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Bt cotton and employment effects for female agricultural laborers in Pakistan

By

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Research highlights

- Employment effects of Bt cotton adoption are analyzed in Pakistan
- Farm survey data and a double-hurdle model with instruments are used
- Bt adoption has increased the demand for hired labor by 55 percent
- Most of this increase is due to higher yields to be harvested
- Gains in employment income are particularly large for female laborers

Abstract

The literature about economic and social impacts of Bt cotton adoption on farm households in developing countries is growing. Yet, there is still uncertainty about wider implications of this technology for rural development, including effects for landless rural laborers. Bt-related yield advantages may lead to intensified production and higher demand for labor. Building on farm survey data collected in Pakistan and using double-hurdle regression models, we analyze employment effects of Bt cotton adoption. Model estimates show that Bt adoption has increased the demand for hired labor by 55 percent. Manual harvesting, which is common in Pakistan, is a labor-intensive activity primarily carried out by female laborers. Accordingly, gender disaggregation shows that the employment-generating effects are particularly strong for women, who often belong to the most disadvantaged groups of rural societies. These results suggest that Bt technology can contribute to additional employment income for the poor and more equitable rural development.

Key words: *Bt cotton, employment, gender effects, double-hurdle model, Pakistan*

JEL codes: J43, O33, Q11, Q16

1. Introduction

Productivity and profit enhancing agricultural technologies are considered essential tools for poverty alleviation and rural development in developing countries [1]. Recent advancements in modern biotechnology and genetic engineering are quickly gaining in importance. However, in spite of the rapid adoption of genetically modified (GM) crops in some parts of the world, this technology remains contentious. Especially when it comes to the use of GM crops in the small farm sector there are concerns about possible negative social consequences [2-6]. Bt cotton is one example of a GM crop that is widely used in the small farm sector. Bt cotton contains Cry genes isolated from the soil bacterium *Bacillus thuringiensis* (Bt). These Cry genes induce the plant to produce substances that are toxic to insect pests of the lepidopteran order, especially cotton bollworms. Bollworms infest 88 percent of the global cotton area and are accountable for large crop damage and intensive chemical pesticide applications [7]. The company Monsanto instigated the commercialization of Bt cotton in the USA in the mid-1990s. In 2014, GM cotton was already planted on 62 million acres worldwide, including in Asia, Africa, and the Americas [8]. In Pakistan, Bt cotton was officially approved for the first time in 2010 [9]. However, unofficial cultivation of Bt varieties had already commenced in 2002, through leakages from research stations as well as smuggling in of seeds from neighboring India and China [10, 11]. With 7.1 million acres of Bt cotton in 2014 (88 percent of the total national cotton area), Pakistan is now the country with the fourth largest GM cotton area in the world [8].

A growing body of literature referring to different countries demonstrates that the adoption of Bt cotton has reduced bollworm damage and pesticide sprays while significantly increasing crop yields and farmer profits [9, 12, 13, 14, 15]. Wider effects of this technology for rural development were rarely analyzed. Many of the rural poor in developing countries, including landless families, depend on the labor market for their livelihood [16, 17]. Hence, knowledge about the employment effects of new technologies is important from a poverty and development perspective. Recent studies have analyzed rural labor market impacts of different institutional innovations [18-22], but the employment effects of GM technology adoption in the small farm sector are not yet sufficiently understood.

A few studies have compared labor costs between farms with and without Bt cotton adoption using descriptive statistics [23, 24]. However, simple comparisons may be misleading, as they cannot control for possible confounding factors. Farmers who adopted Bt varieties might have

different labor costs even without this technology, so observed differences cannot be simply attributed to Bt adoption alone. We are aware of only one study that has analyzed employment effects of Bt cotton more thoroughly using data from rural India and a simulation model [25]. Simulation models are useful to assess possible impacts at early stages of technology adoption, but they build on several restrictive assumptions. Here, we contribute to this body of literature by analyzing employment effects of Bt cotton adoption in Pakistan with regression models. Regression results are more reliable than simulations because they build on fewer assumptions.

In most developing countries, cotton farming is not mechanized but performed by manual labor. This is also true in Pakistan. On the one hand, the adoption of Bt technology may reduce the demand for agricultural labor employed for spraying chemical pesticides. On the other hand, more labor may possibly be employed for harvesting and other operations related to higher cotton yields. Which of these and possible other effects dominates is an empirical question that we address in this article. Previous research has shown that Bt cotton adoption has reduced pesticide use and increased yields in Pakistan [9, 11, 14, 15, 23], although resulting employment effects have not been analyzed up till now. We look at labor use in the aggregate and additionally also disaggregated by the gender of the laborers; male and female workers are often involved in different farming operations. While pest control is often a male activity, harvesting is usually performed by women. In Pakistan and many other developing countries, rural women belong to the most vulnerable groups of society. Labor market participation can improve women's economic status, which is an important factor for family well-being [26, 27].

We use data from a survey of cotton-producing households in Pakistan to estimate the impact of Bt technology adoption on the demand for total hired labor, as well as separately for male and female hired labor. Farmers' labor market decisions are modeled as a two-tier process. In the first tier, farmers decide whether or not to hire external labor at all. In the second tier, they decide how much labor to hire conditional on the first-tier decision being positive. We employ a double-hurdle model. Similar modeling approaches were used before to analyze labor market decisions in other contexts [22].

The rest of this article is structured as follows. The next section describes the survey data and provides sample descriptive statistics. Subsequently, the regression methods are introduced in more detail, before the estimation results are presented and discussed. The final section concludes.

2. Data and Descriptive Statistics

A survey of 352 randomly selected cotton farmers was conducted in 2011, using a pretested questionnaire in four main cotton districts of Punjab Province, Pakistan [9]. The sample comprises 248 Bt adopters and 104 non-adopters. The sample adoption rate is very close to the actual national adoption rate as observed in Pakistan in 2011. Descriptive statistics of sample farmers are reported in Table 1. While there are no significant differences in the mean age between Bt adopters and non-adopters, adopters are better educated. Bt adopters also own more land, even though the area cultivated with cotton does not differ significantly. Bt adopters are less likely to be credit constrained, meaning that they find it easier to obtain credit for agricultural production purposes from formal sources. Even though Bt seeds are relatively cheap in Pakistan and usually not purchased on credit, limited access to financial resources is often associated with higher risk aversion, which can negatively affect technology adoption [28, 29]. Furthermore, information constraints may play a role. Comparison of Bt awareness exposure, which measures the number of years that farmers have known Bt technology, reveals that Bt adopters have an information advantage. All farms in the sample – including Bt adopters and non-adopters – cultivate cotton under irrigated conditions.

Table 1 is here.

Table 2 compares hired labor use across different production activities between Bt and non-Bt plots. The number of cotton plots is larger than the number of farmers surveyed, because many of the Bt farmers were partial adopters in 2011. Partial adoption means that these farmers had both Bt and non-Bt cotton plots. In these cases, we collected input-output details for all of their plots. Hired labor use is measured in days per acre for one cotton season (approximately 6 months). For both technologies, much more female than male hired labor is used in cotton production. But we observe significant differences between the two technologies: total labor use is higher in Bt than in non-Bt cotton. The difference is particularly large for females: on average, female labor use per acre of cotton is eight labor days higher on Bt than on non-Bt plots. Higher female labor demand in Bt cotton is consistent with earlier studies [5, 23, 24] and supports the hypothesis that employment effects may differ by gender. Bt farmers use more female labor for labor-intensive operations such as sowing, weeding, and picking (harvesting). Picking alone is responsible for the largest absolute increase in labor demand, and this activity is predominantly performed by women.

The use of male hired labor is also higher in Bt than in non-Bt cotton. Bt-adopting farmers employ more male labor for operations such as gap filling, thinning, irrigating, and applying fertilizers and herbicides. These activities are not directly related to the effects of Bt technology, but it is not uncommon to observe that technology adoption is associated with higher crop management intensity. In relative terms, the difference between Bt and non-Bt plots is even higher for male than for female laborers. Nevertheless, in absolute terms the effect is much higher for females. The positive effect for female laborers is also more remarkable from a social perspective, because females have fewer alternative employment opportunities than males in rural Pakistan, which is also true in many other developing countries.

Table 2 is here.

Table 3 compares input-output prices and characteristics of Bt and non-Bt plots. Bt cotton fetches slightly higher prices than non-Bt cotton. Differences in wages paid are relatively small. For fertilizers and insecticides we use weighted average prices to account for quality differences of various products [30]. The comparisons show that Bt farmers pay somewhat lower prices for fertilizers and higher prices for insecticides. We also observe some differences in terms of irrigation, crop duration, and market distance. These numbers suggest that Bt adopters are different and have different conditions than non-adopters, so that simple comparisons of labor use may be misleading. To reduce possible bias from confounding factors, we use regression models and include relevant factors as control variables.

Table 3 is here.

3. Empirical Model

3.1. Modeling Bt Impact on Labor Demand

As mentioned, we model farmers' demand for hired labor as a two-tier decision. In the first tier, farmers decide whether or not to hire any labor. Conditional on that decision being positive, they decide about the number of labor days to hire in the second tier. In both decisions, we hypothesize that Bt adoption may have a significant effect because of the changes in pest control and yield levels that this technology causes.

The first tier is a binary decision, which is expressed as:

$$dh_i^* = \gamma x_i + \mu_i: \qquad \mu_i \sim N(0,1) \qquad \text{and} \qquad dh_i = \begin{cases} 1 \; if \; dh_i^* > 0 \\ 0 \; otherwise \end{cases} \tag{1}$$

where dh_i^* is a latent variable for dh_i which is equal to one if the farmer hires any labor on his/her cotton plot i, and zero otherwise. The second tier can be expressed as:

$$Qh_i^* = \beta z_i + \nu_i: \qquad \nu_i \sim N(0,\ \sigma^2) \qquad \text{and} \qquad Qh_i = \begin{cases} Qh_i^* \ if\ Qh_i^* > 0\ and\ dh_i = 1 \\ 0\ otherwise \end{cases} \tag{2}$$

where Qh_i^* is a latent variable for Qh_i which represents the number of labor days hired in by the farmer on plot i. In the above equations, x and z are vectors of covariates that may overlap or also differ. γ and β are vectors of parameters to be estimated, while μ_i and ν_i are random error terms.

Bt adoption is included in x and z as a binary treatment variable that takes a value of one when the plot is cultivated with Bt cotton, and zero otherwise. Positive and significant coefficients for Bt adoption would indicate higher labor demand on Bt cotton plots and thus positive employment effects of the technology. Negative coefficients would imply the opposite.

It should be mentioned that the Bt adoption variable may be endogenous because farmers decide themselves whether or not to use this technology. The discussion in the previous section pointed at differences between Bt and non-Bt adopters in terms of various observed characteristics. Such observed characteristics can be included as control variables. However, if unobserved characteristics are also important, the estimated coefficients for Bt may still be biased. To test and control for unobserved heterogeneity and resulting selection bias, an instrumental variable approach is used [31-33]. This approach involves two steps. In the first step, a probit model is estimated with Bt adoption as dependent variable:

$$Bt_i = \alpha w_i + \varepsilon_i: \qquad \varepsilon_i \sim N(0, 1) \tag{3}$$

where w is a vector of covariates. For proper identification, w needs to contain at least one instrumental variable in addition to x and z. α is a vector of parameters to be estimated, and ε is the error term. In the second step, predicted values of Bt adoption from this probit are used instead of actually observed adoption in the estimation of Eqs. (1) and (2). We use Bt awareness exposure, credit constraint, and market distance as instruments. While one might expect that these variables do not only affect Bt adoption but may also influence the demand for hired labor directly, empirical tests show that this is not the case, so the instruments are valid.

The choice of other covariates affecting hired labor demand is based on the existing literature that highlights the importance of variation in household's resource endowment with land, human capital, and access to markets and technologies [34, 35]. We include area owned, frequency of irrigation, farmer age, education, and gender, as well as participation in off-farm employment activities as control variables. Moreover, market prices and wage rates are included, as is

common in labor demand models. District dummies are used to capture possible regional differences. Finally, scale variables like cotton area and length of the cropping cycle are included as covariates.

3.2. Double-Hurdle Model

Eqs. (1) and (2) can be estimated with a Heckman selection model or with corner solution models [33]. The Heckman selection model is particularly suitable when zero observations of the dependent variable in the first tier are due to missing values, which is not the case in our study. Zero observations in our sample are due to some farmers' deliberate decision not to hire any external labor, for instance due to sufficient family labor availability or financial constraints. In this case, corner solution models are more suitable [36, 37]. One widely used corner solution model is the Tobit estimator [38]. However, one drawback of the Tobit estimator is that it requires x and z in Eqs. (1) and (2) to be identical. The double-hurdle (DH) model is more flexible in this respect [39], because x and z may overlap but are also allowed to differ. The DH model was applied recently to estimate the demand for fertilizer, other inputs and production technologies, and also hired labor [22, 40, 41, 42, 43]. We use the DH model and a likelihood specification [37], which follows the functional forms given in Eqs. (1) and (2):

$$L(Qh_i|x_i, 0) = \left\{\prod_{Qh_i=0}\left[1-\Phi\left(\gamma\, x_i/\sigma_\mu\right)\right]\Phi(\beta z_i/\sigma_v)\right\} \times \left\{\prod_{Qh_i>0}\Phi\left(\gamma\, x_i/\sigma_\mu\right)\Phi(\beta z_i/\sigma_v)\right\} \times \left\{\frac{\phi[Qh_i - \beta z_i]/\sigma_v}{\sigma_v\Phi(\beta z_i/\sigma_v)}\right\} \tag{4}$$

where ϕ and Φ denote the standard normal probability and cumulative distribution functions, respectively. Similarly, σ_μ and σ_v are the standard deviations of μ_i and v_i, respectively. Eq. (4) can be solved for γ, β, and σ^2 through maximum likelihood estimation.

It should be noted that the Tobit is nested in the DH model. Hence, a likelihood ratio (LR) test can be used to establish whether the more flexible DH specification is actually preferable. The log-likelihood of the DH model comprises the summation of the log-likelihood values estimated in the first and second hurdles (tiers) by probit and truncated normal regression techniques. We present and discuss the test results below.

3.3. Estimating Marginal Effects

For better interpretation, marginal effects of the covariates are calculated based on the DH estimates [44]. At first, we compute the probability of hiring or not hiring in labor on cotton plot *i* as follows:

$$P(dh_i^* > 0|x_i) = \Phi(\gamma x_i) \quad (5)$$

$$P(dh_i^* = 0|x_i) = 1 - \Phi(\gamma x_i) \quad (6)$$

Then, given $Qh > 0$, the conditional hired labor quantity for each cotton plot *i* is predicted as:

$$E(Qh_i|Qh_i > 0, z_i) = \beta z_i + \sigma \times \lambda(\beta z_i/\sigma) \quad (7)$$

where $\lambda(\beta z_i/\sigma) = \phi(\beta z_i/\sigma)/\Phi(\beta z_i/\sigma)$ is the inverse mills ratio. The unconditional hired labor quantity is predicted by combining the effects of both hurdles as:

$$E(Qh_i|x_i, z_i) = \Phi(\gamma x_i)[\beta z_i + \sigma \times \lambda(\beta z_i/\sigma)] \quad (8)$$

We calculate the unconditional average marginal effects (UAME) as described in Burke [44]. The UAME are most meaningful for interpretation, as they allow statements about the impact of Bt adoption on labor demand taking into account both hurdles of the two-tier decision process. We estimate the DH model in three different versions, first with total hired labor, second with only female hired labor, and third with only male hired labor as dependent variables. Accordingly, three sets of marginal effects are calculated and reported.

4. Estimation Results

4.1. Bt Adoption and Testing Instrument Validity

Before proceeding with the estimation of the DH models, we estimate the probit model in Eqs. (3) to explain Bt adoption and test for instrument validity. Estimation results are reported in Table 4. All three instruments are highly significant in this model. Bt awareness exposure increases the likelihood of technology adoption, while credit constraints and larger distance to market decrease the likelihood of adoption. The hypothesis of week instruments is rejected at a one percent level of significance. All three instruments do not have a direct influence on the demand for hired labor.

Table 4 is here.

4.2. Labor Demand Estimates

Table 5 shows results of the LR test that is used to test the suitability of the DH model against the more restrictive Tobit specification. In all three versions of the model – for total hired labor,

female hired labor, and male hired labor – the null hypothesis in favor of the Tobit specification is rejected. These test results confirm that the DH specification is more appropriate for our data.

Table 5 is here.

The DH model estimates are shown in Table 6, whereas marginal effects are shown in Table 7. We start the discussion by looking at the model for total hired labor. The results for the first hurdle (the binary decision whether or not to hire any labor) indicate that Bt technology adoption has increased the probability of hiring in labor by 19 percentage points. The results for the second hurdle indicate that the quantity of hired labor use increases by 11 labor days per acre through Bt adoption. This implies an increase in mean conditional demand for hired labor by 40 percent. These findings underscore that Bt adoption improves the employment opportunities for the rural poor. The increase in labor demand is primarily driven by higher yields to be harvested in Bt cotton. As discussed above, hand-picking cotton is a very labor-intensive activity. In addition, higher expected yields from Bt varieties provide incentives for farmers to intensify their production patterns, causing higher labor demand also for other activities such as weeding and fertilization. These findings are in line with simulation results from India [25].

Table 6 is here.

Table 7 is here.

Other variables that affect the probability of hiring in labor are area owned, wage rates, and off-farm employment of the farmer. The effect of area owned is relatively small but positive and statistically significant, implying that larger farms are more likely to hire in labor than smaller farms. This is plausible given that large farmers tend to be richer and have less family labor available per acre of farmland. As expected, the magnitude of the wage rate has a negative effect on labor use. Off-farm employment increases the probability of hiring in labor by 6 percentage points. Off-farm employment is often more lucrative for farmers, so that hiring in relatively cheap unskilled labor for certain farm operations is a rational decision [22]. Results of the second hurdle equation indicate that the quantity of hired labor demand increases with an increase in the cotton area, crop length, and off-farm employment. On the other hand, the wage rate affects the quantity of labor demand negatively. Similarly, household size has a negative effect, which could be expected, because the number of adult equivalents living in the household also determines the availability of family labor for own farming operations.

We now look more closely at the separate DH models for female and male hired labor demand, results of which are shown in parts (2) and (3) of Tables 6 and 7. The marginal effects in both hurdles are all positive and significant, implying that Bt adoption has increased the probability and the quantity of hiring in female and male labor. Yet, the absolute increase in employment through Bt technology is much more pronounced for female laborers (8.7 additional days per acre) than for male laborers (1.7 days per acre). The results for other variables in these gender-disaggregated models are similar to those in the model for total hired labor discussed above.

4.3. Unconditional Effects

The unconditional average marginal effects (UAME) of Bt adoption, which take into account the combined estimates of both hurdles, are shown in Table 8. Bt adoption has increased the demand for total hired labor by 13.7 labor days per acre. Relative to the unconditional expected demand for total hired labor in non-Bt cotton, this is equivalent to a 55 percent increase. The gender-disaggregated results show that Bt has increased the demand for female hired labor by approximately 11.1 labor days per acre, equivalent to a 53 percent change when compared to non-Bt cotton. Similar employment benefits for female laborers were reported for Bt cotton in India [25, 45]. The UAME for male hired labor is smaller in absolute terms. Nevertheless, the relative increase in male labor demand through Bt adoption is 58 percent, which is due to the much lower overall use of male hired labor in cotton production.

Table 8 is here.

We can use these effects for some simple calculations of the additional income that Bt cotton adoption has generated for rural laborers in Pakistan as a whole. These results are shown in the last column of Table 8. They were derived by multiplying the additional labor days per acre by the average wage rates for female and male laborers as observed in our survey and by the total acreage under Bt cotton in Pakistan (5 million acres at the time of the survey in 2011). Obviously, the exact numerical results of such extrapolations should be interpreted cautiously, but the order of magnitude is interesting nonetheless. The value of the additional total employment generated through Bt adoption is around 211 million US$ per season. Close to 80 percent of this overall gain in employment income accrues to female laborers. Previous research showed that women's

empowerment increases importantly with paid employment [27], implying that Bt technology contributes indirectly to empower landless rural women by making them financially more independent. There is also substantial evidence in the literature that female-controlled income is particularly important for child and overall household welfare, because women spend more than men on nutrition and health [46, 47, 48].

5. Conclusions

While there is a growing body of literature about the impacts of GM crops on farm level productivity and profits, broader effects for rural development have rarely been analyzed. Since many of the rural poor depend on the labor market for their livelihoods, better understanding of the employment effects of GM crop adoption is of particular importance. We have addressed this research gap and have analyzed the impact of insect-resistant Bt cotton on the demand for hired labor in Pakistan. Using farm survey data and controlling for confounding factors, we showed that Bt cotton adoption has increased hired labor use significantly. The net effect of Bt adoption is an additional hired labor demand of 13.7 labor-days per acre, equivalent to a 55 percent increase when compared to labor use in non-Bt cotton. This large increase is primarily driven by higher yields to be harvested in Bt cotton. Extrapolation of these results to the total Bt cotton area in Pakistan suggests additional employment incomes of 211 million US$ per season. This additional income from agricultural employment is especially important for landless rural households that often belong to the poorest of the poor.

Gender disaggregation revealed that the largest increase in hired labor demand occurs for female laborers, as farmers predominantly hire women workers for harvesting and other labor-intensive operations in cotton. This is a welcome finding from a development perspective, because women tend to be particularly disadvantaged in rural societies due to higher illiteracy and lower access to productive resources [49]. Paid employment is known to improve women empowerment and quality of life [45, 47]. While not further analyzed here, the development economics literature has also shown that female-controlled income tends to be more beneficial than male-controlled income for the welfare of poor households [46, 47, 48, 49].

We cautiously conclude that Bt cotton adoption has contributed to poverty reduction and gender equity among agricultural labor households in Pakistan. This is an important addition to the previous literature that has demonstrated lower chemical pesticide sprays and higher

agricultural productivity and income through Bt cotton adoption in farming households in Pakistan, India, and other developing countries [9, 11, 13, 50]. These results suggest that Bt cotton adoption can contribute to economic, environmental, and social sustainability.

The results for Bt cotton should not simply be generalized for other GM crops, because impacts always depend on the modified traits and also on the context. Herbicide-tolerant crops, for instance, have so far mostly been deployed in mechanized farming systems where the use of unskilled manual labor is much lower anyway. More research on the wider social effects of different types of GM crops is important and can contribute to the public debate that often lacks differentiation. Future studies should more explicitly address distributional issues between landed and landless households and between males and females. Such distributional issues are often neglected in technology impact studies [51, 52, 53]. We acknowledge that the cross-sectional data used here has limitations in terms of analyzing economic and social dynamics. Longer-term research with panel data would be useful to further add to our knowledge about the wider social implications of GM crops in developing countries.

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Table 1: Descriptive statistics of sample farmers by production technology

Variables	Bt adopters (N = 248)	Non-adopters (N = 104)
Age (years)	40.56 (12.26)	42.44 (13.28)
Education (years of schooling)	8.04** (4.27)	6.77 (4.62)
Household size (adult equivalent)	7.30 (4.56)	6.64 (3.00)
Total area owned (acres)	14.60*** (16.06)	8.84 (11.73)
Cotton area (acres)	9.12 (16.27)	8.07 (11.77)
Credit constrained (%)	27.02***	90.39
Off-farm employment (%)	41.53***	58.65
Bt awareness exposure (years)	4.21***	1.84

***, ** Mean values are significantly different at the 1% and 5% level, respectively.
Note: Mean values are shown with standard deviations in parentheses.

Table 2: Summary of hired labor by gender and production technology

Variables	Female hired labor (days/acre)		Male hired labor (days/acre)	
	Bt plots (N = 248)	Non-Bt plots (N = 277)	Bt plots (N = 248)	Non-Bt plots (N = 277)
Total hired labor	27.50*** (21.32)	19.53 (16.15)	6.49** (5.18)	3.63 (3.45)
Land preparation	-	-	0.43 (2.86)	0.20 (0.33)
Sowing	0.13*** (0.41)	0.05 (0.19)	0.15 (0.40)	0.10 (0.31)
Gap filling	0.00 (0.01)	0.00 (0.02)	0.11*** (0.24)	0.00 (0.02)
Thinning	0.000 (0.00)	0.01 (0.09)	0.38*** (0.77)	0.21 (0.45)
Weeding	0.23** (0.99)	0.08 (0.46)	2.13*** (1.94)	1.68 (1.53)
Irrigation	-	-	1.89*** (1.98)	0.83 (1.22)
Fertilizer application	-	-	0.28*** (0.29)	0.05 (0.10)
Pesticide application	-	-	0.39** (0.55)	0.30 (0.52)
Herbicide application	-	-	0.20*** (0.24)	0.13 (0.16)
Picking	27.14*** (12.61)	19.39 (10.92)	0.62*** (2.16)	0.04 (0.68)

***, ** Mean values are significantly different at the 1% and 5% level, respectively.
Note: Mean values are shown with standard deviations in parentheses.

Table 3: Descriptive statistics of sample plots by production technology

Variables	Bt plots (N = 248)	Non-Bt plots (N = 277)
Cotton price (Rs/maund [a])	3647.50***	3645.63
	(341.94)	(665.26)
Wage rate (Rs/day)	208.45*	223.77
	(99.11)	(97.37)
Price of fertilizer (Rs/kg)	61.84***	78.55
	(19.63)	(24.02)
Price of insecticide (Rs/liter)	842.31**	788.53
	(355.84)	(246.60)
Number of irrigations	10.86***	9.42
	(4.62)	(3.80)
Crop length (days)	234.56***	218.11
	(35.58)	(25.95)
Market distance (km)	9.99***	13.65
	(6.98)	(7.55)

***, **,* Mean values are significantly different at the 1%, 5%, and 10% level, respectively.
[a] One maund is equal to about 40 kg.
Note: Mean values are shown with standard deviations in parentheses.

Table 4: Factors influencing farmers' decision to adopt Bt cotton

Bt adoption	Coefficient	Standard error
Bt awareness exposure (years)	0.15***	0.04
Credit constraint (dummy)	-0.63***	0.14
Market distance (km)	-0.05***	0.01
Total area owned (acres)	-0.01	0.01
Cotton area (acres)	-0.01	0.00
Wage rate (Rs/day)	-0.00	0.00
Price of fertilizer (Rs/kg)	-0.02***	0.00
Price of insecticide (Rs/liter)	0.00*	0.00
Number of irrigations	0.02	0.02
Off-farm employment (dummy)	-0.22*	0.13
Household size (adult equivalent)	0.03**	0.02
Farmer's age (years)	0.01	0.01
Farmers' education (years)	0.01	0.02
Vehari district [a]	0.01	0.21
Bahawalnagar district [a]	0.18	0.19
Bahawalpur district [a]	0.21	0.19
Constant	0.91*	0.52
$\chi 2$ (16)	175.57***	
Observations	525	

***, **, * Significant at the 1%, 5%, and 10% level, respectively.
[a] The base district is Rahim Yar Khan.

Table 5: Model specification tests

Likelihood ratio tests	(1) Total hired labor days	(2) Female hired labor days	(3) Male hired labor days
Log-likelihood of Tobit regression	-1957.18	-1937.25	-1311.80
Log-likelihood of probit regression	-141.55	-142.77	-255.34
Log-likelihood of truncated regression	-1698.00	-1742.61	-1021.15
$\chi 2$ (16)	235.25	103.74	70.61
p-value	0.00	0.00	0.00

Table 6: Determinants of labor demand (double-hurdle models)

Variables	(1) Total hired labor days		(2) Female hired labor days		(3) Male hired labor days	
	Decision to hire	Quantity to hire	Decision to hire	Quantity to hire	Decision to hire	Quantity to hire
Bt adoption (dummy, IV)	1.31***	14.26***	1.23***	13.33***	0.99***	2.51
	(0.46)	(5.03)	(0.46)	(5.11)	(0.35)	(1.53)
Total area owned (acres)	0.020**	0.10*	0.02**	0.12*	0.00	0.01
	(0.01)	(0.06)	(0.01)	(0.06)	(0.01)	(0.02)
Cotton area (acres)	-0.01	0.21***	-0.01	0.14**	-0.01	0.10***
	(0.01)	(0.07)	(0.01)	(0.07)	(0.01)	(0.02)
Wage rate (Rs/day)	-0.01***	-0.14***	-0.01***	-0.16***	-0.00***	-0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Price of fertilizer (Rs/kg)	-0.00	-0.04	-0.00	-0.03	-0.00	-0.01
	(0.01)	(0.06)	(0.01)	(0.06)	(0.00)	(0.02)
Price of insecticide (Rs/liter)	0.00	0.00	0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cotton price (Rs/maund)	0.00	-0.00	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of irrigations	-0.00	-	-0.00	-	-0.03*	-
	(0.02)		(0.02)		(0.02)	
Crop length (days)	-	0.08***	-	0.07**	-	0.03***
		(0.03)		(0.03)		(0.01)
Off-farm employment (dummy)	0.39**	5.03**	0.41**	5.81***	0.01	0.59
	(0.18)	(2.02)	(0.18)	(2.05)	(0.14)	(0.63)
Household size (adult equivalent)	-0.01	-0.37	-0.01	-0.41*	0.00	-0.07
	(0.02)	(0.23)	(0.02)	(0.23)	(0.02)	(0.07)
Farmer's age (years)	0.01	-0.14*	0.01	-0.14	-0.00	-0.00
	(0.01)	(0.09)	(0.01)	(0.09)	(0.01)	(0.03)
Farmers' education (years)	0.00	0.12	0.00	0.10	0.00	0.04
	(0.02)	(0.23)	(0.02)	(0.23)	(0.02)	(0.07)
Vehari district [a]	0.64**	5.03	0.56**	3.30	0.58***	1.96**
	(0.29)	(3.13)	(0.28)	(3.18)	(0.21)	(0.99)
Bahawalnagar district [a]	0.80***	6.85**	0.80***	6.20**	0.77***	0.18
	(0.27)	(2.96)	(0.27)	(3.01)	(0.20)	(0.93)
Bahawalpur district [a]	0.61**	-2.05	0.62**	-2.82	0.53***	-0.12
	(0.25)	(2.94)	(0.25)	(2.99)	(0.19)	(0.93)
Constant	0.63	40.45***	0.62	42.25***	0.34	0.24
	(1.06)	(13.98)	(1.05)	(14.48)	(0.84)	4.04
Sigma		17.26***		16.47***		4.66***
		(0.75)		(0.79)		(0.27)
Wald $\chi 2$ (16)	74.37***		75.40***		59.29***	
Observations	525		525		525	

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Note: Coefficient estimates are shown with standard errors in parentheses. IV, instrumental variable.

[a] The base district is Rahim Yar Khan.

Table 7: Marginal effects for double-hurdle models

Variables	(1) Total hired labor days		(2) Female hired labor days		(3) Male hired labor days	
	Decision to hire	Quantity to hire	Decision to hire	Quantity to hire	Decision to hire	Quantity to hire
Bt adoption (dummy, IV)	0.19***	10.51***	0.18***	8.66**	0.27***	1.65*
	(0.08)	(3.89)	(0.08)	(3.56)	(0.10)	(0.92)
Total area owned (acres)	0.00**	0.08	0.00*	0.08	0.00	0.01
	(0.00)	(0.05)	(0.00)	(0.05)	(0.00)	(0.02)
Cotton area (acres)	-0.00	0.16**	-0.00	0.09**	-0.00	0.06***
	(0.00)	(0.06)	(0.00)	(0.05)	(0.00)	(0.02)
Wage rate (Rs/day)	-0.00***	-0.10***	-0.00***	-0.10***	-0.00***	-0.00
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Price of fertilizer (Rs/kg)	-0.00	-0.03	-0.00	-0.02	-0.00	-0.00
	(0.00)	(0.04)	(0.00)	(0.03)	(0.00)	(0.01)
Price of insecticide (Rs/liter)	0.00	0.00	0.00	0.00*	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cotton price (Rs/maund)	0.00	-0.00	0.00	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of irrigations	-0.00	-	-0.00	-	-0.01*	-
	(0.00)		(0.00)		(0.01)	
Crop length (days)	-	0.06**	-	0.04**	-	0.02**
		(0.03)		(0.02)		(0.01)
Off-farm employment (dummy)	0.06*	3.71**	0.06**	3.77***	-0.00	0.39
	(0.03)	(1.57)	(0.03)	(1.31)	(0.04)	(0.39)
Household size (adult equivalent)	-0.00	-0.27*	-0.00	-0.27*	0.00	-0.05
	(0.00)	(0.15)	(0.00)	(0.14)	(0.00)	(0.03)
Farmer's age (years)	0.00	-0.10*	0.00	-0.09	-0.00	-0.00
	(0.00)	(0.06)	(0.00)	(0.06)	(0.00)	(0.02)
Farmers' education (years)	0.00	0.09	0.00	0.06	0.00	0.03
	(0.00)	(0.17)	(0.00)	(0.13)	(0.01)	(0.05)
Vehari district [a]	0.09**	13.71*	0.08**	2.15	0.16***	1.29**
	(0.04)	(2.04)	(0.04)	(1.81)	(0.05)	(0.66)
Bahawalnagar district [a]	0.12**	5.05**	0.12***	4.03**	0.21***	0.12
	(0.05)	(2.27)	(0.04)	(1.99)	(0.07)	(0.64)
Bahawalpur district [a]	0.09**	-1.51	0.09**	-1.83	0.14***	-0.08
	(0.04)	(2.09)	(0.04)	(1.65)	(0.06)	(0.57)
Observations	525		525		525	

***, **, * Significant at the 1%, 5%, and 10% level, respectively.

Note: Coefficient estimates are shown with bootstrapped standard errors in parentheses. IV, instrumental variable.

[a] The base district is Rahim Yar Khan.

Table 8: Unconditional marginal effects of Bt cotton adoption on hired labor demand

	Unconditional expected demand for labor in non-Bt cotton	Unconditional average marginal effects of Bt adoption	Income benefits for total Bt cotton acreage (US$ million)
Total hired labor (days/acre)	25	13.71*** (3.70)	210.98
Female hired labor (days/acre)	21	11.06*** (3.45)	166.61
Male hired labor (days/acre)	5	2.89*** (0.80)	45.21

***, **, * Significant at the 1%, 5%, and 10% level, respectively.
Note: Bootstrapped standard errors are given in parentheses.