The role of social networks in an imperfect market for agricultural technology products: Evidence on Bt cotton adoption in Pakistan

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Abstract

Social networks play an important role in generating learning externalities that can drive the diffusion of innovative, and potentially poverty-reducing, technologies. This is particularly the case in developing countries where rural education, extension, and agricultural information services are underprovided. The recent introduction of genetically modified insect-resistant Bt (*Bacillus thuringiensis*) cotton in Pakistan represents an example where imperfect markets, weak extension services, and information asymmetries limit the ability of farmers to make informed decisions on how to take best advantage of the technology. This study explores the role of social networks and learning externalities in the adoption of Bt cotton in Pakistan. We model how information from social network members influences farmers' adoption decisions, controlling for farmers' characteristics, cotton growing conditions, and other possible information sources. We apply our model to a representative sample of 728 cotton-growing households randomly selected in 2012-13 from 52 villages across Punjab and Sindh. We also assess the role of input dealers, progressive farmers, public extension agents, and farmers' individual characteristics in the uptake of the technology. Results suggest that communication within social networks helps disseminate information about Bt cotton cultivation and has encouraged its adoption.

Key words: social networks, Bt cotton, Pakistan, technology adoption

1. Introduction

The adoption of productivity- and profit-enhancing agricultural technologies has been an important driver of economic growth and poverty reduction in many developing countries (Self and Garbowski 2007). Although publicly financed extension services are commonly viewed as key providers of information on such technologies to small-scale, resource-poor farmers, the limitations of their reach and capacity are also recognized (Rivera, Qamar, and Crowder 2001). For this reason, the literature on agriculture technology adoption frequently explores the role played by informal social networks in augmenting extension services and, more generally, driving adoption among smallholders. These externalities are particularly important where public extension services or markets for technology products are insufficient means of transmitting information due to geographic remoteness, poor market infrastructure, limited purchasing power or risk aversion among farmers (Anderson and Feder 2007; Birner et al. 2009; Feder et al. 2010). A rich literature dating back to South Asia's "Green Revolution" explores the correlations between farmers' adoption decisions and those of their neighbors (Besley and Case 1994; Foster and Rosenzweig 1995), while more recent literature explores causal pathways and identification in greater details (Bandiera and Rasul 2006; Conley and Udry 2010; McNiven and Gilligan 2012; Magnan et al. 2013; Maertens 2014) and find that farmers' adoption decisions are driven more by learning than, say, mimicry or attributes shared with other network members.

The recent introduction of genetically modified insect-resistant Bt (*Bacillus thuringiensis*) cotton in Pakistan represents an interesting example where poor market regulation, weak extension services, and inefficient information dissemination combine to limit the ability of farmers to make rational, informed adoption decisions. Although Bt cotton was first commercialized in the United States in 1996 and has spread quickly across both developed and developing countries, the technology found its way into Pakistan only through unregulated channels in the early 2000s. Earlier literature suggests that Bt technology was already widespread throughout Pakistan's cotton-growing areas by the time the Government of Pakistan first officially approved and released nine Bt varieties in 2010 and another eight Bt varieties in 2012 (Hayee 2005; Ali and Abdulai 2010; Shafiq-ur-Rehman 2009; Nazli et al. 2012). Most of these approvals were valid for just one or two years and were not renewed in 2013, therefore, there was a large number of official varieties pending renewal of their approval status at the time of our survey in 2013. Furthermore, Pakistan's Bt cotton seed market carries technology products that are thought to be of low quality without appropriate packaging required to convey information about the product and its usage. The toxic Bt protein that is responsible for protecting cotton from *Lepidopteran* pests has been found to be below critical levels in samples from markets and farmers' fields in Pakistan (Ali et al. 2010, 2012). With an unregulated market and a weak public agriculture extension system, farmers are compelled to rely on information from seed dealers or seed company sales representatives, whose information may be biased toward their own products. If not, farmers have to rely on information from neighbors, friends, relatives, progressive farmers, and other informal social networks, whose information may be applicable to their particular local context and not necessarily transferable (Munshi 2004).

This study explores the role of social networks in farmers' adoption decisions in the context of Pakistan's Bt cotton seed market. To our knowledge, none of the previous studies related to this topic have investigated the role of social networks and social learning in the adoption, despite its potential importance for farmers in imperfect markets. As Maertens and Barrett (2012) outlined, there are a few challenges in identifying and measuring the effects of social networks. The first challenge is to define the social network, that is, who is included in this social network? What kind of links qualify a neighbor to be in a farmer's network? Earlier literature defines memberships, often being in the same village, caste, or certain associations, as social networks (Foster and Rosenzweig 1995; Munshi 2004). However, in such networks members may not necessarily communicate with each other. The random matching within sample technique, which matches a farmer with randomly drawn individuals from the sample, has been proven by Santos and Barrett (2008) to be a better way to capture the nature of networks and has been adopted by many later studies (Conley and Udry 2010; Maertens 2010; Santos and Barrett 2010).

Another challenge lies in solving the reflection problem (Manski 1993) which requires the researcher to isolate the endogenous social network effect from the effect of exogenous shocks on farmers' technology adoption decisions. Farmers making the same adoption choice as their neighbors may simply be because they share the same characteristics and conditions with their neighbors and not because they learn about the technology from these neighbors. To disentangle these two effects, some studies take advantage of the nature of panel data to difference out the unobserved fixed exogenous effect that could contribute to farmers' decision making (Conley and Udry 2010; Foster and Rosenzweig 1995; Maertens 2010; Mushi 2004) or use randomized control trials (RCTs) to identify the network effects by comparing adoption choices between the control group and the treatment group (Duflo et al. 2007; Duflo and Saez 2003; Magnan et al. 2013). Both approaches require either panel data or special designs from inception, which may not be feasible for many studies. Besides these two approaches, Manski (1993) suggests that "subjective data" such as "the statements people make about why they behave as they do" could also help identify the network effect as opposed to relying solely on observational data. Conley and Udry (2010) and Maertens and Barrett (2012), among others, collect more detailed subjective data to better capture the linkage between farmers' interactions with their networks and their technology adoption choices.

In our study, we estimate a variety of adoption models with different levels of information exchanges among farmers to explore the relationship between social networks and farmers' adoption decisions.

First, we adopt a multinomial model to check for the role of social networks in different adoption time periods. Then with more detailed data on later years, we investigate how observed communication among farmers, along with farmers' individual characteristics and other controls, may influence their adoption decisions. To better address the reflection problem, our final model follows Conley and Udry (2010) and examines how new information on yield changes, varietal choices etc. obtained from a farmer' social networks in the previous year could influence farmers' adoption decisions in the next time period, controlling for cotton growing conditions and characteristics of cotton farmers. Following Conley and Udry (2010), we ask farmers explicitly whether they learnt about Bt cotton varieties after observing the yield performance of their neighbors' adopted varieties in the past year (2012) and communicating with their neighbors on other cotton growing practices. We, then, examine if such learning is associated with their adoption choices in the current year (2013), assuming that the unobserved correlation in growing conditions between farmers over time is controlled for by the panel structure of the data (2012 and 2013).

We apply our model to a randomly selected cross-section of 728 cotton-growing households drawn in 2013 from 52 villages, which constitutes a representative sample of the main cotton producing areas in Pakistan's six agro-ecological zones across Punjab and Sindh. Our results suggest that social networks play a significant role in Bt cotton adoption in Pakistan. However, we do not observe a strong causal relation between good news versus bad news from neighbors and farmers' adoption decisions in our final model. A possible reason could be that in this very late adoption time period, farmers' have various information sources to learn about the Bt technology and yield information from neighbors is not an important factor to change farmers' adoption behavior. We conclude that communication within social networks is correlated with Bt cotton adoption, and at the same time public extension agents and progressive farmers have a potential role in playing a more effective role in guiding the adoption of Bt cotton in Pakistan.

2. Methodology

We first adopt a multinomial model to verify the role of social networks and individual characteristics in determining when a farmer chooses to adopt Bt cotton. As Rogers (2003) and others (Shinohara and Okuda 2010; Ma and Shi 2014) have observed, technology diffusion usually follows an S curve, i.e., the new technology spreads at an increasing rate at the beginning of the adoption, and then the adoption rate slows down and eventually reaches a relatively constant level. During this process, farmers may choose to adopt a new technology in the early time period, middle time period, late time period, or not adopt at all. Farmer i's decision on when to adopt could be modelled as a function of his or her individual characteristics, information sources from social networks, village level adoption rate, and other unobservable factors which could influence farmers' choices. So,

$$prob(farmer\ i's\ adoption\ time\ period) = \ \gamma X_i + \beta n_{it_{adoptors}} + \delta n_{vt} + \varepsilon_{ivt}\ ,$$

where X_i denotes farmer i's individual characteristics, $n_{it_{adoptors}}$ denotes the number of adopters in farmer i's social networks in the year before farmer i switched to Bt cotton , n_{vt} is the total number of adopters in the village in the same year, and ε_{ivt} is the random error term which includes all other unobservable factors.

We expect social networks to have different roles in different adoption time periods. For example, in the very early stage there may be very few neighbors who have adopted Bt cotton, therefore the social network effect may be hard to capture; in later stages, when farmers are surrounded by adopters who are in their social networks, they could easily get information on Bt cotton seeds from social network members. At the same time, the social network effect should be separated from common shocks at the village level, so we use total number of adopters in the village to control for this.

The above model gives us an overall idea of the social network effect on when a farmer starts to adopt Bt cotton. It does not explain the social network effect in a particular year. Our next model is a static adoption model which analyzes farmers' adoption behavior in year 2012, for which we have more detailed data on farmers' interaction with their social networks. It is similar to the adoption model laid out by Bandiera and Rasul (2006), where farmer i's adoption decision is a function of his or her individual characteristics (X_i), number of adopters in his or her social networks ($n_{i_{adoptors}}$), village fixed effects (Z_v), and a random term ε_{ivt}. Farmer i's unobservable net gains from adopting Bt cotton in village v at time t, a^*_{ivt}, can be specified as

$$a^*_{ivt} = \beta n_{i_{adoptors}} + \gamma X_i + \delta Z_v + \varepsilon_{ivt} \ .$$

The actual adoption decision, a_{ivt}, is a binary choice with[1]

$$a_{ivt}=1 \text{ if } a^*_{ivt} > 0$$

$$a_{ivt}=0 \text{ otherwise.}$$

The probability that farmer i adopts Bt cotton is

$$prob(a_{iv} = 1) = prob\left(\varepsilon_{ivt} > -\left\{\beta n_{i_{adoptors}} + \gamma X_i + \delta Z_v\right\}\right).$$

where a_{iv} denotes farmer i's observed adoption choice. The identification strategy is that controlling for village fixed effect and farmers' own characteristics, the probability of adoption can be explained by the variation in the number of early adopters in their social network, assuming information exchange within the network.

[1] Our data suggest that most of the sample farmers either adopt Bt cotton to all their cotton plots or do not adopt at all. Partial adoption is rare.

Depending on the distribution assumption of ε_{ivt}, this can be estimated by probit or logit model. Bandiera and Rasul (2006) also suggest that it could also be estimated by a linear probability model if the mean of the adoption rate is close to 50 percent. However, in our case the adoption rate is over 70 percent and a linear probability model could yield predicted values well outside the zero to one range. So, later in our empirical model we estimate it using Probit model.[2]

One extension to this model is to add variables that indicate actual information exchange of the individual farmer with his or her social network members:

$$a_{ivt}^{*} = \beta_1 n_{i_{adoptors}} + \beta_2 n_{i_{comm\_adoptors}} + \gamma X_i + \delta Z_v + \varepsilon_{ivt},$$

where $n_{i_{comm\_adoptors}}$ denotes the number of adopted farmers in the network that farmer i communicated and discussed with, especially regarding cotton variety choices prior to the planting season. The rationale is that the networks should be defined in a local context that is related to a social learning module (Maertens and Barrett 2012). Farmers may "know" someone in his or her neighborhood, but they may not necessarily communicate with each other on the use and performance of a certain agricultural technology. Without this information exchange, simply being friends with an early adopter may not produce the learning externality of network effects.

One of the identification problems is the simultaneity of the adoption decisions by individual farmers and their social network members. The above models control for potential simultaneity that could be explained by *observable* factors, such as individual characteristics, the village fixed effects, and communication among farmers. However, they do not control for the potential *unobserved* factors that could induce correlation of farmers' adoption decision and their neighbors' behavior. Our last model is a

[2] Results from the Logit model are not significantly different from the Probit model.

two-year panel model, similar to Conley and Udry (2010), to investigate how yield information from neighbors *last year* affects farmers' own seed choices *this year*. As argued by Conley and Udry (2010), the introduction of panel data is particularly useful in identifying the network effect as it allows the researcher to difference out the unobserved time-invariant factors that affect farmers' adoption behavior. In this model, farmers' subjective assessment of their neighbors' cotton output last year are categorized as either below average (bad news), average, or above average (good news). The hypothesis is that good news from adopted neighbors, or bad news from non-adopted neighbors, may encourage farmers to adopt the new technology, while bad news from adopted neighbors or good news from non-adopted neighbors may discourage farmers from adopting the new technology. Following the notation of Conley and Udry (2010), this model is specified as:

$$\begin{aligned} &prob(farmer\ i\ switch\ to\ adoption) \\ &\qquad = \alpha_1\, s(good, Adopter) + \alpha_2\, s(bad, Adopter) + \alpha_3\, s(good, NonAdopter) \\ &\qquad + \alpha_4\, s(bad, NonAdopter\ ) + \alpha_5\, (change\ of\ growing\ conditions) \\ &\qquad + \alpha_6\, (other\ controls) + \varepsilon_{ivt}\} \end{aligned}$$

where $s(good, Adopter)$ is the share of farmer i's adopted neighbors who have above average yield (good news) in last year according to farmer i's assessment, $s(bad, Adopter)$ is the share of farmer i's adopted neighbors who received below average yield (bad news) in last year according to farmer i's assessment. Similarly, $s(good, NonAdopter)$ and $s(bad, NonAdopter)$ are the shares of farmer i's non-adopted neighbors who received above average yield (good news) or below average yield (bad news) in last year, respectively. As argued by Conley and Udry (2010), we expect that good news from adopted neighbors and bad news from non-adopted neighbors could motivate farmers to switch to the new technology, i.e., α_1 and α_4 should be positive, while bad news from adopted neighbors or good news from non-adopted neighbors may discourage the adoption, i.e., α_2 and α_3 are likely to be negative.

Our data suggests that the change of adoption is not a one-time decision. Some farmers who adopted Bt cotton in 2012 chose to dis-adopt in 2013. Therefore, we extend our above model to a multinomial model by include three scenarios, i.e., adopt, dis-adopt, and status quo. The specification is almost the same as before:

$$prob(adopt, disadopt, status\ quo) = \alpha_1\ s(good, Adopter) + \alpha_2\ s(bad, Adopter) + \alpha_3\ s(good, NonAdopter) + \alpha_4\ s(bad, NonAdopter\ ) + \alpha_5\ (change\ of\ growing\ conditions) + \alpha_6\ (other\ controls) + \varepsilon_{ivt}\}.$$

One identification challenge is that farmers switching to the new technology may be induced by change of growing conditions instead of learning new information from their social networks. Shocks to growing conditions in cotton cultivation are expected to be correlated spatially. Severe weather, drought, or flood, may affect all farmers living in the same village. Soil degradation and pest infestation often decrease productivity in agricultural plots that are spatially connected. Socio-economic changes can also affect growing conditions, for example, an increase in seed prices of popular Bt cotton varieties increases the adoption cost of Bt cotton and therefore discourages farmers' adoption. In our empirical analysis, we control the change of growing conditions by constructing similar variables as Conley and Udry (2010).

3. Background and Data

3.1. Bt cotton in Pakistan

Pakistan is among the top four producers of cotton in the world, preceded only by the U.S., China and India. Due to its extensive backward and forward linkages, cotton-related industries contribute 65 percent of foreign exchange earnings for Pakistan and provide employment and income for many of its population, especially people in the rural areas (Cororaton et al. 2008). Bt technology has proved to be an effective and economic way to control yield loss due to pest damages. When Bt cotton became widely adopted in India in early 2000s, some Bt cotton varieties were smuggled across the border from India to Pakistan and early adopters started selling seeds produced at their own farmers to other farmers (Hayee 2005; Ali and Abdulai 2010). By 2008, about 75 percent of land under cotton cultivation was allocated to Bt cotton (Ali and Abdulai 2010) and in 2009 over 90 percent of cotton crop was produced by unapproved Bt cotton seeds (Shafiq-ur-Rehman 2009). Our own survey data suggest that in 2010, over half of the respondents already adopted Bt cotton, mostly unapproved varieties (Figure 1). Because of the widespread use of unapproved Bt varieties, it is hard to know the exact adoption rate over time, but various sources including our own data clearly suggest that Bt cotton has been widely adopted before the Government of Pakistan first officially commercialized nine Bt varieties in 2010 and then eight Bt varieties in 2012 (Figure 1). However, unapproved Bt cotton varieties are still present in the market and are planted by a large number of cotton farmers even after the official commercialization of Bt cotton in Pakistan.

<< Figure 1 here>>

3.2. Sampling and data collection

The data for this study is collected from a household survey from 728 households representative of all cotton-growing agro-ecological zones in both Punjab and Sindh, which is the main cotton producing area accounting for approximately 99 percent of the cotton cultivated area and cotton lint production in Pakistan (Table 1). These households are selected by two-stage stratified sampling: the sample was first stratified over six cotton-growing agro-ecological zones, then in the first stage 52 villages are chosen with probabilities that are proportionate to population sizes (PPS), and in the second stage 14 cotton households are chosen randomly with equal probabilities. Eight households, however, were dropped out in the final survey because of migration or unavailability so we are left with 720 households in total for our analysis. Figure 2 presents the sites of our sampled villages on a map of Pakistan with all six cotton-growing agro-ecological zones.

<< Table 1 here >>

<< Figure 2 here>>

Among these 720 households, 615 households report that they are Bt cotton adopters and the rest of the 105 households report that they had never adopted Bt cotton to date (2013). Table 2 lists the summary statistics of the individual characteristics for these adopters and non-adopters. It shows that there are significant differences in education, willingness to try new varieties, poverty status, and landholding sizes in these two groups. In general, Bt adopters are better educated, more willing to try new cotton varieties, less poor, and have a significantly larger landholdings compared to non-adopters. They also spend more on food consumptions and have more valuable assets. However, there is not much difference in age, household size, and land ownership between these two groups.

3.3. Social networks

Table 2 also presents summary statistics of the characteristics of farmers' social networks. Both Bt adopters and non-adopters have similar size of social networks. On average, they consider 6 out of 14 farmers to be their friends, which we define as their social network. They also have similar number of progressive farmers among these friends. However, there is huge variation in the information they receive on Bt cotton from their social networks. Bt adopters, in general, have more adopters in their social networks and they discuss, for instance, seed choices with more adopters when they purchase cotton seeds. They also have more access to information from seed dealers and public extension agents. More information available from social networks as well as outsiders, like seed dealers and extension agents, could contribute to farmers' decision of adopting Bt cotton. The logic could also go the other way around, that is, Bt adopters tend to stay with other adopters, and since they adopted Bt cotton they tend to seek information from seed dealers and extension agents. Below, we will try to disentangle these effects by estimating a set of models outlined in Section 2.

4. Results and discussion

4.1. Multinomial model on farmers' adoption time period

First we estimate a multinomial model to check the role of social networks on farmers' choice of adoption time period. Based on our data and the policy change in 2010, we split Bt adoption into three time periods: early time period (2003-2006), middle time period (2007-2009), late time period (2010-1013), with an alternative option of not adopt at all. Table 3 presents the estimation results with non-adoption as the base scenario. We see that the number of adopters in social networks is only weakly significant for early adopters, insignificant for middle adopters, and positive and significant for late adopters. It confirms our expectation that social network effect may be more significant during late adoption period because of: (i) availability of more information on the new technology from neighbors, and; (ii) possible strategic behavior from farmers. As Munshi (2010) and others suggest, farmers may wait for their neighbors to adopt first since information from neighbors is generally free and farmers can free-ride on their neighbors' yield observations.

<< Table 3 here >>

We also observe that the coefficients for the village level adoption are negative and significant in the early and middle adoption time periods but positive and insignificant in the late adoption time period. It is not surprising since the early and middle adopters are among the first group of farmers who experimented with the new technology in the village, and therefore, their adoption decision is negatively correlated with the village adoption rate.

On individual characteristics, we find that younger households are more likely to adopt Bt cotton in each time period. Land ownership does not affect early adopters, but it is negatively correlated with adoption decisions of middle and late adopters. This suggests that if a farmer rents or sharecrops land for cotton cultivation, it is likely that he or she will be a middle or late adopter of Bt cotton. In the other words, without ownership of the land, farmers are less motivated to adopt Bt cotton. Another finding is that if a farmer is less risk-averse, that is, willing to try new varieties, he or she is likely to adopt Bt cotton in all three time periods. We also find that households with a large size per acre tend to adopt Bt cotton late.

4.2. A static adoption model

We estimate a static adoption model for year 2012 as we have more detailed information collected through a comprehensive social network module for this year.[3] Particularly, the 2012 data not only have information on farmers' social networks, but also include observed interaction between a farmer and his or her social network members. The estimation results are presented in Table 4. We estimated two different specifications: in the first specification we include farmers' individual characteristics and most of the social network information without controlling for village fixed effects. Then we add village fixed effects in the second specification to see if there is a change in the estimation of key variables.

[3] There are less observations in the year 2013 data (601 vs. 720). The same estimation with 2013 data yields almost no significant coefficients.

<< Table 4 here >>

We find that in the first specification the variable “number of adopted friends” is positive and significant, which suggests that having more adopters in a farmer’s social network is correlated with a higher adoption probability for this farmer. However, this effect becomes insignificant once we control for village fixed effects. This might be capturing the “reflection problem”, that is, the adoption of a technology by a farmer and his or her social networks might be a result of community level shocks. On the other hand, the variable “number of adopters in their social networks with whom the farmer discussed seed choices when purchasing seed in 2012,” which indicates direct communication between a farmer and early adopters in his or her social network, is positive and significant in both models. This suggests that controlling for individual characteristics, village fixed effects, and other growing conditions, we find that communication with adopted farmers on seed choices could help disseminate information on Bt technology and may therefore promote the adoption of Bt cotton in Pakistan.

Among those individual characteristics, a large household size is negatively correlated with Bt cotton adoption. After controlling for all these individual characteristics, we do not find any evidence to substantiate the hypothesis that poor farmers, i.e., farmers with less wealth and consuming less food per day, are at disadvantage in adopting Bt cotton. Other individual characteristics such as age, education, willingness to try new varieties, are not statistically significant in the static adoption estimation results from the 2012 data. The location of the seed dealer, soil types, self-reported land fertility, are not found to affect the adoption decisions in 2012.

Other controls including farmers' sources of information from their social networks, such as whether they get information from seed dealers, public extension agents, or progressive farmers in their social networks, are insignificant. However, this does not mean that information from these parties are not useful for farmers' cotton cultivation. In fact, over 60 percent of the respondents in the survey report that the information they get from these parties are "useful" or "very useful".

4.3. Two-year dynamic model

For the two-year dynamic model we estimate two different models: one is a Probit model which explains how new information from neighbors may change farmers status from non-adopters to adopters, the other is a multinomial model which tries to capture the effect of new information on all possible adoption decisions , i.e., adopt, dis-adopt, or status quo.

The results from the Probit model is presented in Table 5. We find that good news, i.e., the unexpected high yield from neighbors who adopted Bt in 2012 encourages farmers to adopt Bt cotton in 2013. However, other estimated coefficients are hard to interpret: the share of bad news from neighbors who adopted Bt cotton is positive and significant, which suggests that bad news from neighbors who adopted Bt cotton also encourages adoption. Similarly, the share of bad news from non-adopters actually discourages adoption. These results contradict our expectations that good news from neighbors tend to induce farmers to copy their neighbors' decisions while bad news is likely to motivate farmers to explore other input choices. Similar counter-intuitive results are found in the multinomial estimation (Table 6), which suggests that bad news from adopters and good news from non-adopters encourage adoption, and that both good news and bad news from non-adopter encourage farmers to dis-adopt Bt cotton.

<< Table 5 & 6 here >>

These results on the effect of good news vs. bad news may be explained by the strong effect of growing conditions. In both models we use the change of Bt cotton adoption rate at the village level as a proxy for the change of growing conditions. Similar to Conley and Udry (2010), we expect exogenous shocks to affect farmers locally and the village adoption rate is an indicator of the suitability of Bt cotton growing conditions. This variable is highly significant in both models. This implies that farmers' adoption choices are more affected by the common shocks instead of specific yield information from neighbors. The change in the number of adopters in social networks and the number of adopters with whom farmers discussed seed choices, are both found insignificant in the estimation.

4.4. Farmer perceptions on different information sources

The above estimation results only identify weak social network effects. Also, access to information from seed dealers and extension agents does not have a significant effect in promoting Bt cotton adoption. The possible reason is that our data is very recent, at the very late stage of the adoption, so farmers have various information sources to learn about the Bt technology. In other words, most of the knowledge on this technology has become common knowledge for farmers after more than ten years of introduction of Bt cotton in Pakistan.

In our survey, a majority of farmers receive information on cotton cultivation from four types of sources: seed dealers, extension agents, progressive farmers, and local farmers. We ask the respondents as to how much they trust these information sources and their evaluation of the usefulness of information from these sources. Interestingly, compared to extension agents and progressive farmers, our sample farmers do not trust local farmers much who could be their neighbors, nor do they trust seed dealers. They also think information from extension agents and progressive farmers is, generally, more useful than information from seed dealers and local farmers. This result highlights the importance of extension programs and the potential learning externality from progressive farmers to other farmers.

<< Figure 3 & 4 here >>

5. Conclusion

This study explores the role of social networks in farmers' Bt cotton adopting decisions in Pakistan. Identifying the social network effect is challenging in many ways, especially disentangling the learning effect from unobserved correlation among farmers in the same community. We estimate a variety of models by using data from a household survey in rural Pakistan. Our results suggest that information from social networks, especially direct communication on seed choices, are positively correlated to higher adoption probabilities. We also find that willingness to try a new variety, a large landholding size, and other individual characteristics like household size explain farmers' adoption behavior. Although, we could not identify a strong causal relationship between social network effect and farmers' adoption decisions, we do find that access to information from social networks is correlated with farmers' seed choices.

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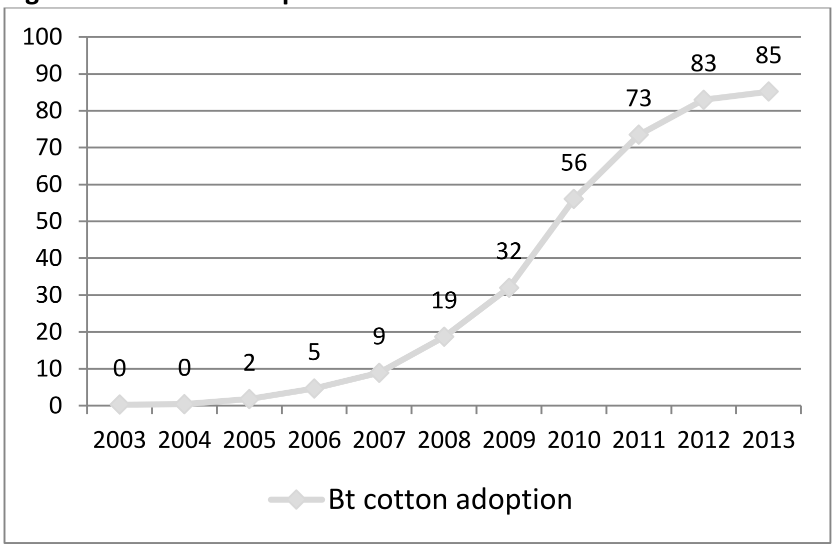
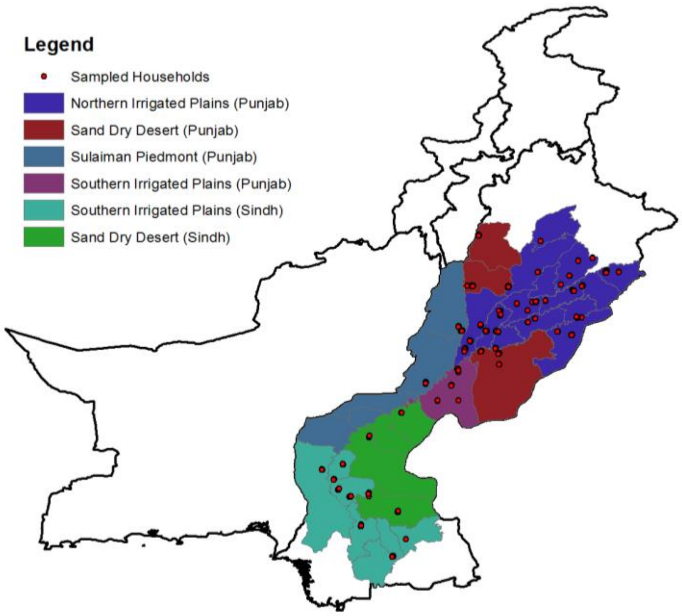
ANNEX

Figure 1: Bt cotton adoption in Pakistan



Source: PSSP cotton survey (2013).

Figure 2. Sample mouzas and agro-ecological zones of Pakistan



Source: PSSP cotton survey (2013)

Figure 3: Farmers' trust on different information sources

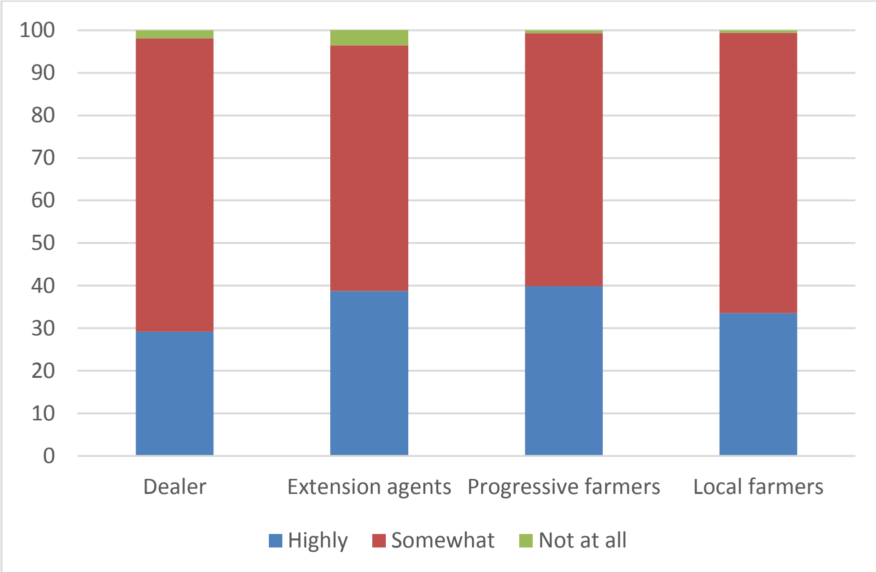


Figure 4: Usefulness of different information sources

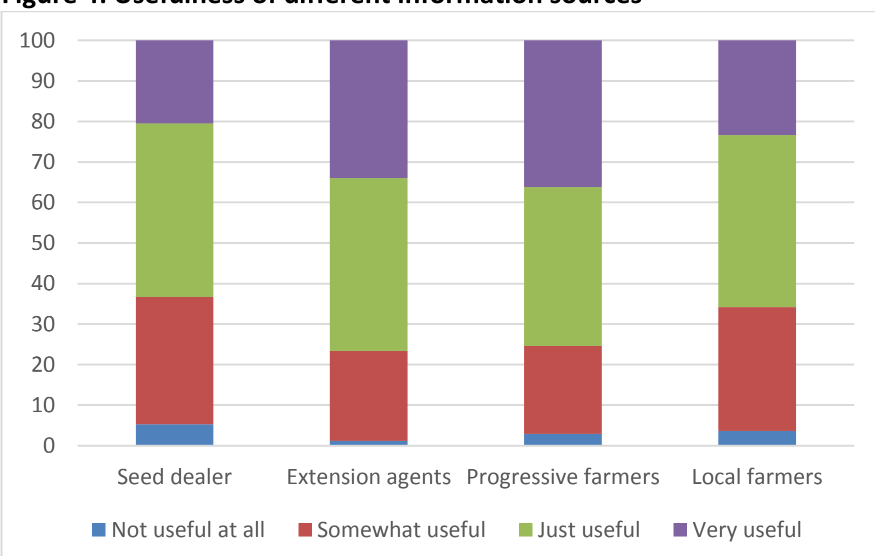


Table 1: Cotton area and cotton lint production shares in Pakistan (percentage distribution)

Year	Area (%)				Production (%)			
	Punjab	Sindh	Others*	Total	Punjab	Sindh	Others*	Total
1985–1990	76.1	23.8	0.1	100	84.3	15.7	0	100
1991–1995	82.2	17.7	0.1	100	86.2	13.8	0	100
1996–1999	79.1	20.5	0.4	100	75.9	23.7	0.4	100
2000–2005	80.1	18.7	1.2	100	77.1	22	0.9	100
2006–2010	79.0	19.9	1.1	100	75.5	23.8	0.7	100

Source: Agricultural Statistics of Pakistan 2010-11 (Pakistan Bureau of Statistics)
Note: *KPK and Baluchistan.

Table 2: Descriptive statistics

Variable	Non-adopters (n=105) Mean	S.D.	Adopters (n=615) Mean	S.D.	
Individual characteristics					
Age	46.65	13.92	46.97	11.33	
Education (years)	3.52	4.53	4.87	4.57	***
Household size	8.96	4.54	9.04	4.69	
Land ownership	0.68	0.47	0.71	0.45	
Willingness to try new varieties	0.49	0.50	0.61	0.49	***
Poor (dummy, 1: poor)	0.69	0.47	0.32	0.47	***
Landholding size	3.63	3.36	9.88	17.28	***
Expenditure (Rupees)	56.77	33.07	80.22	51.35	***
Wealth index [4]	-1.50	0.78	0.27	2.43	***
Fertile of land (dummy, 1: very fertile)	0.40	0.49	0.39	0.49	
Remote seed dealer (dummy, 1: outside of village)	0.67	0.47	0.73	0.45	
Social networks					
If get information from dealer	0.25	0.43	0.39	0.49	***
If get information from extension agents	0.12	0.33	0.36	0.48	***
Number of friends in the village	6.27	3.93	6.53	5.11	
Number of friends who adopted Bt cotton in previous years	1.12	1.83	5.47	4.58	***
Number of progressive farmers in one's social networks	3.28	3.96	2.63	3.80	
Number of adopters with whom the farmer discussed seed choices	0.09	0.31	0.51	1.25	***

Note: 1. ***, **, * denote p<0.01, p<0.05, and p<0.1 for significance of difference.

[4] The wealth index is constructed by principal component analysis with surveys on farmers' assets. The first component scores are used to compute the index.

Table 3: Multinomial model on farmers' adoption time period

Adoption time period	Early Adopter (2003-2006, 33 adopters)	Middle Adopter (2006-2009, 198 adopters)	Late Adopter (2010-2013, 384 adopters)
Individual characteristics			
Age	-0.005	-0.027**	-0.029***
	(0.015)	(0.011)	(0.010)
Education (years)	0.006	0.016	-0.004
	(0.041)	(0.031)	(0.031)
Household size	-0.390**	-0.235***	-0.049
	(0.186)	(0.090)	(0.052)
Willingness to try new varieties	1.149***	0.845***	1.113***
	(0.357)	(0.272)	(0.265)
Expenditure	-0.006*	-0.000	-0.000
	(0.004)	(0.000)	(0.000)
Wealth	0.165	0.116	0.181
	(0.145)	(0.133)	(0.131)
Land tenure status	-0.162	-0.841***	-0.976***
	(0.439)	(0.304)	(0.296)
Landholding size	-0.003	-0.005	-0.005
	(0.031)	(0.030)	(0.030)
Fertile of land	-0.501	0.086	-0.309
	(0.360)	(0.265)	(0.257)
Remote seed dealer	0.328	0.224	0.030
	(0.415)	(0.292)	(0.278)
Punjab	3.234***	3.880***	3.861***
	(0.490)	(0.403)	(0.375)
Social networks			
Number of adopters in social networks	0.566*	-0.044	0.117**
	(0.336)	(0.070)	(0.053)
Number of adopters in the village	-1.122***	-0.270***	0.016
	(0.322)	(0.051)	(0.042)
Constant	-0.226	1.020	0.358
	(1.053)	(0.714)	(0.655)
Log likelihood		-469.856	
Observations		720	

Source: Authors' own estimation.

Note: 1. Standard errors in parentheses, ***, **, * denote p<0.01, p<0.05, and p<0.1 for significance.

Table 4: Estimation results from the static adoption model (year 2012)

Dependent Variable: Growing Bt cotton in 2012	(1)	(2)
Individual characteristics		
Age	-0.006	-0.007
	(0.005)	(0.007)
Education (years)	0.017	0.031
	(0.015)	(0.020)
Household size	-0.101***	-0.102*
	(0.038)	(0.054)
Willingness to try new varieties	0.045***	0.035*
	(0.015)	(0.019)
Expenditure	0.126	0.037
	(0.130)	(0.179)
Wealth	-0.000	-0.001
	(0.000)	(0.002)
Land tenure status	-0.082*	-0.011
	(0.045)	(0.060)
Landholding size	-0.196	-0.283
	(0.147)	(0.185)
Fertile of land	-0.103	0.054
	(0.132)	(0.180)
Remote seed dealer	0.027	0.185
	(0.141)	(0.201)
Punjab	2.273***	2.437***
	(0.282)	(0.762)
Information and social networks		
Information from dealer	-0.060	0.045
	(0.135)	(0.185)
Information from extension agents	-0.258*	-0.254
	(0.144)	(0.190)
Number of friends who adopted Bt cotton in previous years	0.072***	0.017
	(0.021)	(0.028)
Number of progressive farmers in one's social networks	-0.043**	0.007
	(0.021)	(0.037)
Number of adopters in one's social networks with whom he discussed seed choices when purchasing seeds in 2012	0.195**	0.229**
	(0.081)	(0.094)
Soil type control	Yes	Yes
AEZs control	Yes	Yes
Village control	No	Yes
Constant	-1.320***	-1.945***
	(0.447)	(0.734)

Log likelihood	-273.991	-202.253
Pseudo (R^2)	0.337	0.297
Observations	720	497[2]

Source: Authors' own estimation.

Note: 1. Standard errors in parentheses, ***, **, * denote p<0.01, p<0.05, and p<0.1 for significance.

2. Some villages are automatically dropped by the Probit estimation routine in Stata in the last two models when village controls are included. The reason is that in these villages either all farmers switched to Bt cotton, or no farmers adopted Bt cotton, so the village dummy predicts the adoption outcome perfectly and therefore it returns a likelihood either 0 or 1. Log(0) is undefined and log(1) equals to 1 which does not add anything to the total log likelihood. So dropping these observations does not affect the estimation.

Two-year dynamic model:

Table 5: Probit model: If farmers switch from non-adoption in 2012 to adoption in 2013.

Dependent variable: farmers switch to Bt varieties	(1)	(2)	(3)
Good news vs. bad news			
Share of good news from neighbors who adopted	2.596*	3.870*	3.155*
Bt cotton in 2012	(1.567)	(2.004)	(1.909)
Share of bad news from neighbors who adopted		1.884***	2.374***
Bt cotton in 2012		(0.681)	(0.835)
Share of good news from neighbors who did not		-2.192	-0.892
adopt Bt cotton in 2012		(2.715)	(2.622)
Share of bad news from neighbors who did not		-0.908	-2.573**
adopt Bt cotton in 2012		(0.894)	(1.276)
Change of growing conditions and information set			
Change of village adoption rate			3.867***
			(0.758)
Change of number of adopters in social networks			0.015
			(0.109)
Change of number of adopters in one's social			-0.297
networks with whom he discussed seed choices			(0.257)
when purchasing seeds			
Constant	-0.219**	-0.259**	-0.726***
	(0.098)	(0.109)	(0.152)
Log likelihood	-116.538	-111.615	-94.582
Pseudo (R^2)	0.013	0.055	0.199
Observations	173	173	173

Source: Authors' own estimation.

Note: 1. Standard errors in parentheses, ***, **, * denote p<0.01, p<0.05, and p<0.1 for significance.

Table 6: Multinomial Probit model: if farmers dis-adopt or adopt Bt cotton from 2012 to 2013 (the base scenario is status quo)

	(1)		(2)		(3)	
VARIABLES	Dis-adopt	Adopt	Dis-adopt	Adopt	Dis-adopt	Adopt
Good news vs. bad news						
Share of good news from	-0.043	-0.247	-0.360	-0.470	-0.013	-0.419
adopters	(0.981)	(0.828)	(1.087)	(0.904)	(1.086)	(0.970)
Share of bad news from			-0.227	0.621	-0.661	0.923*
adopters			(0.744)	(0.474)	(0.896)	(0.541)
Share of good news from			4.493*	3.795	5.711**	4.729*
non-adopters			(2.625)	(2.376)	(2.635)	(2.517)
Share of bad news from			1.009	1.689**	2.554**	-0.605
non-adopters			(1.110)	(0.846)	(1.132)	(1.066)
Change of growing conditions and information set						
Change of village adoption					-4.333***	5.449***
rate					(0.914)	(0.751)
Change of number of					-0.033	-0.076
adopters in social					(0.132)	(0.111)
networks						
Change of number of					0.060	-0.062
adopters with whom the					(0.105)	(0.099)
farmer discussed seed						
choices						
Constant	-2.160***	-1.680***	-2.199***	-1.785***	-2.258***	-2.304***
	(0.113)	(0.091)	(0.122)	(0.100)	(0.152)	(0.148)
Log likelihood	-368.444		-362.561		-310.714	
Observations	701		701		701	

Source: Authors' own estimation.

Note: 1. Standard errors in parentheses, ***, **, * denote p<0.01, p<0.05, and p<0.1 for significance.