Technical Efficiency of *Bacillus thuringiensis* Cotton in China: Results from Household Surveys

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I. Introduction

As of 2016, approximately 18 million farmers across 26 countries planted *Bacillus thuringiensis* (Bt) cotton. In fact, the adoption rate for Bt cotton in India, China, and the United States—the three largest cotton producers—is more than 90% (James 2017). Studies have used household data to show that the short-term impact of Bt cotton (i.e., reduced pesticide use and labor input plus increased yield) is significant and universal (Pray et al. 2001; Huang, Rozelle, and Pray 2002; Huang et al. 2003; Qaim 2003; Qaim and Zilberman 2003). In addition, recent studies have emphasized that the benefits generated from Bt cotton are sustainable over time (Kathage and Qaim 2012; Qiao 2015; Qiao, Huang, and Zhang 2016) and that these significant benefits have resulted in its rapid spread worldwide.

However, few studies have examined the technical efficiency (TE) of Bt cotton adoption in the long run. The TE of Bt cotton was first estimated in South Africa by Thirtle et al. (2003). A decade later, Abedullah, Kouser, and Qaim (2015) revisited the subject by analyzing panel household data collected in Pakistan, while Veettil, Krishna, and Qaim (2017) did the same in India. They showed that Bt farms are technically more efficient than non-Bt farms. This result, however, is inconsistent with prevailing expectations because Bt technology is new to farmers who have planted non-Bt cotton for decades. Thus, it seems imperative to extend investigations on factors determining the TE of Bt technology.

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Numerous factors affect the TE of a new technology, of which the diffusion of the new technology, for example, is key, particularly in the early stages (Klenow and Rodríguez-Clare 1997; Comin and Hobijn 2010). Previous studies have shown that broad and rapid diffusion patterns can enhance the impact of a technology (Feder, Just, and Zilberman 1985; Garicano and Rossi-Hansberg 2015). Similarly, an individual's experience and social networks contribute to the TE dynamics of a new technology (Umetsu, Lekprichakul, and Chakravorty 2003; Genius et al. 2014; Barham et al. 2015). However, are these studies' findings consistent with the dynamics of Bt cotton's TE? To answer this question, it is also important to identify major factors determining the TE of Bt cotton.

This study aims to estimate the TE of Bt cotton and document its dynamics in the long run and to identify the major factors affecting the TE of Bt cotton and quantitatively measure their effects. Importantly, it contributes to the literature by empirically analyzing the TE of Bt cotton using seven waves of household survey data collected in rural China between 1999 and 2012. The results reveal that although the productivity of Bt technology is significantly higher than that of non-Bt technology, the TE of Bt cotton is lower than that of non-Bt cotton in China because the former has been newly introduced to farmers. This finding differs from those of previous studies based in other countries (Thirtle et al. 2003; Abedullah, Kouser, and Qaim 2015; Veettil, Krishna, and Qaim 2017). Nevertheless, we find that the TE of Bt cotton has increased over time in China, approaching that of non-Bt cotton. Further, farmers' planting experiences and the diffusion of the new technology within their communities improve the TE of Bt cotton in the long run.

The remainder of this paper is organized as follows. Section II presents the seven waves of household survey panel data collected in China's major cotton-producing regions. Section III discusses the dynamics of the econometric model developed to estimate the TE of Bt cotton. Section IV sets up the econometric models to identify and estimate the major determinants and then provides the estimation results. Section V concludes.

II. Data Collection

This study significantly benefited from the unique household panel data collected in China. The data set was compiled from the seven waves of field surveys in 1999–2001, 2004, 2006–7, and 2012. Because Bt cotton was first commercialized in 1997 in China, it had already been cultivated for 15 years when we conducted the final round of field surveys in 2012. To the best of our knowledge, the period of the data collection, using field surveys with a focus on Bt cotton, is the longest among surveys worldwide.

TABLE 1

COMPARISON OF YIELD AND INPUTS OF BT AND NON-BT COTTON PLOTS

	Bt	Non-Bt
Number of observations	3,709	185
Number of households	493	69
Seed cotton yield (kg/ha)	3,132.70	2,185.54
Labor use (days/ha)	350.33	450.50
Pesticide cost (yuan/ha)	547.61	936.18
Fertilizer cost (yuan/ha)	1,690.68	1,092.36
Seed cost (yuan/ha)	499.19	152.75
Plot size (ha)	.22	.24
Age of household head (years)	48.02	44.77
Schooling of household head (years)	7.14	7.09
Cadre dummies (yes = 1)	.35	.04
Share of time on cotton	14.30	20.97
Training dummy (yes = 1)	.35	.09
Share of Bt sown area in a village	96.20	58.81
Share of Bt plots in a village	.94	.76
Distance to county headquarters (km)	18.19	21.04

Source. Authors' survey.
Note. Bt = *Bacillus thuringiensis.*

The field surveys were conducted by the Center for Chinese Agricultural Policy (CCAP) of the Chinese Academy of Agricultural Sciences.[1] Data were collected from 3,894 cotton plots of 493 households in China's four major cotton-producing provinces: Henan, Shandong, Hebei, and Anhui.[2] According to the National Bureau of Statistics of China (2013), the four provinces accounted for 1.83 million hectares of sown area (or 39% of the national total) at the time of the final round of field surveys in 2012. Pray et al. (2001), Huang et al. (2003), Liu and Huang (2013), and Qiao, Huang, and Zhang (2016) discuss further details of the sample selection. Table 1 presents the basic characteristics of the major variables used in this study.

During all seven waves, farmers were asked to provide detailed information about their households, each household member, and cotton production. A survey questionnaire was designed to collect socioeconomic information and included several blocks. The first section addressed and recorded basic household characteristics, such as farm size, labor endowments, and the year in which Bt cotton was first planted. The second section collected demographic information on each household member (e.g., age, education, share of time spent on cotton production, and participation in agricultural technology training programs).

[1] The CCAP was relocated to Peking University in 2015.

[2] Households and plots that were revisited are each counted as one observation. Shandong, Hebei, Anhui, and Henan are the second-, third-, fifth-, and sixth-largest cotton-producing provinces in China (National Bureau of Statistics of China 2013).

Our questionnaire also included a detailed section on cotton production in each cotton plot of the sampled households. Even though most of the sampled farmers planted only half a hectare of cotton or less, they generally had more than one cotton plot.[3] For each plot, we recorded detailed information on cotton yield and all inputs, such as seeds (e.g., whether they were of Bt variety and cost), fertilizer, and labor.

III. Technical Efficiency of Bt Cotton in the Long Run

We use the following stochastic frontier production function to obtain the TE value:

$$\ln \text{Yield}_{ijt} = \alpha_0 + \sum_{k=1}^{k=5} \alpha_k \ln X_{kijt} + \frac{1}{2}\sum_{k=1}^{k=5}\sum_{l=1}^{l=5} \alpha_{kl} \ln X_{kijt} \ln X_{lijt} + \alpha_6 \text{Year\_dummy} + \sum_{i}^{N-1} \text{ID}_i + v_{ijt} - u_{ijt}, \tag{1}$$

where Yield is cotton yield; X is a vector of input variables that includes four input variables (fertilizer, labor, pesticide, and seed) and one parcel characteristics variable (area). The input variable fertilizer denotes chemical fertilizer cost; labor is total labor input; pesticide is total pesticide cost; and seed is seed cost per hectare of a cotton field. We added farm size (area) to account for the impact of economies of scale. All values are presented in their natural logarithmic forms. In addition, we incorporated six 1-year dummies (Year_dummy) for 2000, 2001, 2004, 2006, 2007, and 2012 (using 1999 as the base year), considering that the impact of various factors (e.g., rainfall and temperature) on cotton yield differs by year. Subscript i is the ith household, j is the jth cotton plot, t is tth year, v is the error term, and u denotes TE.[4]

Taking advantage of the panel data, we added individual dummies (IDs) to capture the fixed effects of individual characteristics. In other words, we added these dummies to account for factors that are consistent in the long run for each individual. In doing so, we developed an individual fixed-effects model. Consequently, farmers with only one cotton plot were omitted.[5]

[3] The average household in our study area had approximately five plots of land with a total area of 0.73 hectares, of which 3.4 plots were allocated to cotton production.

[4] Because our samples are located in the North China Plain, where all lands were irrigated during the first survey in 1999, we excluded the irrigation question from our survey.

[5] We excluded 125 Bt plots and 104 non-Bt plots, both of which account for 5.55% of the total sample. Further investigations revealed that the excluded plots had lower yields and higher (or similar) inputs than those used in the analysis. In other words, the TEs applied in this study may be overestimated. Nevertheless, the log generalized likelihood ratio tests show that the fixed-effects model is appropriate for both Bt cotton plots (with a test statistic of 101.90) and non-Bt cotton plots

Scholars have debated whether a single production frontier is appropriate to analyze both Bt and non-Bt cotton plots. Some studies account for differences in technologies in efficiency estimation and estimate equations separately, whereas others use a single production frontier for all technologies (Battese, Rao, and O'Donnell 2004; Rao, Brümmer, and Qaim 2012; Abedullah, Kouser, and Qaim 2015). The production practices for Bt cotton (e.g., pesticide use) vary from those for non-Bt cotton, owing to the differences between genetically modified and traditional technologies. In other words, if Bt cotton adopters apply traditional production methods, the TE of Bt cotton will be underestimated. Therefore, this study applied two separate production frontiers for Bt and non-Bt cotton.[6]

Following Yang et al. (2016), we normalized all output and input variables for the production function by their respective sample means prior to the estimation. We then performed generalized likelihood ratio tests to determine whether the log-linear Cobb-Douglas model or translog model, including interaction and square terms that allow for interactions and nonlinearities in the data, is appropriate. The results showed that the translog model is appropriate for Bt cotton plots, whereas the Cobb-Douglas model is adequate for non-Bt cotton plots.

Table 2 presents the estimation results. In general, most of the regression results are in line with our expectation.[7] In addition, the table shows that most of the estimated coefficients of the input variables are of the expected signs and statistically significant. Following the estimation of the stochastic production function, we calculated the TE of Bt and non-Bt cotton.

Drawing on Kathage and Qaim (2012) and Qiao, Huang, and Zhang (2016), we combined observations from three consecutive rounds to compare the mean value between Bt and non-Bt cotton plots. In doing so, we derived data for three periods: 1999–2001 (early adoption period), 2004–7 (midadoption period), and 2012 (late adoption period).

(with a test statistic of 2,007.52). That is, the estimation bias could be severe if the impacts of these individual-related and time-invariant factors are omitted. Thus, we excluded households with only one Bt plot and/or one non-Bt plot and estimated the fixed-effects models accordingly.

[6] We also adopted a single production frontier for both Bt and non-Bt samples but found no clear trend for the TE of both Bt and non-Bt plots. In addition, the TE of non-Bt cotton is neither consistently higher nor lower than that of Bt cotton. This result is inconsistent with our expectation and the theory of new technology diffusion.

[7] The estimated elasticities of inputs are small for two reasons. First, instead of using a total production function that includes planting area as an independent variable, this study applied the yield (i.e., output per unit of land) function. Second, high-level use of major inputs, including pesticides and fertilizers, is a common phenomenon in China's crop production, and thus the sum of the estimated elasticities for inputs is low. Similarly, Huang et al. (2002, 2005) found low yield elasticities for inputs per unit land.

TABLE 2

ESTIMATION RESULTS OF STOCHASTIC FRONTIER PRODUCTION FUNCTION

	Log of Cotton Yield (kg/ha)	
	Bt	Non-Bt
Log of labor	.0254	−.0535
	(2.10)**	(−.55)
Log of seed	.0183	−.0352
	(7.72)***	(−1.26)
Log of pesticide	.0382	.0035
	(4.72)***	(.08)
Log of fertilizer	.0339	.1527
	(3.52)***	(2.29)**
Log of plot size	.0098	−.0140
	(2.77)***	(−.39)
Log of labor^2	.0197	
	(3.23)***	
Log of seed cost^2	.0022	
	(1.58)	
Log of pesticide^2	−.0004	
	(−.10)	
Log of fertilizer^2	.0029	
	(1.84)*	
Log of land size^2	.0018	
	(.55)	
Log of labor × labor of seed	−.0023	
	(−.88)	
Log of labor × labor of pesticide	−.0469	
	(−4.01)***	
Log of labor × labor of fertilizer	−.0033	
	(−1.04)	
Log of labor × labor of plot size	.0142	
	(2.01)**	
Log of seed × labor of pesticide	.0137	
	(2.58)***	
Log of seed × labor of fertilizer	−.0086	
	(−3.62)***	
Log of seed × labor of plot size	.0018	
	(.39)	
Log of pesticide × labor of fertilizer	.0075	
	(1.88)*	
Log of pesticide × labor of plot size	−.0190	
	(−3.59)***	
Log of fertilizer × labor of plot size	.0056	
	(.99)	
Constant	7.9569	6.9335
	(289.26)***	(14.76)***
Number of observations	3,709	185

Note. Values in parentheses are *z*-statistics. Bt = *Bacillus thuringiensis.*
* $p < .10$.
** $p < .05$.
*** $p < .01$.

TABLE 3
COMPARISON OF THE TECHNICAL EFFICIENCY OF HOUSEHOLDS WITH A MINIMUM OF EITHER TWO BT PLOTS OR TWO NON-BT PLOTS

	Households with at Least Two Bt Cotton Plots		Households with at Least Two Non-Bt Cotton Plots	
	Technical Efficiency (1)	t-Value (2)	Technical Efficiency (3)	t-Value (4)
1999–2001	.7988		.9971	
2004–7	.8038	−.76[a]	.9971	.03[a]
2012	.8417	−4.81[a],***		

Source. Authors' survey.
Note. Bt = *Bacillus thuringiensis.*
[a] Compared with that in 1999–2001.
*** $p < .01$.

As shown in table 3, the TE of non-Bt cotton is higher than that of Bt cotton. At our sample sites, cotton is considered to be a major crop, and farmers have been planting (non-Bt) cotton for decades. Thus, the high TE value for non-Bt cotton was expected. However, Bt cotton was commercialized in 1997 in China. Even though the requirements do not significantly differ between the planting of Bt and non-Bt cotton, farmers have taken a while to accept and become familiar with the technology. Consistent with our expectation, the TE of non-Bt cotton was higher than that of Bt cotton in both the early and mid-adoption periods.[8]

Interestingly, table 3 also shows that the TE of Bt cotton has consistently increased over time, that is, from the early to middle periods and then to the late adoption period. A further analysis revealed a statistically significant increase in the TE of Bt cotton in the long run. The TE of Bt cotton increased from less than 0.80 in the early period to 0.84 in the late period (table 3, col. 1). The difference between the early and late periods is statistically significant (col. 2). However, the difference in TE values of non-Bt cotton between the early and middle periods is statistically insignificant (cols. 3 and 4), indicating that the TE of the non-Bt value remained consistent over time. This increasing trend over time alludes to the possibility of Bt cotton adopters improving their mastery of the new technology (i.e., Bt cotton) in the later years—thus increasing its TE—by learning from their own, neighbors', or others' planting experiences.

Figure 1, first, compares the productivity of Bt cotton with that of non-Bt cotton in a more intuitive manner. By estimating the frontier production function,

[8] The data include only three non-Bt cotton plots that belong to three households for 2012. Because none of the three households had been visited in the previous years, data for non-Bt cotton's TEs are unavailable for 2012.

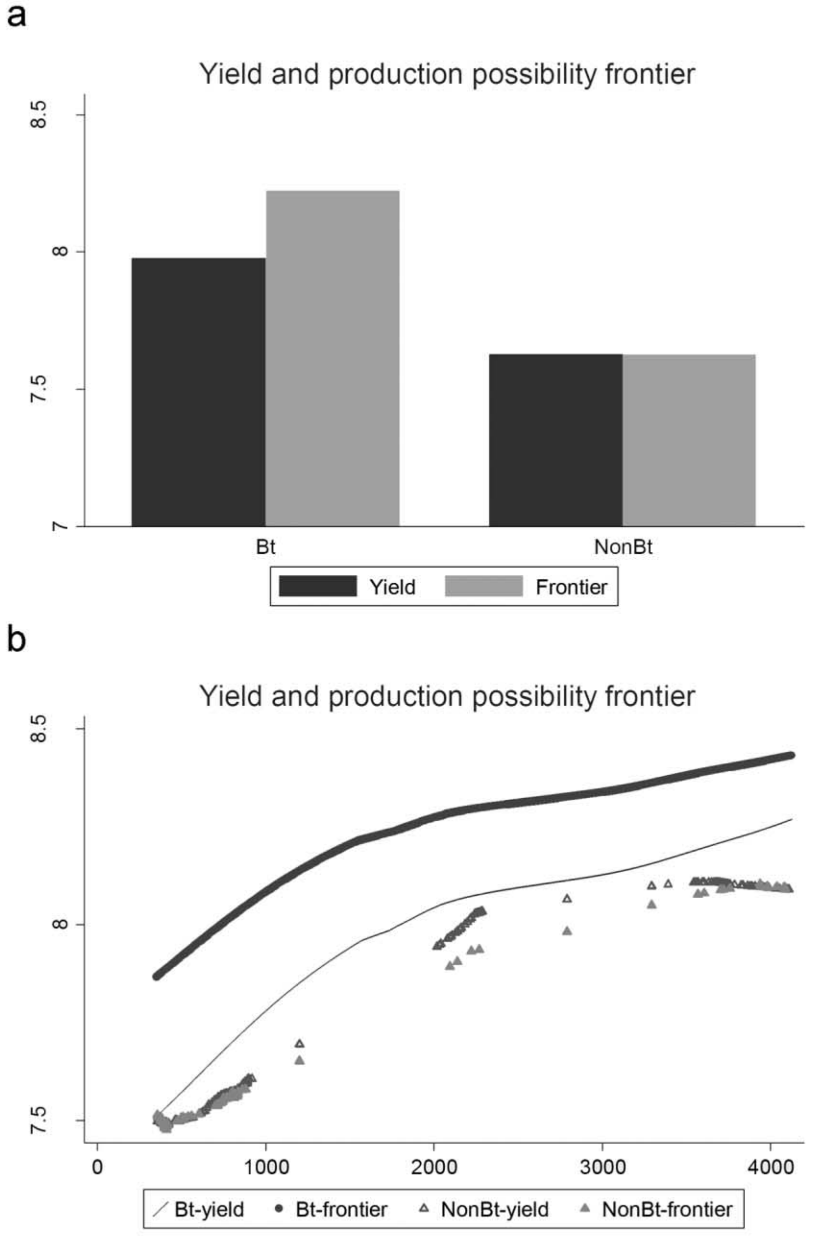

Figure 1. Technical efficiency of *Bacillus thuringiensis* (Bt) and non-Bt cotton. *a*, Average values of the real yield and smoothed production possibility frontier of Bt and non-Bt cotton. *b*, The real yield and smoothed production possibility frontier of Bt and non-Bt cotton. A color version of this figure is available online.

we can predict the smoothed production possibility frontier. The higher the production possibility frontier, the greater is the possible cotton yield. As shown in panel *a*, both the average values of the smoothed production possibility frontier and the real yield of Bt cotton were higher than those of non-Bt cotton, which is consistent with our expectations.

Second, figure 1 compares the TE of Bt cotton with that of non-Bt cotton. The magnitude of TE is measured by the difference between the smoothed production possibility frontier and smoothed real cotton yield; that is, a larger difference denotes a smaller TE value. As shown in panel *b*, the difference for Bt cotton was larger than that for non-Bt cotton, indicating that the TE of Bt cotton was less than that of non-Bt cotton. However, the estimation of non-Bt cotton's TE and the comparison between Bt and non-Bt should be interpreted with caution given the small sample size for non-Bt cotton.

Finally, figure 1 also presents the dynamics of TE for both Bt and non-Bt cotton. Interestingly, panel *b* in figure 1 shows that the TE of Bt cotton increased from the early period to the later period (i.e., the difference between real production and the production possibility frontier decreases). In contrast, the TE of non-Bt cotton seemed to remain constant. These results are consistent with those presented in table 3.

In figure 2, we attempted to link the TE of Bt cotton to its key determinants. First, we related the TE of Bt cotton to its diffusion. We used two variables to denote the spread of Bt cotton: share of sown area for Bt cotton and that of other farmers' Bt cotton plots in a village. As shown in panel *a*, the fitted relationship between the share of sown area for Bt cotton and the TE of Bt cotton is positive: in other words, as the share of the Bt cotton area expanded, its TE also increased. We obtain a similar result if we use the share of Bt cotton plots to denote the diffusion of Bt cotton, as shown in panel *b* of figure 2.

Second, we related the TE of Bt cotton to each farmer's planting experience. Accordingly, we divided all samples into three groups: households with 0–4 years of experience (29% of the sample), those with 5–9 years of experience (47%), and those with at least 10 years of experience (23%). As shown in panel *c* of figure 2, farmers with greater experience in planting were more likely to report higher TE for Bt cotton. In other words, the TE of Bt cotton is positively related with farmers' planting experiences.

IV. Determinants of Bt Cotton's TE

In addition to analyzing the descriptive statistics, in this section we develop a series of econometric models to isolate the impact of Bt cotton diffusion and farmers' planting experiences on the TE of Bt cotton. We do so because the

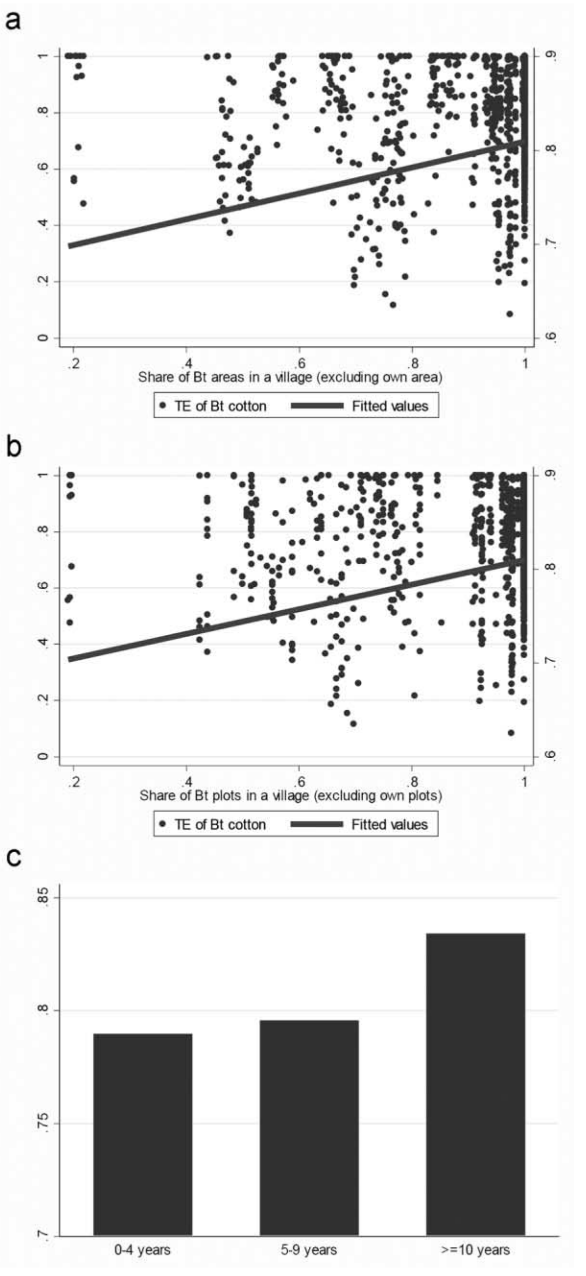

Figure 2. Relationship between the technical efficiency (TE) of *Bacillus thuringiensis* (Bt) cotton and its important determinants. *a*, Relationship between the TE of Bt cotton and share of Bt area in a village (excluding own area). *b*, Relationship between the TE of Bt cotton and share of Bt plots in a village (excluding own plots). *c*, Relationship between the TE of Bt cotton and farmer's planting experience. A color version of this figure is available online.

descriptive results in Section III may be misleading because they do not exclude the effects of other factors that simultaneously affect the TE of Bt cotton.

According to Genius et al. (2014), the TE of a new technology is affected by extension services, social networks, and a farmer's planting experience (i.e., learning by doing). Hence, the econometric model for Bt cotton's TE can be written as follows:

$$\begin{aligned} \mathrm{TE}_{it} = {} & \beta_0 + \beta_1 \mathrm{Bt\_diffusion}_{it} + \beta_2 \times \mathrm{Experience}_{it} \\ & + \beta_3 \times \mathrm{Individual}_{it} + \beta_4 \times \mathrm{Household}_{it} \\ & + \beta_5 \times \mathrm{Year\_dummy}_t + \sum_{t}^{N-1} \mathrm{ID}_i + \varepsilon_{it} \end{aligned} \tag{2}$$

where dependent variable TE denotes the TE of Bt cotton, which is calculated on the basis of the estimation for equation (1). The average value is used for households with more than one Bt or non-Bt cotton plot per year.

We used Bt_diffusion to capture the impact of Bt cotton diffusion on TE. As discussed earlier, this variable is specified in one of two ways (used in separate models): share of Bt plots and that of the Bt area sown by other farmers in a village. To exclude possible endogeneity, the original household's Bt cotton was excluded when calculating the share of Bt cotton plots and sown areas in a village.

The Experience variable is the number of years that farmers have planted Bt cotton. This variable is employed to capture the impact of a farmer's planting experience on the accumulation of knowledge, that is, the effect on the TE of Bt cotton. Learning by doing is a more important measure of farmers' increase in knowledge about a new technology. We expect the TE of Bt cotton to increase with a rise in a farmer's experience in planting Bt cotton.

The Individual variable is a vector of household heads' characteristics that may account for some of the heterogeneity affecting the TE of Bt cotton. A more important individual variable affecting Bt cotton's TE is a training dummy variable (Training_dummy). In China, a local agricultural extension station generally conducts a training course on new technology and farm management for major crops, which in the case of our studied areas is cotton. This dummy variable equals 1 if the farmer participated in any training course and 0 otherwise. In addition to this variable, we included several other variables to capture the impact of household heads, such as age, square of age, and education. We also added the proportion of time spent on cotton (Time_on_cotton) to measure its importance in the famers' agricultural production. We expect the TE of Bt cotton to show a more rapid increase if this share is high (i.e., farmers pay more attention if cotton is their major agricultural income source), and vice versa.

Similar to the Individual variable, Household is a vector of household characteristics that may account for some heterogeneity across households affecting the TE of Bt cotton. We used farm size (Farm_size) to estimate economies of scale. To measure the impact of a local information source, we added distance to county headquarters as a variable to measure the impact of agricultural extension stations, which are generally located at the county headquarters.

As discussed in equation (1), we added six 1-year dummies to consider the effect of factors that differ by year. Taking advantage of the panel data, we added IDs to capture the fixed effects of individual characteristics. However, after adding IDs, time-invariant variables (e.g., age, education, and distance to county headquarter) were excluded. As a result, the fixed-effects model can be written as

$$\begin{aligned}\Delta \text{TE}_{it} = {} & \gamma_0 + \gamma_1 \times \Delta\text{Bt\_diffusion}_{it} + \gamma_2 \times \Delta\text{Experience}_{it} \\ & + \gamma_3 \times \Delta\text{Training\_dummy}_{it} + \gamma_4 \times \Delta\text{Farm\_size} \\ & + \gamma_5 \times \Delta\text{Time\_on\_cotton}_{it} + \varsigma_{it}.\end{aligned} \tag{3}$$

In equation (3), we added the Delta symbol to denote the change in a variable from its mean. The variables were defined similarly to those used earlier. The average experience of all farmers in a village, except for this household, was highly correlated with the share of Bt cotton plots (or areas) and the farmers' experience. Thus, this variable was excluded from the estimation. For similar reasons, we omitted another variable, the share of other farmers who participated in training programs in the village. As discussed in related studies (e.g., Genius et al. 2014), the collinearity of such variables is a rather common phenomenon.[9]

To consider the nonlinear relationship between the TE of Bt cotton and a farmer's experience (Experience), we estimated an alternative scenario. Instead of adding the Experience variable, we incorporated the square root of the Experience variable. By doing so, we were able to estimate a concave relationship between a farmer's experience in planting Bt cotton and its TE; that is, TE rises, albeit at a decreasing pace, with an increase in experience.

[9] Drawing on Genius et al. (2014), we also attempted to employ a factor analysis to resolve the collinearity problem; however, the major components have no obvious economic meaning.

TABLE 4

ESTIMATION RESULTS OF INDIVIDUAL FIXED-EFFECTS MODELS TO ESTIMATE DETERMINANTS OF THE TECHNICAL EFFICIENCY OF BT COTTON

	Benchmark Scenario		Alternative Scenario	
	Bt Area	Bt Plots	Bt Area	Bt Plots
Social network:				
Share of BT cotton area in the village (excluding own area)	.0836 (1.85)*		.0750 (1.62)	
Share of Bt cotton plots in the village (excluding own plots)		.0752 (1.74)*		.0662 (1.49)
Learning by doing:				
Experience of planting Bt (years)	.0037 (2.69)***	.0037 (2.71)***		
Square root of experience of planting Bt			.0174 (2.64)***	.0176 (2.65)***
Extension services:				
Agricultural training dummy (yes = 1)	.0227 (1.92)*	.0228 (1.92)*	.0252 (2.18)**	.0253 (2.19)**
Others:				
Percentage of time spent on cotton (%)	−.0010 (−1.14)	−.0010 (−1.20)	−.0011 (−1.28)	−.0011 (−1.34)
Farm size (ha)	−.0044 (−.28)	−.0043 (−.27)	−.0050 (−.32)	−.0049 (−.31)
Constant	.7056 (16.25)***	.7143 (17.37)***	.6976 (16.28)***	.7064 (17.40)***
Observations	1,660	1,660	1,660	1,660
R^2	.025	.025	.025	.024
Number of households	493	493	493	493

Source. Authors' survey.
Note. Values in parentheses are *t*-statistics. Bt = *Bacillus thuringiensis.*
* $p < .10$.
** $p < .05$.
*** $p < .01$.

Table 4 presents the estimation results for equation (3).[10] Most of the regression results are consistent with those of the descriptive analysis (Sec. III). In addition, a majority of the estimated coefficients for the control variables are of the expected signs and statistically significant. Table 4 shows that both the diffusion of Bt cotton and farmers' experience significantly affect Bt cotton's TE. Hereinafter, we discuss their effects.

First, the estimation results show that the diffusion of Bt cotton significantly affects the TE of Bt cotton. More specifically, as the technology diffuses, farmers

[10] In general, a one-step procedure is preferred to estimate TE and its determinants; however, the method does not allow for a fixed-effects estimation owing to the nonlinear nature of the model. As discussed in n. 5, it is appropriate to use a fixed-effects model to estimate the determinants of an efficiency equation to address unobserved heterogeneity. Therefore, we adopted the two-step procedure and separately estimated the frontier production function and determinants of efficiency.

are likely to accumulate more knowledge about this new technology, and as a result, the TE of Bt cotton is expected to increase. Table 4 also shows that the estimated coefficients for both the share of area sown with Bt cotton and the share of Bt cotton plots are positive and statistically significant. In other words, the TE of the new technology rises with an increase in Bt cotton diffusion.

Second, farmers' planting experience positively affects the TE of Bt cotton. As shown in table 4, the estimated coefficient for farmers' experience is significantly positive, indicating that farmers' experience is a more important factor affecting the TE of Bt cotton. To elaborate, the longer the duration of the farmers' experience in planting Bt cotton, the greater is the TE of the new technology.

Interestingly, we found that the impact of farmers' planting experience on TE increases with a decreasing pace. This exemplified a farmer's real learning curve for a new technology. Further, the estimated coefficient for the square root of experience is positive and statically significant (table 4). In other words, the estimation results show that the TE of Bt cotton rises with an increase in farmers' experience; however, this increase occurs at a decreasing pace.

Finally, the results show that participation in an agricultural technology training program positively affects the TE of Bt cotton. As shown in table 4, the estimated coefficient for the participation dummy variable is positive and statistically significant, indicating that farmers who participated in training programs reported higher TEs than those who did not. Because Bt is a new technology, training programs better equip farmers in mastering the technology and, as a result, the TE of Bt cotton is expected to increase.

V. Conclusions and Policy Implications

Although studies have well documented the economic benefits of planting Bt cotton (Kathage and Qaim 2012; Qiao 2015; Qiao, Huang, and Zhang 2016), few have addressed the TE of Bt cotton adoption and its dynamics. Thus, using China as a case study, we first attempted to show that the productivity of Bt cotton is higher. Then we showed that although the TE of Bt cotton is initially lower, it gradually approaches that of non-Bt cotton over a path of Bt cotton diffusion. These results differ from those of similar previous studies based in other countries, although they are consistent with technology diffusion theory; that is, the TE of Bt cotton increases over time. Second, we highlighted that the increase in TE is influenced by not only an adopter's planting experience but also by the diffusion of the new technology.

The results of this study have important policy implications. First, they confirm that Bt cotton can significantly improve the productivity of cotton production. However, many developing countries are yet to adopt this technology nearly 20 years after the first adoptions worldwide. Moreover, in recent years, the public and media in numerous developing countries have reported growing negative attitudes toward the new technology (Kathage and Qaim 2012; Qiao 2015). This phenomenon has affected not only consumer attitude but also investments in and the commercialization of genetically modified crops. From the perspectives of productivity and efficiency, we showed that Bt technology generates higher productivity in comparison to traditional technologies. Undoubtedly, our results contribute to a wider public debate in China as well as other countries and, thus, to the development of Bt technology worldwide.

Second, there is significant room to further increase the productivity of a new technology such as Bt cotton by improving its TE in its initial years of diffusion. Our study shows that expanding Bt cotton diffusion and increasing the number of farmer adoptions within a village can help all farmers raise their TE, which is also known as the social network impact. Moreover, the capacity of the seed industry to generate sufficient seeds and make them available for more farmers in the initial stage of technology diffusion is critical to increasing the TE of new technology for all farmers.

Third, our finding that learning by doing positively affects the TE of Bt cotton suggests that providing farmers with more information on the appropriate uses of new technology will help accelerate learning. A potential way to do so is through village-based field demonstration plots or centers for farmers to visit and learn about new agricultural technology.

Finally, a better extension service could help increase farmers' proximity to the frontier of new technology. Although this is not a novel finding, extension services in China and many developing countries are faced with considerable challenges. Thus, provision of better services to the multitude of small-scale farmers and investments and reforms in agricultural extension are proving critical to China and other developing countries (Hu et al. 2012; Babu et al. 2015).

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