**Labor-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 labor, cost, and input substitutability for smallholders in South Africa. Data was collected during the 2009-2010 maize production season from 184 households with a total of 212 maize plots in two regions, Hlabisa and Simdlangetsha, located in KwaZulu-Natal, South Africa. Producers of Roundup Ready® (RR) maize use significantly less child, female, and male labor than non-RR producers, resulting in lower costs in spite of significantly higher herbicide, seed, and fertilizer prices.

An unrestricted cost function approach is used to evaluate the differences in cost between maize varieties, assuming that households use different input allocations to minimize cost while producing a fixed level of output. A treatment effects model used to control for selection bias shows that the entire cost advantage and more can be attributed to the Roundup Ready® technology. 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. These results are confirmed using a nonparametric kernel density estimator. Elasticities of factor substitution indicate strong substitutability among inputs; however, lack of statistical significance limits interpretation of results.



***Key words:*** cost function, elasticities of factor substitution, genetically modified, labor-saving, maize, nonparametric regression, Roundup Ready®, South Africa


## Introduction

In the face of challenges such as population growth, food price spikes, and climate change in Africa, the development of pertinent agricultural technology which boosts crop productivity for smallholders must be of upmost importance in the strategy for reducing hunger and poverty. Of all staple food crops in Africa, maize is the most prominent in terms of production and consumption (Smale, Byerlee and Jayne 2011, Tumusiime, et al. 2010). The success of genetically modified (GM) maize is well-documented worldwide; for example, in 2010 GM maize added nearly $5 billion or 3.5 percent to the total value of global maize production (Brookes and 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 use detailed maize production data to estimate the impact of GM maize on labor, 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 and Quicoy 2006), even after controlling for selection bias and censoring (Mutuc and Yorobe 2007, Mutuc, et al. 2012). In South Africa, research shows that Bt maize has an output advantage which declines as pest pressure decreases, and net returns to Bt maize are often higher but they do not always outweigh the high cost of Bt seed (Gouse, Piesse and Thirtle 2006, Gouse, Piesse and Thirtle, et al. 2009). Bt maize also reduces the use of expensive insecticides and minimizes plant exposure to fumonisin, a toxin associated with esophageal cancer and birth defects in humans and potentially fatal to livestock (Piesse and Thirtle 2008, Pray, et al. 2009). Herbicide tolerant Roundup Ready® (RR) maize, coupled with no-till practices, increases output, reduces labor, (Piesse and Thirtle 2008, Gouse, Piesse and Thirtle 2006) has higher gross margins despite higher seed costs in most regions, (Gouse, Piesse, et al. 2009) and reduces smallholder net returns risk (Regier, Dalton and Williams 2012). An overview of the impact of GM maize on smallholders finds evidence of its advantage throughout several years of study (Gouse 2012).

## Data

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 and slower among smallholders (Gouse, Piesse, et al. 2009, James 2010). This study takes place in KwaZulu-Natal, a region of South Africa characterized by high land ownership by smallholders in contrast to a 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 agroecological characteristics. The average rainfall is around 980 mm per year, much of it falling during the maize production season, but average maize yields is low (1500 kilograms/hectare) due to marginal land quality (Gouse, Piesse and Poulton, et al. 2008, Gouse, Piesse and Thirtle, et al. 2009).

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

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

The mean farm size is 1.85 hectares and the average maize plot is 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 which 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 favorable one, with producers reporting good rainfall and minimal pest pressure on both GM and non-GM plots in both regions. Because of low pest pressure, no significant yield advantage was observed on Bt maize plots (see Gouse et al. 2009). Average maize yield was 1645 kilograms per hectare, with no particular maize type dominating in both regions. Of the RR maize plots, 71% are

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

planted to no-till compared to only 3% of non-RR plots. No-till significantly reduces labor requirements as herbicide application replaces weeding labor, resulting in significantly less child, male, female, and total labor for RR maize adopters (Table 1). These results are unchanged when data is disaggregated into regions. Although it appears that producers of Bt maize also use significantly less labor, 35 out of 53 Bt adopters are actually BR producers planting no-till; therefore, when BR producers are excluded there is no significant difference in labor use.

**Table 1. Family and Hired Labor 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] indicates significantly different labor 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 labor due to urban migration of agricultural workers and a high HIV/AIDS infection rate (Gouse, Piesse, et al. 2009). If labor 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 as well as those taking advantage of the labor-saving potential of RR maize to expand onto additional land. The substitution effects of RR maize are examined later in this paper.

The reduction in labor results in lower labor costs for both Bt and RR producers; however, most of the labor-savings of Bt maize can be attributed to the BR maize which is planted no-till (Table 2). Bt producers have significantly higher seed and oxen/tractor costs which outweighs the labor-savings advantage and results in total costs per hectare which are very similar to non-adopters. Producers of RR maize spent significantly less on oxen/tractor and labor 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 fertilizer costs as well; as a result, total costs are significantly lower per hectare for adopters of RR maize.

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

| | Full sample ($n$ = 212) | Non-GM ($n$ = 82) | Bt ($n$ = 18) | RR ($n$ = 77) | BR ($n$ = 35) |
|---|---|---|---|---|---|
| Labor | 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 dollars ($) at the constant exchange rate of 7.44 Rand per US dollar, based on 2009-2010 exchange rates.

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

**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 minimize cost while producing a fixed level of output. The benefit a cost function is that it uses input prices which can be considered exogenous, thus eliminating endogeneity which is a persistent issue in production functions (Binswanger 1974). First, we jointly estimate the impact of RR and Bt maize on total costs using Ordinary Least Squares (OLS), specified as

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

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 $\delta$ measuring the impact of Bt or RR maize, and $\varepsilon_i$ is a random error term. The OLS results show that RR maize has significantly lower costs than non-RR maize (Table 4). The entire value of $\delta$ cannot necessarily by attributed only to RR maize, however, 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 use 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

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

where $RR_i = 1$ if $RR_i^* > 0$, and 0 otherwise, $w_{ij}$ is a vector of explanatory variables that explain RR maize adoption, $\gamma_j$ 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 $u_i$ and $\varepsilon_i$ (equations 1 and 2) are correlated.[2] As a result, the expected impact of RR maize on total cost is determined by

$$\begin{aligned} E[C_i|RR_i = 1] &= \sum_{j=1}^{n} \beta_j x_{ij} + \delta + E[\varepsilon_i|RR_i = 1] \\ &= \sum_{j=1}^{n} \beta_j x_{ij} + \delta + \rho\sigma\widehat{\lambda_i} \end{aligned} \tag{3}$$

where $\widehat{\lambda_i}$ is the inverse Mills ratio[3] computed from the estimates of the probit model, $\gamma_j$ (equation 2) defined as

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

where $\phi(a_i)$ is the probability density function, $\Phi(a_i)$ is 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 $\beta_j$ and $\delta$ in the OLS model (Maddala 1983, Greene 2003, Key and McBride 2003).

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[2] The error terms are also assumed to have normal distribution.

[3] 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 labor, fertilizer, herbicide, and seed, land in hectares since no reliable price information was available, and maize output in kilograms (Table 3).[4] 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.

**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)[a] | 343 | 350 | 466 | 275 | 414 |
| | *(156)* | *(171)* | *(136)* | *(77)* | *(189)* |
| Labor (USD/hour) | .80 | .79 | .81 | .82 | .78 |
| | *(.15)* | *(.11)* | *(.17)* | *(.19)* | *(.12)* |
| Fertilizer (USD/kilogram) | .59 | .57 | .58 | .61 | .58 |
| | *(.05)* | *(.05)* | *(.06)* | *(.02)* | *(.06)* |
| Herbicide (USD/liter) | 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)* | | | | |

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

| | | | | | |
|---|---|---|---|---|---|
| Bt maize (1 = Bt, 0= non-Bt) | .25<br>*(.43)* | 0 | 1 | 0 | 1 |
| *Additional variables used in probit model* | | | | | |
| Education (1= Primary education or higher, 0= No formal education) | .67<br>*(.47)* | .74<br>*(.44)* | .78<br>*(.43* | .52<br>*(.50* | .77<br>*(.43)* |
| Experience Using Herbicide (years) | 3.5<br>*(2.0)* | 3.1<br>*(2.3)* | 4.5<br>*(1.3* | 3.5<br>*(1.7* | 4.0<br>*(2.1)* |
| Total household assets (2010 US dollars) | 8031<br>*(7999)* | 7746<br>*(8510)* | 8309<br>*(8088)* | 7936<br>*(6673)* | 8761<br>*(9564)* |
| Distance to maize plot (minutes) | 8.5<br>*(9.3)* | 11.4<br>*(10.5)* | 15.7<br>*(8.3)* | 3.6<br>*(4.6)* | 9.2<br>*(9.7)* |
| People in household (total number) | 6.2<br>*(2.1)* | 6.3<br>*(1.6)* | 6.1<br>*(1.2)* | 6.2<br>*(2.7)* | 6.0<br>*(2.2)* |
| Head of household age (1 = head of household above 60, 0 = below 60 years old) | .51<br>*(.50)* | .39<br>*(.49)* | .56<br>*(.51)* | .68<br>*(.47)* | .40<br>*(.50)* |
| Dependency ratio | .84<br>*(.75)* | .95<br>*(.70)* | 1.06<br>*(.88)* | .64<br>*(.62)* | .94<br>*(.95)* |

[a]All monetary units are converted from South Africa Rand to US dollars ($) at the constant exchange rate of 7.44 Rand per US dollar, based on 2009-2010 exchange rates.
*, **, and *** indicates significantly higher at the 0.10, 0.05 and 0.01 levels respectively using a one-sided t-test

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 fertilizer, herbicide, and seed prices, due in part to significantly lower labor costs. RR producers are less educated, but have a greater number of active household members as indicated by significantly lower dependency ratios.

The first step of the Heckman two-step regression is a probit model, used to estimate the probability of RR maize adoption. 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 | Std. Err. |
|---|---|---|
| Intercept | -1.55*** | 0.41 |
| Hlabisa dummy | 1.95*** | 0.30 |
| Assets | 0.00 | 0.00 |
| Formal education | 0.05 | 0.26 |
| Experience with herbicide | 0.24*** | 0.06 |
| Dependency ratio | 0.04 | 0.14 |
| Distance to maize plot | -0.02 | 0.01 |

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

Results of the regression equations show a great deal of similarities exists between the OLS and treatment effects models (Table 5). As expected, the coefficients on 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 all increase total costs. In the treatment effects model, fertilizer 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 realized when pest pressure is high as indicated previously.

**Table 5. Regression Results**

| | WLS | | Treatment Effects | |
|---|---|---|---|---|
| (*n* = 212) | Coefficient | Huber-White SE | Coefficient | Std. Err. |
| Intercept | -2841.48* | 1571.70 | -2390.88** | 1142.86 |
| Labor | 347.86 | 2024.07 | 85.18 | 1034.24 |
| x labor | -27.43 | 82.53 | -44.50 | 100.50 |
| x fertilizer | -632.11 | 3755.69 | -46.20 | 1829.96 |
| 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 |
| Fertilizer | 6383.41** | 3014.75 | 5502.59** | 2396.85 |
| x fertilizer | -2483.56*** | 885.90 | -2298.81*** | 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 | -1094.87 | 734.94 | -1103.73 | 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 | 1594.37*** | 506.31 | 1531.21*** | 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 – $\chi^2$ | | | 1885.72*** | |
| $H_0$: squared and interaction terms = 0 (Wald test) | 3.64*** | | 127.82*** | |

*, **, 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, 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).

**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 a kernel density estimator, the most common approach, 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 which allows nonlinearity (Cameron and Trivedi 2009, Greene 2003).

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

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

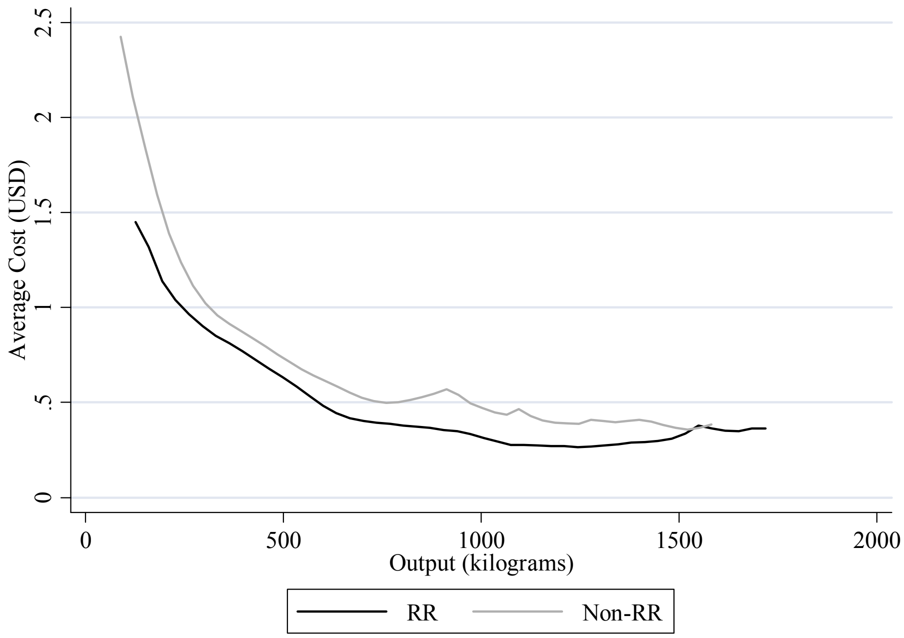
where the weights $w_i(x_i, x^*, h)$ sum over $i$ to one and decrease as the distance between $x_i$ and $x^*$ increases.

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 neighborhood 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 (Cameron and Trivedi 2009, Greene 2003). No method exists for determining optimal bandwidth; therefore, a bandwidth of 100 was chosen since it allows for variation in the estimator without it becoming too smooth (Greene 2003).

**Figure 1. Nonparametric Representation of Average Cost**




In order to estimate total cost nonparametrically, 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). 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 most levels of output (Figure 1). As seen in Figure 1, producers with an output of at least 1000 kilograms of maize are able to minimize average cost.

**Elasticities of substitution**

The cost function analysis shows that the labor-savings of RR maize significantly reduces cost, providing new insights into the impact of GM maize on smallholders. These results stand in spite of significantly higher prices that RR maize producers pay for seed, herbicide, and fertilizer 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 labor-savings of RR maize depends on input availability; if labor is abundant, labor incomes may fall and poverty increase, but if land is plentiful, planting area and output could increase, resulting in higher labor use and higher wages. The authors suggest that South Africa has abundant marginal land and a constrained supply of labor; therefore, as long as producers are able to easily substitute land for labor, an increase in labor productivity should result in higher wages and maintained employment. In this surveys data from the 2009-2010 season, RR maize more than doubles labor productivity, from 4.11 kilograms of maize per hour labor to 9.46 kilograms of maize suggesting 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 fertilizer, herbicide, seed, and land as the wage rate increases. Compensated derived input demands, conditional on output, can be estimated directly from the cost function using Shephard's lemma; however, the response of derived-demands to changes in input prices, computed directly from the Hessian matrix of the cost function, is of greater interest (Chambers 1988, Capalbo and Antle 1988). 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

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

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 labor will have a different effect on input demand for producers of RR and non-RR maize (Table 5). On RR maize plots, producers will use more fertilizer and less labor, herbicide, and seed as wages rise. On non-RR maize plots, fertilizer, herbicide, seed, and land all have a complementary relationship with labor; therefore, none of these inputs are a good substitute for labor as wages increase. Own price elasticities are mostly negative as expected on both RR and non-RR maize plots, with producers especially sensitive to changes in herbicide prices.

**Table 5. Price elasticities of demand**

| ***RR adopters (n=112)*** | Labor | Fertilizer | Herbicide | Seed | Land Preparation | Land |
|---|---|---|---|---|---|---|
| *Cost shares* | *0.25* | *0.19* | *0.26* | *0.26* | *0.05* | |
| Labor | -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* | |
| Labor | 1.87 | 10.86 | -3.14 | 0.72 | -1.91 | -0.79 |
| Fertilizer | 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 *** indicates significantly different than zero at the 0.10, 0.05 and 0.01 levels respectively, estimated using the delta-method

The Morishema 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 $\mathrm{w}_j$. It is simply the cross-price elasticity of demand minus the own-price elasticity of demand (Chambers 1988), defined as

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

The effect of varying the *j* th price is divided into two parts; $\epsilon_{ij}$ is the effect of varying $\mathrm{w}_j$ on $x_i$, and $\epsilon_{jj}$ shows the effect of varying $\mathrm{w}_j$ on $x_j$ (Dalton, Masters and Foster 1997). Input *j* is a direct Morishima substitute for input *i* if $\sigma_{ij}^{M} > 0$ when increasing the $j^{\text{th}}$ 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 and Russell 1989).

The results show much stronger relationships between inputs on RR maize plots, most of them complementary (Table 6). Results of the split regression (see Table A-1) used to derive the Morishima elasticities of substitution are quite messy; therefore, little confidence can be placed in these results.

**Table 6. Morishima elasticities of substitution**

| ***RR adopters (n=112)*** | Labor | Fertilizer | Herbicide | Seed | Land Preparation | Land |
|---|---|---|---|---|---|---|
| Labor | 0 | 398.52*** | -36.66** | -29.13 | -1.42 | -3.24 |
| Fertilizer | -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)*** | | | | | | |
| Labor | 0 | 20.28 | 1.61 | 0.18 | -2.89 | -0.002 |
| Fertilizer | 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 *** indicates significantly different than zero at the 0.10, 0.05 and 0.01 levels respectively, estimated using the delta-method

## 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 labor-savings effects of Roundup Ready® maize. Although RR maize adopters pay significantly more for herbicide, seed, and fertilizer, summary statistics indicate that the labor-savings of RR maize significantly reduces cost for smallholders. To test this hypothesis, a Heckman two-step approach is used to control for selection bias by disentangling the lower costs attributed to RR maize from those associated with farm and farmer characteristics. We find that after controlling for selection bias, the entire cost advantage and more can 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 labor-savings, RR maize increases labor 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 labor-savings of Roundup Ready® maize through lower costs and greater substitutability between inputs. Bt maize provides no evident yield or cost benefit in this season, most likely due to low pest pressure.

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**Appendix**

**Table A-1. Split Regression Results for RR and Non-RR Maize**

| (*n* = 212) | **RR** Coefficient | Huber-White SE | **Non-RR** Coefficient | Huber-White SE |
|---|---|---|---|---|
| Intercept | 15426.03*** | 4903.40 | -1172.53 | 2550.65 |
| Labor | -8874.76*** | 1878.46 | -1774.05 | 1923.11 |
| x labor | -30.22 | 115.40 | 168.78 | 224.34 |
| x fertilizer | 17655.18*** | 4214.07 | 4505.58 | 2926.72 |
| 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 |
| Fertilizer | -25206.54*** | 8231.33 | 2072.14 | 4785.31 |
| x fertilizer | -10744.35*** | 3312.16 | -1833.22 | 1850.04 |
| 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 | 4749.86* | 2784.06 | -1225.69 | 1081.74 |
| 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 | -2722.25 | 1863.73 | 1841.72* | 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 *** indicates significantly different than zero at the 0.10, 0.05 and 0.01 levels respectively.