

Pesticide Productivity and Transgenic Cotton Technology: The South African Smallholder Case

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(Original submitted June 2003, revision received May 2004, accepted October 2004.)

This paper empirically investigates how the productivity of pesticide differs in Bt versus non-Bt technology for South African cotton smallholders, and what the implications for pesticide use levels are in the two technologies. This is accomplished by applying a damage control framework to farm-level data from Makhathini flats, KwaZulu-Natal. Contrary to findings elsewhere, notably China, that farmers over-use pesticides and that transgenic technology benefits farmers by enabling large reductions in pesticide use, the econometric evidence here indicates that non-Bt smallholders in South Africa under-use pesticide. Thus, the main potential contribution of the new technology is to enable them to realise lost productivity resulting from under-use. By providing a natural substitute for pesticide, the Bt technology enables the smallholders to circumvent credit and labour constraints associated with pesticide application. Thus, the same technology that greatly reduces pesticide applications but only mildly affects yields, when used by large-scale farmers in China and elsewhere, benefits South-African smallholder farmers primarily via a yield-enhancing effect.

1. Introduction

As debate over the desirability of GM technology for smallholder farming continues, the first wave of farm-level commercial (as against trial) evidence involving pesticide-substituting Bt² varieties has become available. The initial evidence relied on comparing traditional and Bt technologies using farm management accounting techniques, such as gross margins and pesticide use rates. These comparisons are valuable in providing broad overviews, but cannot provide answers to the more subtle production economics questions posed by the new technology.

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² The *Bacillus Thuringensis* (Bt) gene in Bt varieties produces a natural insecticide.

One key question centres on the mechanism by which pesticides and the Bt variety interact in affecting output, the consequences for use levels and use efficiencies of pesticide input for farmers, and the resulting benefits to smallholders. Cotton is susceptible to an array of pests, and pesticide applications around the world are perceived to be large compared to competing crops. Given this situation, a key benefit anticipated from the adoption of Bt cotton varieties would be a significant reduction in pesticide use, resulting in cost savings for farmers and better environmental outcomes for the broader public. A widespread perception exists, substantiated by plenty of empirical evidence, that pesticides are often ‘overused’ (*i.e.* applied beyond the economic optimum) around the world, resulting in heightened interest in pesticide-substituting technologies. Some of the recent evidence has supported this perception. Huang *et al.* (2002) found that Bt adoption in China cut pesticide rates by a factor of over five, although yield effects were only marginal. Farmers were found to be applying pesticides far in excess of optimal levels under both technologies, although the Bt users were somewhat more efficient.

The South African case investigated here differs from the Chinese in several ways. The South African smallholders operate at a far smaller scale and are more likely to be affected by market failure. Problems such as difficulty in procuring inputs at the right time and lack of access to spraying equipment are common. A question that arises is whether the ‘overuse’ characterisation is valid for the South African smallholder, and if not, what is the predominant source of benefits from the new technology?

The focus of this paper is to investigate the economically optimum use levels for pesticides under the two technologies for the South African smallholder case and to compare current use levels with optima to determine use efficiency. When the results are viewed alongside those from China (Pray *et al.*, 2001) and Argentina (Qaim *et al.*, 2003), a picture emerges about where Bt technology may be expected to benefit farmers, primarily by its pesticide saving attribute, and where the yield enhancing effect is likely to predominate. Proceeding towards such a characterisation is important in this debate, often dominated by media and lobby-groups, where both attributes are touted as virtues of the new technology by the ‘pro’ camp, and where a failure of either attribute to materialise is taken as indication of the failure of the technology by the ‘anti’ camp. As other developing countries have started to introduce such technology at the farm level (*e.g.* India, Indonesia) and others are debating its desirability, it is important that expectations be informed by cross-country farm level experience and the generalisations we can draw from them.

In establishing pesticide productivity patterns and computing economic optima for pesticide use, it is important to explicitly take into account the nature of pesticide as an ‘abatement’, rather than as a conventional ‘output-increasing’ input. Thus, in parallel with the work of Huang *et al.* (2002) for China, Qaim *et al.* (2003) for Argentina, and Qaim and Zilberman (2003) for India, this study takes a ‘damage

control' approach to estimating the role of pesticides and Bt technology. This is in contrast to Ismael *et al.* (2000) and Thirtle *et al.* (2003) who consider the same South African smallholder case, but treat pesticide as a conventional input. In the process of estimation, important econometric issues concerning the endogeneity of pesticide use and the adoption of Bt technology are accounted for and analysed. Additionally, instead of imposing the precise pathway by which the new Bt varieties affect cotton output, we let the data and the econometric model determine the precise specification.

The next section discusses the background to Bt cotton in South Africa generally and Makhathini flats in particular. Section 3 describes the data and section 4 briefly reviews previous literature on econometric pesticide productivity modelling. Sections 5 and 6 describe the econometric framework and report the results from estimation. Section 7 uses the estimates to compute optima, analyse use efficiencies and make cross-technology comparisons, while section 8 concludes.

2. Bt Cotton and the Makhathini Smallholders

South Africa was the first country in the African continent to release GM crops commercially. The GMO Act, 1997, approved importation and use of GM seeds and the establishment of the institutions required for evaluation. Although there have been hundreds of crop trials, only herbicide tolerant soybeans and cotton, and Bt maize and cotton, have gained commercial approval. Cotton accounts for about 1% of total South African agricultural production, generating approximately US\$50 million annually (Kock, 2000). About two thirds is grown under dry-land conditions, with 1,530 larger, commercial farmers, mostly in Limpopo Province, but also in the Free State and KwaZulu-Natal, producing over 90% of the output.

About 3,000 Zulu smallholders growing rain fed cotton in Makhathini Flats, KwaZulu-Natal, and another 500 in Tonga, Mpumalanga, together account for about 98% of smallholder cotton grown in South Africa (Hofs and Kirsten, 2002). In 1998/99, with strong support provided by a private input supply company called VUNISA, a few smallholders in Makhathini Flats started planting a genetically modified cottonseed variety, NuCOTN 37-B. The insecticide produced by this variety provides resistance to bollworm, which is the most troublesome class of pest in the area (followed by cotton aphids and jassids).

Uptake fuelled by VUNISA's campaign was rapid thereafter, and just two years since introduction, 40% of the producers, representing almost two thirds of the area planted, had taken up the new technology. Some estimates indicate adoption may well have reached 90% by 2002. The Bt gene, used by Delta Pineland in developing NuCOTN 37-B, belongs to Monsanto. In addition to a premium payable per bag of Bt seed over conventional seed, Bt users also pay a technology fee. At the time of the data collection for this research, VUNISA Cotton was the sole supplier of seed, chemicals and support services for the farmers through their extension officers, including credit for land preparation, chemicals and seed, based on their credit

history. VUNISA bought cotton from the farmers at prices fixed by Cotton South Africa, but has faced competition from a new gin since 2002.

The background to this study has been extensively discussed in Ismael *et al.* (2002), Gouse *et al.* (2002) and Kirsten *et al.* (2002). Features of relevance to this research are as follows:

- (i) Agriculture is the main livelihood source in Makhathini. Smallholder farms grow between 1 and 3 hectares of rainfed cotton. Some maize and beans are grown, predominantly for subsistence, but cotton occupies the most acreage and is the main source of cash income.
- (ii) Smallholder cotton cultivation in the area is marked by relatively low yields. Irrigated cotton yields in China are on average in excess of 3000 kg/ha, while smallholder dry land cotton yields in Makhathini seldom exceeded 600 kg/ha prior to the introduction of Bt technology. Lack of irrigation is a major constraining factor.
- (iii) Many of the input availability concerns that hinder African agriculture generally are prevalent in Makhathini flats. A range of pests, particularly bollworm, jassids and aphids, regularly decimates the cotton crop. However, pesticide application is both costly and arduous. Apart from the costs of pesticide and difficulties in obtaining credit, poorer farmers cannot afford the required knapsack sprayer. Water for spraying often has to be transported considerable distances and smallholders spend the best part of a day, and walk up to 20 km, for every hectare sprayed (Kirsten *et al.*, 2002). In addition, hired labour is difficult to obtain in an agricultural economy characterised by male out-migration to towns.
- (iv) In this early stage in the diffusion of the new innovation, the role of VUNISA has been crucial. Without the provision of credit by the Landbank, channelled to farmers by VUNISA, and the provision of information and guidelines, poor and often uneducated farmers would struggle to take advantage of the new technology.

3. Data

The cross-sectional data used here relate to the 1999/2000 season. Survey data were obtained on 100 Makhathini cotton smallholders. After deletion of observations with missing values, 91 observations are available for analysis, with 58 Bt adopters and 33 non-Bt farmers. The data include quantities of inputs and outputs, cost and revenue information for the cotton crop, as well as a range of socio-economic variables. Sample means for the inputs and cotton output are presented in Table 1.

Table 1. Sample Means for Inputs and Outputs, 1999/2000.

	Whole Sample (91 farms)	Bt adopters (58 farms)	Non-adopters (33 farms)
Output (kg)	1896	2176	1400
Land (ha)	5.3	6.0	3.9
Labour (days)	20.8	22.0	18.8
Seed (25 kg bags)	2.1	2.2	1.9
Pesticide (litres)	7.5	6.8	8.6
Yield (kg/ha)	439	478	342
Labour per ha (days/ ha)	5.9	5.8	6.0
Seed rate (bags/ha)	0.50	0.46	0.57
Pesticide rate (litres/ha)	1.4	1.1	2.2

Several interesting features emerge from the figures in Table 1. Firstly, Bt cotton has provided a yield advantage for 1999/2000. The year was one of relatively high pest infestation and average yields for both technologies are somewhat higher in average years.

Second, pesticide application rates are fairly modest even for the non-adopters, although Bt adoption halves it. In comparison, the average use reported by Huang *et al.* (2002) for China is approximately 60 kg per hectare for non-adopters, and 12 kg for Bt adopters. In the face of relatively small applications pitted against large pest problems, it is difficult to visualise a large degree of overuse for the South African smallholders. The exact degree of use efficiency will be determined by econometric methods. Third, information on fertilisers is not included in the table because the smallholders use only small amounts of animal manure. Fourth, on the basis of observations in the field as well as the per-hectare seeding rate figures seen in Table 1, the smallholders seem to be offsetting the extra costs of the Bt seed by lowering the seeding rate per hectare. This suggests that seed quantity should be a factor of production, unlike in typical empirical production analysis, where constant-seeding rates enable this input to be omitted. Fifth, the adopters seem to have farms of larger size. Given that credit availability was a key to adoption of the new technology, and that VUNISA targeted the larger, richer farmers during its adoption, this is not surprising.

4. Previous Literature on Pesticide Productivity Modelling

Investigation of the productivity of pesticides has a long tradition in agricultural economics. Much of the early econometric work used data on inputs and outputs, including pesticide, in a Cobb-Douglas production function framework to analyse the marginal product of pesticide and compare it to pesticide price. Such analysis (*e.g.* Headley (1968), Campbell (1976)) typically found the estimated marginal product of pesticide to be far greater than the factor price, indicating significant under use. This was surprising, since anecdotal evidence and conventional wisdom indicated that pesticide application in developed country agriculture was characterised by use in excess of the economic optimum. Parallel with this

econometric work, a literature on bio-economic modelling using detailed entomological information was developing (e.g. Regev *et al.* (1983); Talpaz and Borosh (1974)).

Lichtenberg and Zilberman (1986) presented a critique of the econometric work, and offered an alternative, more intuitive way to model the role of pesticide in the agricultural production process. Drawing inspiration from the bio-economic literature, they posited that pesticides belong to a class of ‘damage control’ inputs. Damage control inputs are different from conventional inputs in that they affect output only indirectly, by reducing the extent of damage in the event that damage occurs. In contrast, conventional inputs such as fertiliser and labour increase output directly.

Following the notation of Lichtenberg and Zilberman, if Y denotes output, \mathbf{Z} is a vector of ‘conventional’ inputs, and \mathbf{X} a vector of ‘damage control’ inputs, then $Y = F[\mathbf{Z}, G(\mathbf{X})]$, with $F(\bullet)$ concave in \mathbf{Z} and $G(\mathbf{X})$. $G(\mathbf{X})$, the ‘abatement function’, is defined on the $[0, 1]$ interval and is increasing in \mathbf{X} . As \mathbf{X} increases, $G(\mathbf{X}) \rightarrow 1$ and $Y \rightarrow F(\mathbf{Z})$, *i.e.* a greater part of maximum potential output is realised. As \mathbf{X} decreases, $G(\mathbf{X}) \rightarrow 0$, and $Y \rightarrow F(\mathbf{Z}, 0)$, *i.e.* output falls towards the level consistent with maximum destructive capacity.

For reasons of econometric identification, the practice in empirical work is to simplify the damage control function to a proportional one, *i.e.*

$$Y = F(\mathbf{Z})G(\mathbf{X}) \quad (1)$$

In the context of pest management, (1) implies that as pesticide input \mathbf{X} increases, abatement $G(\mathbf{X}) \rightarrow 1$, and at the limit $Y = F(\mathbf{Z})$, *i.e.* there is no destruction due to pest damage and maximum potential output is realised. As pesticide application declines towards 0, $G(\mathbf{X}) \rightarrow 0$, and $Y \rightarrow 0$. Since Y is now proportional to $G(\mathbf{X})$ and $G(\mathbf{X})$ is between 0 and 1, $G(\mathbf{X})$ represents the percentage of maximum potential output realised for a given level of pesticide use, \mathbf{X} . Since $G(\mathbf{X})$ lies in the $[0, 1]$ interval, a choice of several cumulative distribution functions is available to model $G(\mathbf{X})$. Based on their abilities to capture the biological response of damage to pesticide applications, the most popular of these have been:

$$\text{Weibull:} \quad G(\mathbf{X}) = 1 - \exp\{-\mathbf{X}^c\} \quad (2)$$

$$\text{Exponential:} \quad G(\mathbf{X}) = 1 - \exp\{-\mathbf{m}\mathbf{X}\} \quad (3)$$

$$\text{Logistic:} \quad G(\mathbf{X}) = [1 + \exp\{\mu - \sigma\mathbf{X}\}]^{-1} \quad (4)$$

Where the damage control representation is appropriate, Lichtenberg and Zilberman demonstrate that using conventional specifications can lead to serious bias and erroneous conclusions about the productivity and use efficiencies of pesticides as well as the other conventional inputs included in the analysis. In particular, they

propounded that when a Cobb-Douglas conventional specification is used instead of a damage control one, the bias leads to an overestimation of the marginal productivity of pesticides. In other words, previous papers using Cobb-Douglas specifications were overestimating the marginal product of pesticide, leading to the puzzling result indicating pesticide under-use. Applied studies of pesticide productivity have embraced the Lichtenberg and Zilberman framework. Carrasco-Tauber and Moffitt (1992) revisited the question initially raised by Headley regarding pesticide use efficiency in the USA, comparing Cobb-Douglas and damage control specifications. Babcock *et al.* (1992) applied the damage control framework to investigate output quality as well as quantity dimensions of pesticide use in North Carolina.

Several methodological issues in damage control estimation and their implications for measuring pesticide productivity have also been explored. Hall and Moffitt (2002) established that Lichtenberg and Zilberman's derivation evaluated marginal products at an arbitrary point, and the direction of bias in comparing Cobb-Douglas with damage control specifications cannot be established *a priori*. In other words, while one may expect a Cobb-Douglas (or other conventional) specification to wrongly estimate the productivity of pesticides, whether the misspecification leads to an under or over estimation of pesticide productivity cannot be determined prior to estimation. Thus, a Cobb-Douglas form may *underestimate* the marginal product of pesticide. Fox and Weersink (1995) showed that increasing marginal returns to pesticide is possible under common damage control specifications, implying that profit-maximising farmers would opt for either no control or control at the ceiling. Consequently, farmer response to price or cost changes could be non-continuous.

Most econometric analysis of pesticide productivity is typically handicapped by a lack of incorporation of entomological information and detailed, stage-by-stage data on pest infestation and pesticide application. Hall and Moffitt (2002) point out how information on infestation can improve the reliability of damage control estimates by purging the error term of potential correlation with pesticide input. The lack of detailed information also generally hampers risk analysis of pesticide use. The use of prophylactic pesticide *versus* sequential application in response to pest attacks may relate to the risk properties of the input. Without recording the extent of infestation and the precise timing of applications, these avenues are harder to explore. Nevertheless, given the limitations imposed by recall farm survey data, Lichtenberg and Zilberman's framework provides a more accurate framework for the analysis of pesticide productivity compared to traditional production function analysis. It has been profitably employed in the analysis of Bt cotton evaluation by Huang *et al.* (2002) and Qaim *et al.* (2003), and is the framework used here.

5. Estimation Framework

Huang *et al.* (2002), Qaim and Zilberman (2003) and Qaim *et al.* (2003) have analysed the effects of Bt variety adoption on pesticide productivity by introducing dummy variables for Bt varieties into the damage control specifications above. The Bt variety produces a naturally occurring toxin that substitutes for pesticides. Given

this characterisation, interesting modelling issues arise in introducing Bt varieties into a damage control framework. If farmers are found to be partially adopting Bt varieties, *i.e.* using Bt varieties in some plots and conventional varieties in others, one could conceive of modelling whole-farm cotton production with the proportion of Bt adoption as a continuous variable input. In other words, one could introduce substitutability between the proportion of plots on which Bt varieties are planted and pesticide applications at the farm level, much as one would model substitutability between two conventional inputs. This would be consistent with the characterisation that the farmer can achieve an increased degree of pest control either by applying more pesticides, or by bringing a greater proportion of plots under Bt varieties.

The above studies have simplified the problem by undertaking the modelling on a per-plot basis. On any given plot, either a Bt variety or a conventional variety is grown, and hence the introduction of Bt varieties into the production framework reduces to the use of a dummy variable. In the South African smallholder case, the problem is resolved by the simple fact that adoption was not partial, with the farmers either adopting Bt varieties or retaining conventional varieties on all cotton hectares. Thus we are able to proceed by modelling cotton production at the farm-level (*i.e.* output on all cotton hectares rather than on a per-hectare basis), while retaining a dummy characterisation for Bt varieties.

In the case of the exponential form in (3), assuming X is a scalar pesticide variable, it is simple to confirm that if $G'(X) > 0$, then it has to be true that $G''(X) < 0$. Now, $G'(X) > 0$, *i.e.* abatement increasing in pesticide input is an expected outcome. However, this imposes concavity of abatement in pesticides, which is less clear. It is quite possible that over some range, pesticide input increases damage control at an increasing rate. The exponential is an inferior choice if this flexibility is desired. Based on these points, and due to the Weibull specification providing poor and counter-intuitive results for our data, the logistic characterisation, used in Qaim *et al.* (2003), is the specification of choice for $G(X)$. Due to the relatively small size of the available sample, a Cobb-Douglas specification is used for $F(\mathbf{Z})$, rather than a flexible functional form.

A parsimonious way to model Bt technology would be to specify the Bt dummy as affecting cotton output only through its interaction with pesticide input. However, transgenic cotton technology often arrives in the form of cultivars that are entirely new to the local area rather than as selected modification of existing, locally predominant varieties. There is thus scope for the introduction of Bt varieties to affect cotton output by affecting the output elasticities of other inputs, or through an input-independent upward shift of the production function, apart from via the interaction with pesticide. In other words, two extreme ranges of models can be envisaged:

$$Y = (a_0 + a_1Bt) \prod_{i=1}^n Z_i^{b_i + c_i Bt} [1 + \exp\{\mu - \sigma X - \lambda Bt\}]^l \tag{5}$$

Or simply

$$Y = a_0 \prod_{i=1}^n Z_i^{b_i} [1 + \exp\{\mu - \sigma X - \lambda Bt\}]^l \tag{6}$$

Where $Bt = 1$ if the smallholder has planted the Bt variety and $Bt = 0$ if a conventional variety is grown. In (5), all parameters vary by Bt technology, while in (6) the effect on output is only through pesticide productivity. The choice is made on the basis of specification tests.

6. Estimates

Prior to estimating the damage control specification, it is useful to estimate a conventional specification for comparative purposes. This conventional Cobb-Douglas model is also used as a basis to carry out two important specification tests that are easier to handle in the log-linear Cobb-Douglas framework rather than the non-linear damage control framework. These concern the potential endogeneity of the pesticide input and of Bt technology adoption. Thus, while the maintained assumption is that the conventional model is mis-specified relative to the damage control model, it is nevertheless considered useful in providing a simplifying basis for carrying out the necessary endogeneity tests.

6.1. Conventional Cobb-Douglas Results

The results of a simple Cobb-Douglas regression for the entire sample are shown below in column 1 of Table 2.

The signs of the coefficients conform with theory, and the coefficients sum to just greater than unity, indicating approximately constant returns to scale. However, the pesticide coefficient is small and insignificant, indicating that the pesticide input has little productivity at current use levels and is therefore ‘overused’. This is surprising, since there were significant pest infestations in the 1999/2000 season and the use levels were modest by international standards for cotton.

6.2. Pesticide Endogeneity: A Hausman Test

One long-standing problem with direct estimation of the production function is that the inputs are treated as exogenous, when really the farmers decide their levels. This causes a simultaneity problem and correlation between inputs and the error term can render the estimates inconsistent. Although this problem applies to all inputs, it is especially true of pesticides, since they are often applied sequentially, in response to production shocks in the form of pest attacks. Where endogeneity is a problem, consistent estimates can be obtained by suitably instrumenting the relevant variable. On the other hand, where endogeneity is not a significant problem, the least squares estimator is more efficient than instrumental variables. Thus, one would prefer the original variable to be used in empirical analysis instead of the instrumental

variable if endogeneity is not severe. Accordingly, a Hausman test was performed to test for the endogeneity of pesticide, under the conventional framework.

Table 2. Cobb-Douglas Estimates & Pesticide and Adoption Endogeneity Tests^{§±}

Variable	Cobb-Douglas	Hausman	Selectivity – Adopters	Selectivity – Non Adopters
Intercept	0.01 (0.05)	-0.09 (0.45)	-0.04 (0.53)	-1.2 (1.16)
Land	0.46 (0.12)***	0.42 (0.12)***	0.46 (0.11)***	0.06 (0.38)
Labour	0.39 (0.16)**	0.28 (0.17)	0.37 (0.15)***	0.03 (0.32)
Seed	0.22 (0.14)	0.20 (0.14)	0.15 (0.11)	0.27 (0.33)
Pesticide	0.01 (0.02)	0.27 (0.16)*	0.02 (0.06)*	0.52 (0.26)**
Residual		-0.24 (0.18)		
IMR			0.56 (0.35)	-1.47 (1.04)
R^2	0.46	0.47	0.64	0.52

± Standard errors in parentheses § * significant at the 10% level, ** at 5% level and *** at 1% level

The Hausman test can be implemented in several equivalent ways. The version used in this case begins by regressing the pesticide input levels on the following instruments: an intercept, and the previous year's pesticide use and output levels³. The residuals from this regression are then added to the original model as an additional regressor. If the residuals term is insignificant in the new regression, the null hypothesis of no correlation between the input and the error term cannot be rejected. The results, reported in the second column of Table 2, show that the 'residuals' variable is insignificant, and it can be concluded that pesticide endogeneity is not severe enough to bias the results. This is consistent with the smallholders applying pesticide largely on a pre-determined, prophylactic basis, rather than in response to pest attacks. Kirsten *et al.* (2002) note that responding to pest attacks by applying pesticide is often a futile venture for the South African smallholders since a number of bottlenecks prevent timely response. Thus, pesticide inputs are used instead of instrumental variables in the rest of the analysis.

³ Data for the same producers for 1998/99 were also available from the survey, but were not used in the rest of the analysis since it was the first year of adoption, and adoption rates were very small. Using ($t-1$) values of input and output levels as instruments is fairly common in panel data production function estimation.

6.3. *Adoption Endogeneity: A Sample Selectivity Test*

To compare Bt and non-Bt technologies, varying parameter models are to be estimated, as outlined in (5) and (6). Huang *et al.* (2002) and Qaim *et al.* (2003), treat adoption, which is the Bt dummy variable in (5) and (6), as exogenous. Where adoption or non-adoption depends strongly upon farmer or farm characteristics, the resultant endogeneity prevents models like (5) and (6) being estimated simply with the $Bt = 0,1$ representation. Instead, a model would have to be derived and applied where $Bt = 1$ is instrumented by the probability that $Bt = 1$. We argue that sample selection concerns relate primarily to farm size, and these are ignorable given the model we estimate. These arguments are presented below, along with a selectivity test based on a simpler Cobb-Douglas setting.

(i) Bt ‘Adoption’ and ‘non-adoption’ rates in Makhathini in the early years were largely ‘supply-led’ (*i.e.* determined on the basis of VUNISA’s promotional strategies, abilities and constraints) rather than determined by ‘demand’ factors (farmer choice). In Makhathini, VUNISA had a captive audience, given the attractiveness of the technology and the generous availability of credit. VUNISA had a deliberate policy of promoting Bt to the larger cotton farmers in the initial years, with the belief that smaller farmers would be carried along by ‘copy adoption’ in future years.

(ii) If Bt technology adoption is systematically related to a number of farmer-specific variables, such as farmer wealth, credit rating, *etc.*, a probit model of adoption, with sufficient farm level covariates would explain adoption rates. We tried a number of such specifications, using variables such as farm size, credit rating, distance from seed supplier, education, age, gender, non-farm income, *etc.* However, most of these key variables were consistently insignificant and failed to explain adoption patterns, the only exception being farm size. The ‘best’ specification (one where at least some parameters were significant, and goodness of fit statistics were highest) is presented in the appendix. Farm size is the only variable significant at the 5% level. One interpretation of these findings is that adoption in the early stage reflected the time, personnel and credit supply constraints faced by VUNISA in spreading the message and making available the technology to farmers, rather than endogenous choices made by the smallholders.

(iii) Merely two years after our survey, adoption rates were close to 90% (Kirsten *et al.*, 2002). If adoption were constrained by several farm-specific co-variates, this would not be expected. This development is consistent with the notion that initial adoption followed VUNISA’s targeting of larger farmers, with smaller farmers picked up in later years. These arguments suggest that if a selectivity/endogeneity problem exists in this dataset, it is related predominantly to farm size.

(iv) The ‘treatment effects’ strand of the sample selection literature is relevant to our case, where two alternative technologies are available, and farmers self select themselves into either regime. If the factors that cause farmers to choose one technology over the other also cause differential performance regardless of

technology chosen, selectivity bias would be present, and various comparisons of the performance of the technology would be erroneously computed if selectivity were not controlled for. However, as Barnow *et al.* (1980) point out, assuming the effects that cause the sample selection problem are observable, including those variables in the outcome, regression (damage control production function regression) would correct for the sample selection problem. This standard regression based method has been called ‘ignorability of treatment’ (Rosenbaum and Rubin, 1983), and ‘selection on observables’ (Heckman and Robb, 1985) in the literature. Loosely, treatment is random/ignorable, conditional on those variables that affect both selection and outcomes.

This can also be viewed as a solution to a missing variable problem. If observable variables are affecting selection as well as outcomes, an outcome regression that leaves out such variables is not consistently estimated. This is because, when these variables are not included in the regression, their effects are included in the error term. Then the treatment dummy variable is obviously correlated with the error term, since these missing variables affect both selection as well as outcomes. The obvious solution to this problem is to include data on these variables so that estimation is consistent, *i.e.* once we condition on these observables, treatment effects are consistently estimated. In our case, we have argued in (i), (ii) and (iii) that cotton acreage, which constitutes the most significant portion of farm size, is the main variable systematically affecting adoption. However, this variable is already a part of the production function regression, and thus we are already conditioning for sample selection. Given this assumption, the existing estimates are consistently estimated.

(vi) Nevertheless, we perform a formal test for selectivity. We perform a simple pre-test for selectivity bias in a linear setting. Using the probit estimates described in the appendix, Heckman’s two-stage selectivity model was applied to the conventional Cobb-Douglas model. This requires computing inverse Mills ratios (IMR) from the first stage probit for each member of the cross-section and including this as an additional explanatory variable in separate regressions for adopters and non-adopters. If the IMR is insignificant for a sub-sample, it can be concluded that the sub-sample could have been consistently estimated on its own. The results are presented in columns three and four of Table 2. The IMR variable is insignificant in both sub-samples; lending support to the argument that adoption endogeneity is not a critical issue. Therefore, the rest of the analysis proceeds by treating adoption as exogenous.

6.4. *Damage control model estimates and model choice tests*

There is little *a priori* guidance available to determine whether the specified model should allow all parameters to vary with the new technology, only the pesticide parameter, or some, but not all parameters. Consequently, three versions of the logistic damage control specification described in (5) are estimated. In all three models, a separate Bt dummy variable appears in the damage control function $G(\bullet)$. In Model 1, all parameters in the potential output function $F(\bullet)$ also vary by

Bt adoption status; in Model 2 only the multiplicative constant in $F(\bullet)$ varies; in Model 3 none of the parameters in $F(\bullet)$ vary according to adoption status.

The most striking aspect of the models reported in Table 3 is that all the damage control parameters are significant and highly so for the more parsimonious models 2 and 3. The signs also conform to expectations.

Table 3. Logistic Damage Control Model Estimates[±]

Variable	Model 1 [§]	Model 2 [§]	Model 3 [§]
<u>Conventional $F(Z)$</u>			
Constant	2.66 (1.05)**	2.29 (0.80)***	1.84 (0.64)***
Constant*Bt	-1.34 (1.31)	-0.57 (0.55)	
Land	0.23 (0.21)	0.32 (0.10)***	0.31 (0.10)***
Land*Bt	0.12 (0.24)		
Labour	0.005 (0.20)	0.12 (0.14)	0.12 (0.14)
Labour*Bt	0.23 (0.29)		
Seed	0.31 (0.21)	0.16 (0.12)	0.16 (0.12)
Seed*Bt	-0.24 (0.27)		
<u>Damage control $G(X)$</u>			
Constant (μ)	2.29 (0.84)***	2.25 (0.67)***	1.69 (0.44)***
Bt (λ)	2.34 (1.25)*	2.20 (0.86)**	1.32 (0.40)***
Pesticide (σ)	0.10 (0.04)**	0.10 (0.03)***	0.10 (0.04)**

F -statistic: model 1 vs model 2 : 0.57. $F(3, 80)$ critical value = 2.73

F -statistic: model 2 vs model 3: 1.33. $F(1, 83)$ critical value = 3.97

LR statistic: model 1 vs model 2: 1.94. $\chi^2(3)$ critical value = 1.94

LR statistic: model 2 vs model 3: 1.45. $\chi^2(1)$ critical value = 3.84

§ Approximate standard errors in parentheses ± * indicates significantly different from zero at 10% level, ** at 5% level and *** at 10% level.

In the exponential form in (4), if $X = 0$ $G(X) = [1 + \exp\{\mu\}]^{-1}$, and some output is still produced although as μ gets larger, $G(X)$ and output get closer to 0. The estimated value of μ is not excessively large, and hence there seems to be a floor to the amount of damage resulting from pest attacks even when pesticide is not

applied. The positive and significant values for the coefficient of the Bt dummy (λ) confirms that adoption of Bt varieties is effective in controlling pest damage. Last, the positive, significant value for the pesticide parameter (σ) is necessary and sufficient for $G'(X) > 0$: that is, for increased pesticide to produce more abatement.

The upper part of Table 3 reports the results for the conventional $F(Z)$ part of the model. None of the interactions of the Bt model with conventional inputs or the multiplicative constant are significant in any of the models, suggesting that the depiction of Bt technology as influencing output primarily through pest control is reasonable. In this event, the more parsimonious specifications are preferable. Although there does not appear much to choose from between models 2 and 3, model 1 appears over-parameterised, leading to the land variable becoming insignificant. However, rather than choose one of the models arbitrarily, nested tests of model choice were performed. Since alternative tests of the same hypothesis can produce contradictory results in nonlinear small-sample models, we performed two different tests, an F test, and a Likelihood Ratio test, the results of which are in the bottom of Table 3. In each case the null hypothesis is that the restrictions implied by the restricted model are valid (additional parameters in the larger model are jointly =0), and we find that none of the null hypotheses cannot be rejected. Thus, we proceed with the most parsimonious model, Model 3, for further analysis.

7. Implications and Predictions

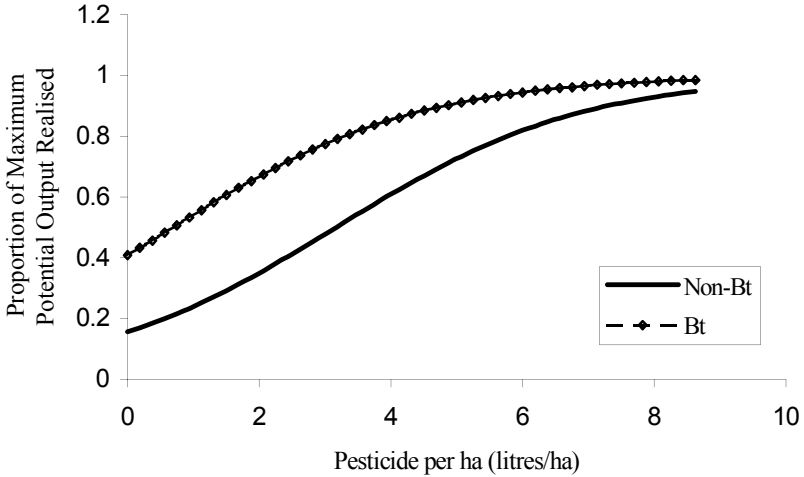
The estimates from Model 3 are first applied to the analysis of the implications of pesticide use and Bt adoption for damage control, along the lines of Qaim *et al.*, (2003). These computations are illustrated in Figure 1, which shows the per hectare effect of pesticide use.

The significant gap between the non-Bt and Bt curves illustrates the pest control efficacy of Bt adoption. With no pesticide applied, non-Bt producers would realise only about 16% of potential output. By shifting to Bt use, about 40% of potential output can be recovered even without application of insecticide. At each point, the slope of the Bt curve is lower than the slope of the non-Bt curve, suggesting that Bt adoption reduces the marginal productivity of pesticide by providing a substitute. At the current average application rate of 2.2 litres per hectare, a non-adopter attains only about 36% of potential output. A Bt user, at the current average application rate of 1.1 litres per hectare (half of the non-adopter average) realises 55% of potential output. Although use efficiency cannot be determined without reference to input costs, realisation proportions of 36 and 55% do not suggest excessive use. Another key point to note from the diagram is that the non-Bt damage control curve is convex for a significant portion, indicating the increasing marginal efficacy of insecticide input at lower ranges. This has an important implication for current use efficiencies.

The efficiency of insecticide use was explored by computing the Value Marginal Product (VMP) of insecticide and comparing it to the (then) insecticide price of 50 Rand (\$5) per litre. These computations were done holding all other inputs constant

at the sample average values and varying the insecticide quantity. Note that our estimation has been done on total cotton hectares on each farm, rather than on a per-hectare basis. Thus when we discuss the marginal product of insecticide for the average farm, we imply the extra total quantity of cotton produced by spreading one additional litre of insecticide over 5.3 hectares.

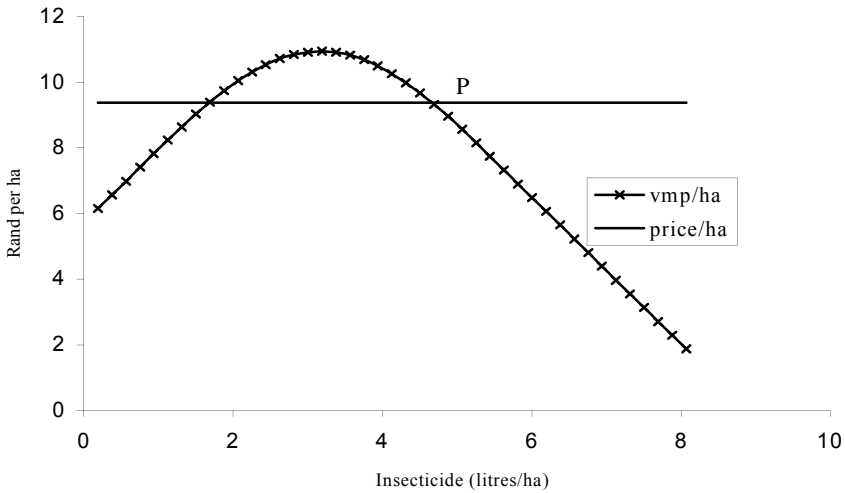
Figure 1: Damage Control and Pesticide Application



However, insecticide applications are more intuitively grasped on a per-hectare basis, and hence the calculations from the total cotton hectares were converted to a per-hectare basis for presentation below. Thus, an additional litre of insecticide for the farm implies extra input cost of approximately 9.3 Rand (\$0.93) per hectare. The per-hectare depiction for non-Bt users is provided in Figure 2 below.

Figure 2 is striking in that the VMP curve has an inverted U shape instead of the typical monotonically declining shape. However, this is not too surprising given the convex non-Bt damage control curve encountered in Figure 1. As Lichtenberg and Zilberman (1986) showed, this can be a fairly typical shape under the damage control specification and by ruling it out, conventional specifications like the Cobb-Douglas can miscalculate the productivity of pesticide input. More surprising, is the current average use level of 2.1 litres per hectare, which is sub-optimal, since it lies on the rising portion of the VMP curve. Given the shape of the VMP curve, the two potential optima are either the corner solution of zero use, or the point *P* (4.7 litres/ha), where the declining VMP intersects the input price. Calculations reveal that variable profits at point *P* exceed those at zero insecticide use by about 13 Rand (\$1.3) per hectare. Thus, 4.7 litres per hectare is the optimal rate for the average producer and current level of 2.1 litres per ha represents under use.

Figure 2: Per Hectare Pesticide Productivity (Non-Bt)



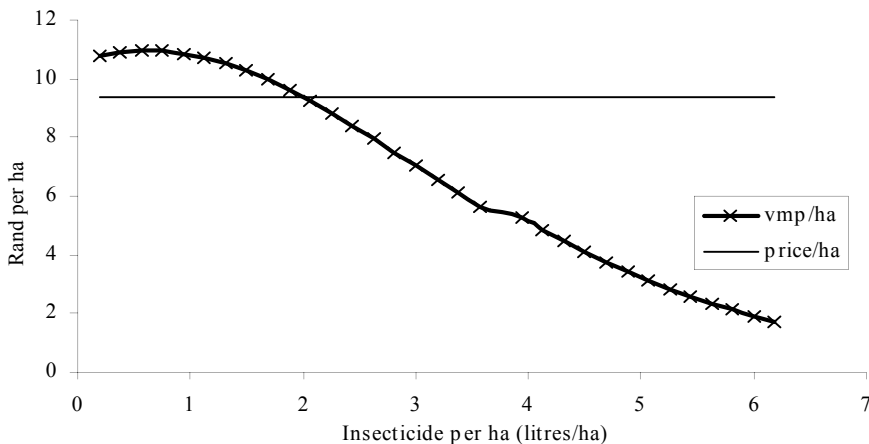
This under-use should not be surprising. There are several factors that could cause this outcome in Makathini. First, there are financial reasons for under-use. Pesticide purchases require larger cash outlays than are available to smallholders, particularly mid-season when reserves are low and other crops and activities compete for available cash. Some, who can afford the chemicals, do not own a knapsack sprayer and would hire someone to perform the task. But, labour availability for spraying poses a similar dilemma. Over the Christmas/New Year period, an important time in the South African cotton cycle, hired labour is often unavailable (Kirsten *et al.*, 2002). Thus a farmer who wishes to increase applications may find himself or herself unable to do so. Second, cross-sectional analysis is inevitably handicapped with regard to analysing pest problems. Pest infestations vary considerably over the years and if farmers apply insecticide proactively on the basis of long-run experience, a difficult pest year may well find applications short of optimality for that particular year.

The results of a similar analysis of the Bt users are shown in Figure 3. The shape of the VMP curve is more in line with expectations, declining monotonically with increased pesticide applications. The optimal application rate in this case is unambiguous and at current average applications rates of about 1 litre per hectare, Bt users are also under-applying insecticide relative to the optima of almost 2 litres per hectare. Given the additional private costs of applying pesticides, the degree of sub-optimality may be considered low.

For both the adopters and non-adopters, these private optimal application rates take no account of the environmental and health costs of pesticide use, which would reduce the socially optimal application rate. Thus, the under-use reported here

would be further reduced if negative externalities could be measured and allowed for.

Figure 3: Per Hectare Pesticide Productivity (Bt)



The employment effects of the new technology are important from a development economics perspective. There are understandable concerns that the mass introduction of a pesticide-saving technology in the developing world may exacerbate rural unemployment by reducing the demand for spraying labour. Those selling labour services are often the poorest, and a case can be made that their welfare needs to be weighted heavily. Our analysis has shown that, although Bt technology practically halves application, these applications were modest to start with. The ‘pesticide-reducing’ effect is dominated by a ‘yield-increasing’ effect, in contrast to the Chinese case. Hand-harvesting cotton is at least as labour intensive as spraying, and it is unlikely that the net result is a significant reduction in hired labour use.

Two simple computations from the data shed light on this. First, as seen from Table 1, average labour (man-days) per hectare was 6.0 for non-adopters and 5.8 for Bt users, hardly a large difference. The advantage of this measure is that it compares labour use across technologies within the same year. An alternative measure is the average labour use of the same smallholders across two years, in which case the farms remain the same, although the years are different. Computation of average labour use for those Bt adopters in the sample, who had been non-adopters in the previous year, showed a net increase of 3.6%. Taken together, these two pieces of evidence lend support to our proposition that Bt technology is not labour saving in the South African smallholder case.

8. Conclusion

By casting our production economics analysis of smallholders in a damage control framework, we have been able to explore the intricate relationships governing pesticide applications, damage abatement and productivity. The insignificant productivity of pesticide input indicated by a conventional representation of pesticides in the production process disappears once the analysis is cast in a damage control framework. Smallholders in South Africa use modest levels of pesticide in a situation characterised by severe pest problems, and insignificant pesticide productivity, indicating overuse, is at odds with expectations. The damage control framework reveals smallholders to be currently under using pesticide under both non-Bt and Bt technologies.

Most previous farm-level analysis of pesticide productivity under Bt technology has come from analysis of large farms in the USA and well-supported farmers in China. The benefits from Bt in the China studies (Pray *et al.*, 2001; Huang *et al.*, 2002) show little gain in yields as a result of the Bt technology. The gains come from large reductions in pesticide inputs, due to removing over-applications of pesticide inputs under the conventional technology. This analysis shows why data reported in South African smallholder studies, such as Ismael *et al.* (2002), have found large increases in yields and modest reductions in pesticide use. In Makathini Flats, the benefits come from allowing farmers to capture lost potential yields that were not being realised because of inadequate pesticide use arising from bottlenecks and constraints associated with pesticide application. By producing naturally occurring pesticide, the Bt variety partially overcomes these constraints and increases yields by 40%. The concern about Bt technology threatening the livelihoods of the poorest section of rural society, *i.e.* hired labourers, appears to be unfounded, since the expansion of harvest labour compensates for the reduction in spraying labour.

The year of our analysis, 1999/2000, appears to have been an ideal one for conducting a 'with and without' comparison of the new technology. This is because in preceding years, the technology was new and adoption had only just begun. In the years immediately following, so rapid was the diffusion that non-adopters represented only about 10% of the cotton smallholder population. Nevertheless, much interesting work remains to be done. This study has been cast in a traditional production economics mode, with only casual arguments made regarding other smallholder issues such as labour availability and cash/credit constraints. Production economics is well equipped to characterise technology, but much less so to answer questions relating to diffusion, long-term viability and farmer welfare in a development context. It is fully acknowledged that a household economics framework, with more extensive data, can throw light on a host of other issues that are important in more fully evaluating the technology and determining its viability. For instance, credit provision in Makhathini flats has been generous due to the monopolist input supplier's stake in the new technology, and government interest in the area. In a situation where smallholder credit constraints to pay for the technology becomes binding, diffusion may be much slower and the technology less viable. Another acknowledged limitation is the cross-sectional nature of our

data. With pest shocks varying considerably from year to year, and producers making decisions on pesticide application on the basis of experience and expectations over the longer run, cross-sectional analysis such as this one can only paint a limited picture. Similarly, production risk aspects of the new technology, together with characterisation of downside risk aversion, and the potential 'insurance' function provided by Bt technology need to be investigated.

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APPENDIX: PROBIT MODEL OF Bt ACCEPTANCE

Variable	Coefficient	Standard Error
Constant	-0.75	0.83
Farm Size	0.06	0.03**
Non-farm income	0.59	0.34*
Age	0.01	0.01
Gender	-0.19	0.30
McFadden's R^2 : 0.08		