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Labour savings of Roundup Ready maize: Impact on cost and input substitution for South African smallholders

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Abstract

This study examines the impact of genetically modified maize on labour, cost and input substitutability for smallholders in South Africa. Producers of Roundup Ready® (RR) maize use significantly less child, female and male labour than non-RR producers, resulting in lower costs despite significantly higher herbicide, seed and fertiliser costs. A treatment effects model controlling for selection bias shows that the entire cost advantage and more can be attributed to the Roundup Ready® technology. These results are supported using a nonparametric kernel density estimator. Elasticities of factor substitution indicate strong substitutability among inputs; however, a lack of statistical significance limits the interpretation of the results.

Key words*:* cost, maize, labour saving, Roundup Ready®, South Africa

1. Introduction

Many authors argue that technological innovation, aimed at increasing the agricultural productivity of smallholder farmers in sub-Saharan Africa, is an essential component in strategies to reduce hunger and poverty and to confront challenges such as rapid population growth, food price volatility and climate change. Of all staple food crops in Africa, maize is the most prominent in terms of production and consumption (Tumusiime *et al*. 2010; Smale *et al*. 2011). The success of genetically modified (GM) maize is well documented worldwide; for example, in 2010, GM maize added nearly $5 billion or 3.5% to the total value of global maize production (Brookes & Barfoot 2012). Therefore, the relevance of GM maize technology and the role that it plays in poverty reduction for smallholders is of particular interest. In this study we used detailed maize production data to estimate the impact of GM maize on labour savings, input cost and input substitutability for smallholders in KwaZulu-Natal, South Africa.

Previous research on GM maize reveals several benefits to smallholders in the Philippines and South Africa, where smallholder adoption has been the highest, but many issues regarding the impact of GM maize on smallholders remain unexplored. Studies on insect-resistant Bt maize in the Philippines show higher yields and net returns (Yorobe & Quicoy 2006), even after controlling for selection bias and censoring (Mutuc & Yorobe 2007; Mutuc *et al*. 2012). In South Africa, research shows that Bt maize has an output advantage that declines as pest pressure decreases, and that net returns to Bt maize are often higher, although they do not always outweigh the higher cost of Bt seed (Gouse *et al*. 2006, 2009). Bt maize also reduces the use of insecticides and minimises plant exposure to fumonisin, a toxin associated with oesophageal cancer and birth defects in humans and that is potentially fatal to livestock (Piesse & Thirtle 2008; Pray *et al*. 2009). Herbicide-tolerant Roundup Ready® (RR) maize, coupled with no-till practices, increases output, reduces labour (Gouse *et al*. 2006; Piesse & Thirtle 2008), has higher gross margins despite higher seed costs in most regions (Gouse *et al*. 2009), and reduces smallholder net returns risk (Regier *et al*. 2012). An overview of the impact of GM maize on smallholders finds evidence of its advantage throughout several years of study (Gouse 2012).

2. Data and approach

GM white maize became the first GM staple food crop when it was released to smallholders in South Africa in 2001; since then, adoption has been widespread, especially among commercial farmers, but also among smallholders (Gouse *et al*. 2009; James 2010). This study takes place in KwaZulu-Natal, a region of South Africa characterised by high land ownership by smallholders, in contrast to the majority of South Africa, where land is owned by commercial farmers (Department of Agriculture, Forestry and Fisheries 2011). The two regions within KwaZulu-Natal examined in this study are Hlabisa and Simdlangetsha, which lie within close proximity to each other and share many agro-ecological characteristics. The average rainfall is around 980 mm per year, much of which falls in the maize production season, but average maize yields are low (1 500 kilograms/ hectare) due to marginal land quality (Gouse *et al*. 2008, 2009).

Data was collected from 184 households with a total of 212 maize plots in the two regions during the 2009/2010 maize production season. Information on the timing, quantity and prices of inputs and labour used during each stage of production, from land preparation until harvest, was gathered by experienced enumerators supervised by researchers from the University of Pretoria during seven visits throughout the season in order to reduce recall bias (see Gouse (2012) for details). Other information collected was on demographics, education, experience using herbicide, access to extension and credit, household consumption habits, assets, expenses and non-farm income.

The majority of the farmers in this study were relatively well endowed, with average assets of nearly $8 000, and 96% had access to either a bank account or informal credit. The average age of the producers was 55 years, and slightly more than half of the respondents were female. The average household size was 6.2 persons, with an average of 3.3 active household members, resulting in a dependency ratio[1] of 0.84. Close to half of the respondents, especially those who had returned from jobs in the city to retire on their farms, claimed that a monthly pension cheque from the government was their primary source of income. The majority of maize produced by the farmers was consumed within their households.

The mean farm size was 1.85 hectares and the average maize plot was 0.49 hectares, with farmers planting five primary types of maize. Two were improved hybrid varieties, referred to as Pannar and Carnia after the names of the seed companies that released these varieties. The other three were GM hybrid varieties; Bt, which is insect resistant, RR, which is herbicide tolerant, and BR, which is "stacked", containing both Bt and RR traits.

The 2009/2010 maize production season was a favourable one, with producers reporting good rainfall and minimal pest pressure on both the GM and non-GM plots in both regions. Because of low pest pressure, no significant yield advantage was observed on the Bt maize plots (see Gouse *et al*. 2009). Average maize yield was 1 645 kilograms per hectare, with no particular maize type

[1] The dependency ratio is defined in this study as the number of people aged 0 to 15 and 65 or older, divided by the working population aged 16 to 64.

dominating in either region. Of the RR maize plots, 71% were planted to no-till, compared with only 3% of non-RR plots. No-till significantly reduces labour requirements, as herbicide application replaces weeding labour (Regier *et al*. 2012), resulting in significantly less child, male, female and total labour for adopters of RR maize (Table 1). At the same time, hired labour was not significantly different across the maize varieties. This reveals that RR producers place a high value on their family labour, and RR maize allows them to allocate labour to a more profitable or preferred activity. These results are unchanged when data is disaggregated into regions.

Table 1. Family and hired labour by seed type (hours/hectare)

	Full sample (*n* = 212)	Non-GM (*n* = 82)	Bt (*n* = 18)	RR (*n* = 77)	BR (*n* = 35)
Child	30	56 [c,d]	42 [c,d]	8	13
Female	91	129 [c,d]	122 [c,d]	59	60
Male	70	105 [c,d]	70	46	43
Hired	98	101	93	95	103
Total	291	391 [c,d]	327 [c,d]	207	219

[a], [b], [c] and [d] indicate significantly different labour use compared to Non-GM, Bt, RR, and BR respectively at the 0.05 level using Tukey's HSD test

Previous literature indicates that KwaZulu-Natal has an abundant supply of land but a constrained supply of labour due to the urban migration of agricultural workers and a high HIV/AIDS infection rate (Gouse *et al*. 2009). If labour is constrained, then RR maize certainly seems like an attractive option for farmers – both those who are older and cannot handle the physical activity required for weeding, and those taking advantage of the labour-saving potential of RR maize to expand onto additional land. The substitution effects of RR maize on labour and land are examined later in this paper.

The reduction in labour results in lower labour costs for both BR and RR producers (Table 2)[2]. Bt producers have significantly higher seed and oxen/tractor costs, which outweigh the labour-savings advantage and result in total costs per hectare that are very similar to those of non-adopters. Producers of RR maize spent significantly less on oxen/tractor and labour than non-adopters, as a higher percentage of them planted the maize using no-till with pre-emergent herbicide and hand hoes. RR maize producers had much lower fertiliser costs as well; as a result, total costs were significantly lower per hectare for adopters of RR maize. Part of the reason that RR producers have lower fertiliser costs is regional differences; however, the cost function disentangles these differences with a regional binary variable.

Table 2. Biochemical, mechanical and labour costs (USD/hectare[a])

	Full sample (*n* = 212)	Non-GM (*n* = 82)	Bt (*n* = 18)	RR (*n* = 77)	BR (*n* = 35)
Labour	223	300 [c,d]	251 [c,d]	159	168
Fertilizer	292	415 [c,d]	430 [c,d]	131	291 [c]
Herbicide	131	85	124	171 [a,b]	153 [a]
Seed	150	121	151 [a]	168 [a]	179 [a,b]
Insecticide	6	13 [c,d]	0	1	0
Oxen/Tractor	65	72 [c,d]	71 [c]	53	57
Total	749	841	851	630	743

[a] All monetary units are converted from South Africa Rand to US dollar ($) at the constant exchange rate of 7.44 Rand per US dollar, based on 2009/2010 exchange rates
[a], [b], [c] and [d] indicate significantly different input use compared to Non-GM, Bt, RR and BR respectively at the 0.05 level using Tukey's HSD test

[2] Labour costs were calculated using the average wage rate paid to hired labour. The full wage rate was applied to both hired and family labour to account for the opportunity cost of time.

3. Cost function estimation

An unrestricted cost function approach is used to evaluate the differences in cost between maize varieties, assuming that households use different input allocations to minimise cost while producing a fixed level of output. The benefit of a cost function is that it uses input prices that can be considered exogenous, thus eliminating endogeneity, which is a persistent issue in production functions (Binswanger 1974). First, we jointly estimated the impact of RR and Bt maize on total costs using ordinary least squares (OLS), specified as

$$C_i = \alpha_0 + \sum_{j=1}^{n} \beta_j x_{ij} + \delta I_i + \varepsilon_i \qquad (1)$$

where C_i is the total cost for maize plot i, and x_{ij} is a set of all explanatory variables j on maize plot i (including dummy variables), except I_i, the binary variable for either RR or Bt maize, with the scalar parameter δ measuring the impact of Bt or RR maize, and ε_i is a random error term. A comparison of mean values revealed that RR maize had significantly lower input costs than non-RR maize (Table 2); however, the entire value of δ cannot necessarily be attributed only to RR maize, since farmers who produce RR maize at low costs may be more skilled farmers or plant RR maize on their best land. Failure to control for the farmer and plot selection bias may lead to an overestimation of the cost benefits of RR maize (Barrett *et al*. 2004).

To control for selection bias, we used the treatment effects model, a type of Heckman's two-step estimation procedure (Greene 2003). The first step of the treatment effects model is the adoption decision model, which controls for self-selection by estimating factors that influence RR adoption. It is estimated using the probit model

$$RR_i^* = \sum_{j=1}^{n} \gamma_j w_{ij} + u_i \qquad (2)$$

where $RR_i = 1$ if $RR_i^* > 0$, and 0 otherwise, w_{ij} is a vector of explanatory variables that explain RR maize adoption, γ_j is a parameter to be estimated, and u_i is the error term. If the decision to plant RR maize seed is determined by unobservable variables as predicted, the error terms ε_i and u_i (equations 1 and 2) are correlated.[3] As a result, the expected impact of RR maize on total cost is determined by:

$$E[C_i|RR_i = 1] = \sum_{j=1}^{n} \beta_j x_{ij} + \delta + E[\varepsilon_i|RR_i = 1] = \sum_{j=1}^{n} \beta_j x_{ij} + \delta + \rho\sigma\widehat{\lambda_i} \qquad (3)$$

where $\widehat{\lambda_i}$ is the inverse Mills ratio[4] computed from the estimates of the probit model, γ_j (equation 2), defined as

$$\widehat{\lambda_i} = \frac{\phi(a_i)}{\Phi(a_i)} \; if \; RR_i = 1 \qquad (4)$$

where $\phi(a_i)$ is the probability density function, $\Phi(a_i)$ is the cumulative density function, and $a_i = -\sum_{j=1}^{n} \gamma_j w_{ij}$. The second step of the treatment effects model is to run an ordinary least squares model including the inverse Mills ratio, $\widehat{\lambda_i}$, in the estimation. If $\widehat{\lambda_i}$ is significant, it is effectively controlling for selectivity bias, and correcting for biased estimators β_j and δ in the OLS model (Maddala 1983; Greene 2003).

[3] The error terms are also assumed to have normal distribution.
[4] The inverse Mills ratio is also called the hazard rate in the treatment effects model.

The variables used to explain total cost are the input prices of labour, fertiliser, herbicide and seed, land in hectares, since no reliable price information was available, and maize output in kilograms (Table 3).[5] Binary variables are included for location as well as maize type, represented by RR and Bt to capture the effects of the RR and Bt technologies, with BR maize included in both dummy variables since it contains both technologies.

According to Table 3, producers of Bt maize have higher costs and pay significantly higher prices for herbicide and seed. They tend to farm larger plots, are better educated, and have more experience using herbicide than their non-Bt maize counterparts. RR maize producers, on the other hand, have significantly lower costs than non-RR producers, in the midst of significantly higher fertiliser, herbicide and seed prices, due in part to significantly lower labour costs. RR producers have less formal education, but have a greater number of active household members as indicated by significantly lower dependency ratios.

Table 3. Descriptive statistics of regression variables

	Full sample (*n* = 212)	**Non-GM (*n* = 82)**	**Bt (*n* = 18)**	**RR (*n* = 77)**	**BR (*n* = 35)**
Total cost (US dollars)	343	350	466	275	414
	(156)	*(171)*	*(136)*	*(77)*	*(189)*
Labour (USD/hour)	.80	.79	.81	.82	.78
	(.15)	*(.11)*	*(.17)*	*(.19)*	*(.12)*
Fertiliser (USD/kilogram)	.59	.57	.58	.61	.58
	(.05)	*(.05)*	*(.06)*	*(.02)*	*(.06)*
Herbicide (USD/litre)	13.8	10.7	9.4	16.3	17.8
	(4.6)	*(2.9)*	*(3.8)*	*(2.7)*	*(5.2)*
Seed (USD/kilogram)	9.0	6.8	8.9	10.6	10.6
	(2.2)	*(1.6)*	*(1.1)*	*(.9)*	*(1.0)*
Land preparation (USD/hectare)	65	71	71	60	59
	(19)	*(21)*	*(18)*	*(15)*	*(17)*
Land (hectares)	.48	.44	.56	.46	.58
	(.23)	*(.25)*	*(.20)*	*(.17)*	*(.26)*
Maize output (kilograms)	754	630	775	845	831
	(526)	*(626)*	*(627)*	*(397)*	*(417)*
Hlabisa (1 = Hlabisa, 0 = Simdlangetsha)	.46	.18	.00	.87	.43
	(.50)	*(.39)*	*(.00)*	*(.34)*	*(.50)*
RR maize (1 = RR, 0 = non-RR)	.47	0	0	1	1
	(.50)				
Bt maize (1 = Bt, 0= non-Bt)	.25	0	1	0	1
	(.43)				
Additional variables used in probit model					
Formal education (1 = Primary education or higher, 0 = No formal education)	.67	.74	.78	.52	.77
	(.47)	*(.44)*	*(.43)*	*(.50)*	*(.43)*
Experience using herbicide (years)	3.5	3.1	4.5	3.5	4.0
	(2.0)	*(2.3)*	*(1.3)*	*(1.7)*	*(2.1)*
Total household assets (2010 US dollars)	8031	7746	8309	7936	8761
	(7999)	*(8510)*	*(8088)*	*(6673)*	*(9564)*
Distance to maize plot (minutes)	8.5	11.4	15.7	3.6	9.2
	(9.3)	*(10.5)*	*(8.3)*	*(4.6)*	*(9.7)*
Dependency ratio	.84	.95	1.06	.64	.94
	(.75)	*(.70)*	*(.88)*	*(.62)*	*(.95)*

*, ** and *** indicate values significantly higher at the 0.10, 0.05 and 0.01 levels respectively using a one-sided t-test

[5] Due to difficulties in collecting accurate information on prices, labour price information is available for only 40% of the maize plots that used hired labour. Therefore, the average labour price was calculated for each region, averaging \$0.79 and \$0.81 per hour in Simdlangetsha and Hlabisa respectively.

The first step of the Heckman two-step regression is a probit model, used to estimate the probability of RR maize adoption. The results of the probit indicate that the probability of adopting RR maize is both significantly and positively influenced by location (Hlabisa) and experience using herbicide in years (Table 4). The likelihood ratio chi-square is 98.91 (p = 0.000), indicating that the model is statistically significant as a whole.

Table 4. Probit model results (*n* = 212)

Variable	Coefficient	Standard Error
Intercept	-1.55***	0.41
Hlabisa dummy	1.95***	0.30
Total household assets	0.00	0.00
Formal education	0.05	0.26
Experience using herbicide	0.24***	0.06
Dependency ratio	0.04	0.14
Distance to maize plot	-0.02	0.01

*, ** and *** indicate values significantly different to zero at the 0.10, 0.05 and 0.01 levels respectively

The results of the regression equations show a great deal of similarities between the OLS and treatment effects models (Table 5). As expected, the coefficients of seed, land and output are positive and significant in both models, indicating that an increase in the price of seed, hectares of land or kilograms of output will increase total costs. In the treatment effects model, fertiliser and land are positive, with negative squared terms. Both models suggest that farmers in Hlabisa can expect costs to be $187.44 and $156.81 lower per maize plot in the OLS and treatment effects models respectively. Similarly, farmers planting RR maize can expect costs to be $75.69 lower according to the OLS model. The inverse Mills ratio in the treatment effects model is positive and significant, indicating that the treatment effects model is correcting for selectivity bias, as we predicted it might. However, the treatment effects model reveals that RR maize producers have $102.44 (30%) lower costs per maize plot after taking into consideration the inverse Mills ratio, suggesting that the OLS model *underestimated* the cost-reducing effect of RR maize. Therefore, the entire cost advantage and more can be attributed to RR maize, after isolating the effect of RR maize on total cost by disentangling the lower costs attributed to RR maize from those associated with farm and farmer characteristics. The binary Bt variable is not significant in either regression, likely due to the fact that benefits from Bt maize are only realised when pest pressure is high, as indicated previously.

Table 5. Cost function regression results under two assumptions

	WLS		Treatment effects	
(*n* = 212)	Coefficient	Huber-White SE	Coefficient	Standard error
Intercept	-2 841.48*	1 571.70	-2 390.88**	1 142.86
Labour	347.86	2 024.07	85.18	1 034.24
x labour	-27.43	82.53	-44.50	100.50
x fertiliser	-632.11	3 755.69	-46.20	1 829.96
x herbicide	9.89	29.61	2.79	15.72
x seed	10.25	19.97	12.82	26.33
x land prep	1.25	1.33	1.13	1.43
x land	-104.02	171.94	-45.98	178.32
x output	-0.05	0.09	-0.06	0.08
Fertiliser	6 383.41**	3 014.75	5 502.59**	2 396.85
x fertiliser	-2 483.56***	885.90	-2 298.81***	852.79
x herbicide	41.05	60.51	54.70	42.19
x seed	-145.22*	74.62	-144.99**	60.81
x land prep	-11.96	8.17	-11.28	6.98
x land	-1 094.87	734.94	-1 103.73	736.08
x output	-1.02**	0.43	-0.94***	0.31
Herbicide	-42.67	43.13	-47.22*	26.17
x herbicide	-0.01	0.15	0.02	0.10
x seed	2.65**	1.03	2.88***	0.68
x land prep	-0.04	0.11	-0.05	0.10
x land	-6.82	10.24	-5.56	7.11
x output	0.00	0.00	0.00	0.00
Seed	80.05*	45.14	74.55*	41.73
x seed	-0.94	0.74	-0.89	0.76
x land prep	-0.07	0.14	-0.04	0.13
x land	-7.78	19.38	-11.18	13.55
x output	0.00	0.01	0.01	0.01
Land preparation	9.17**	4.35	8.60**	4.35
x land prep	-0.01	0.01	-0.01	0.01
x land	-1.93	1.67	-1.65	1.79
x output	0.00	0.00	0.00*	0.00
Land	1 594.37***	506.31	1 531.21***	494.08
x land	-329.54**	131.22	-326.17***	116.31
x output	0.24**	0.10	0.26***	0.07
Output	0.69**	0.28	0.65***	0.20
x output	0.00	0.00	0.00**	0.00
Hlabisa	-187.44***	26.80	-156.81***	25.61
RR	-75.69***	16.30	-141.70***	36.48
Bt	3.88	10.69	5.62	10.55
Inverse Mills ratio or Hazard rate			39.26**	19.51
R-squared	0.91			
F-value	103.16***			
Wald test statistic – χ^2			1 885.72***	
H_0: squared and interaction terms = 0	3.64***		127.82***	
(Wald test)				

*, ** and *** indicates significantly different than zero at the 0.10, 0.05 and 0.01 levels respectively

The OLS model, using heteroscedasticity-robust Huber-White standard errors, is a good fit, with an R-squared value of 0.91 and significant squared and interaction terms (p = 0.000). The model rejects the Shapiro-Wilk W test for normality (p = 0.000), which does not suggest that the least squares estimates are still unbiased, but only that it is not possible to run valid hypothesis testing

(Chen *et al*. 2003). In the treatment effects model, the Wald test statistic indicates that the model significantly explains the difference in total cost (p = 0.000), as well as significant squared and interaction terms (p = 0.003).

4. Nonparametric regression estimation

The results of the cost functions provide strong evidence that RR maize reduces cost for maize producers. However, a nonparametric function allows for a more general graphical comparison of RR and non-RR maize, by depicting the relationship between average cost as maize output increases. Unlike parametric models, which require strong assumptions about functional form, homoscedasticity, correlation and distribution, nonparametric models abandon most of these assumptions. Thus, although they provide less precise information, such as statistical significance, the information they do provide is extremely robust (Just 2000). Examining both parametric and nonparametric models provides different perspectives and produces a more robust analysis (Greene 2003).

The nonparametric function is estimated with the most common approach, a kernel density estimator, by fitting a relationship between maize output, y, and average cost, x. The relationship is local, meaning that separate fitted relationships are determined for different levels of x. A bandwidth parameter is used for smoothing. With regard to the cost function, it is expected that, as maize output increases, average cost decreases until it reaches the optimal level of output. The relationship between y and x are represented by the nonparametric regression

$$y_i = \mu(x) + \varepsilon \tag{5}$$

where y_i represents the independent variable of observation i, and $\mu(x)$ is an unspecified conditional mean function that allows nonlinearity (Greene 2003; Cameron & Trivedi 2009).

The predicted value of $\mu(x)$ at $\boldsymbol{x} = x^*$ is a local weighted average of y_i, where $\boldsymbol{x}$ is a vector of all independent variables and x^* is the mean value of the independent variables at y_i. A greater weight is placed on observations where x_i, the individual independent variable, is close to x^*, and little or no weight when x_i is far from x^*. The general form of the conditional mean estimating function, $\mu(x)$, is defined as

$$\hat{\mu}(x^*) = \sum_{i=1}^{n} w_i(x_i, x^*, h)\, y_i \tag{6}$$

where the weights $w_i(x_i, x^*, h)$ sum over i to one and decrease as the distance between x_i and x^* increases.

The Epanechnikov kernel-weighted regression estimator is used to provide a smoother estimate of the conditional mean function. It is defined as

$$\hat{\mu}(x_i, x^*, h) = \frac{\sum_{i=1}^{n} \frac{1}{h} K\left[\frac{x_i - x^*}{h}\right] y_i}{\sum_{i=1}^{n} \frac{1}{h} K\left[\frac{x_i - x^*}{h}\right]} \tag{7}$$

where $K[z] = .75(1 - .2z^2)/2.236\ if\ |z| \leq 5,\ 0$ otherwise. The Epanechnikov kernel function, $K[z]$, creates a smoother estimation by explicitly defining a neighbourhood of points that are close to x^* and weighting extreme observations as zero. The bandwidth parameter, which controls the width of the bin and thus the smoothness of the estimation, is defined by h. As the bandwidth parameter h increases, more weight is placed on observations where x_i is closer to x^*. This wider bandwidth creates more bias in the estimation, but it also creates a smoother function since it reduces variance (Greene 2003; Cameron & Trivedi 2009). A bandwidth of 100 was chosen because it allows for variation in the estimator without it becoming too smooth (Greene 2003).

In order to estimate total cost non-parametrically, predicted values of total cost were first estimated from the split regression of RR and non-RR maize using the OLS quadratic regression (Table A-1 in Appendix). Average cost was then calculated by dividing the predicted total cost by maize output. The result of the nonparametric regression show that average cost decreases for both RR and non-RR maize as output increases, with RR maize costs lower across all levels of output, with the exception of plots with an output of around 1 500 kilograms (Figure 1). Producers with an output of at least 1 000 kilograms of maize are able to minimise average cost, and RR maize producers have cost savings of about 16% at the mean output of 754 kilograms.

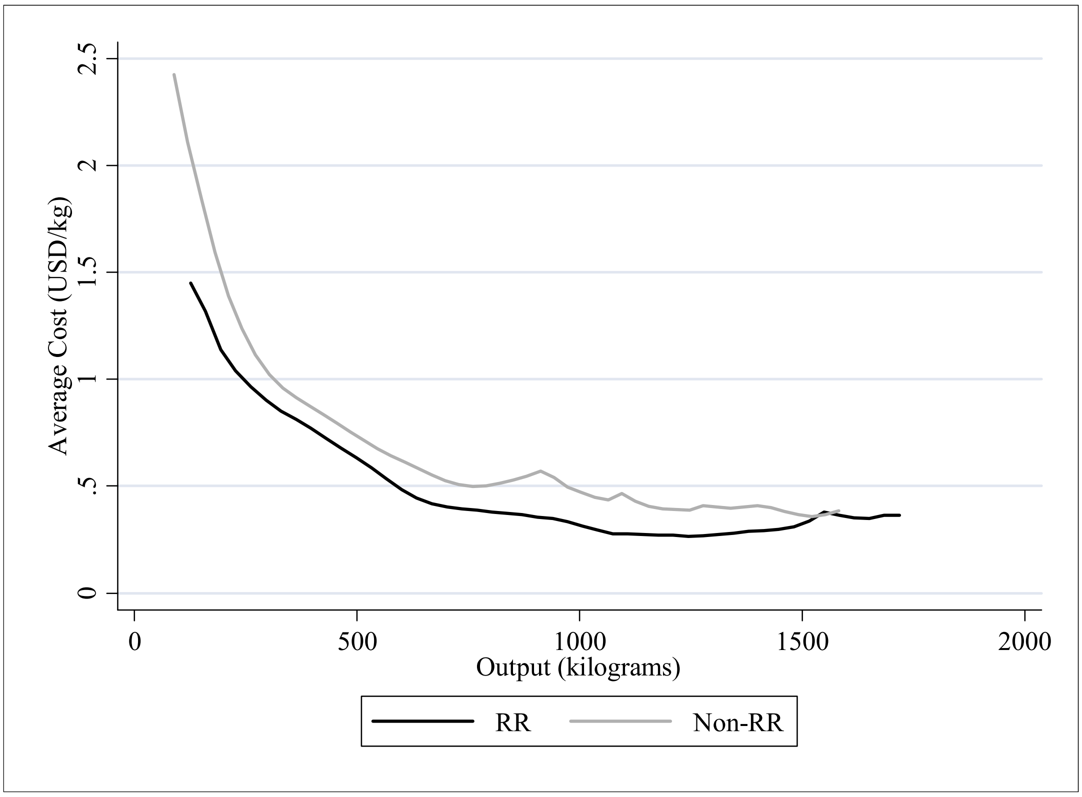

Figure 1. Nonparametric representation of average cost

5. Elasticities of substitution

The cost function analysis shows that the labour savings of RR maize significantly reduce cost, providing new insights into the impact of GM maize on smallholders. These results stand in spite of the significantly higher prices that RR maize producers pay for seed, herbicide and fertiliser, and even when controlling for farm and farmer characteristics that may cause biased results. Although these results are useful in revealing the impact of RR maize on smallholders, they tell us little of the impact of GM maize on wages and rural employment, issues explored by Piesse and Thirtle (2008). The impact of the labour savings of RR maize depends on input availability; if labour is abundant, labour incomes may fall and poverty increase, but if land is plentiful, planting area and output could increase, resulting in higher labour use and higher wages. Previous literature suggests that KwaZulu-Natal has abundant marginal land and a constrained supply of labour (Piesse & Thirtle 2008; Gouse *et al*. 2009); therefore, as long as producers are able to substitute land for labour easily, an increase in labour productivity should result in higher explicit and implicit wages and maintained employment. In this survey's data from the 2009/2010 season, RR maize more than doubles labour productivity, from 4.11 kilograms of maize per hour labour to 9.46 kilograms of maize, which may result in upward pressure on wages.

In this section we use factor elasticities of demand and elasticities of factor substitution, derived from an unconstrained cost function, to examine the substitutability of fertiliser, herbicide, seed and land as the wage rate increases. The own and cross price elasticities of demand, measured as the percentage change in quantity demanded of input j resulting from a one percent increase in the price of input i, provide the most intuitive results for understanding the response of derived demands to input price changes. They are defined as

$$\epsilon_{ij} = \frac{\partial x_i(w,y)}{\partial w_j} \cdot \frac{w_j}{x_i(w,y)} \tag{8}$$

where x_i is the quantity of input i and w_j is the price of input j (Chambers 1988). Because a majority of RR maize producers plant no-till, use more expensive seed and herbicide, and spend almost no time weeding, separate cost functions are estimated for both RR and non-RR maize plots (Table A-1).

The results show that a rise in the price of labour (in the first column) will have a different effect on input demand for producers of RR and non-RR maize (Table 6). On RR maize plots, producers will use more fertiliser and less labour, herbicide and seed as wages rise. On non-RR maize plots, fertiliser, herbicide, seed and land all have a complementary relationship with labour; therefore, none of these inputs is a good substitute for labour as wages increase. Own price elasticities are mostly negative, as expected, on both the RR and non-RR maize plots, with producers especially sensitive to changes in herbicide prices. The results from the RR regression are robust, with 42% of price elasticities of demand significant, but the non-RR elasticities of demand are less conclusive.

Table 6. Price elasticities of demand

RR adopters (n = 112)	**Labour**	**Fertiliser**	**Herbicide**	**Seed**	**Land preparation**	**Land**
Cost shares	*0.25*	*0.19*	*0.26*	*0.26*	*0.05*	
Labour	-1.95	434.44***	-40.85**	-21.05	-2.56	-4.21
Fertilizer	-39.67***	35.92***	-5.43	-23.38*	-34.69***	-6.51
Herbicide	-3.81**	5.55	-4.19***	-5.48***	-6.28***	-0.80
Seed	7.68	-93.36*	21.42***	8.08	2.83	-1.60
Land preparation	0.29	-42.46***	7.52***	0.87	-1.15	-1.33**
Land	-0.76	12.91	-1.56	0.79	2.15**	-0.97
Non-RR adopters (n = 100)						
Cost shares	*0.36*	*0.29*	*0.10*	*0.16*	*0.07*	
Labour	1.87	10.86	-3.14	0.72	-1.91	-0.79
Fertiliser	8.11	-9.43	0.76	-5.22	-3.89	-2.11
Herbicide	6.10	-1.98	-4.75*	0.51	-1.80	0.07
Seed	0.88	-8.55	-0.32	0.54	-0.81	0.52
Land preparation	6.49	17.72	-3.16	2.26	0.99	4.34
Land	-0.41	-1.45	-0.02	0.22	-0.66	-0.79*

*, ** and *** indicate values significantly different than zero at the 0.10, 0.05 and 0.01 levels respectively, estimated using the delta-method

The Morishima elasticity of substitution (MES) of input i for input j provides a direct measure of how the input ratio i, j responds to a change in w_j. It is simply the cross-price elasticity of demand minus the own-price elasticity of demand (Chambers 1988), defined as

$$\sigma_{ij}^{M} = \frac{\partial \ln(x_i^*(w,y)/x_j^*(w,y))}{\partial \ln \mathrm{w}_j} = \epsilon_{ij} - \epsilon_{jj} \qquad (9)$$

The effect of varying the j^{th} price is divided into two parts; ϵ_{ij} is the effect of varying w_j on x_i, and ϵ_{jj} shows the effect of varying w_j on x_j (Dalton *et al*. 1997). Input j is a direct Morishima substitute for input i if $\sigma_{ij}^{M} > 0$ when increasing the j^{th} price increases the optimal quantity of input *i* relative to the optimal quantity of input *j*; inputs *i* and *j* are complements if the inequality is reversed (Blackorby & Russell 1989).

The results show much stronger relationships between inputs on RR maize plots, most of them complementary (Table 7). The results of the split regression (see Table A-1) used to derive the Morishima elasticities of substitution show many significant variables for RR maize, while less confidence can be placed in the results for non-RR maize, as they are quite messy.

Table 7. Morishima elasticities of substitution

RR adopters (n = 112)	**Labour**	**Fertiliser**	**Herbicide**	**Seed**	**Land preparation**	**Land**
Labour	0	398.52***	-36.66**	-29.13	-1.42	-3.24
Fertiliser	-37.72***	0	-1.25	-31.46**	-33.55***	-5.54
Herbicide	-1.86	-30.37***	0	-13.56	-5.13***	0.17
Seed	9.63	-129.28**	25.60***	0	3.98	-0.62
Land preparation	2.24	-78.37***	11.71***	-7.21	0	-0.35
Land	1.19	-23.01***	2.63*	-7.29	3.29*	0
Non-RR adopters (n = 100)						
Labour	0	20.28	1.61	0.18	-2.89	-0.002
Fertiliser	6.25	0	5.52	-5.76	-4.88	-1.32
Herbicide	4.23	7.45	0	-0.03	-2.79	0.87
Seed	-0.99	0.88	4.43	0	-1.80	1.31
Land preparation	4.62	27.15	1.59	1.72	0	5.13
Land	-2.28	7.97	4.73	-0.32	-1.64	0

*, ** and *** indicate values significantly different than zero at the 0.10, 0.05 and 0.01 levels respectively, estimated using the delta-method

6. Conclusion

Using an unrestricted and nonparametric cost function, this study uses detailed maize production data from the 2009/2010 season in KwaZulu-Natal, South Africa to provide insight into the labour-savings effects of Roundup Ready® maize. Although RR maize adopters pay significantly more for herbicide, seed and fertiliser, summary statistics indicate that the labour savings of RR maize significantly reduce cost for smallholders. To test this hypothesis, a Heckman two-step approach was used to control for selection bias by disentangling the lower costs attributed to RR maize from those associated with farm and farmer characteristics. We found that, after controlling for selection bias, the entire cost advantage and more could be attributed to the Roundup Ready® technology itself. The cost-reducing benefits of RR maize are further confirmed across all levels of output using a nonparametric cost function.

Because of its labour savings, RR maize increases labour productivity, which leads to higher implicit wages. However, the impact of RR maize on real wages and rural unemployment are unknown, since these are determined my multiple factors. Morishima elasticities of substitution, derived from a split unrestricted cost function, reveal that RR maize allows for much greater substitutability among inputs than non-RR maize, including land, which is considered the most abundant resource. Therefore, RR maize allows producers to expand production area, resulting in higher income and reduced poverty. This research reveals that smallholders are able to take advantage of the labour savings of Roundup Ready® maize through lower costs and greater substitutability between inputs.

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Appendix

Table A-1. Split regression results for RR and non-RR maize

	RR		Non-RR	
(*n* = 212)	**Coefficient**	**Huber-White SE**	**Coefficient**	**Huber-White SE**
Intercept	15 426.03***	4 903.40	-1 172.53	2 550.65
Labour	-8 874.76***	1 878.46	-1 774.05	1 923.11
x labour	-30.22	115.40	168.78	224.34
x fertiliser	17 655.18***	4 214.07	4 505.58	2 926.72
x herbicide	-59.88**	25.93	-61.99	41.66
x seed	-49.68	78.17	51.78	82.50
x land prep	-1.06	2.57	-5.67	3.58
x land	-204.46	241.52	-268.14	519.07
x output	-0.02	0.11	-0.17	0.33
Fertiliser	-25 206.54***	8 231.33	2 072.14	4 785.31
x fertiliser	-10 744.35***	3 312.16	-1 833.22	1 850.04
x herbicide	115.69	107.62	25.73	94.98
x seed	802.26**	313.70	-237.91	164.32
x land prep	210.46***	73.89	-13.32	12.58
x land	4 749.86*	2 784.06	-1 225.69	1 081.74
x output	-2.20***	0.77	-0.45	0.89
Herbicide	203.27***	54.67	-2.38	76.62
x herbicide	-1.59***	0.30	1.35	0.83
x seed	-6.56***	1.96	-0.42	2.04
x land prep	-1.34***	0.30	0.14	0.19
x land	-20.63	16.87	-2.20	14.28
x output	0.00	0.01	-0.01	0.01
Seed	-343.86*	196.34	105.24	126.85
x seed	-1.87	3.38	0.63	1.10
x land prep	-0.25	0.63	-0.17	0.26
x land	16.17	48.17	6.05	36.08
x output	0.06***	0.02	0.01	0.01
Land preparation	-109.15***	40.94	13.92	8.44
x land prep	0.03	0.03	0.00	0.02
x land	8.00**	3.46	-4.79	3.62
x output	0.00	0.00	0.00	0.00
Land	-2 722.25	1 863.73	1 841.72*	954.72
x land	-215.02	219.42	-397.45*	220.71
x output	0.18	0.15	0.35**	0.14
Output	0.90**	0.40	0.41	0.52
x output	0.00	0.00	0.00*	0.00
Hlabisa	-228.76***	22.71	-150.49***	47.83
R-squared	0.95		0.93	
F-value	165.92***		246.24***	
H_0: squared and interaction terms = 0				
(Wald test)	15.68***		2.78***	
H_0: normal distribution				
(Shapiro-Wilk W test)	0.99		0.98	

*, ** and *** indicate values significantly different than zero at the 0.10, 0.05 and 0.01 levels respectively