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Bt cotton, damage control and optimal levels of pesticide use in Pakistan

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ABSTRACT. We use farm survey data and a damage control framework to analyze impacts of Bt cotton on yields and pesticide use in Pakistan. We also derive optimal levels of pesticide use with and without Bt, taking into account health and environmental externalities. This has not been done previously in the literature. Conventional cotton growers suffer from significant insect crop damage; they underuse pesticides from a profit-maximizing perspective. Yet, the picture is reversed when externalities are also considered. The social optimum of pesticide use is much lower than the private optimum, and both optima are lower with Bt than without this technology. Bt controls pest damage more effectively. Hence, yields on Bt farms are about 20 per cent higher in spite of lower pesticide use. Large pest damage is a typical phenomenon in developing countries. In such situations, Bt can contribute to productivity growth, while reducing pesticide applications and associated negative externalities.

1. Introduction

Bt cotton has been genetically modified with genes from *Bacillus thuringiensis* (Bt) to make the plant resistant to the bollworm, a major insect pest in cotton production. As one of the first genetically modified (GM) crops, Bt cotton was commercialized in the United States in 1996. Since then, this technology has been approved and widely adopted in several other cotton-growing countries. In 2012, GM cotton was grown on 60 million acres worldwide (James, 2012). Studies show that Bt has substantially

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reduced chemical pesticide use while increasing crop yields in farmers' fields (Huang *et al.*, 2002; Qaim and Zilberman, 2003; Thirtle *et al.*, 2003; Bennett *et al.*, 2004, 2006; Qaim and de Janvry, 2005; Shankar and Thirtle, 2005; Qaim *et al.*, 2006).

Nevertheless, there are open questions concerning Bt cotton impacts. First, most of the existing studies concentrated on China, India, and a few other countries; it is unclear whether the observed effects would also hold under different conditions. Second, most impact studies have looked at differences in yield and pesticide use between Bt adopters and non-adopters without controlling for possible selection bias (Crost *et al.*, 2007). Third, reductions in chemical pesticide use through Bt could bring about important health and environmental benefits. While some health and environmental benefits were identified in previous research (Shelton *et al.*, 2002; Bennett *et al.*, 2004; Hossain *et al.*, 2004; Wolfenbarger *et al.*, 2008; Kouser and Qaim, 2011), they were not monetized and integrated into broader economic analysis. This is considered important for a better understanding of how GM crops can contribute to sustainable development. We address some of these research gaps by focusing on Bt cotton in Pakistan.

Pakistan is the fourth largest cotton producer in the world with a total cotton area of 8.4 million acres (Government of Pakistan, 2012). Although unapproved Bt cotton varieties had been grown in Pakistan since 2002 (Hayee, 2004), Bt technology was officially approved only in 2010. Unlike other countries, where Bt cotton was commercialized by the US company Monsanto, Bt varieties were developed by different public and private sector organizations in Pakistan. In 2012, 6.9 million acres were grown with Bt varieties in Pakistan, equivalent to 82 per cent of the country's total cotton area (James, 2012). Two recent studies found that Bt adoption is beneficial for Pakistani cotton farmers, resulting in higher productivity and income (Ali and Abdulai, 2010; Nazli *et al.*, 2012). These studies build on data from 2007 and 2009, before officially approved Bt varieties were available. Ali and Abdulai (2010) and Nazli *et al.* (2012) compared cotton yields and pesticide use between adopters and non-adopters, using propensity score matching techniques.

We add to this existing research on Bt cotton impacts in Pakistan by using more recent survey data collected in late 2010, and by employing a production function and damage control framework (Lichtenberg and Zilberman, 1986). This framework is well suited to model insect pest damage and the damage-abating nature of Bt and chemical pesticides (Huang *et al.*, 2002; Qaim and de Janvry, 2005; Kuosmanen *et al.*, 2006). More importantly, we add to the international literature by calculating optimal levels of pesticide use with and without Bt, also taking into account the health and environmental externalities of pesticide use. This has not been done previously, but is important to better understand the potential of Bt technology to contribute to sustainable agricultural development.

The rest of this article proceeds as follows. The next section discusses the survey data and descriptive statistics. Section 3 presents the methodology, including details of the damage control framework and the calculation of optimal pesticide use levels. Estimation results are presented and discussed in section 4, while section 5 concludes.

2. Data and descriptive statistics

2.1. Farm survey

We carried out a survey of cotton farmers in Punjab, Pakistan, starting in late 2010, right after the harvest for the 2010 season, the first season in which officially approved Bt cotton varieties were grown. With 80 per cent of the country's total cotton area, Punjab is the leading cotton-growing province in Pakistan. Within Punjab, a multi-stage sampling procedure was used. First, four major cotton-producing districts were purposively selected, namely Vehari, Bahawalnagar, Bahawalpur and Rahim Yar Khan. These four districts account for 42 per cent of the total cotton area in Punjab (Government of Pakistan, 2009). Then, we randomly selected two tehsils (administrative units) in each district and four villages in each tehsil, resulting in a total of 32 villages. At the last stage, a complete list of cotton farmers was prepared in each village, from which 11 farmers were randomly selected. Thus, our sample consists of 352 cotton farmers, of which 248 are Bt adopters and 104 are non-adopters. Among the 248 adopters, 75 have completely switched to Bt, while 173 are partial adopters growing Bt in addition to conventional cotton. The sample is representative of cotton farmers in this part of Pakistan.

We used a structured questionnaire, including questions on general socioeconomic characteristics of the farm household and details about inputs used and output obtained in the cotton enterprise during the preceding season. The face-to-face interviews were conducted by a team of four enumerators, who were selected, trained and supervised by the researchers.

2.2. Descriptive statistics

For most sample farmers, cotton is the main crop because of its high profitability. In addition, farmers grow wheat, rice, maize, vegetables and a few other crops. Some general descriptive statistics are shown in table 1. While cotton holdings of Bt adopters and non-adopters are similar in size, Bt adopters have significantly larger farms than non-adopters. They are also better educated and are more likely to own a tractor. Furthermore, Bt adopters are less likely to be credit constrained. Bt seeds are not much more expensive than conventional cotton seeds in Pakistan. But even when no credits are required for purchasing Bt seeds, constrained access to financial resources is often associated with higher risk aversion, which can negatively affect technology adoption (Feder *et al.*, 1985; Marra *et al.*, 2003). We also asked farmers whether or not they had heard about Bt cotton. In most cases, the answer was yes; we then asked in a follow-up question when they had first learned about Bt. Based on this, we constructed a Bt awareness exposure variable, measured in years. Diagne and Demont (2007) and Kabunga *et al.* (2012) pointed at the importance of considering awareness exposure in technology adoption research. Unsurprisingly, Bt adopters have known the technology for longer than non-adopters, as is shown in table 1. These comparisons suggest that there are systematic differences between adopters and non-adopters, which need to be accounted for in impact assessment.

Table 1. *Descriptive statistics of sample farm households*

Variables	*Bt adopters (N = 248)* Mean	*Bt adopters (N = 248)* Standard deviation	*Non-adopters (N = 104)* Mean	*Non-adopters (N = 104)* Standard deviation
Age (years)	40.56	12.26	42.44	13.28
Education (years of schooling)	8.04***	4.27	6.77	4.62
Household size (number)	5.85	1.85	5.73	1.79
Farm size (acres)	25.39***	32.09	12.42	14.62
Cotton area (acres)	9.12	16.27	8.07	11.77
Tractor ownership (%)	62.10***	–	40.79	–
Credit constrained (%)	27.02***	–	55.96	–
Off-farm employment (%)	41.53*	–	49.82	–
Distance to market (km)	11.14	0.51	11.23	0.51
Bt awareness exposure (years)	4.21***	1.74	3.27	2.06

Notes: For identifying differences in mean values, an independent sample t-test was used for continuous and a chi-square test for categorical variables.
***, **, * indicate that mean values are significantly different at the 1%, 5% and 10% level, respectively.

Table 2 shows comparisons between Bt and non-Bt cotton at the plot level. For partial adopters, we collected input-output data for both Bt and conventional plots, so that the number of plot observations is larger than the number of farmers interviewed. Cotton yields are significantly higher on Bt than on non-Bt plots; the observed yield difference is 28 per cent. This difference is not due to higher genetic yield potentials of Bt varieties, but due to reduced crop damage. In spite of chemical pesticide applications, bollworms cause sizeable yield damage in conventional cotton, which can be controlled more effectively with Bt technology. Significant yield advantages were also reported in earlier studies on Bt cotton impacts in Pakistan (Ali and Abdulai, 2010; Nazli *et al.*, 2012), India (Bennett *et al.*, 2006; Subramanian and Qaim, 2010; Kathage and Qaim, 2012), China (Pray *et al.*, 2002), and other developing countries (Qaim, 2009).

Table 2 shows that fertilizer use, irrigation and labor inputs are higher on Bt than on non-Bt plots. This is not due to higher input requirements of Bt cotton. However, higher yields through better damage control provide incentives for intensified production. In the production function framework below we will control for these inputs to establish the net treatment effects of Bt technology. As expected, for chemical pesticides the pattern is reversed: farmers use significantly lower pesticide quantities on Bt than on non-Bt plots. To further differentiate between

Table 2. *Descriptive statistics of sample plots*

	Bt-plots (N = 248)		*Non Bt-plots (N = 277)*	
Variables	*Mean*	*Standard deviation*	*Mean*	*Standard deviation*
Yield (kg/acre)	972.50***	16.83	759.28	14.26
Pesticide quantity (liters/acre)	2.73***	1.07	3.46	1.40
Fertilizer (kg/acre)	106.00***	37.22	83.89	33.29
Labor (hours/acre)	68.62***	29.70	51.09	16.42
Irrigation (hours/acre)	25.71***	9.22	19.30	6.51
Seed (kg/acre)	7.75	2.75	7.73	2.38
Crop duration (days)	234.56***	35.58	218.11	25.95
Soil quality (low = 1 to high = 4)	3.38	0.86	3.26	0.97

Notes: ***, **, * indicate that mean values are significantly different at the 1%, 5% and 10% level, respectively.

types of pesticides, we used the pesticide hazard categories of the World Health Organization (WHO, 2010). Figure A1, in the online appendix available at http://journals.cambridge.org/EDE, shows that the biggest differences between Bt and non-Bt plots are observed for pesticides of high and moderate toxicity. Pesticides in these categories are often responsible for significant health and environmental problems, especially in developing countries where agro-chemicals are not always handled with sufficient care (Jeyaratnam, 1990; Krishna and Qaim, 2008; Asfaw *et al.*, 2010). Hence, pesticide reductions through Bt can cause significant health and environmental benefits.

3. Methodology

3.1. Controlling for selection bias

Many earlier studies on Bt cotton were criticized for providing biased impact estimates, because heterogeneity between Bt adopters and non-adopters was not properly accounted for. Such heterogeneity may stem from observable factors, such as farmers' education, access to extension, and soil quality, or from unobservable factors, such as farmers' ability and motivation. There are different ways to avoid or reduce selection bias. One option is to use an experimental approach and randomly assign the treatment. This was not possible in our case, because farmers had self-selected into the group of Bt adopters. Another option is to use difference-in-difference or fixed-effects estimators, as was recently done for Bt cotton in India (Crost *et al.*, 2007; Kathage and Qaim, 2012; Krishna and Qaim, 2012; Qaim and Kouser, 2013). The advantage of such estimators is that time-invariant heterogeneity cancels out. The drawback is that panel data are required. When only cross-section data are available, as is true for our case in Pakistan, either propensity score matching or instrumental variable (IV) techniques can be used (Rosenbaum and Rubin, 1983; Smith and Todd, 2001; Deaton, 2010). While propensity score matching only controls for observed heterogeneity, IV approaches can also control for unobserved heterogeneity, when suitable instruments are available (Heckman and Vytlacil, 2005; Greene, 2008).

In this study, we use an IV approach to estimate the impact of Bt on cotton productivity. The model consists of two stages, the selection and the outcome equation. The selection equation is a binary choice model, where farmers choose whether or not to adopt Bt based on farm, household and contextual characteristics:

$$Bt = \alpha C + \mu \tag{1}$$

where Bt is a dummy variable for Bt cotton adoption, C is a vector of covariates, α is a vector of parameters to be estimated, and μ is an error term with mean zero and variance σ_{μ}^{2}. The outcome equation is a cotton production function:

$$Y = \theta Bt + \beta L + \varepsilon \tag{2}$$

where Y is cotton yield, L is a vector of inputs and other control variables and ε is a random error term. For proper model identification, C contains the same variables as L plus at least one instrument that is correlated with Bt adoption but uncorrelated with yield. We discuss the concrete instruments used further below. The IV estimator (treatment effect model), which uses predicted values for Bt in the outcome equation, controls for observed and unobserved heterogeneity between adopters and non-adopters. Therefore, θ is an unbiased estimate of the impact of Bt on cotton yield.

3.2. Damage control specification

Unlike normal inputs in a production function – like fertilizer, labor or irrigation, which directly contribute to increasing yield – chemical pesticides and Bt do not increase yield but help control possible crop damage due to pests. Lichtenberg and Zilberman (1986) were the first to point out that a damage control function should be used for estimating the productivity of pest control agents, rather than directly including them in the production function. A damage control framework was used in several studies for estimating Bt productivity effects (Huang *et al.*, 2002; Qaim and Zilberman, 2003; Qaim and de Janvry, 2005; Shankar and Thirtle, 2005; Shankar *et al.*, 2008). The general form of the damage control framework is:

$$Y = F(X)G(Z) \tag{3}$$

where X is a vector of normal yield-increasing inputs, and Z is a vector of damage control agents like chemical pesticides and Bt. $G(Z)$ is the damage control function, which is linked to the production function $F(X)$ in a multiplicative fashion. $F(X)$ is concave in X, and $G(Z)$ is defined in the [0, 1] interval and increasing in Z. When Z increases, $G(Z)$ approaches 1, meaning that crop damage is effectively controlled. On the other hand, when Z

decreases, approaches 0, meaning that significant crop damage due to pests occurs; in the extreme case there is complete crop damage.

For $F(X)$, we employ a quadratic functional form, which is popular in micro-level production function research. For comparison, we will show that alternative functional forms lead to similar results. For $G(Z)$, different functional forms were suggested and used in the literature, such as logistic, Weibull or exponential specifications (Lichtenberg and Zilberman, 1986; Qaim and de Janvry, 2005; Shankar *et al.*, 2008). All of these lead to comparable results in our case, as we demonstrate further below. For the main analysis, we employ the exponential specification. Thus,

$$G(Z) = 1 - e^{-\gamma_1 Q - \gamma_2 Bt} \tag{4}$$

where Q represents pesticide quantity (measured in liters/acre), Bt is the instrumented adoption dummy, and γ_1 and γ_2 are the respective parameters to be estimated. Using subscripts, the full production function and damage control model is

$$Y_i = \left[\beta_0 + \sum_j \beta_j X_{ji} + \sum_j \sum_k \beta_{jk} X_{ji} X_{ki} + \sum_l \beta_l H_{li} + \sum_m \beta_m D_{mi}\right] \times [1 - e^{-\gamma_1 Q_i - \gamma_2 Bt_i}] + \varepsilon_i \tag{5}$$

where Y_i is cotton yield (in kg/acre) on a given plot i. X_j is a vector of j different normal production inputs, including fertilizer (in kg/acre), labor (in hours/acre) and irrigation (in hours/acre). The term with the double summation sign describes the input interaction terms for all $j \neq k$, and square terms for all $j = k$. H_l includes l different human capital variables referring to the farmer who is cultivating plot i, such as age and education (in years of schooling), while D_m is a vector of dummies for m districts to control for variation in regional conditions.

Equation (5) is estimated with a non-linear least squares estimator. To control for selection bias, we employ a two-stage estimation technique, using predictions of the Bt treatment variable from the first-stage selection equation, as explained above. However, while this two-stage estimator is consistent in linear models, this is not always the case in non-linear models (Amemiya, 1974). Terza *et al.* (2008) showed that two-stage residual inclusion estimation is a consistent alternative for some non-linear specifications, such as limited dependent variable or count data models. This procedure is less straightforward in our case, because equation (5) has both linear and non-linear components, which are combined in a multiplicative way. We therefore use the conventional two-stage approach for estimation, which was also done in previous damage control studies (Huang *et al.*, 2002; Qaim and Zilberman, 2003; Qaim and de Janvry, 2005). When interpreting the results, it should be kept in mind that some inconsistency may be possible. We will return to this issue further below.

3.3. *Optimal level of pesticide use*

Based on the estimates of the production function and damage control model, we can calculate the optimal level of pesticide use at sample mean

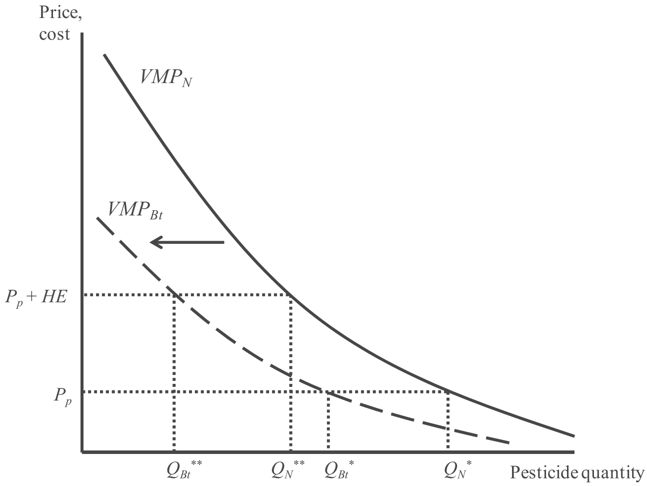

Figure 1. *Private and social optimal pesticide use with and without Bt cotton*

values. From production theory we know that the optimal level is where the value marginal product (*VMP*) of pesticide use is equal to pesticide price (P_p). *VMP* is calculated as the physical marginal product (*PMP*) multiplied by cotton output price (P_c). *PMP* is derived by taking the partial derivative of equation (5) with respect to pesticide. Hence, *VMP* is calculated as:

$$VMP = P_c * PMP = P_c * F(X)\gamma_1 e^{-\gamma_1 Q - \gamma_2 Bt} \tag{6}$$

PMP is estimated separately for Bt and non-Bt cotton by using mean values of all explanatory variables in both subsamples. Equating *VMP* for each technology with pesticide price results in the optimal level of pesticide use:

$$Q^* = \frac{ln(F(X)\gamma_1) - ln\left(\frac{P_p}{P_c}\right) - \gamma_2\, Bt}{\gamma_1}. \tag{7}$$

When Bt controls pest damage effectively, the last term to be subtracted in the numerator ($\gamma_2 Bt$) is positive. Hence, the optimal level of pesticide use with Bt will be smaller than without Bt. This is shown in figure 1. The continuous line represents *VMP* for non-Bt cotton (VMP_N). Bt adoption reduces pesticide productivity at any given Q, which causes a leftward shift in the curve from VMP_N to VMP_{Bt}. Optimal levels of pesticide use with and without Bt are Q^*_{Bt} and Q^*_N, respectively.

Up till now, we have only considered pesticide price as the cost of pesticide use, which is the private perspective of farmers. Therefore, Q^*_{Bt} and Q^*_N can be termed private optimal levels of pesticide use with and without Bt. Yet, as is well known, the social cost of chemical pesticide use is higher, because pesticide active ingredients cause negative health and environmental externalities (Pingali, 2001; Arias-Estévez *et al.*, 2008).

Pimentel (2005) estimated that the external costs of pesticide use are US$9 billion per year in the United States alone, including human health impacts, groundwater contamination and other environmental losses. For developing countries, such costs have not been quantified comprehensively. They may be much higher, because pesticide regulations are laxer. Moreover, in developing countries chemical pesticides are often applied manually without protective clothing, so that farmers are exposed to significant toxic loads during spraying operations. Accordingly, incidents of acute pesticide poisoning are commonplace in developing countries (Jeyaratnam, 1990; Krishna and Qaim, 2008).

Figure 1 includes negative externalities of pesticide use. From a social perspective, the optimal level of pesticide use is where *VMP* equals pesticide price (P_p) plus health and environmental costs (*HE*). For simplicity, we assume that *HE* is constant for each liter of pesticide applied. Hence, socially optimal levels of pesticide use are Q^{**}_{Bt} and Q^{**}_{N} for Bt and non-Bt cotton, respectively. Unsurprisingly, these social optima are lower than the private ones, and the Bt optimum is lower than the non-Bt one. Using the damage control estimates and inserting mean values for the Bt and non-Bt subsamples, the socially optimal levels can be calculated as:

$$Q^{**} = \frac{ln(F(X)\gamma_1) - ln\left(\frac{P_p + HE}{P_c}\right) - \gamma_2 Bt}{\gamma_1}. \tag{8}$$

This analysis shows that – in addition to private financial gains – Bt adoption can cause health and environmental benefits by reducing negative pesticide externalities. This is backed up by empirical evidence. Studies show that Bt cotton has substantially reduced pesticide poisoning symptoms among smallholder farmers in China, India and South Africa (Bennett *et al.*, 2003; Huang *et al.*, 2003; Hossain *et al.*, 2004; Kouser and Qaim, 2011). There is also research showing the positive environmental effects of Bt crops, including enhanced biocontrol services through higher diversity of beneficial insects, and better soil and groundwater quality through lower pesticide contamination (Shelton *et al.*, 2002; Knox *et al.*, 2006; Morse *et al.*, 2006; Wolfenbarger *et al.*, 2008; Lu *et al.*, 2012).

Kouser and Qaim (2013) tried to quantify and monetize the positive health and environmental impacts of Bt cotton adoption in Pakistan. They carried out a choice experiment with the same sample of farmers as is used in this study. Based on the choice experimental data, Kouser and Qaim (2013) estimated farmers' willingness to pay (WTP) for a reduction in negative pesticide impacts on health, farmland biodiversity, and soil and groundwater contamination. Thus, they calculated health and environmental costs per unit of pesticide use. Multiplying this cost per unit of pesticide by the Bt-induced reduction in pesticide quantity results in a value that can be interpreted as the reduction in pesticide externalities through Bt adoption, or the health and environmental benefit caused by Bt technology. Kouser and Qaim (2013) did not calculate privately or socially optimal levels of pesticide use.

We take the per-unit cost estimates by Kouser and Qaim (2013) as the health and environmental costs of pesticide use, which we termed *HE* in the analysis above. One disadvantage is that Kouser and Qaim (2013) carried out their WTP analysis only with farmers. As the non-farm community may also have a WTP for lower pesticide contamination, they probably underestimate the full magnitude of negative pesticide externalities. This would also affect our results: underestimated negative externalities would result in an overstated social optimum of pesticide use. On the other hand, stated preference data from a choice experiment may suffer from hypothetical bias (e.g., Florax *et al.*, 2005; Travisi and Nijkamp, 2008; Kouser and Qaim, 2013), which could lead to overestimated externalities with the opposite effect on the social optimum. Such uncertainty is normal when dealing with monetary values of health and environmental effects, but should be kept in mind when interpreting the concrete numerical results.

4. Estimation results

4.1. Bt cotton adoption

Before focusing on the production and damage control functions we estimate a Bt cotton adoption model, as shown in equation (1) above. Building on the innovation adoption literature (Feder *et al.*, 1985; Abdulai and Huffman, 2005; Kabunga *et al.*, 2012), we first specify a model that only considers typical adoption determinants, without including other exogenous variables required for the IV approach. Estimation results for this adoption model are shown in column (1) of table 3. The estimates are based on a probit model and expressed in terms of marginal effects at sample mean values. Farmers' age and education have no influence on Bt cotton adoption. But the duration of awareness exposure has a positive and significant effect. Each additional year of exposure increases the probability of adoption by four percentage points. Sources of information also seem to matter. If fellow farmers were named as the primary source of agricultural information, the likelihood of Bt cotton adoption is 12.7 percentage points higher than when other sources – such as extension officers – were mentioned. This makes sense, as illegal Bt cotton varieties had already been traded informally before official Bt varieties were approved in 2010. Bandiera and Rasul (2006) and Matuschke and Qaim (2009) also pointed out that informal social networks can play an important role in innovation adoption. Other important determinants of Bt adoption are tractor ownership (as a proxy for productive assets) and access to credit. A credit constraint decreases the probability of adoption by 21.2 per cent.

This adoption model also helps to identify possible instruments for Bt that can be used in the two-stage IV regressions to control for selection bias. We use Bt awareness exposure and credit constraint as instruments. Both are significantly correlated with Bt adoption, as was shown in table 3. At the same time, we tested that these two variables are not directly correlated with yield. In theory, one may suppose that awareness exposure and credit constraint could be correlated with individual characteristics that might also affect cotton productivity. For instance, farmers who have known about Bt for longer may also be more informed about other innovations. Similarly, access to financial markets may be correlated with access to

Table 3. *Determinants of Bt cotton adoption*

	(1) Adoption model		(2) First stage of IV model	
Variables	*Marginal effects*	*Standard errors*	*Marginal effects*	*Standard errors*
Age (years)	0.002	0.002	0.003	0.002
Education (years)	0.001	0.006	0.014**	0.007
Bt awareness exposure (years)	0.041***	0.013	0.056***	0.015
Info source fellow farmer (dummy)	0.127**	0.053	–	–
Tractor ownership (dummy)	0.100*	0.055	–	–
Farm size (acres)	−0.0003	0.001	–	–
Credit constrained (dummy)	−0.212***	0.051	−0.165***	0.058
Distance to market (km)	−0.002	0.003	–	–
Household size (number)	−0.003	0.013	–	–
Off-farm employment (dummy)	−0.144***	0.050	–	–
Pesticide (liters/acre)	–	–	−0.262***	0.028
Fertilizer (kg/acre)	–	–	0.014***	0.004
Square of fertilizer	–	–	−0.00002	0.00001
Labor (hours/acre)	–	–	0.020***	0.005
Square of labor	–	–	−0.0001	0.0001
Irrigation (hours/acre)	–	–	0.064***	0.017
Square of irrigation	–	–	−0.001*	0.0003
Fertilizer–labor interaction	–	–	−0.00002	0.00004
Fertilizer–irrigation interaction	–	–	−0.0002	0.0001
Labor–irrigation interaction	–	–	0.0001	0.0003
Seed rate (kg/acre)	–	–	−0.003	0.013
Crop length (days)	–	–	0.003***	0.001
Soil quality(low = 1 to high = 4)	0.024	0.026	−0.013	0.030
Vehari district	0.043	0.068	−0.131	0.080
Bahawalpur district	−0.002	0.067	0.063	0.083
Rahim Yar Khan district	0.097	0.069	0.087	0.082
Model statistics				
Observations	525		525	
Wald χ^2	88.91***		190.42***	

Notes: Standard errors are robust.
***, **, * indicate that estimates are statistically significant at the 1%, 5% and 10% level, respectively.

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agricultural inputs. However, such correlation is only problematic when unobserved variables are important. In our outcome equations, we control for all relevant inputs, and we also include farmer education and age as human capital variables and as proxies for entrepreneurial skills. Hence, we argue that our two instruments are valid, although we recognize that a small degree of uncertainty remains. Finding exogenous instruments for Bt adoption, which are completely unrelated to yield from a theory perspective, is very difficult with observational data. Results from the first-stage selection equation are shown in column (2) of table 3. Next to the two instruments, all exogenous variables from the production function are now included as covariates.

4.2. Production function and damage control estimates

We now turn to the production function, which is estimated as the second-stage outcome equation in the IV model (treatment effect model). First, we specify a normal production function, where pest control agents are included just like normal yield-increasing inputs (equation (2)). As was mentioned above, we use a quadratic specification. Table A1 in the online appendix demonstrates that the signs and significant levels of the main variables of interest are also the same with other functional forms, such as the Cobb–Douglas and Translog. Estimation results with the quadratic specification are presented in column (1) of table 4. The significance of the ath (ρ) parameter, which is based on a likelihood-ratio test and shown at the bottom of the table, indicates that the null hypothesis of zero correlation between the error terms of the selection and outcome equations has to be rejected. Hence, the IV approach – as used here – is preferred over the ordinary least squares estimator.

The estimation results in column (1) of table 4 suggest that Bt increases cotton yield by 187 kg per acre. Compared to mean cotton yields on non-Bt plots, this is equivalent to a yield gain of 25 per cent. Pesticide use also affects cotton yield positively. One additional liter increases yield by 75 kg per acre. These results underline the severity of insect pest damage in Pakistani cotton production. Other significant factors for cotton yield are fertilizer use and irrigation, while the labor effect is positive but insignificant. Crop length has a positive impact on yield. This is expected, because keeping the crop longer on the field usually means one additional round of manual picking. Education has a small but significantly negative effect on yield. As education often improves access to higher-paying off-farm activities, better educated farmers may spend less management time on cotton farming.

In column (2) of table 4 we use the damage control specification, as discussed in equations (3)–(5) above. The coefficients of the normal inputs and other farm and household characteristics are similar to those in the standard production function (compare with column (1)). Some of them are slightly larger, which is to be expected. In column (1) the effect is interpreted as the contribution to actual output, while in column (2) the influence on potential output is measured. The damage control estimates are shown in the lower part of column (2). The coefficients demonstrate that

Table 4. *Production function and damage control estimates*

	(1) Standard production function		(2) Damage control specification	
Variables	*Coefficients*	*Standard errors*	*Coefficients*	*Standard errors*
Bt adoption (dummy, IV)	187.214***	50.620	–	–
Pesticide (liters/acre)	75.370***	9.246	–	–
Fertilizer (kg/acre)	2.498**	1.041	3.758***	1.112
Square of fertilizer	−0.001	0.003	−0.003	0.003
Labor (hours/acre)	1.090	1.460	3.348**	1.424
Square of labor	−0.006	0.011	−0.014	0.012
Irrigation (hours/acre)	9.917**	4.853	13.992***	4.334
Square of irrigation	−0.066	0.103	−0.085	0.072
Fertilizer–labor interaction	0.004	0.008	0.001	0.011
Fertilizer–irrigation interaction	−0.050	0.034	−0.064*	0.034
Labor–irrigation interaction	0.086	0.063	0.096	0.064
Seed rate (kg/acre)	−3.613	3.194	−5.929	3.672
Crop length (days)	0.930***	0.261	1.170***	0.277
Soil quality (low = 1 to high = 4)	−6.539	7.194	−6.165	8.708
Age (years)	−0.631	0.512	−0.574	0.660
Education (years)	−3.965**	1.689	−3.295*	1.946
Vehari district	7.728	21.791	18.116	24.770
Bahawalpur district	57.788***	19.127	80.198***	23.136
Rahim Yar Khan district	3.845	19.638	29.892	23.668
Constant	−66.004	111.101	67.071	128.577
Damage control function				
Pesticide (liters/acre)	–	–	0.619***	0.063
Bt adoption (dummy, IV)	–	–	0.693***	0.094
Model statistics				
Observations	525		525	
R-squared	0.70		0.97	
ath(ρ)	−0.240**		–	

Notes: Standard errors are robust.
***, **, * indicate that estimates are statistically significant at the 1%, 5% and 10% level, respectively.

both pesticides and Bt contribute significantly to controlling crop damage due to insect pests.

Some robustness checks for these damage control estimates are provided in table A2 in the online appendix. Above we discussed the fact that the two instruments that we used for Bt adoption may not be perfect. In column (1) of table A2 we show the results without the IV approach; that is, we use observed instead of predicted values for Bt adoption. Both the pesticide

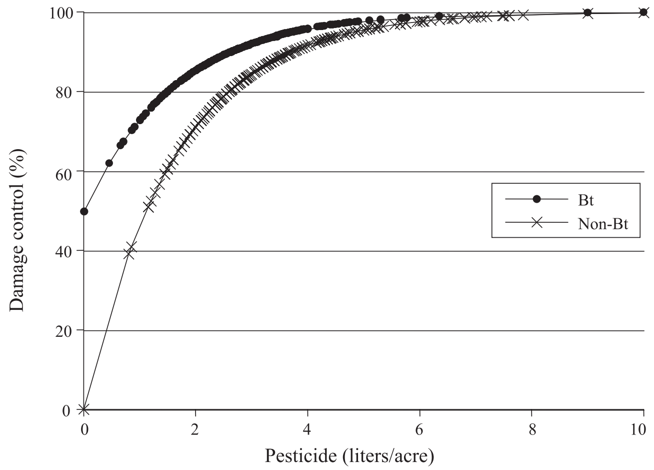

Figure 2. *Predicted damage control function with and without Bt cotton*

and Bt coefficients are also positive and significant. The Bt coefficient is slightly larger than the one shown in table 4, which we would expect when there is positive selection bias. While this is not a proof of instrument validity, the comparison adds further confidence in the estimation results. Furthermore, the similarity between the IV and single-equation estimates suggests that the two-stage estimation procedure probably does not introduce a significant bias in this non-linear context, which was another concern discussed above. Finally, we tested whether the results are potentially driven by the exponential specification of the damage control function. We ran the same model also with logistic and Weibull specifications, results of which are shown in columns (2) and (3) of online appendix table A2. As one would expect, the coefficient magnitudes vary, but the signs and significant levels are consistent across functional forms for both pesticide and Bt adoption.

4.3. Crop damage with and without Bt

We use the damage control estimates from table 4 to predict crop damage with and without Bt at different levels of pesticide use. The results are shown in figure 2. In non-Bt cotton, we predict zero damage control when no pesticides are used. This result occurs by definition in the exponential damage control specification; it is of little practical relevance, as there are hardly any non-Bt cotton growers who use zero chemical pesticides. In Bt cotton, damage control without chemical pesticides would be around 50 per cent. Most of the remaining damage is probably due to sucking pests, which are not controlled by Bt. At mean values of pesticide use, damage control in Bt cotton is around 89 per cent, which is significantly higher than in non-Bt cotton. More effective damage control with Bt is also the reason for the positive yield effects of this technology. According to this specification, the Bt impact on effective yield is around 22 per cent.

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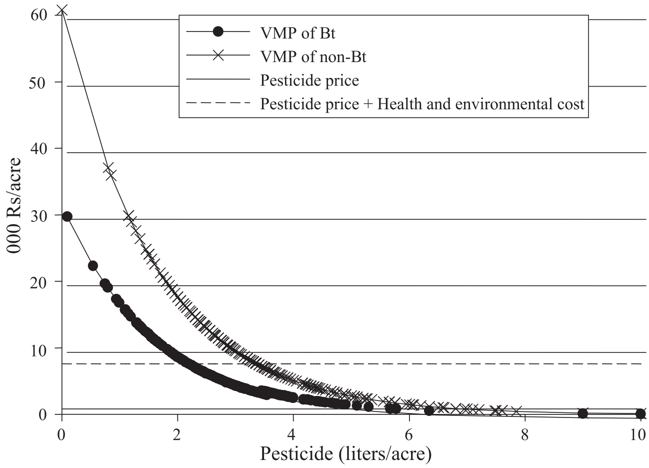

Figure 3. *Predicted value marginal product (VMP) curves and optimal levels of pesticide use with and without Bt cotton*

These results support the hypothesis by Qaim and Zilberman (2003) that Bt yield effects are higher in situations where crop damage is not effectively controlled through chemical pesticides. Similar effects were also observed in Argentina, India and South Africa (Thirtle *et al.*, 2003; Qaim and de Janvry, 2005; Shankar *et al.*, 2008; Kathage and Qaim, 2012). In the United States, Australia, and partly also in China, Bt yield effects are lower due to more effective chemical pest control in conventional cotton (Qaim, 2009).

4.4. Optimal levels of pesticide use

We use equation (6) and the damage control estimates to calculate *VMP* curves for pesticide use in Bt and non-Bt cotton. These curves are displayed in figure 3. As expected, *VMP* decreases with increasing pesticide use, and for any given level of pesticide, *VMP* is lower in Bt than non-Bt cotton. This is why farmers have an incentive to use lower pesticide quantity with Bt technology. Figure 3 also shows a horizontal line for mean pesticide price, which is around 1,000 Pakistani Rupees (Rs) per liter. Equation (7) was used to calculate private optimal pesticide use, which is 5.8 and 6.7 liters per acre for Bt and conventional cotton, respectively. The difference of about one liter is equivalent to a reduction of 14 per cent through Bt adoption. This relatively small difference is due to the fact that the pesticide price line crosses both *VMP* curves in their very flat part.

The private optima are much higher than actual levels of pesticide use among sample farmers. According to this calculation, average Bt adopters and non-adopters underuse chemical pesticides by 53 per cent and 48 per cent, respectively. Hence, farmers could increase their profits by applying more pesticides. In principle, pesticide underuse may be due to three reasons. First, farmers may not be sufficiently aware of pest damage and chemical pest control options. This is not untypical in developing countries,

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Table 5. *Estimated health and environmental costs of pesticide use*

Type of effect	*Monetary value (Rs/ml)*
Health effects	1.96***
	(0.13)
Farmland biodiversity effects	1.80***
	(0.004)
Soil and groundwater effects	3.04***
	(0.12)

Notes: Standard errors are given in parentheses.
*** indicates statistical significance at the 1% level.
Source: Kouser and Qaim (2013).

especially when agricultural training and extension systems are weak. Second, cash and credit constraints may restrict farmers' timely access to chemical pesticides. Third, farmers may deliberately use lower levels of pesticides, because they also consider health and environmental costs. Which of these reasons dominates cannot be established based on the data available.

We now look at health and environmental costs more specifically to calculate the social optimum of pesticide use. As explained, we use monetary values of the negative impacts per unit of pesticide on farmers' health, farmland biodiversity, and soil and groundwater, as derived by Kouser and Qaim (2013). These values are shown in table 5. Summing up, chemical pesticides cause health and environmental costs worth 6.8 Rs per ml, or 6,800 Rs per liter. This is much larger than the mean pesticide price of around 1,000 Rs per liter, pointing to large negative externalities.

We use these values for health and environmental costs in connection with equation (8) to calculate socially optimal levels of pesticide use. The social optimum is at 2.2 and 3.0 liters per acre for Bt and non-Bt plots, respectively. The significant difference between the two technology alternatives is due to the greater distance between the *VMP* curves for Bt and non-Bt cotton at this higher cost level (see figure 3). Comparing with actual mean values of pesticide use, both Bt and non-Bt farmers overuse chemical pesticides from a social perspective.

5. Conclusions

While there is a growing body of literature on the impacts of GM crops, there are still open questions about how these crops can contribute to sustainable agricultural development. We have analyzed the impacts of insect-resistant Bt cotton on yields and pesticide use in Pakistan, employing a damage control framework and instrumental variables to control for selection bias.

The estimates demonstrate that conventional cotton growers in Pakistan suffer from significant crop damage due to insect pests. This damage is not effectively controlled by chemical pesticides. Hence, yield levels obtained in non-Bt cotton are relatively low. More effective damage control would not only add to farmers' profits, but would also contribute to higher productivity and agricultural growth. Given that land and water resources are becoming increasingly scarce, productivity growth should be a central component of any development strategy. Encouraging farmers to use more pesticides would be one option, but this would also cause additional negative health and environmental externalities. Our estimates suggest that increasing pesticide use is not desirable, when negative externalities are taken into account. In other words, while Pakistani cotton farmers underuse pesticides from a private profit-maximizing perspective, the picture is reversed when the full social cost of pesticide use is considered. In this situation, Bt technology can be a much more sustainable alternative. Our results show that Bt adoption reduces insect crop damage significantly and thus contributes to higher yields. Net Bt yield gains are above 20 per cent. At the same time, Bt adoption reduces chemical pesticide use and associated negative externalities.

Finding perfect instruments was difficult with the observational data used in this study. Furthermore, the two-stage estimation procedure that we used may not be fully consistent in the non-linear damage control context. While robustness checks were carried out, these limitations should be kept in mind when interpreting the exact numerical results.

Large insect pest damage is a typical phenomenon in developing countries, especially in the tropical small farm sector, where pest damage is severe and technical, financial, human capital and institutional constraints are widespread. In such situations, Bt crops can contribute to sustainable productivity growth. Obviously, the effectiveness of pest control could also be increased by means other than Bt or chemical pesticides, for instance through integrated pest management (IPM). However, IPM is relatively labor intensive and requires substantial site-specific knowledge, which is also why widespread adoption in developing countries has not yet occurred. Bt can complement and facilitate IPM strategies. GM technologies should not be seen as a substitute for better agronomy or other natural resource management technologies. Sustainable development requires a smart combination of innovations from all areas of agricultural research.

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