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Bt cotton and employment effects for female agricultural laborers in Pakistan: An application of double-hurdle model

By

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Abstract

The literature dealing with impacts of Bt cotton is growing. Nevertheless, the question remains about how this technology can contribute to employment generation of rural poor. Bt-related yield benefit may intensify production and enhance labor demand for harvesting. Building on farm survey data of 352 cotton farmers in the South Punjab of Pakistan and using double-hurdle model, Bt employments effects are analyzed. Estimates show that Bt adoption has increased the probability and demand for hired labor by 6% and 17%, respectively. Cotton picking is labor intensive and female dominated activity in Pakistan. Labor disaggregation by gender enunciates the employment effects of Bt cotton for rural women, who belong to the neglected group of the society. Hence, Bt technology can play a vital role to poverty alleviation if seed quality and credit constraints are properly addressed.

Keywords: *Bt cotton, labor demand, women empowerment, double hurdle model, Pakistan*

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1. Introduction

Productivity and profit enhancing agricultural technologies are considered as essential tools for employment generation, economic growth and poverty alleviation in developing countries (Lipton, 2007; Self and Garbowski, 2007). Recent advancements in agricultural science and technology through genetic modification are quickly gaining in importance where conventional breeding approaches have been failed (FAO, 2002; Vanloqueren and Baret, 2009). Transgenic cotton is one example of biotech crop that entails Cry genes produced by the soil bacterium *Bacillus thuringiensis* (*Bt*). These genes encode for producing toxins to provide resistance to selective insects in particular cotton bollworms. These bollworms are incredibly detrimental to cotton crop and are accountable for intensive pesticide spray (Zehr, 2010). Monsanto instigated the commercialization of Bt cotton in 1996 in USA. Since then, this technology has been successfully planted on more than 247 million acres in the world (James, 2011). After 15 years of commercialization, Bt varieties officially approved in 2010 in Pakistan (Kouser and Qaim, 2013). However, illegal plantings of Bt cotton had already commenced before 2010, through black marketing of unapproved and unregulated Bt seed from neighboring countries like India and China (Ali and Abdulai, 2010). With 81% adoption rate in 2011, the country had the 4th largest Bt cotton area of 6.4 million acres.

A growing body of literature for adopting countries demonstrates that in-built resistance in Bt cotton has reduced Bollworm damage and substantially increased crop yield while reducing pesticide applications (Huang *et al.*, 2002; Thirtle *et al.*, 2003; Qaim and de Janvry, 2005; Bennett *et al.*, 2006; Kouser and Qaim, 2013). Nevertheless, the question remains about how this technology can contribute to employment generation of rural poor. The expectation of higher yield provides incentives to farmers to intensify crop production and delayed harvesting for more picking operations. This may lead to increased demand for hired laborers. There are few studies showing through descriptive statistics that Bt has increased labor cost and returns on labor (Pray *et al.*, 2001; Kouser and Qaim, 2013). However, hardly any impact study so far has attempted to quantify positive employment effects of Bt adoption after controlling for possible confounding factors, which could be the reason for enduring debate surrounding the negative social repercussions and sustainable rural development challenges of biotech crops (Lipton, 2007; Glover, 2010; Gruere, and Sengupta, 2011; Stone, 2011). Subramanian and Qaim (2010) have estimated income and employments effects of Bt cotton through simulation for a self-selected village in India. However, impact evaluation after introducing the exogenous shock does not necessary to portray the real situation.

Employment generation particularly in rural areas is strongly linked with innovation in agricultural technology. On-farm earning is an imperative source of income for majority of landless rural community (Reardon, 1997; Kijima et al., 2006). Because of low investment on agricultural research in developing countries, off-farm income comprises major share in household's income (Maertens, 2009; Babatunde and Qaim, 2010). Many studies have observed that high-value supply chains have great employment impacts for the poorest segment of the society in particular for rural women (Damiani, 2003; Maertens and Swinnen, 2009; Rao and Qaim, 2013).

Adoption of Bt technology may have important gender implications. In cotton production system of Pakistan, females are excluded from income benefits of Bt cultivation because of limited ownership of productive assets such as land. However, Bt may enhance the demand of female rural laborers hired for specific operations like sowing, weeding and harvesting. Subramanian and Qaim (2010) have estimated employment benefits for female labourers employed for additional cotton picking due to increased production. Rural women belong to the most vulnerable group of the society. However, they can improve their well-being and economic independence by participating in labor markets (Zhang et al., 2004; Quisumbing and McClafferty, 2006). In this regard, Bt technology is expected to play a significant role to empower women in Pakistan.

This article contributes by estimating the spillover effects of Bt cotton adoption on demand for total hired labor. In addition, hired labor is segregated into male and female labor to explore gender effects of the technology. A two-tier or double-hurdle model is employed because demand for hired labor is a two-step decision: the first tier accounts for the factors responsible for general decision to hire because all farmers don't hire labor and the second tier measures the intensity of hired labor. The second advantage of this model is that it has the ability to handle excessive zeros indicating not hiring by some farmers.

The analysis employs primary data of self-administered farm survey conducted in Pakistan which is 4th largest cultivator and 3rd largest consumer of cotton. Being an important cash crop, cotton accounts for 6.7% of the value addition in agriculture (Government of Pakistan, 2014) and together with textile industry, it contributes about 9% to GDP (APTMA, 2010). Cotton and textile industries dominate country's exports and contribute 55% to the foreign exchange earnings (Government of Pakistan, 2009). Bt cotton may boost the country's economy. Recent studies in Pakistan have shown that Bt varieties have increased farmer's profitability and environmental sustainability (Ali and Abdulai, 2010; Nazli *et al.*, 2012; Kouser and Qaim, 2013; Kouser and Qaim, 2014; Abedullah, Kouser and Qaim, 2015). According to the best of our knowledge, gender impact assessment of Bt cotton has not been undertaken in such a systematic way. Such empirical evidence could have serious policy implications of Bt adoption for rural development.

Remaining of this article proceeds as follows: following section discusses the survey data and descriptive statistics. Section 3 presents the econometric methodology, while estimation results are described in section 4. The final section concludes with policy recommendations.

2. Data and Descriptive Statistics

A farm survey of randomly selected 352 cotton farmers was conducted in four main cotton districts of South Punjab of Pakistan in 2010-11 (detail is given in Kouser and Qaim, 2014). This sample comprises 248 Bt and 104 non-Bt adopters that represents of 71% of Bt adoption rate. Descriptive statistics of sample farmers and farms are reported in Table 1. Bt adopters own significantly larger land area than non-adopters but no significant difference is observed in cotton holdings. All farmers belong to same age brackets but Bt adopters are better educated. Furthermore, Bt adopters are less likely to be credit constrained. Seed cost of open pollinated Bt varieties is almost similar to conventional ones in Pakistan. Even though, no additional credit is required to purchase Bt seed, 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). In order to overcome these constraints non-Bt adopters are found to be more intensively involved in off-farm activities. Bt farmers aware from insect resistance Bt technology longer than non-adopters.

Table 1 is here.

Table 2 shows comparisons between Bt and non-Bt plots. Out of 248 Bt farmer, 175 are partial adopters. We gathered input-output details of both Bt and non-Bt plots of such farmers. Hence, observations of Bt plots is larger than number of Bt farmers. A meaningfully large proportion of hired labor is employed on Bt plots which is consistent with the findings by Pray *et al.* (2001), Subramanian and Qaim (2010) and Kouser and Qaim (2013). These studies strengthen our hypothesis of higher employment effects by Bt cotton adoption. Disaggregation of hired labor demand shows a significant gender differentiation between Bt and non-Bt plots. Bt farmers significantly hire more female labor than their counterparts which is in line with Subramanian and Qaim (2010). We find only slight difference in wage rate between both plots. Bt farmers receive slightly higher output prices that motivates them to purchase highly quality inputs. Prices of fertilizers and insecticides are estimated through weighted average procedure to account for quality differences (Kouser and Qaim, 2011). Their mean comparison shows that Bt farmers are significantly paying lower prices for fertilizers and higher prices for insecticides. It may be due to higher application of fertilizer and lower application of insecticides by Bt farmers than their counterparts (Abedullah, Kouser and Qaim, 2014; Kouser and Qaim, 2014). Bt farmers irrigate more frequently and delay harvesting for more cotton pickings. Picking operations are dominated by females. Therefore, gender disaggregation of labor demand is crucial. Bt plot is relatively closer to input-output market.

Table 2 is here.

3. Empirical Model

3.1. Modeling Bt Impact on Labor Demand

As mentioned earlier, Bt impact on demand for additional hired labor days may be a two-step decision (double-hurdle). Farmers may initially decide whether to hire or not (first hurdle), if hiring occurs then may decide for how many labor days to hire (second hurdle). The first step of hiring 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 the latent variable for dh_iwhich is equal to '1' if farmer hires the labor on its main cotton plot *i*, otherwise it is '0'. The second step encompasses the decision about exact quantity of hired labor days, which is signified as:

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

where Qh_i^* is the latent variable for Qh_i which represents the intensity of hired labor days by the farmer on its main cotton plot *i*. In the above equations, x and z are vectors of covariates which may or may not consist of same variables. γ and β are vectors of associated parameters, respectively. μ_i and ν_i are random error terms. Bt adoption is a treatment dummy variable which is ‘1’ if farmers have cultivated insect resistance Bt technology, otherwise it is ‘0’. Bt adoption dummy is included in both x and z covariates. Its positive and significant coefficients in both hurdles would imply that Bt adoption has increased the probability and intensity to hire the labor. This treatment variable may be endogenous as farmers decide themselves whether to adopt Bt technology or not on the base of their intrinsic and extrinsic characteristics. Table 1 discussed above, points towards possible heterogeneity between Bt and non-Bt adopters in terms of education, landholdings, credit constraint and off-farm participation. Therefore, control function approach as suggested by Rivers and Vuong (1988) and Smith and Blundell (1986) is used to test and control for self-selection bias associated with Bt regressor. This approach comprises two equations: reduced form equation and structural (outcome) equation. Reduced form equation in our case is a binary choice model estimated by probit regression, where regressand is a Bt adoption dummy:

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

where w is a vector of covariates containing at least one instrumental variable in addition to x and z variables for proper model identification. α is a vector of parameters to be estimated, and ε is an error term. Following the correlation statistics and existing adoption literature, we use Bt awareness exposure, credit constraint dummy and market distance as instruments (Kouser and Qaim, 2014). The significant coefficient of error term estimated from reduced form equation in Equations 1 and 2 (structural equations) indicates endogenity problem and also controls for observed and unobserved heterogeneity between adopters and non-adopters (Wooldridge, 2002).

The choice of other regressors affecting hired labor demand is based on the existing literature that highlights the significance of variation in household’s resource endowment with land, human capital and access to market and technologies on their decision of labor supply and demand (Eswaran and Kotwal, 1986; Brosig et al., 2007; Lovo, 2012). Sadoulet et al. (1998) observe that transaction costs influence household’s decision of labor supply and demand in the market. To better asses Bt technology impact on hired labor demand, farm and farmer specific characteristics such as owned area, irrigation, age, education, gender, and participation in off-farm employment, that can spur the relationship, are controlled. Moreover, market variables such as own (wage rate) and related prices (fertilizer and insecticide prices) are also included. District dummies are used to capture possible geographical effects. Finally, the scale variables like cotton area and length of cropping cycle are used because hired labor quantity is measured per cotton area (i.e., one acre) and for one cotton season.

3.2. Double-Hurdle Model

To estimate the Eqs. (1) and (2) we follow the corner solution model instead of selection model[1] because many farmers in our sample decide not to hire labor, inspite of availability of hired labor, due to financial constraint or availability of surplus family labor. So the data on hired labor contains observable zero values, not the missing values. Moreover, this regressand behaves like a corner solution variable because it is truncated at some positive values.

Tobin (1958) proposes tobit estimator to estimate a corner solution model. However, a major drawback of the tobit is that it requires the decision to hire the labor and the quantity to hire are measured by identical underlying mechanisms. To handle a corner solution model, a double-hurdle (DH) model is a more flexible approach proposed by Cragg (1971) because it provides a way to estimate both decisions (hurdles) influenced by different processes (the vectors γ and β). So DH allows the same factors to affect the probability and intensity to hire the labor differently. DH model is applied recently to estimate models of fertilizer demand, hired labor demand and production technology demand (Shiferaw et al., 2008; Xu et al., 2009; Ricker-Gilbert et al., 2011; Noltze et al., 2012; Rao and Qaim, 2013). Jones (1989) designed the likelihood specification of DH model as:

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

This specification follows the functional forms given in Eqs. (1) and (2) and independent assumption between error terms of two hurdles as postulated by Cragg (1971). 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 ν_i, respectively. Eq. (4) can be solved for γ, β and σ^2 through maximum likelihood estimation.

Tobit is nested in DH model so the appropriateness of the DH model against the Tobit can be evaluated through likelihood ratio (LR) test. Log-likelihood of DH model comprises the summation

[1]Heckman selection technique can only handle unobserved zero values (Jones, 1989; Wooldridge, 2002).

of log-likelihoods estimated in first and second hurdles by probit and truncated normal regression techniques, respectively.

3.3. Estimating Marginal Effects

For better interpretation, marginal effects of the covariates are calculated using DH estimates as elaborated by Burke (2009). But before, we need to compute probability to hire additional labor or not on main cotton plot *i* of the farmer:

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

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

Conditional hired labor intensity for each cotton plot *i* is predicted, given $Qh > 0$ as:

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

where $\lambda(\beta z_i/\sigma) = \phi(\beta z_i/\sigma)/\Phi(\beta z_i/\sigma)$ is the inverse mills ratio. Unconditional hired labor intensity *i* is predicted after combing the effect of first hurdle as:

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

Average marginal effects of each covariate are computed and reported in Table 4. Their standard errors are obtained by bootstrapping.

4. Estimation Results

4.1. Control Function Estimates

Before proceeding with the estimation of DH model, existence of possible endogeneity in Bt variable is tested through control function approach as discussed above. Results of reduced form equation are reported in Table 3. Suggested instruments in section 3.1 are significantly correlated with Bt adoption. Each additional year of Bt awareness increases adoption likelihood by 15 percentage points. However, possibility of credit constraint and increased market distance decreases adoption likelihood by 63 and 5 percentage points, respectively. These three instruments are also tested against hypothesis of week instruments which is rejected at less than one percent level of significance.

Table 3 is here.

4.2. Double-Hurdle Estimates

Results of LR tests are presented in Table 4 to decide about the appropriate specification of the model. The null hypothesis in favour of tobit model has been rejected at less than one percent level of significance for total, male and female hired labor days, indicating that DH model is more appropriate for this truncated data set. DH model estimates and marginal affects for total hired labor demand are shown in columns 1 and 2 in Table 5 and 6, respectively. These results are robust for observable and unobservable heterogeneities between Bt and non-Bt adopters. Hired labor quantity is elicited for main cotton plot *i* of the farmer. These estimates show the impacts of various factors on probability and intensity of hiring. The positive and significant marginal effect of predicted Bt adoption in hurdle 1 indicates that Bt technology has increased the hiring probability by 19 percentage than conventional cotton. Hurdle 2 indicates that hiring intensity increases by 11 labor days per acre with Bt adoption. These findings are consistent with our hypothesis that Bt adoption increases the employment opportunities for rural poor due to enhanced yield level. Moreover, higher production by Bt adoption motivates farmers to intensify vegetable production. These findings are consistent with the prediction by Subramanian and Qaim (2010).

Table 4 is here.

Table 5 is here.

Table 6 is here.

Higher wage rate negatively affect but off-farm participation positively affect farmers' likelihood of hiring labor. Intensity to hire increases with increase in cotton area, crop length, and off-farm employment. However, coefficient of adult equivalent (adjusted for age, gender, and occupation) indicates that large family size discourage farmers to hire labor.

To capture gender employment effect, separate DH models for female and male hired labor demands are estimated, their coefficients and marginal effects are shown in the next columns of Table 5 and 6, respectively. The coefficient of predicted Bt adoption is highly significant in female and male hired models, implying that Bt adoption increases the probability and intensity of hiring both female and male laborers but this effect is more pronounced for poor female pickers. Almost similar trend is seen for other covariates in these models. Hence, these results suggest that Bt adoption has largely increased the job opportunities for poor rural women. Pesticide reduction is negatively associated with male hiring but additional cotton production is positively associated with female hiring as cotton picking is a female dominated activity.

4.3. Unconditional effects and implications

In addition to the conditional marginal effects discussed so far, we calculated unconditional marginal effects, which are combined effects of both hurdles. These are usually more relevant for policymaking purposes. UAMEs of Bt adoption covariate are shown in Table 7 for the three models. Bt adoption increases the demand for total hired labor by 10 labor days. Compared to the unconditional expected demand for total hired labor, this implies an increase of 55%. The unconditional effect for male labor demand is small but statistically significant. Yet, consistent with the results discussed already, the increase in the demand for female hired labor is similar to the total effect. Around 21 additional labor days for female workers means an increase of 53%.

These results underline that Bt adoption has employment effects in Pakistan, especially for women. Literature shows that female spend major proportion of their income on child nutrition and household welfare (Hoddinott and Haddad, 1995; Quisumbing, 2003).

5. Conclusions

A growing body of literature exists on the impacts of GM crops but still there are open questions about how these crops can contribute to employment generation of rural poor. This study analyses impacts of insect-resistant Bt cotton on demand for total hired labor, female and male hired labor using farm survey data of major cotton growing districts of Punjab, Pakistan. The estimates demonstrate that Bt adoption has increased employment for rural laborers in general and for resource constrained women in particular. Employment generation for rural women have significant welfare implications. Literature shows that female spend major proportion of their income on child nutrition and household welfare (Hoddinott and Haddad, 1995; Quisumbing, 2003). The findings here provide empirical evidence that these employment effects originate from additional hiring of females for cotton picking due to increased production by Bt varieties. Hoddinott and Quisumbing and McClafferty (2006) found that women's empowerment increases with paid employment. Hence, this study concludes that Bt technology contributes to rural development by not only enhancing farm income but also by increasing income of rural women. However, such employment effects are very small compared to those for India reported by Subramanian and Qaim (2010). It could be due to seed adulteration of registered Bt varieties with illegal ones, cultivated before official cultivation. We did not analyse it but it could be done with detailed data on Bt toxin concentration.

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Table 1: Descriptive statistics of sample farmers and farms by production technology

Variables	Bt adopters (N = 248)	Non-adopters (N = 104)
Age (years)	40.557	42.442
	(12.261)	(13.282)
Education (years of schooling)	8.044**	6.769
	(4.271)	(4.618)
Household size (adult equivalent)	7.295	6.636
	(4.564)	(3.002)
Total area owned (acres)	14.604***	8.837
	(16.056)	(11.729)
Cotton area (acres)	9.116	8.067
	(16.269)	(11.770)
Credit constrained (%)	27.016***	90.385
Off-farm employment (%)	41.532***	58.654
Bt awareness exposure (years)	4.206***	1.837

***, **,* Mean values are significantly different at the 1%, 5%, and 10% level, respectively.
Note: Mean values are shown with standard deviations in parentheses.

Table 2: Descriptive statistics of sample plots by production technology

Variables	Bt plot (N = 248)	Non-Bt plot (N = 277)
Total hired labor days	33.988***	23.163
	(23.704)	(17.563)
Female hired labor days	27.496***	19.534
	(21.322)	(16.148)
Male hired labor days	6.492**	3.628
	(5.179)	(3.453)
Wage rate (Rs/day)	208.448*	223.773
	(99.108)	(97.368)
Price of fertilizer (Rs/kg)	61.835***	78.551
	(19.630)	(24.021)
Price of insecticide (Rs/liter)	842.313**	788.530
	(355.842)	(246.599)
Cotton price (Rs/maund)	3647.500***	3645.632
	(341.943)	(665.26)
Total irrigation (No.)	10.863***	9.415
	(4.617)	(3.800)
Crop length (days)	234.561***	218.112
	(35.582)	(25.946)
Market distance (km)	9.992***	13.650
	(6.977)	(7.552)

***, **,* Mean values are significantly different at the 1%, 5%, and 10% level, respectively.
Note: Mean values are shown with standard deviations in parentheses.

Table 3: Results of reduced form equation

Bt adoption	Coefficient	Standard error
Bt awareness exposure (years)	0.153***	0.036
Credit constraint (dummy)	-0.634***	0.138
Market distance (km)	-0.051***	0.009
Total area owned (acres)	-0.005	0.005
Cotton area (acres)	-0.007	0.004
Wage rate (Rs/day)	-0.001	0.001
Price of fertilizer (Rs/kg)	-0.022***	0.003
Price of insecticide (Rs/liter)	0.000*	0.000
Total irrigation (No.)	0.024	0.016
Off-farm employment (dummy)	-0.224*	0.132
Household size (adult equivalent)	0.031**	0.015
Farmer's age (years)	0.008	0.005
Farmers' education (years)	0.006	0.016
Vehari district[a]	0.013	0.205
Bahawalnagar district[a]	0.176	0.191
Bahawalpur district[a]	0.210	0.186
Constant	0.914*	0.515
$\chi 2$ (16)	175.57***	
Observations	525	

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

Table 4: Model specification tests

Likelihood ratio tests	Total hired labor days	Hired female labor days	Hired male labor days
Log-likelihood of Tobit regression	-1957.175	-1937.250	-1311.795
Log-likelihood of Probit regression	-141.548	-142.769	-255.343
Log-likelihood of Truncated regression	-1698.002	-1742.610	-1021.150
$\chi2$ (16)	235.249	103.744	70.605
p-value	0.000	0.000	0.000

Table 5: Determinants of labor demand (Double-hurdle model)

Variables	Total hired labor days		Hired female labor days		Hired male labor days	
	Decision to hire	Quantity to hire	Decision to hire	Quantity to hire	Decision to hire	Quantity to hire
Predicted Bt adoption (dummy)	1.308***	14.261***	1.234***	13.328***	0.990***	2.506
	(0.463)	(5.029)	(0.459)	(5.114)	(0.349)	(1.526)
Total area owned (acres)	0.019**	0.103*	0.019**	0.119*	0.002	0.012
	(0.009)	(0.062)	(0.009)	(0.061)	(0.005)	(0.020)
Cotton area (acres)	-0.006	0.210***	-0.005	0.144**	-0.005	0.095***
	(0.006)	(0.071)	(0.006)	(0.069)	(0.005)	(0.021)
Wage rate (Rs/day)	-0.007***	-0.139***	-0.007***	-0.159***	-0.003***	-0.002
	(0.001)	(0.012)	(0.001)	(0.014)	(0.001)	(0.003)
Price of fertilizer (Rs/kg)	-0.003	-0.036	-0.004	-0.030	-0.002	-0.006
	(0.005)	(0.057)	(0.005)	(0.057)	(0.004)	(0.018)
Price of insecticide (Rs/liter)	0.000	0.003	0.000	0.004	-0.000	-0.001
	(0.000)	(0.003)	(0.000)	(0.003)	(0.000)	(0.001)
Cotton price (Rs/maund)	0.000	-0.003	0.000	-0.003	0.000	-0.001
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.001)
Total irrigation (No.)	-0.003	-	-0.004	-	-0.030*	-
	(0.022)		(0.022)		(0.016)	
Crop length (days)	-	0.082***	-	0.065**	-	0.027***
		(0.030)		(0.030)		(0.009)
Off-farm employment (dummy)	0.393**	5.032**	0.408**	5.806***	0.005	0.591
	(0.181)	(2.019)	(0.181)	(2.046)	(0.137)	(0.625)
Household size (adult equivalent)	-0.010	-0.369	-0.008	-0.414*	0.001	-0.071
	(0.021)	(0.225)	(0.022)	(0.229)	(0.015)	(0.069)
Farmer's age (years)	0.009	-0.141*	0.010	-0.141	-0.004	-0.002
	(0.007)	(0.085)	(0.007)	(0.086)	(0.006)	(0.026)
Farmers' education (years)	0.003	0.121	0.003	0.098	0.002	0.040
	(0.022)	(0.231)	(0.022)	(0.233)	(0.016)	(0.073)
Vehari district[a]	0.635**	5.031	0.563**	3.302	0.577***	1.957**
	(0.286)	(3.131)	(0.282)	(3.179)	(0.209)	(0.989)
Bahawalnagar district[a]	0.799***	6.851**	0.801***	6.200**	0.771***	0.179
	(0.266)	(2.961)	(0.266)	(3.006)	(0.204)	(0.933)
Bahawalpur district[a]	0.607**	-2.052	0.618**	-2.822	0.526***	-0.117
	(0.254)	(2.941)	(0.253)	(2.993)	(0.190)	(0.928)
Constant	0.625	40.446***	0.617	42.252***	0.337	0.237
	(1.058)	(13.980)	(1.054)	(14.481)	(0.839)	4.044
Sigma		17.261***		16.465***		4.656***
		(0.755)		(0.787)		(0.267)
Wald $\chi2$ (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.

[a]The base district is Rahim Yar Khan.

Table 6: Marginal effects for double-hurdle model

Variables	Total hired labor days		Hired female labor days		Hired male labor days	
	Decision to hire	Quantity to hire	Decision to hire	Quantity to hire	Decision to hire	Quantity to hire
Predicted Bt adoption (dummy)	0.193***	10.505***	0.184***	8.658**	0.270***	1.650*
	(0.076)	(3.889)	(0.075)	(3.557)	(0.096)	(0.917)
Total area owned (acres)	0.003**	0.076	0.003*	0.077	0.001	0.008
	(0.002)	(0.048)	(0.002)	(0.051)	(0.002)	(0.017)
Cotton area (acres)	-0.001	0.155**	-0.001	0.094**	-0.001	0.063***
	(0.002)	(0.062)	(0.001)	(0.045)	(0.001)	(0.022)
Wage rate (Rs/day)	-0.001***	-0.103***	-0.001***	-0.103***	-0.001***	-0.002
	(0.000)	(0.009)	(0.000)	(0.008)	(0.000)	(0.003)
Price of fertilizer (Rs/kg)	-0.001	-0.027	-0.001	-0.019	-0.001	-0.004
	(0.001)	(0.043)	(0.001)	(0.034)	(0.001)	(0.012)
Price of insecticide (Rs/liter)	0.000	0.002	0.000	0.003*	-0.000	-0.001
	(0.000)	(0.003)	(0.000)	(0.002)	(0.000)	(0.001)
Cotton price (Rs/maund)	0.000	-0.002	0.000	-0.002	0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)
Total irrigation (No.)	-0.000	-	-0.001	-	-0.008*	-
	(0.004)		(0.003)		(0.005)	
Crop length (days)	-	0.060**	-	0.042**	-	0.018**
		(0.026)		(0.021)		(0.007)
Off-farm employment (dummy)	0.058*	3.707**	0.061**	3.771***	-0.001	0.389
	(0.031)	(1.568)	(0.026)	(1.305)	(0.043)	(0.394)
Household size (adult equivalent)	-0.002	-0.272*	-0.001	-0.269*	0.000	-0.047
	(0.003)	(0.148)	(0.003)	(0.142)	(0.004)	(0.034)
Farmer's age (years)	0.001	-0.104*	0.001	-0.092	-0.001	-0.001
	(0.001)	(0.056)	(0.001)	(0.058)	(0.002)	(0.016)
Farmers' education (years)	0.000	0.089	0.000	0.064	0.001	0.027
	(0.004)	(0.173)	(0.003)	(0.132)	(0.006)	(0.047)
Vehari district[a]	0.094**	13.706*	0.084**	2.145	0.157***	1.289**
	(0.043)	(2.040)	(0.043)	(1.812)	(0.049)	(0.659)
Bahawalnagar district[a]	0.118**	5.047**	0.119***	4.028**	0.210***	0.118
	(0.047)	(2.273)	(0.044)	(1.994)	(0.065)	(0.641)
Bahawalpur district[a]	0.090**	-1.512	0.092**	-1.833	0.143***	-0.077
	(0.042)	(2.089)	(0.044)	(1.654)	(0.056)	(0.573)
Observations	525		525		525	

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

Note: Coefficient estimates are shown with bootstrapped standard errors in parentheses.

[a]The base district is Rahim Yar Khan.

Table 7: Unconditional marginal effects of Bt cotton on labor demand

	Unconditional expected demand for labor days in non-Bt cotton	Unconditional average marginal effects	% increase
Total hired labor days	25	13.713*** (3.699)	55
Hired female labor days	21	11.056*** (3.451)	53
Hired male labor days	5	2.890*** (0.797)	58

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