (8.92E-06)	**
Year 2002 [a]	-214.87 (30.71)	***	-244.43 (30.58)	***
Year 2004 [a]	-70.22 (28.14)	**	-103.73 (27.19)	***
Household characteristics				
Farm size (Acres owned by the farmer)	-1.73 (1.73)			
Farm size squared	0.01 (0.02)			
Cotton experience (Years of experience)	4.63 (3.42)			
Cotton experience squared	-0.14 (0.08)	*		
Education (Years of schooling)	-2.50 (2.25)			
Age (Age of respondent farmer in years)	-2.00E+00 (9.16E-01)	**		
Maharashtra [b] (Dummy variable for Maharashtra state)	71.56 (43.80)			
Andhra Pradesh [b] (Dummy variable for Andhra Pradesh state)	100.21 (41.28)	**		
Karnataka [b] (Dummy variable for Karnataka state)	34.50 (42.10)			
Number of observations	846		846	
Hausman test	-		25.18	***
R^2	0.43		0.43	
Net productivity effect of Bt	38%		28%	

*Note: Figures in parentheses are standard errors; ***, **, * significant at 1%, 5%, and 10%, respectively*
[a] The reference variable for the year dummies is Year 2006; [b] The reference variable for the state dummies is Tamil Nadu

Pradesh are negative but insignificant, which is due to climatic and topological factors and accounts for possible regional effects. The overall explanatory power of the adoption model is relatively low; however, this has also been found in other Bt-cotton studies referring to India and other developing countries (e.g., Crost et al., 2007; Thirtle et al., 2003).

Production Function Analysis

Regression Results. This section focuses on the estimation of a fixed-effects production function with quadratic specification, including the use of Bt cotton as a dummy variable. Similar to the step followed by Crost et al. (2007), the results of the fixed-effects model are compared with those of a pooled cross-sectional model, and a Hausman test is undertaken to test for a fixed vs. pooled model. The dependant variable is the yield of raw cotton per acre and the explanatory variables are listed in Table 6. Various functional forms were attempted to fit the production function, of which the quadratic form provided the best results. The Hausman test result from the production function clearly shows the existence of a correlation of unobserved heterogeneity with at least one of the endogenous variable, as they are all endogenously determined. It is observed that Bt adoption significantly increases yield levels while the insecticide effect is found to be insignificant. In both the models, the Bt effect is significantly higher than the insecticide effect.

The advantage of a fixed-effects panel approach is observed with the Bt effect, where the yield effect of Bt cotton is significantly higher in the pooled model than in the fixed-effects model. This clearly depicts that the yield effect estimated by the pooled model is indeed biased upwards, which is due to the ignorance of individual heterogeneity. Crost et al. (2007) have also observed similar results on the impact of Bt cotton in the state of Maharashtra using a two-period panel dataset. In the next step, the net productivity gains from both the models are calculated at sample mean levels. The results show that from the pooled model the net productivity gains of Bt cotton when compared to non-Bt cotton works out to 38%, which is almost equal to the 37% gain obtained in the simple yield comparisons over the three seasons. The net productivity gain observed in the fixed-effects model is 28%, which is still sizeable. Yet the difference suggests that controlling for a selection bias is important. Strikingly, the 28% figure is quite close to the 31% effect obtained by Crost et al. (2007), who also used a fixed-effects approach. Building on cross-section data, yield effects in other studies for Bt cotton in India range from a minimum of 21% to a maximum productivity gain of 54% (Bambawale et al., 2004; Bennett, Ismael, Kambhapati, & Morse, 2004; Bennett, Ismael, & Morse, 2005; Gandhi & Namboodiri, 2006; Narayanmoorthy & Kalamkar, 2006; Qaim et al., 2006).

The insignificance of insecticides in both the models shows that they are being used in very inefficient ways by farmers. Due to such indiscriminate use of all categories of insecticides in the pre-Bt introduction years, bollworm and white fly had developed resistance to almost all the insecticides used to control them (Kranthi, Jadhav, Wanjari, Ali, & Russell, 2001; Ramasubramanyam, 2004; Venugopal, 2004). Also, the negative value of the square of the insecticides exhibits diminishing marginal effects. This shows that as the application of insecticides increases beyond a certain threshold level, the yield levels would decrease. Similar trends were observed by previous studies on Bt cotton in India by Bennett et al. (2006), Qaim et al. (2006), and Crost et al. (2007).

The effect of season length is found to be higher in the fixed-effects model than in the pooled model. So correcting for the selection bias helps in estimating the unbiased farm-level effects more precisely. The positive and high significance of season length indicates that longer the season length, the higher the cotton yields. But, the variable also exhibits diminishing marginal effects as indicated by the square of the season length. Another interesting effect is of soil status, which is negative and insignificant in the pooled model but becomes significant in the fixed model. The soil status is a dummy variable that indicates whether the soil is a black soil or another type. The negative and significant soil variable shows that farmers with black soil experience lower yield levels. This could be due to the availability of a wide range of Bt cotton hybrids suitable for all kinds of local conditions that have made the necessity of black soils for high yields irrelevant. Yet the availability of irrigation significantly increases the yield levels to a greater extent. The coefficient for fertilizer cost is positive and significant in the pooled model but becomes insignificant in the fixed-effects model. Irrigation and labor are found to significantly influence the yield in an expected way. The size of influence of irrigation is higher in the pooled model, while the influence of labor is slightly higher in the fixed-effects model. But labor exhibits diminishing marginal effects, as shown by negative significance of the squared term. Nevertheless, both irrigation availability and higher labor days significantly influence the yield levels of cotton.

The year dummy variables have shown negative influence on cotton yields and are significant. Farmers realized higher cotton yields in 2006-07 when compared to 2002-03 and 2004-05. This was already established from the descriptive statistics of agronomic effects that the yields in the early stages of Bt cotton introduction in India were comparatively lower than the following years. Also, the difference has been declining from year to year, as is the significance. Farmers learn with the technology as the years pass and would make better use of the technology as they gain experience with it. Hence, after controlling for individual heterogeneity with the help of a fixed-effects panel approach, Bt cotton in India is found to have a significant yield advantage over non-Bt cotton. Insecticides are found to be used in an ineffective manner by farmers, and that has resulted in a decline of its effect over the years and has contributed to development of resistance in insect pests.

Profit Function Analysis

The other major contribution of this study is the estimation of the profitability effect of Bt cotton technology. While clearly yield-enhancing, the increase in production due to Bt technology will require an increase in input costs, making its profitability less certain. Despite the large number of studies and rapid adoption of the technology, studies of Bt cotton profitability remain

Table 7. Estimated coefficients of the profit function.

Variable and description	Pooled model		Fixed-effects model	
Constant	902.39 (1,456.73)		899.53 (972.73)	
Bt adoption (Dummy)	1,908.54 (505.50)	***	1,308.96 (595.49)	**
Insecticide (Amount of insecticide [kg/acre])	-425.49 (105.66)	***	-388.70 (118.82)	***
Insecticide squared	3.69 (1.54)	**	3.87 (1.74)	**
Rotation (Dummy: 1=follows crop rotation, 0=otherwise)	1,028.22 (530.14)	*	1,193.39 (609.39)	*
Season length	27.08 (11.25)	**	41.47 (13.57)	***
Season length squared	-0.03 (0.04)		-0.06 (0.05)	
Soil (Dummy: 1=black soil, 0=otherwise)	0.05 (484.95)		-768.02 (661.18)	
Fertilizer cost (Cost of fertilizer [kg/acre])	-0.66 (0.23)	***	-1.20 (0.28)	***
Fertilizer cost squared	-4.53E-06 (5.01E-06)		6.35E-06 (6.01E-06)	
Irrigation (Dummy: 1=irrigated, 0=otherwise)	2.30E+03 (4.45E+02)	***	1,615.49 (580.17)	***
Labor (Days of hired and household labor)	-1.31 (2.02)		-0.13 (2.18)	
Labor squared	1.55E-04 (1.71E-04)		2.69E-05 (1.85E-04)	
Year 2002 [a]	-1.76E+03 (6.23E+02)	***	-1,960.64 (635.33)	***
Year 2004 [a]	-1,026.00 (571.07)	*	-1,451.04 (564.85)	**
Household characteristics				
Farm size (Acres owned by the farmer)	-33.25 (35.16)			
Farm size squared	0.17 (0.40)			
Cotton experience (Years of experience)	116.59 (69.42)	*		
Cotton experience squared	-3.13 (1.65)	*		
Education (Years of schooling)	-76.86 (45.67)	*		
Age (Age of respondent farmer in years)	-55.21 (18.59)	***		
Maharashtra [b] (Dummy variable for Maharashtra state)	3,660.68 (888.63)	***		
Andhra Pradesh [b] (Dummy variable for Andhra Pradesh state)	1,453.64 (837.57)	*		
Karnataka [b] (Dummy variable for Karnataka state)	1,741.08 (854.18)	**		
Number of observations	846		846	
Hausman test			25.71	***
R^2	0.24		0.22	
Net profitability effect of Bt	80%		55%	

*Note: Figures in parentheses are standard errors; ***, **, * significant at 1%, 5%, and 10% respectively*
[a] The reference variable for the year dummies is Year 2006; [b] The reference variable for the state dummies is Tamil Nadu.

inconclusive. Hence, this section estimates the impact of Bt cotton on per-acre profit using a fixed-effects panel approach, which is supposed to be the first of its kind; other studies done so far have concentrated only on the productivity effect of Bt cotton technology. The profit-per-acre equation estimates—which are estimated using the same methods as with the yield estimates—are shown in Table 7. The dependent variable, profit per acre, is defined as the difference between gross revenue and the total variable cost. Similar to the production function, a pooled model and fixed-effects model are estimated for the purpose of comparison. The pooled model ignores the effect of selection bias, but it is accounted for in the fixed-effects model. The pooled model shows that Bt cotton adoption significantly increases the profit per acre to the extent of Rs. 1,909, while the estimates of the fixed-effects model provide a profit per acre of Rs. 1,309 due to adoption of Bt cotton.

Further, the net profitability of Bt cotton over non-Bt cotton from both the models are shown in the last row of Table 7. The pooled model provided net profitability from Bt cotton of 80%, while the same from the fixed-effects model is 55%. This difference is clearly due to ignorance of unobserved heterogeneity by the pooled model. This 80% effect is close to the 89% effect observed from the cross-sectional analysis. On the other hand, the insecticide amounts have a significant negative effect on cotton profits. The negative effect of insecticides is clearly evident from both the models. Insecticides are found to decrease profits from Bt cotton by Rs. 425 per acre in the pooled model, while from fixed-effects model they are found to decrease profits by Rs. 389 per acre. Hence, while Bt technology has a profit-enhancing effect, insecticides have a profit retarding effect on cotton.

The other significant variables having an impact on profit from Bt cotton are crop rotation and longer crop days, as depicted by season length. The effects of these two variables are more prominent in the fixed-effects model rather than in the pooled model. Irrigation also showed a similar effect—it is more significantly prominent in the fixed-effects model than in the pooled model. A similar effect is observed with the fertilizer variable but with an opposite sign. Similar observations were made by Crost et al. (2007) on pesticide and fertilizer inputs in estimating the productivity effects. Hence, higher fertilizer costs also retard Bt cotton profits. This shows that as fertilizer application increases profits from Bt cotton appear to decline significantly. It also shows the lower fertilizer requirement of Bt cotton hybrids. The availability of irrigation facilities on the plot significantly influences farm profit in a positive direction; it also significantly increased yield levels. The year dummies are significantly negative in both models, which indicate that when compared to year 2006 the profit levels were lower and has been increasing in the recent years.

While the pooled model suggests that land holdings have no impact on profit levels from cotton, older farmers experience lower profit levels even though cotton experience enhances profit levels. Education has also a significant, negative influence on profit from cotton. Also, farmers in the states of Maharashtra, Andhra Pradesh, and Karnataka have been reaping higher profits when compared to farmers in Tamil Nadu. Hence, the profits from cotton increases with an increase in Bt cotton adoption following crop rotation with experienced farmers. Profits from cotton cultivation is found to decline significantly with indiscriminate use of insecticides and with application of higher fertilizer amounts.

Conclusion

The results indicate that Bt technology is very successful in India. Adopting farmers have realized significant benefits through pesticide reductions, higher effective yields, and higher profits. The agronomic and economic advantages have been sustainable over the first five years of widespread technology use, and there are no signs of declining benefits over time. Even though the diffusion of Bt was a learning process for farmers in the beginning, aggregate adoption has increased steadily and has reached over 80% of India's total cotton area by 2008. Bt technology has helped in achieving a record cotton harvest in India, at a time when other cotton-producing countries are facing a slowdown in production. Both small- and large-scale cotton farmers in India are now very satisfied with the innovation.

The study emphasizes the advantages of using panel-data econometrics in improving our understanding of technology adoption and impacts. A random-effects probit adoption model shows that Bt technology is scale-neutral. Therefore, the common notion that transgenic crops are only suitable for rich and large-scale farmers is not confirmed under Indian conditions. However, farmers with more formal education and those with better knowledge and information about the technology are more likely to be among the early adopters, underlining that structural constraints need to be overcome. Net impacts on cotton yields and profits are analyzed using fixed-effects panel models. The estimation results confirm yield- and profit-enhancing impacts of Bt cotton. While the panel data models result in somewhat lower net impacts than simple regressions with cross-section or pooled data, the results are still sizeable and highly significant: controlling for the non-random selection bias, the net yield gain of Bt technology is 28%, while the net profit gain is 55%. These findings confirm and extend previous studies on Bt cotton impacts in India and other developing countries, building on a unique dataset. Nonetheless, further research is needed on long-term aspects of transgenic crops, including economic, social, and environmental implications under different conditions. The panel-data methodology applied here can be a foundation for future technology adoption and impact studies.

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