

IMPACT OF GENETICALLY MODIFIED MAIZE ON RISK, OUTPUT AND COST AMONG
SMALLHOLDERS IN SOUTH AFRICA

by

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Abstract

Previous research in low-income countries reveals that genetically modified (GM) maize has the potential to increase yield and reduce labor use; however, other issues, especially regarding Roundup Ready (RR) maize, remain mostly unexplored. This research examines the impact of GM maize on yield, cost, and risk among 184 smallholders during the 2009-10 maize production season in two regions in KwaZulu-Natal, South Africa; Hlabisa and Simdlangetsha. Two hybrid maize varieties; Pannar and Carnia, and three GM varieties; Bt, RR, and BR (stacked with Bt and RR) are produced. In both regions, producers of RR and BR maize pay 47% more per kilogram of seed and use 44% less labor per hectare compared to other varieties. Due to low labor costs, net returns from RR and BR varieties are 25% and 40% higher than other varieties in Hlabisa and Simdlangetsha, respectively.

Stochastic dominance analysis is used to compare net returns of all five varieties in both regions. RR maize is second-degree stochastic dominant to all other varieties in Simdlangetsha, while no variety is stochastically dominant in Hlabisa. Stochastic efficiency with respect to a function (SERF) analysis indicates that RR maize is the preferred variety for producers over the entire range of risk preferences in both regions. While average maize gross returns are \$713 per hectare, risk premiums between \$18 and \$221 must be paid to RR maize producers, depending on region and farmer risk preference, to persuade them to switch to the second-most preferred variety.

Econometric analysis indicates significant yield gains of at least 8% from RR maize, although the yield gain varies greatly when input endogeneity is taken into account. Elasticities of output with respect to labor are 0.41 and 0.82 for RR and non-RR maize respectively, and 0.61 and 0.33 with respect to land. A cost function analysis indicates that RR maize has 19% lower costs per maize plot, which increases to at least a 35% advantage when controlling for selectivity bias. Nonparametric kernel density estimation also reveals consistently lower total and average costs of RR maize at most levels of output, suggesting technological benefits to smallholder farmers from RR maize not available through conventionally-bred hybrids.

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Chapter 1 - Introduction

The State of Agricultural Production in Sub-Saharan Africa

Since 1960 growth in agricultural production has increased at a rate of 2-3 percent per year in most low-income countries, but growth in Sub-Saharan Africa has been less than 1 percent annually. Since 1980, growth in agricultural production has slowed down to only 0.4 percent annually (Evenson 2003). In the last several decades, population growth in Sub-Saharan Africa has outpaced agricultural production, causing per capita food production to fall by about 20 percent. Population growth has also outpaced agricultural expansion into new land, creating a 39 percent drop in arable land per capita (Tumusiime, et al. 2010). Sub-Saharan Africa's population will continue to increase at a rate much higher than the rest of the world, and their food requirements are expected to more than double by 2050. In the region of the world with the highest rate of food insecurity, where more than 30 percent of the population is malnourished, factors such as environmental degradation, poor infrastructure, and limited access to inputs will increasingly put downward pressure on agricultural production. Meanwhile, climate change is expected to reduce crop yields in many Sub-Saharan African countries by more than 20% by 2050 (Lobell and Burke 2010). Needless to say, investing in technology to boost agricultural productivity should be a priority in the strategy for reducing hunger and poverty in Sub-Saharan Africa.

The objective of this research is to examine if investment in genetically modified (GM) maize should be part of a strategy to increase agricultural productivity in Sub-Saharan Africa. Of particular interest are any benefits that GM technology offers smallholders. Chapter 1 introduces the topic of maize production in Sub-Saharan Africa, constraints to increasing productivity, and the potential of GM maize to address these constraints. Chapter 2 provides an overview of current research on GM crops and their impact on smallholders in low-income countries, followed by an overview of data used in this research in Chapter 3. Building on the previous research and data overview, the subsequent chapters test a set of hypotheses. Chapter 4 test the first hypothesis, that GM maize has higher output than non-GM maize, using a production function approach. The second hypothesis that GM maize reduces risk is tested in Chapter 5, using stochastic dominance and stochastic efficiency with respect to a function. Chapter 6 test

the third and final hypothesis, that GM maize has lower costs, using both an econometric cost function approach and a nonparametric regression.

Maize Production

Sub-Saharan Africa

Maize, Africa's most prominent grain, covered 27% of cereal area and represented 34% of cereal production from 2005 to 2008. In Sub-Saharan Africa, 77% of maize is consumed directly by humans, compared to only 3% in high income countries (Smale, Byerlee and Jayne 2011). Maize is a vital source of nourishment, as it represents 22% of total daily caloric intake in Sub-Saharan Africa, and 31% in South Africa (Tumusiime, et al. 2010).

Total maize production in Sub-Saharan Africa has increased almost 4-fold since 1962, but most of this increase has come from extending the area under cultivation rather than increasing yield (Evenson 2003). Average maize yields in Sub-Saharan Africa, excluding South Africa, have stagnated around 1.5 tonnes per hectare, significantly below the world average of 5 tonnes per hectare (FAOSTAT 2011). Net maize imports average less than 5% of total maize consumption, but this number is expected to continue to increase as Africa's population continues to grow, especially in urban areas (Smale, Byerlee and Jayne 2011).

Low maize yields in Sub-Saharan Africa can be explained by multiple factors including low adoption rates of modern varieties, low use of external inputs like fertilizer and pesticides, and poor soil management. Another explanation lies in a unique characteristic of maize. Unlike rice and wheat, maize demonstrates "hybrid vigor" or significant yield advantages when it cross-pollinates. Hybrid vigor is quickly lost if farmers reuse seed. Therefore, smallholder maize farmers are reliant on a seed industry which is only sustained through strong demand for seed (Smale and Jayne 2003).

South Africa

In contrast to the rest of Sub-Saharan Africa, maize yields in South Africa increased from around 1.5 tonnes per hectare in 1962 to well over 4 tonnes per hectare¹ in the last decade (Directorate Agricultural Information Services 2011). Between 2005 and 2009, South Africa

¹ This yield is equal to 24 to 64 bushels per acre respectively at 56 pounds of maize per bushel.

produced 22.5% of total maize in Sub-Saharan Africa, while only using 10% of total land in maize production (FAOSTAT 2011). High maize yields have allowed South Africa to remain the primary maize exporting country in Sub-Saharan Africa, despite the fact that land cultivated into maize has actually decreased significantly in the last 15 years. In 2011, South Africa exported 2,070 million tons of maize, or 17% of their total crop, mostly to other Southern African countries (Directorate Agricultural Information Services 2011).

The high yields of maize and other crops in South Africa can be attributed in part to its emphasis in agricultural research. Although South Africa holds only 8% of arable land available across Sub-Saharan Africa, its public sector invested \$137 million in 2000, representing 27% of total agricultural funding to public research while hiring 8% of total agricultural research staff in Sub-Saharan Africa (Beintema and Stads 2006, FAOSTAT 2011). Research in maize is a priority in South Africa, since maize is the most important cereal, covering 19% of arable land and representing 44% of the total value of cereals (Department of Agriculture, Forestry and Fisheries 2011).

In 1999, South Africa became the first nation in Africa to approve genetically modified (GM) maize, when Monsanto introduced insect resistant (IR) yellow maize. Since then, many insect resistant and herbicide tolerant (HT) varieties of maize have been developed, tested, and approved.² Adoption has been rapid as GM maize in South Africa covered 1.9 million hectares, representing 77% of total maize area in 2010. Of the GM maize, 46% of area was planted to Bt maize, followed by 41% to stacked maize (both Bt and RR) and 13% to Roundup Ready maize (James 2010). Economic benefits from all GM crops (maize and cotton) in South Africa were estimated at US\$142 million in 2009 (Brookes and Barfoot 2011) although most benefits went to large-scale farmers, who own 87% of the land and produce over 90% of the maize crop (Gouse, Piesse, et al. 2009). In 2001, Bt white maize became the first GM crop released as a staple food to smallholders, followed by RR white maize in 2004. Currently, adoption of all types of GM maize has been slower among smallholders (Gouse, Piesse, et al. 2009).

² Since all maize varieties that are insect resistant are Bt and all herbicide tolerant varieties are Roundup Ready in this study, they will be referred to as Bt and RR respectively.

Biotic and Abiotic Stress and its Effect on Maize Yield

Plant stress, both biotic and abiotic, can significantly reduce yield. Biotic factors include insects, weeds, and disease, while abiotic factors consist of temperature, rainfall, sunlight, and wind. Different management strategies allow farmers to mitigate stress in various ways. This includes crop rotations, leaving land fallow, using abating inputs such as pesticide or irrigation, or the use of seed with built in protection against biotic or abiotic stresses.

Biotic Stress

Insect pests pose a direct threat to maize yield, especially in tropical areas where pest pressure is high (Qaim and Zilberman 2003). The conventional method to control insects is through the use of insecticides. Insecticide are typically expensive, must be applied at the optimal time and numerous times, may cause environmental damage by polluting water bodies, kill non-target insects, and jeopardize farmer health. Another method to control pests is through the use of crop rotations, but this is only effective with area-wide farmer cooperation, and does not eliminate, only reduces the threat of insect damage. Insect-resistant varieties of GM maize, although more expensive, produce a natural insecticide which eliminates the need for insecticides in most cases, require little management, and kill only targeted insects.

The conventional method to control weeds during plant growth is tillage, whether it is tractor-powered cultivators, oxen, or hand hoes. Cultivation using tractors with cultivators is costly and does not provide complete control of weeds, and hand hoeing is very labor intensive. Crop rotations, crop planting patterns, and high leaf area coverage are effective ways to manage weed growth, unless weed pressure is high. Pre-emergent herbicides are effective in controlling weeds early in the growing season, but they may only be sprayed prior to the emergence of the maize plant. Most post-emergent herbicides are used to control broadleaf weeds, but have little control over grasses – only a few post-emergent herbicides kill both grasses and broadleaves without killing the maize plant. These maize plants have been genetically modified to be herbicide tolerant (HT); therefore, the seed is typically more costly. However, HT maize usually reduces the overall cost of weed control and often result in more complete weed control than other methods.

Most diseases common to maize are funguses that attack the leaves, stock, or ear, taking nutrients from the plant and reducing yield. Fungicides can control fungal growth, but they are

expensive, require precise timing of application, and may not always be effective. Crop rotation and crop removal limit fungal diseases, but only to an extent. One of the root causes of fungicide damage to maize is due to insect damage. Therefore, proper control of insects to limit damage to the maize plant is the most effective way to control fungal infections, especially fumonisins, a type of toxic fungus which poses a threat to the health of both animals and humans (Pray, et al. 2009).

Abiotic Stress

Abiotic stress is caused primarily by fluctuations in temperature, rainfall, salinity, sunlight, and wind. While these stresses are already challenges faced by many farmers in Sub-Saharan Africa, it is projected that climate change will lead to even higher temperatures and lower rainfall. Since maize is highly reliant on water, it will be the most impacted crop in Southern Africa. By 2030, yields are expected to decline by at least 10% and as much as 30% (Lobell, et al. 2008). Weather related risk is usually mitigated by irrigation, but many farmers in Sub-Saharan Africa either find irrigation to be cost-prohibitive or lack the necessary groundwater resources.

Maize can be bred to be more tolerant of abiotic stress. Traditional plant breeding selects for maize plants that survive in stressful conditions, leading to more drought-tolerant varieties. GM technology has led to the discovery of certain genes which control certain operations in the plant, allowing it to perform even under drought or heat stress (Fukuda-Parr 2007).

GM Maize Applications to Address Yield Stress

Genetically modified (GM) crops differ from conventional and hybrid varieties, only in the method used to develop a new variety. Conventional breeding requires a sexual cross between two varieties, whereas genetic modification allows for the identification of specific genes in one organism to be transferred directly to another. This allows for a more precise and efficient breeding process, expanding the possibilities of developing varieties with certain characteristics, and reducing the years it takes to introduce a new variety (Fukuda-Parr 2007).

Herbicide-Resistant Maize

The herbicide *Roundup*[®], a “kill-all” herbicide with the generic name of glyphosate, was developed by Monsanto in 1976. In the early 1980s, scientists noticed that certain bacteria

among waste outside the manufacturing plants were immune to glyphosate. Monsanto scientists speculated that genes from these bacteria could be transferred to crops, giving them resistance to glyphosate as well. The project was successful, and Roundup Ready[®] corn, cotton, and soybeans were commercially released in 1996, opening up a whole new market of seed, and extending Monsanto's control in the glyphosate market another 20 years (Glover 2010). Today, Roundup Ready[®] (RR) crops are the most prominent genetically engineered crop in the world (James 2010).³

RR maize has many benefits; herbicide-resistance allows farmers to spray entire fields without causing damage to the maize plant. Although RR maize seed is more expensive, glyphosate is typically a cheaper herbicide, results in high weed control, and is less toxic than other herbicides. RR maize also allows for conservation farming practices such as no-till, which reduce erosion, minimize nutrient runoff, and increase soil carbon content (Hurley, Mitchell and Frisvold 2009). Concerns that weeds sprayed with glyphosate will develop resistance are well-founded, but weeds develop resistance to every herbicide given enough time. To extend the life of glyphosate as long as possible, farmers should rotate the use of herbicides. Additional herbicides have been developed to make this possible.

Insect-Resistance Maize

Insect resistance maize called *Yieldgard*[®] was first introduced in the United States in 1996 and to South Africa in 1998. It is usually called “Bt” since it originates from a naturally occurring bacterium *Bacillus thuringiensis*.⁴ The protein in this bacterium is toxic to certain insect species that feed on maize plants. Upon ingestion of the maize plant, the Bt protein interacts with proteases in the midgut of the insect, killing the insect by disrupting the midgut membrane. Bt has been used as an organic insecticide for over 60 years, but it was in the early 1990s when genes from the bacteria which create the Bt proteins, Cry proteins, were transferred to maize plants using genetic engineering techniques (Al-Deeb, et al. 2003). One advantage of Bt maize is that it targets only the lepidopteran insects which feed on maize plant matter, including

³ Roundup[®] herbicide, synonymous with glyphosate, and Roundup Ready[®] seed are trademarks of Monsanto Technology, LLC. Throughout the entirety of the thesis they are referred to as “Roundup” and “Roundup Ready” or “RR” respectively.

⁴ Yieldgard[®] seed is a trademark of Monsanto Technology, LLC., referred to as “Bt” throughout the thesis.

the corn borer, stem borer, stock borer and rootworms. Concern has been expressed that Bt maize could harm non-target organisms, especially Monarch butterflies, earthworms and micro-organisms, but a review of numerous studies shows “no indication of direct effects of Bt plants on natural enemies” (Romeis, Meissle and Bigler 2006).

Bt maize reduces reliance on conventional insecticides, which decreases health risks to farm workers through less exposure to insecticides. It also reduces insecticide drift which can kill non-target organisms and contaminate water sources (Qaim and de Janvry 2005). Since the insecticide is in the seed, much of the uncertainty in timing of pesticide application is removed, reducing the need to scout fields as frequently to check for insect damage (Kruger, Van Rensburg and Van den Berg 2009). Bt maize is an especially suitable technology in South Africa, where high stem borer pressure is estimated to have reduced the maize crop by 10% annually before the use of Bt technology (Gouse et. al 2006).

Another benefit to Bt maize is that it reduces exposure to a type of mycotoxin called fumonisin, a toxic fungus associated with esophageal cancer and birth defects in humans, and potentially fatal to livestock. Bt maize reduces insect damage to the maize plants, which limits fungal colonization. In a study in South Africa between 2004 and 2007, Bt maize showed levels of mycotoxin fumonisin 28% lower than conventional varieties. Since maize represents a large portion of dietary consumption, this reduction could have a significant impact on human and animal health (Pray, et al. 2009).

Recently there have been legitimate concerns that lepidopteran insects which feed on maize plants will develop resistance to the Cry toxin more quickly than they would with the Bt pesticide. If not managed correctly, Bt maize leads to prolonged exposure of toxins to insects. Many governments require farmers to plant 20% of their crop to non-Bt “refuge acres” which allows the pests to reproduce without exposure to Cry toxins. These surviving insects mate with those with developed resistance, slowing down the rate that resistance builds up in the insect. Most target pest populations remain susceptible to Bt to date, due to proper management, with only three known insect species showing resistance to Bt (Tabashnik, Van Rensburg and Carrière 2009). In an ex ante study, Qaim and de Janvry (2005) simulate resistance development over a 15-year period in Argentina. Beginning with an initial resistance level of 0.1, results under a 20% refuge area show that the level of resistance remains low, but under a 0% refuge area, pest resistance increases to 1 after only 6 to 7 years. Kruger, Van Rensburg, and Van den Berg (2011)

show that high pest resistance to Bt maize has developed in the Northern Cape Province of South Africa. When Bt maize was introduced in South Africa in 1998, only 7.7% of farmers planted refuge acres. By 2007, 92.3% were planting refuge acres, but the Bt technology was losing effectiveness and 55% of large-scale farmers were forced to use insecticides to control stem borer damage to Bt maize. The lack of refuge acres was due to little government enforcement of refuge and separation requirements, and farmer perception that Bt maize requires less management than non-Bt maize (Kruger, Van Rensburg and Van den Berg 2011).

Another concern of Bt maize is that it will cross pollinate with conventional varieties, decreasing biodiversity. This has led to the requirement for separation distances between Bt and non-Bt maize fields in certain countries, which reduces benefits to the technology, prohibiting adoption. A study in Kenya estimates that if separation distances of just 50 meters were required, benefits of Bt maize to farmers would be reduced by 32.5% (Tumusiime, et al. 2010). In South Africa the separation distance requirement is 400 meters, but very few farmers comply and it is not strictly enforced (Kruger, Van Rensburg and Van den Berg 2009).

Drought Tolerant Maize

Drought tolerant (DT) maize is the most recent development in GM maize technology. In a wet or normal year, there is no expected yield difference between DT and non-DT maize. But under hot and dry conditions, DT maize will produce a higher yield than non-DT maize, effectively reducing yield variation and risk to farmers. The African Agriculture Technology Foundation (AATF) predicts that by limiting variation in yield, DT maize has the potential to increase overall production by 24 to 35 percent (AATF 2012).

DT maize could offer more benefits to smallholder farmers, especially in areas of Sub-Saharan Africa that are directly affected by drought. Unlike many hybrid maize varieties, DT maize does not require high fertilizer, chemical, or irrigation use to realize benefits. DT maize is a scale-neutral technology that can be grown on marginal lands, that is more likely to be adopted by smallholders (AATF 2012).

“Stacked” Maize Traits

DT maize requires a complex array of genes, each gene representing a different drought resistant characteristic in the plant. As mentioned previously, genetic modification allows for the isolation of specific drought tolerant traits. Once a gene is isolated, it can be combined with any

number of other genes, a process called “stacking.” Only genetic modification allows plant breeders to stack multiple genes to create a plant with optimal drought tolerant characteristics, with each gene making a small contribution to the overall drought tolerance of the plant. Using stacking techniques, these traits may be transferred to varieties in any particular region of the world in a fraction of the time that it would take using conventional breeding methods (Fukuda-Parr 2007). One of the most popular stacks to this point is “BR” which has both the Bt and RR genes. BR maize was approved in South Africa in 2005 (James 2007).

Research and Development of GM Crops

Genetic modification allows scientist to target specific genes in order to address biotic and abiotic stresses. Research and development of GM crops has led to lower costs and higher productivity, with high economic benefits that have been realized in numerous countries (James 2010). Aside from cotton farmers in China and India, many of the beneficiaries are large-scale farmers in high-income countries for whom the technology was targeted. The potential benefits for smallholders, particularly in Sub-Saharan Africa, remain mostly unexplored (Fukuda-Parr 2007). This lack of investigation of potential benefits of GM crops for smallholders is partly due to low investment and restrictive policy.

Investment in GM Crops Worldwide

Investment in GM maize to explore these scientific possibilities for smallholders remains low for several reasons. First, GM maize research is largely funded by the private sector in high-income countries, unlike past research which was heavily funded by the public sector. This is due in part to policy such as strong patent protection for transgenic life-forms, provided under the Diamond versus Chakrabarty case and the Bayh-Dole Act in 1980. These policies created an incentive for the private sector to purchase biotechnology research from public universities and invest in developing new varieties. Monsanto’s state-of-the-art research center in St. Louis, established in 1981 with a research budget of \$275 million (\$694 million in terms of 2012 US dollars), is a direct result of these policies (Glover 2010, US Bureau of Labor Statistics 2012). The privatization of GM seeds reduced the spillover of GM maize technology to countries without the institutional infrastructure needed to monitor use and collect royalties for private firms. This has slowed down the process of GM maize dissemination and increased the need for public-private partnerships to disperse the GM technology to low-income countries. Another

reason that investment in low-income countries is low is that research and development of GM crops requires large upfront costs, since the technology is knowledge-intensive, and requires expensive equipment and highly-trained personnel (Fukuda-Parr 2007).

One of the greatest hindrances to investment in GM maize in low-income countries is the controversy surrounding GM crops. While the international community recognizes that the economic returns from investment in technology to boost agricultural productivity for smallholders are high, GM crops are often left out of the discussion. The controversy centers on the question of whether GM crops are fundamentally different than non-GM crops, and pose higher risks to human health or the environment (Fukuda-Parr 2007). No adverse effects to human health have been reported, and studies have shown that GM crops, particularly Bt maize and cotton, reduce insecticide use which improves farmers' health and the environment (Qaim and de Janvry 2005). GM medicines, on the other hand, have been met with little social or political opposition, although they represent about 25 percent of new drugs on the market in both the US and the EU (Paarlberg 2008).

Policy of GM Crops in Sub-Saharan Africa

The primary international regulatory system of GM crops is the Cartagena Protocol on Biosafety (CPB), created in 1996 by the United Nations to ensure safe transfer, handling and use of transgenic products. The CPB requires that member countries develop national biosafety frameworks (NBFs) prior to the commercialization of GM crops. The NBFs are used to implement national policies, laws, administrative and technical instruments (such as permits) in order to ensure safety of the environment and human health. Governments are also required to establish a Biosafety Clearing House for registration and documentation of GM products before their release into the environment (Makinde, Mumba and Ambali 2009).

The results of the CPB and other similar initiatives have been quite poor: out of 53 countries in the African Union, 45 have signed the Cartagena Protocol, but only 16 countries have regulations related to modern biotechnology, and 11 have established the necessary regulatory structures necessary to commercialize GM products (Makinde, Mumba and Ambali 2009). As of 2010, only 3 countries have approved the commercialization of GM crops; South Africa, Burkina Faso, and Egypt, but both Uganda and Kenya plan to market GM crops for the first time in 2014 (Khisa 2012).

The Cartagena Protocol provides such thorough regulation that the release of GM products poses little risk to human health and yet most countries appear to have a “wait and see” attitude regarding approval of GM crop research. Some argue that this attitude is due to skepticism based on unscientific data circulated about the potential risks of GM products and a concern for certain donors’ positions rather than scientific data (Fukuda-Parr 2007).

Current GM Maize Research and Development Projects in South Africa

South Africa became the first African nation to accept GM crops, beginning in 1989 when Delta and Pine Land seed company began to perform field trials of GM cotton (Wolson 2007). Today South Africa is still the only country that has truly embraced genetically modified crops, receiving adamant support from both private and public sector in several ongoing projects as indicated below.

Improved Maize for African Soils Project (IMAS) focuses on developing maize varieties that use nitrogen more efficiently. They are using cutting-edge biotechnology tools such as molecular markers and transgenic approaches, with a goal of increasing yields by 30-50% with the same amount of nitrogen fertilizer applied. The main partners are the Bill & Melinda Gates Foundation, USAID, DuPont, Pioneer Hi-Bred, Kenya Agricultural Research Institute (KARI) and South African Agricultural Research Council (ARC) (CIMMYT n.d.).

The Water Efficient Maize for Africa (WEMA) partnership is an effort led by the African Agricultural Technology Foundation, a non-for-profit with a mission to promote access to appropriate technologies to increase productivity of smallholder farmers in Sub-Saharan Africa. The five year project, funded by the Gates Foundation, focuses on maize since it makes up a large percentage of smallholder’s dietary intake: 31 percent of diets in South Africa and 42 percent in Kenya (Tumusiime, et al. 2010). Hybrid varieties of maize are already being used extensively throughout Sub-Saharan Africa, but WEMA uses the latest techniques in marker assisted breeding and biotechnology from the International Maize and Wheat Improvement Center (CIMMYT) and Monsanto. The *Bacillus* protein gene *cspB*, which has shown significant increase in yield under drought stress conditions, will be introduced into African maize varieties at five key national agricultural research systems (NARS) in East and Southern Africa, a major maize-producing area (Thompson and Shepherd 2010, Castiglioni et al 2008). The NARS in South Africa, Mozambique, Tanzania, Kenya, and Uganda, are responsible for supporting

research efforts, conducting risk assessment of the new varieties, and creating public awareness and acceptance of new varieties. New varieties that are produced will be developed royalty-free, and sold by local agro-dealers. As of May 2011, confined field trials had been performed in South Africa, Uganda, and Kenya, and had been approved but not yet completed in the other two countries (AATF 2012).

A second project using biotechnology to create more drought tolerant maize is being conducted by the University of Cape Town. The resurrection plant, *Xerophyta viscosa*, has the ability to lose over 90% of its relative water content, survive in this state for prolonged periods of time, and resume growth within 72 hours when water becomes available. Researchers have isolated several genes from the resurrection plant and transferred them to tobacco plants, which have shown improved drought stress. Future research aims to introduce these same genes into maize, with expectations of similar results (Thompson and Shepherd 2010, Garwe, Thomson and Mundree 2006).

Research on maize resistant to Maize Streak Virus (MSV) is also being investigated at the University of Cape Town, with support from Pannar Seed Company. Researchers are using genes which contain the proteins Rep and RepA and inserting the genes into Pannar maize varieties to create maize resistant to MSV. Field trials are set to begin in 2012-13 (Thompson and Shepherd 2010). These projects reveal the private and public support that South Africa has given to genetic modification as a means to increase agricultural productivity. Unlike other governments in the region, South Africa paved the way early for new investment in crop biotechnology research.

Chapter 2 - Literature Review

Since GM crops were commercially introduced in the US in 1996, relatively thorough research has been conducted to measure their farm-level impact. Most of the research on GM maize conducted in high-income countries has shown that Bt maize has the potential to lower pesticide use and reduce yield loss due to pests, and that Roundup Ready (RR) maize can reduce costs, increase weed control, allow farmers to plant no-till, and boost yield. (Smale, Zambrano, et al. 2008, Qaim and Matuschke 2005). Brookes and Barfoot (2009) examine the worldwide impact of GM crops in 2007, and conclude that cotton, maize, canola, and soybeans added 4.4% to the value of global production after taking both yield impact and seed premiums into consideration. While much of the past research to examine the impact of GM crops has been conducted in high-income countries, low-income countries grew 43% of total GM crops by area and were responsible for 58% of the additional global value from GM crops as of 2007 (Brookes and Barfoot 2009). This chapter, which is organized into two sections, focuses on the research that is available from low-income countries. The first section looks at literature which measures the impact of GM crops on yield and profit in low-income countries. In the second section, the current research which addresses the issues of endogeneity and selectivity bias is examined.

Studies of GM Crops in Low-Income Countries

In 2007, the additional value of GM crops in low-income countries came from three primary sources: 44% from soybeans grown mostly by commercial farmers in South America, 50% from smallholder cotton farmers in China and India, and only 6% came from maize, mostly grown in South America on industrialized farms (Brookes and Barfoot 2009). More than 90% of smallholders growing any type of GM crop come from farmers growing cotton in India and China. Therefore, only a small body of literature examines GM maize among smallholders in low-income countries, primarily in the Philippines and South Africa, where yield gains for maize appears to be higher than in high-income countries (Zilberman and Sexton 2011, James 2007). The following section examines the farm-level impact of GM crops in low-income countries, mostly among smallholders.

Bt Cotton in India

Qaim and Zilberman (2003) demonstrate that Bt technology used in cotton has led to decreased pest damage, less pesticide use, less toxic pesticides, and higher yields in India. The researchers assume that benefits to Bt cotton will be greater in India, where a tropical climate leads to insect damage between 50 to 60% compared to damage of 12% and 15% in the US and China respectively. Data were collected from 157 farms, covering 25 districts in three major cotton-producing states. Using a nonparametric function allowed the researchers to estimate Bt and non-Bt yield-density functions, in which the Bt maize distribution shifts noticeably to the right, with a mean yield 80% higher than that of non-Bt maize. Then, econometric analysis using a logistic damage-control function estimates that Indian farmers planting non-Bt cotton would have to triple pesticide use to achieve the same level of damage control offered by Bt cotton.

Bt Cotton in Argentina

Qaim and de Janvry (2005) determine that farmers planting Bt cotton achieve higher yields with lower pesticide use in Argentina. Adoption of Bt cotton is low, however, presumably due to a relatively high technology fee. A survey was given to 89 Bt and 210 non-Bt small and large-scale farmers. First, a regression with insecticide use as the dependent variable shows that Bt maize plots use 1.2 kg less pesticide than non-Bt. To eliminate bias, the predicted pesticide quantities are used in a quadratic production function, which reveals that Bt cotton yields are 506 kg per hectare, or 32% higher than non-Bt yields. Next, a damage control function shows that Bt yield effects will be larger among small-scale producers, who use less pesticides and have more to gain from Bt technology than large-scale producers. On average, Bt cotton farmers could decrease pesticide use by 73%, and net yield gain is predicted to be 17% for large-scale producers and 42% for smallholders.

Bt, RR, and Stacked Maize in South Africa

Gouse, Piesse, and Thirtle (2006) use a stochastic frontier production model to show that RR maize increases overall farmer efficiency by allowing for no-till farming, which increases output, reduces labor use, and reduces land preparation. Data were collected from smallholders in Kwazulu-Natal, of whom 48 plant Bt maize, 25 plant no-till, and 62 use both conventional seed and tillage methods during the 2003-04 season. A Cobb-Douglas stochastic frontier production model estimates the technical efficiency of each farmer using farm-specific variables.

No-till maize increases output, and decreases land preparation and labor. Other results show that no-till farmers are 11% more efficient than conventional farmers, while Bt farmers are 12% less efficient than non-Bt farmers. This contrast from most other literature in South Africa, and may be due to the dry year in which pest pressures were low. Therefore, the benefits from Bt maize do not always outweigh the high cost of Bt seed. This emphasizes that benefits to Bt maize will vary from year to year, and increase as pest pressure increases, while benefits of no-till may be more consistent.

A second study by Gouse, Piesse, et al. (2009) shows that farmers planting Bt and RR maize use less labor, but pay more for their seed. The study is based on data from the 2006-07 maize production season in South Africa. Descriptive statistics show that labor use for Bt and RR maize was 28.2% and 13.7% lower than conventional seed respectively, while seed prices were 27-30% higher. Data were fit to a Cobb-Douglas stochastic production frontier model, as well as an inefficiency production function to estimate factors influencing yield. Estimates from the frontier model show that seed cost has the biggest impact on output, as a 1% increase in seed costs results in a 0.42% increase in output, while a 1% increase in land and labor leads to a 0.14% and a 0.13% increase in output respectively. All output elasticities are significantly different than 0 and sum to 1.049, signifying slight increasing returns to scale. Results of the inefficiency production function are mostly insignificant.

Other studies of Bt maize in Kwazulu-Natal reveal that smallholders use far too few pesticides, which could lead to impressive yield gains from Bt maize (Thirtle, Piesse and Gouse 2005). Yield benefits decrease, however, as pest pressure drops. This has been demonstrated by a study of smallholders in South Africa over three consecutive seasons from 2001-04, in which yield benefits of Bt maize were recorded of 32%, 16%, and 5% as pest pressure declined (Gouse et. al 2006).

Studies of GM crops in Low-Income Countries: Controlling for Endogeneity and Selectivity Bias

Endogeneity and selectivity bias are both issues that can create inconsistent estimates when using least squares estimation. Endogeneity is an issue which creates biased estimates in production function estimation. It can occur for two reasons; first, when the farmer makes a decision regarding input quantity during the production season and second, due to unobserved

farmer characteristics such as motivation, access to credit, or experience. Instrumental variables which are correlated with the endogenous variables can correct for endogeneity bias and create unbiased and consistent estimates. Selectivity bias, on the other hand, occurs when adoption of a new technology such as RR maize is determined endogenously. If RR maize producers are better farmers, the RR maize variable will overestimate the effects of the RR technology. Several methods are used to control for selectivity bias, including a fixed-effects model (Croston, et al. 2007) or a Heckman two-step estimation using the full sample (Shankar and Thirtle 2005, Mutuc and Yorobe 2007). The following studies in this section examine the impact that GM crops have on yield, cost, and net returns while controlling for either endogeneity or farmer self-selection bias.

Bt Cotton in India

Croston, Shankar, Bennett and Morse (2007) control for selection bias using a fixed-effects model which reveals that more efficient farmers are more likely to adopt Bt cotton, but Bt cotton yield is still significantly higher. Panel data from six villages in India were collected during the 2002-03 seasons among 338 cotton farmers with a total of 718 plots. Two Cobb-Douglas production functions are estimated, one which only uses the pooled data and the other which is a fixed effects model to control for selectivity bias. Results show that when controlling for selectivity bias, the seed and labor coefficients become insignificant. The yield effect is only half as large in the fixed effects model, but it is still positive and significant, thus, controlling for selectivity bias reveals that the pooled model overestimated the impact of Bt cotton. Using average prices for seed and output, the yield advantage is still large enough to offset the higher price of Bt seed and lead to higher net returns for Bt farmers.

Bt Cotton in China

Huang, et al. (2002) find that Bt cotton significantly lowers pesticide use among smallholders in China. Data were collected from 337 Bt and 45 non-Bt farmers. Both a Cobb-Douglas and damage control production function were used to estimate the impact of pesticide and Bt cotton on productivity, where both pesticides and Bt cotton are considered damage abatement inputs. Pesticide was also expected to be endogenous, as more pesticide is applied when pest pressure is high. Therefore, an instrumental variable approach was used for each of the models, where Bt cotton as an instrumental variable significantly explains pesticide use.

Results show that Bt cotton reduces pesticide use by 58%. Results of the Cobb-Douglas function reveal that age, education, and Bt cotton all significantly positively impact yield. The results are similar in the damage control function, which uses both the Weibull and Exponential specifications. The damage control models also show that producers of Bt and non-Bt cotton are both using pesticides about three times above their optimal levels of use. While the study indicates that Bt cotton may lead to higher yields, the greatest benefit in China where pesticide use is excessively high, is that Bt cotton farmers use significantly fewer pesticides.

Bt Cotton in South Africa

Shankar and Thirtle (2005) reveal that Bt cotton allows farmers to sidestep credit and labor constraints that limit pesticide use in South Africa during the 1999-2000 season. A damage control framework applied to a production function is used to analyze 58 Bt and 33 non-Bt cotton farmers. It is predicted that pesticide is an endogenous independent variable in the production function, since it is applied in response to insect attacks during the production season. Using instrumental variables of the previous year's pesticide and output levels, the Hausman test reveals that pesticide use is not endogenous to production. Therefore, ordinary least squares regression is considered more efficient and instrumental variables are not included in the model. Further testing using the Heckman's two-step model reveals that the inverse Mills ratio is not significant, so adoption endogeneity is not an issue. Results show that by adopting Bt cotton, farmers have much more potential to increase output that non-Bt produces since they use less than half the optimal rate of insecticide. Other results show that Bt cotton is not labor-saving in this case in South Africa as labor use is not significantly different between Bt and non-Bt producers.

Bt Maize in the Philippines

Yorobe and Quicoy (2006) use econometric techniques which indicated that Bt maize significantly increases both yields and net returns in comparison to non-Bt maize. Information was collected from 107 Bt and 363 non-Bt yellow maize farmers in four regions of the Philippines during both the wet and dry maize season in 2003-04. To control for agro-climatic variability, non-Bt farmers that are adjacent to Bt adopters are randomly selected. First, a Cobb-Douglas production function finds that Bt maize results in a 35% statistically significant increase in yield. Next, a two-stage Heckman net returns function was estimated to control for selection

bias; the first stage consisted of a probit to estimate Bt adoption, and the second stage predicted net returns based on the probabilities of adoption derived in the first stage. Factors that significantly increase the probability of Bt maize adoption include education, hired labor, net income, agricultural training, and farmer's risk perception of the impact of Bt maize on health and the environment. Although Bt seeds are almost twice the price of non-Bt seeds, profit is nearly twice as high due to a large savings in insecticide use.

Mutuc, Rejesus, Pan and Yorobe (2012) reveal that controlling for censoring in addition to the control of selection bias reduces the the impact of Bt maize in the Philippines. The same data is used from the previous study of 107 Bt and 363 non-Bt maize farmers during the 2003-04 growing season. A quadratic profit function is used to derive maize output supply and pesticide input demand functions to control for simultaneity bias. The first step of the model uses a bivariate probit model to estimate the Bt adoption and pesticide use decisions simultaneously to control for selection bias. Results show that the error correlation between Bt adoption and pesticide use is insignificant. Maize price, rice price, fertilizer and pesticide prices and off-farm income all impact Bt maize adoption, while factors which impact pesticide use include off-farm income, pesticide price, and extension. Next the parameters of each equation are estimated individually, using a univariate Tobit model to estimate the parameters of the censored pesticide variables. A multivariate Tobit regression is then used to re-estimate the parameter vector. Results of the censored and uncensored impact model reveal that Bt maize has a much smaller, yet still significant impact on yields. The impact on net returns is similar between the two models. This study reveals that while most research reveals a significant impact of Bt maize on yield, not controlling for censoring could greatly impact the results.

Chapter 3 - Data Overview

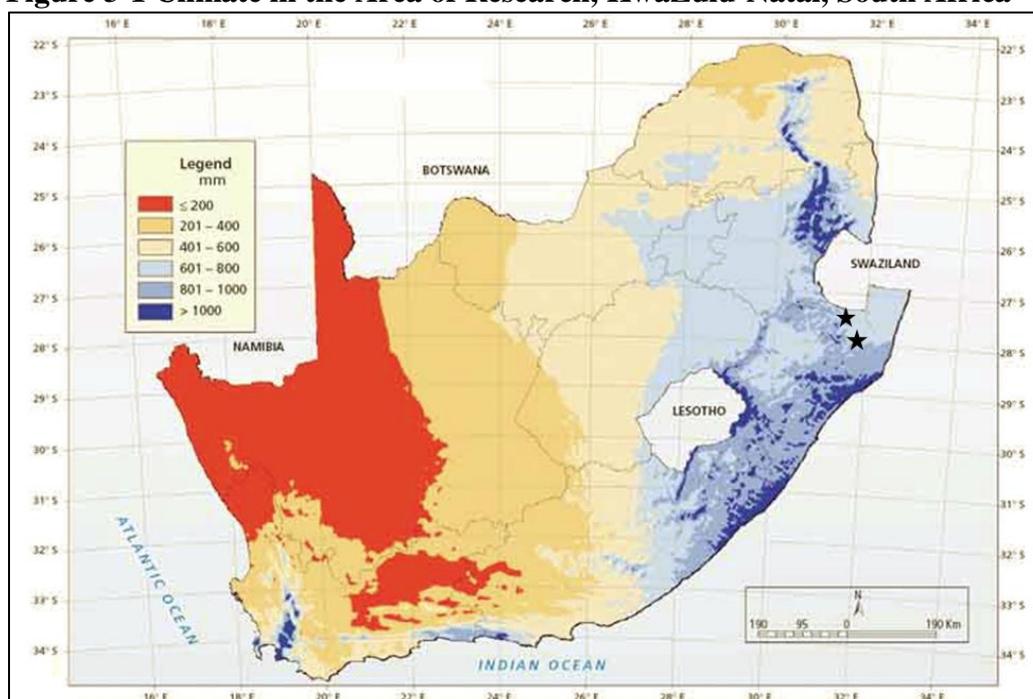
This chapter provides a detailed look at the data used in this research. The first section focuses on household demographics and the potential for maize production in the region of KwaZulu-Natal, South Africa. Next, the quantity and cost of both inputs and labor used in each stage of maize production are examined, from planting to harvest. In the final section, maize yield, total costs and net returns are examined across all five maize types in both regions. The information in this chapter is meant to present an accurate representation of the data in order to provide a reference point to test hypotheses presented in subsequent chapters.

Maize Production in KwaZulu-Natal

KwaZulu-Natal is a sub-humid region located in Northeastern South Africa (see Figure 3-1). As one of 9 provinces, it is home to 21% of the population of South Africa. Arable land covers only 13% of KwaZulu-Natal, while a majority of land is used for grazing, nature reserves and forestry. In comparison to the rest of South Africa, KwaZulu-Natal contains about 7% of land used for cereals and produces 4% of the total maize crop. More than 39% of total area is owned by smallholders as opposed to commercial farmers, in comparison to only 14% in the rest of the country (Department of Agriculture, Forestry and Fisheries 2011).

The research focuses on two regions in KwaZulu-Natal; Hlabisa and Simdlangetsha, which lie within close proximity to each other and share many similar agro-ecological characteristics (see stars in Figure 3-1). Annual rainfall in these regions is around 980mm (38 inches), and much of it falls during the maize production season (Gouse, Piesse and Poulton, et al. 2008). The land is marginal with low potential in all areas and little variation exists in topography between farms, so there is no need to adjust for land quality (Gouse, Piesse, et al. 2009). Average maize yield is typically around 1.5 tonnes per hectare (24 bushels per acre), similar to average maize yields throughout Sub-Saharan Africa. In comparison, average maize yields are closer to 4 tonnes per hectare on commercial farms in South Africa and 9 tonnes per hectare in the United States (FAOSTAT 2011).

Figure 3-1 Climate in the Area of Research, KwaZulu-Natal, South Africa



Source: FAO (2005)

Bt maize became the first genetically modified maize planted in South Africa when it was first grown by commercial farmers in the 1998-99 season and smallholders in 2001-02. Roundup Ready maize was first planted in the 2004-05 season, soon followed by BR stacked maize, which contains genes for both Bt and RR (Gouse, Piesse, et al. 2009). By 2010, Bt, BR, and RR maize was planted on more than three-fourths of total maize area in South Africa, mostly by commercial farmers who are responsible for over 90% of maize production (James 2010). All three types of GM maize are planted by smallholders in KwaZulu-Natal, the region of focus for this research.

Data were collected during the 2009-10 maize production season from a sample of 184 maize producers planting both GM and non-GM maize. Twenty-eight of the farmers have two maize plots, so the total number of maize plots is 212. Producers of both GM and non-GM maize were randomly selected, although the adoption rate of GM maize in the region is lower than the data indicate as GM maize producers were targeted in the study (Gouse 2012). The original data included a third region, Dumbe, and four other observations which were removed due to unreliable and incomplete information.

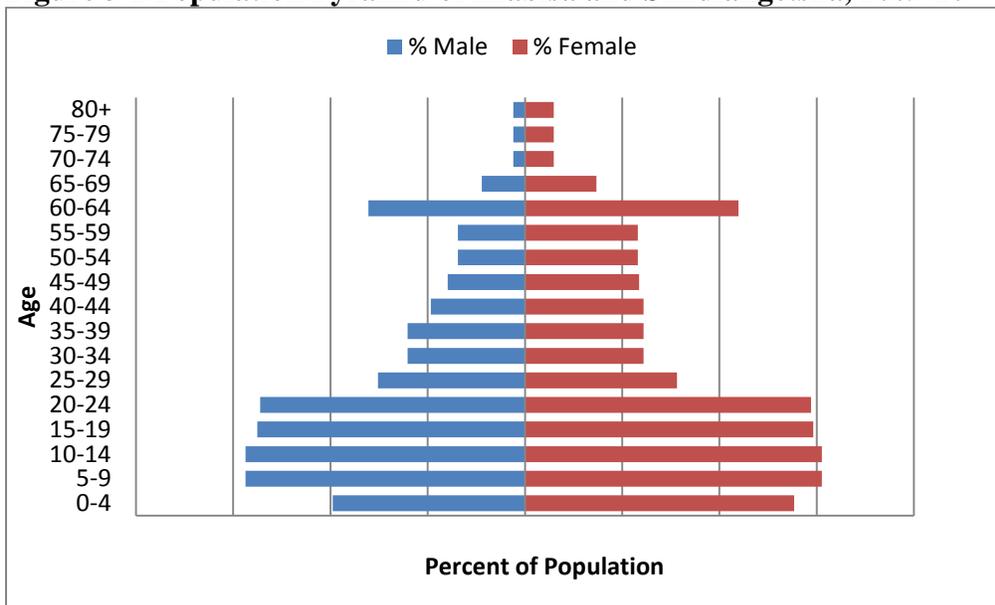
Data collection was completed by the University of Pretoria in South Africa. The team of researchers and enumerators has considerable past experience researching smallholder adoption of GM cotton and maize. Information was collected from the farms through three visits during the maize growing season from November 2009 through June 2010 in order to reduce recall bias. Data was collected on the timing, quantity, and prices of inputs and labor used during each stage of production, from land preparation until harvest. Other information was collected on demographics, education, experience using herbicide, access to extension and credit, household consumption habits (Table 3-1), assets, expenses, and non-farm income. A fourth survey was completed in the fall of 2010 which surveyed producers on preferences of maize seed and willingness to pay for certain maize traits. All indications show that the 2009-10 maize production season was a typical year, as producers reported that rainfall was good in both Simdlangetsha and Hlabisa throughout the entire growing season.

Household Demographics

HIV/AIDS and Population

Among the 184 households surveyed, 56% of inhabitants are under the age of 25, compared to the average of 52% across South Africa. This is due to high population growth and an HIV/AIDS rate of 15.9% in South Africa among the working age population. The HIV/AIDS infection rate is even higher in KwaZulu-Natal, where 26.4% of the working age population is HIV-positive (Thurlow et. al, 2009). The most affected people in KwaZulu-Natal are males, ages 35-49 (41.3%); females, ages 20-34 (43.3%), and unskilled workers in agriculture (38.2%). In KwaZulu-Natal, 40% of people are unemployed and 33% live below the poverty line of US\$2/day (Thurlow et. al 2009). The impact of a high population growth and HIV/AIDS is apparent in Figure 3-2.

Figure 3-2 Population Pyramid of Hlabisa and Simdlangetsha, 2009-10



It is apparent in Figure 3-2, which is based on data from the survey taken in Hlabisa and Simdlangetsha, that there are fewer men than women above the age of 40, which is most likely due to the migration of men from rural areas to urban centers to find work. These findings match with previous literature which indicates that the labor supply is more constrained due to high levels of HIV/AIDS and migration of agricultural workers to urban centers (Gouse, Piesse, et al. 2009). The reduced supply of labor is expected to result in relatively high labor costs, which has implications on the profitability and adoption of labor-saving technologies such as RR maize.

Household Characteristics, Consumption of Maize, and Access to Credit

Household characteristics in Hlabisa and Simdlangetsha are similar in many ways, such as number of people per household, average age of the head of household, access to credit, member of farmer association, and education (Table 3-1). Almost half of the households grew maize solely for home consumption, and 28% of all households bought maize meal in the previous six months because they did not harvest enough maize, mostly in Simdlangetsha. All households in Hlabisa consume maize at least three times per week compared to only half of households in Simdlangetsha. Almost all farmers had access to credit through a financial group or bank in both regions; therefore, it is expected that farmers can purchase inputs needed for maize production.

Table 3-1 Household Characteristics, Maize Consumption, and Access to Credit

	Hlabisa	Simdlangetsha	Total
<i>People per household</i>	6.1	6.4	6.2
<i>% of respondent that was female</i>	66	56	61
<i>Average age of head of household</i>	57	53	55
<hr/>			
% of Households (1=yes)			
<i>Member of Farmer Association</i>	100	93	97
<i>Head of household with education above primary</i>	16	31	23
<i>Highest educated member of household with high school diploma</i>	20	11	15
<i>Sold part of maize crop</i>	65	44	55
<i>Bought extra maize last 6 months</i>	11	46	28
<i>Ate rice more than 3 times week</i>	78	23	52
<i>Ate bread more than 3 times week</i>	97	71	85
<i>Ate maize more than 3 times week</i>	100	49	76
<i>Access to bank account</i>	65	83	73
<i>Access to financial group</i>	83	70	77
<i>Access to credit</i>	96	97	96

Household Expenses, Income, and Assets

Producers in the two regions have similar expenses and income, but livestock assets are significantly higher in Hlabisa and non-farm assets are significantly higher in Simdlangetsha (Table 3-2). When examining individual households, there is a large difference in the value of their assets. The 20% of producers with the most assets have \$21,139 in assets on average, while the bottom 20% had average assets of \$386.⁵ This is partly due to livestock which accounts for more than two-thirds of total wealth, but are owned by only 63% of producers.

⁵ All monetary units are converted from South Africa Rand to US dollars (USD) at the constant exchange rate of 7.44 Rand per US dollar. This is the average rate of exchange between the dates of initial land preparation and planting from late October until harvest in late April. Actual variation is slight during this period, from 7.39 Rand per USD on October 23rd, 2009 to 7.49 on April 30th, 2010.

Table 3-2 Land Area, Expenses, Income, and Assets across Regions (USD)^a

	Site					
	Hlabisa		Simdlangetsha		Total	
	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
Total Land Area (ha)	.97	.44	2.83	1.27	1.85	1.31
Maize Plot Area (ha)	.42	.18	.57	.25	.49	.23
School Expenses	52	31	45	26	49	29
Remittances	121	113	108	130	115	121
Animal Income	224	260	224	264	224	261
Maize Income by Plot	362	180	296	254	326*	225
Livestock Assets	6109	5511	4567	5144	5380*	5381
Farm Assets	1414	1814	1421	2903	1417	2384
Non-farm Assets	566	975	1546	4454	1029**	3172
Total Assets	8089	6996	7533	8478	7826	7715

**,* Significantly different at the 1% and 5% levels respectively using a two-tailed t-test.

^aat an exchange rate of 7.44 Rand per US dollar

Note: N = 184; Hlabisa = 97; Simdlangetsha = 87

In KwaZulu-Natal, the average household received approximately US\$115 in remittances during an 8 month period, an important source of income. In comparison, the average household received \$224 in livestock income per year. Pension is the top source of income for 53% of households; male and females above the age of 60 in each household also receive a \$168 pension each month, which is not accounted for in Table 3-2 (Gouse 2012). The pension is especially important to maize producers in KwaZulu-Natal, as close to half of household heads are over the age of 60. Some of these producers have returned from jobs in the city to retire on their farms, which may explain why there are a large number of males and females ages 60 to 64 (Figure 3-2). Full-time or part-time off-farm employment is the second-most important top income source, while crop production is the top income source for only 5% of respondents.

Table 3-3 Household Expenses, Income, and Assets across Maize Types (USD)^a

	Seed Type					Total
	BR	Bt	Carnia	Pannar	RR	
School Expenses	49	52	48	49	49	49
Remittances	132	114	120	86	123	115
Animal Income	261	174	242	201	221	222
Maize Income by Plot	347	296	215	296	391	326
Livestock Assets	5038	5891	4694	4420	6065	5288
Farm Assets	1432	1521	1608	1215	1388	1402
Non-farm Assets	2291	897	1412	2134	483	1340
Total Assets	8761	8309	7715	7769	7936	8031

^aat an exchange rate of 7.44 Rand per US dollar

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

Household expenses and income are very similar, regardless of what variety the producer used (Table 3-3). Several differences exist between livestock and non-farm assets, but total assets are statistically the same across all five maize types. Due to the large difference between assets among producers, it was hypothesized that producers with more assets would have greater income, and thus purchase more inputs leading to higher yields. At 95% confidence, the 20% of producers with the most assets had significantly higher total input costs and output per hectare than the 20% of producers with the fewest assets.

Sources of Agricultural Income other than Maize

Of the 184 producers, maize was their primary crop. An additional 36% planted beans, 9% pumpkins, 5% groundnuts, and 5% planted sweet potatoes, as well as other vegetables. Almost all farmers raised chickens, 63% owned cattle, accounting for more than half of the total value of assets, and 49% had goats. Producers that grew maize were targeted in the study, so this information is not representative of the entire region.

Summary of Maize Production Activities

Farmers planted 10 different maize varieties on 212 plots, as seen in Table 3-4. The maize varieties are categorized into five maize types based on seed characteristics. The first three categories are genetically modified: Bt, RR, and BR maize. Both RR and BR maize are herbicide tolerant (HT). Since RR maize is currently the only type of HT maize available commercially, the terms “RR” and “HT” are interchangeable throughout this research. The terms “stacked” and

“BR” are also interchangeable, since BR is the only type of stacked maize referred to in this study. The final two categories of maize are hybrids; Pannar hybrids, sold by Pannar seeds, and Carnia hybrids, produced by Monsanto.⁶ Since the yield and net returns of Pannar maize are both significantly higher than Carnia, they are placed in separate categories.

Table 3-4 Categories of Seed Types based on Seed Variety, Company, and Technology

<i>Seed Type</i>	<i>Seed name</i>	<i>Seed Company</i>	<i>Technology</i>
Bt	DKC 78-15B	Monsanto	YieldGard®
RR	Phb 30D04R	Pioneer	Roundup Ready®
	DKC 78-35R	Monsanto	Roundup Ready Plus®
BR	Phb 31M84BR	Pioneer	YieldGard® and Roundup Ready®
	DKC 80-40BR ^a	Monsanto	YieldGard® and Roundup Ready Plus®
Pannar	Pan 6043	Pannar	
	Pan 6611	Pannar	
	Pan RO 413	Pannar	
Carnia	CRN 3549	Monsanto	
	CRN 3505	Monsanto	

Sources: www.monsanto.co.za; www.pannar.co.za; southafrica.pioneer.com

^aThe maize variety DKC 80-40BR, planted on two plots, is yellow maize, all other maize is white maize.

The data summary is organized chronologically by production operation, from land preparation to harvest, to highlight differences in input and labor quantity and cost among the five maize types. By examining these differences from several angles, the impact on final yield and net returns can be seen more clearly. Hlabisa and Simdlangetsha share many similar characteristics including climate and agro-ecology, but at times it is useful to compare the regions since quantity and cost of inputs and labor are different in each region. Data can also be summarized by the 25 producers that grow both GM and non-GM maize on separate plots. This allows an unbiased comparison that is taking into account immeasurable farmer characteristics such as motivation or knowledge. A final way to analyze the data is by a comparison of RR and BR varieties which are herbicide tolerant and the remaining varieties which are not.

⁶ Pannar seeds also sells YieldGard® and Roundup Ready Plus® white maize seed, but this seed was not purchased by farmers in this study.

Land Preparation

Producers prepare their land for planting maize by plowing with oxen or a tractor, or with herbicide and a hand hoe. When maize producers use herbicide and a hand hoe, they are preparing their land without tilling, called no-till or planting without plowing (PWP). Herbicide, often applied with backpack sprayers, is a relatively new way for producers to control weeds before planting as a majority of producers report that they did not use herbicide prior to 2004. Of plots containing RR or BR maize, 86% and 40% are prepared using no-till respectively, while a majority of non-HT plots use conventional tillage (Table 3-5). Although no-till is not labor-saving during initial land preparation since it requires hoeing, it pays off during the rest of the season when no-till farmers use less labor to weed (Table 3-11). Land preparation included also included the application of fertilizer.

Table 3-5 No-till, Experience with Herbicide, Labor, and Land Size in Land Preparation

SeedType	% of Producers Planting No-till	Years of Experience with Herbicide	Land Preparation Labor (hours/ha)	Days Land was Prepared Before Planting	Land Area (hectares)
BR	.40	4.3	27	2.3	.58
Bt	.00	4.5	17	2.1	.56
Carnia	.00	4.1	19	2.2	.47
Pannar	.06	4.5	43	2.5	.42
RR	.86	3.8	26	.7	.46

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

According to Table 3-6, most producers who plow their land do so to open up a furrow to plant, and 70% then spray a pre-emergent herbicide between the rows to control weeds, typically within one day of planting (Gouse 2012). Roundup is the herbicide of choice for controlling weeds prior to planting on 97% of maize plots, even by producers who did not plant RR maize. A significantly higher percent of no-till farmers used herbicide, although the farmers using conventional tillage spent more time applying herbicide (Table 3-6).

Table 3-6 Pre-Emergent Herbicide Use for Land Preparation

Seed Type	% of Producers Who Applied Herbicide	Labor to Apply Herbicide (hours/ha)	Herbicide (litres/ha)	Herbicide (\$/litre)	Days Herbicide was Applied Before Planting
BR	.43	4	3.2	16.7	2.4
Bt	.94	29	6.8	10.3	.6
Carnia	.85	31	6.4	10.1	.4
Pannar	.44	14	3.2	9.9	.7
RR	.86	10	5.2	16.9	5.0
No-till	.99**	10	5.7**	17.2**	.4
Conventional	.51	18**	4.1	10.1	2.6**

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77; No-till = 83, Conventional tillage = 129

**,* Indicates significantly higher at 1% and 5% respectively using a one-sided t-test.

Non-RR maize producers used less labor in applying pre-emergence herbicide, but this is most likely because the labor used to apply herbicide was already accounted for in land preparation labor. The total cost of land preparation is not significantly different for no-till producers (Table 3-7).

Table 3-7 Land Preparation Input and Labor Costs (USD/hectare)

SeedType	Land Prep Labor	Pre-Emergence Herbicide Labor	Total Labor	Oxen	Tractor	Pre-Emergence Herbicide	Total Cost
BR	21	3	24	15	31	52	122
Bt	13	22	35	7	64	67	173
Carnia	15	23	38	5	65	64	173
Pannar	33	11	44	12	44	31	131
RR	20	7	28	15	9	86	137
No-till	25	8	33	19**	0	99**	150
Conventional	20	14**	33	8	56**	40	137

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77; No-till = 83, Conventional tillage = 129

**,* Indicates significantly higher at 1% and 5% respectively using a one-sided t-test.

Planting

As previously mentioned, two primary methods are used for preparing land to plant maize in KwaZulu-Natal. In one method of planting, producers use a plow to open furrows for planting with either hired tractors or oxen. Other producers use only a hand hoe to open the soil, plant the seed, and close the furrow (Gouse 2012). Many of these producers, using HT varieties or not, still use pre-herbicide on their plots to control weeds, since neither method of planting

eliminates the weed problem. This may explain in part why planting labor is consistently higher for non-HT maize varieties (Table 3-8). Another reason may be intercropping, which is used primarily for non-HT maize. Producers who plant HT maize typically spray the plot with Roundup later in the season, which severely limits them from planting any crop which is not tolerant of Roundup, in this case pumpkins and beans. Of the 19% of producers that intercropped with the maize, 78% used pumpkins and the remaining intercropped with beans.

Table 3-8 Planting Labor, Intercropping, and Planting Date

Site	Seed Type	Planting Labor (hours/ha)	% Planted with a Hoe	% Intercropping	Planting Date (dd/mm/year)
Hlabisa	BR	70	1.00	.07	21.11.2009
	Pannar	107	.27	1.00	23.11.2009
	RR	92	1.00	.04	19.11.2009
Simdlangetha	BR	60	.65	.05	18.10.2009
	Bt	75	.67	.17	18.10.2009
	Carnia	76	.59	.09	25.10.2009
	Pannar	77	.79	.39	23.10.2009
	RR	67	.50	.10	29.10.2009

Note: N = 212; Hlabisa = 97; Simdlangetha = 115; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

Planting date varies by region, from the middle of October in Simdlangetha until the middle of November in Hlabisa. Seed cost is highest for GM varieties, especially HT varieties, which may explain why the seeding rate is lowest among GM varieties (Table 3-9). Total planting cost is highest for HT varieties due to the high seed costs. The same tradeoff between seed cost and seeding rate is evident with the 25 farmers who planted GM and non-GM on separate plots (Table 3-10).⁷

⁷ An additional three farmers planted two plots of GM maize.

Table 3-9 Planting Seed, Labor, and Total Costs

SeedType	Seeding Rate		Seed (\$/ha)	Planting Labor (\$/ha)	Total Planting Cost (\$/ha)
	Seed (\$/kg)	(kg/ha)			
BR	11	17.0	179	49	228
Bt	9	17.0	151	58	209
Carnia	8	17.1	131	58	189
Pannar	6	18.5	115	66	181
RR	11	15.8	168	68	236
Total	9	16.9	150	62	212

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

Table 3-10 Planting Seed, Labor, and Total Costs of Farmers with 2nd plot

Seed Type	N	Seeding Rate		Seed (\$/ha)	Planting Labor (\$/ha)	Total Planting Cost (\$/ha)
		Seed (\$/kg)	(kg/ha)			
BR	14	10	17	172	49	221
Bt	7	9	18	164	50	213
Carnia	12	9	18	154	56	209
Pannar	13	6	20	121	72	193
RR	4	12	15	172	56	228
Total	50	9	18	153	57	210

Farmers must have either savings or credit in order to purchase GM or hybrid maize seed, as opposed to using seed saved from the previous season. In this case, nearly all farmers have access to some type of credit, and many have non-farm income. In fact, 51% of smallholders used government payments (including pension and child grants), and 24% used wage income or remittances to pay for their maize seed. Regardless of good access to credit, 22% of smallholders were not able to get their first choice of seed; of these, 80% reported that the reason was that the seed was not available and 88% preferred to buy RR or BR maize seed.

Post-Emergence Weed Control

The average experience of each producer using herbicide does not vary much across maize types, and did not seem to influence their preference for RR or BR maize (Table 3-5). Herbicide was used to control weeds on a majority of plots for all maize types except Pannar, which relied heavily on weeding (Table 3-11). Prices of herbicide were higher for RR and BR maize plots which used Roundup in contrast to non-RR maize plots which used mostly 2,4-D and Atrazine. Roundup is a considerably more effective herbicide, and probably explains why RR and BR plots required almost no manual weeding. Twenty-five percent of non-RR producers also

used either Roundup or another herbicide in-between the maize rows, being careful not to touch the maize plant with the herbicide. These may be producers that recognized the control that Roundup has over weeds, but were not able or willing to purchase RR maize seed at the beginning of the season. Pannar stands out as having much higher labor use than any other variety. This is because more than half of Pannar producers use weeding, not herbicide, to control weeds while a majority of producers of all other maize types used herbicide to control weeds.

Table 3-11 Post-Emergence Weed Control Using Herbicide and Weeding in No-till Maize

Seed Type	% Applied Post-Emergence Herbicide	Post-Emergence Herbicide (litres/ha)	Post-Emergence Herbicide (\$/litre)	Post-Emergence Herbicide (hours/ha)	Weeding Labor (hours/ha)
BR	1.00	6	7	20	0
Bt	.94	7	8	28	23
Carnia	.94	7	7	33	15
Pannar	.42	3	3	15	127
RR	.99	5	14	11	4
No-till	.95**	5	17**	8	6
Conventional	.78	5	8	25**	53**

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77; No-till = 83, Conventional tillage = 129

**,* Indicates significantly higher at 1% and 5% respectively using a one-sided t-test.

The tradeoff between RR and non-RR varieties is obvious (Table 3-12); either herbicide, labor or a combination of both can be used to control weeds. Proper allocation of resources will depend on the price of both inputs. If the price of labor is high in the region, which the previous section suggested, then maize producers will be more likely to adopt RR maize for its labor-saving characteristics. If herbicide prices are high, the opposite will occur. The cost of Roundup Ready herbicide was by far the most expensive part of weed control for RR and BR maize; however, Pannar maize has significantly higher weeding labor cost than all other varieties, and significantly higher total weed-control costs than Bt, Carnia, and RR maize.⁸

⁸ P-values calculated using a one-tailed t-test.

Table 3-12 Post-Emergence Herbicide versus Weeding Input and Labor Cost (USD/hectare)

SeedType	Post-Herbicide Labor	Post-Emergence Herbicide	Weeding Labor	Total Cost
BR	16	101	0	117
Bt	21	57	18	97
Carnia	25	59	12	96
Pannar	12	28	98	137
RR	9	85	3	97

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

Fertilizer

According to previous literature, the average use of fertilizer on maize in Sub-Saharan Africa is about 17 kg/ha compared to about 100 kg/ha in other low-income countries and 270 kg/ha in high-income countries⁹ (Smale, Byerlee and Jayne 2011). Forty percent of fertilizer in Sub-Saharan Africa is used for maize where fertilizer prices are at times 6 to 8 times higher per unit than in the US (Sanchez 2003). The difference in fertilizer use and price in Kwazulu-Natal appears to be less extreme. Farmers in Kwazulu-Natal used an equivalent of about 50 kg/ha¹⁰ and paid approximately 60% more per unit fertilizer than farmers in the US (Appendix Table A-1).

Prior to planting, an average of 206 kg/ha of fertilizer with a relatively low nitrogen content between 6.3% and a 12.5% was applied on 211 maize plots (Table 3-13). Another 33 maize producers used an additional 312 kg/ha of organic fertilizer (kraal manure), which is even lower in nutritional content than other fertilizer. An additional 108 plots in Simdlangetsha received an average of 257 kg/ha of LAN top dressing which is higher nitrogen content. LAN is 28% nitrogen, and it was applied on average 33 days after planting.

⁹ 100 kilograms per hectare is equal to 89 pounds per acre.

¹⁰ Farmers in this study used 206 kg/ha of fertilizer, but the nitrogen content is approximately one-fourth the concentration of fertilizer used in developed countries.

Table 3-13 Fertilizer, Manure and Top Dressing (kilograms/hectare)

	N	Mean	Median	Std. Deviation	Minimum	Maximum
Fertilizer (kg/ha)	211	205	175	99	20	498
Manure (kg/ha)	33	312	204	347	64	1363
Top Dress (kg/ha)	108	257	240	79	80	498
Total Fertilizer (kg/ha)	212	384	307	297	20	1884

Total fertilizer in kilograms per hectare is misleading, since there is so much variation in the nutritional content of each fertilizer. Therefore, Table 3-14 breaks down each fertilizer by its N:P:K ratio, which stands for nitrogen, phosphorous, and potassium, the three most essential macronutrients. The N:P:K ratio of kraal manure was calculated by a study conducted in KwaZulu Natal (Mkhabela et. al 2000).

Table 3-14 Fertilizer Type as a Percentage of Nitrogen, Phosphorus, and Potassium

	Frequency	% N	% P	% K
2:3:2 (22)	57	6.3	9.4	6.3
3:2:1 (25)	91	12.5	8.3	4.2
3:2:1 (25) Zn	6	12.5	8.3	4.2
4:3:4 (30)	12	10.9	8.2	10.9
MAP	30	11	52	0
LAN	108	28	0	0
Kraal Manure	33	1.7	1.1	2.7
Water Fertilizer	15	-	-	-
Total	212	-	-	-

Fifteen producers in Simdlangetsha used “water fertilizer” in the 2009-10 season, a bi-product of 2:3:2 (22) fertilizer which has not been used before or since. Water fertilizer was bought in a concentrated form and diluted with between 1:10 and 1:50 parts water before being applied to maize (Gouse 2012). Since water fertilizer is a product sold informally to maize producers, the N:P:K content is unknown.¹¹

¹¹ The N:P:K content of water fertilizer is unknown, both the quantity and price are biased, creating a challenge when estimating production and cost functions. To control for quantity, the total cost of water fertilizer was divided by the average price of fertilizer. For example, 5 kilograms of water fertilizer is costs \$20.18/\$0.59per kilogram =

Table 3-15 Fertilizer by Region in terms of Nitrogen, Phosphorus, and Potassium (kilograms/hectare)

	Site					
	Hlabisa		Simdlangetsha		Total	
	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
Nitrogen	19	6	89	35	57	43
Phosphorus	13	4	54	57	35	47
Potassium	7	2	15	13	11	10
Top Dressing – Nitrogen	0	0	67	28	36	39

Note: N = 212; Hlabisa = 97; Simdlangetsha = 115

Recommendations for Kwa-Zulu Natal vary depending on region, from 10 kilograms of phosphorous per hectare (kg P/ha) to between 40 and 60 kg P/ha as government research indicates that most soils in Kwa-Zulu Natal are deficient in phosphorous (Mkhabela 2004, Manson n.d.). In Simdlangetsha average use is 54 kg P/ha, but in Hlabisa farmers use less than 13 kg P/ha (Table 3-15). It may be difficult to come to strong conclusions regarding phosphorous since no soil nutrient recommendation information for farmers specifically in Hlabisa or Simdlangetsha and phosphorous binds to the soil and is available for the plant to use for several years. Phosphorous does not need to be applied every year like nitrogen which easily leaches through the soil; therefore, data from one production season may not capture actual phosphorous available.

To achieve 7000 kilograms of maize per hectare in Kwa-Zulu Natal, Mkhabela (2004) recommended using 120 kg N/ha, 10 kg P/ha, and 56 kg K/ha (Mkhabela 2004). Farmers surveyed are using an average of 57 kg N/ha, 35 kg P/ha, and 11 kg K/ha. Nitrogen and potassium use is far below the suggested amount, which may partly explain why yields are well below 7000 kilograms of maize per hectare, or this may be the result of planting maize on marginal land. This low use of fertilizer suggests that farmers are producing in stage one or two of the production curve.

34.2 equivalent kilograms of 2:3:2 (22) fertilizer. To control for price, the price of water fertilizer is set to the average price of fertilizer of \$0.59.

Table 3-16 Fertilizer, Manure, Top Dressing, and Labor Cost

Site	Seed Type	Fertilizer Price (\$/kg)	Fertilizer (kg/ha)	Fertilizer (\$/ha)	Manure (\$/ha)	Top Dressing (\$/ha)	Top Dressing Labor (\$/ha)	Total Fertilizer (\$/ha)
Hlabisa	BR	.62	167	98	1	0	0	98
	Pannar	.62	196	121	0	0	0	121
	RR	.62	154	86	1	0	0	88
	Total	.62	162	94	1	0	0	94
Simdlangetsha	BR	.61	519	270	3	120	42	435
	Bt	.64	500	254	5	118	52	430
	Carnia	.55	640	305	6	145	41	496
	Pannar	.57	600	275	11	128	50	464
	RR	.62	471	244	2	120	52	419
	Total	.59	571	277	6	129	46	459
HT								

Note: N = 212; Hlabisa = 97; Simdlangetsha = 115; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

Producers in Simdlangetsha also applied top dressing to their fields, while no producers in Hlabisa used top dressing (Table 3-16). Fertilizer costs are higher for Pannar and significantly different than BR and RR maize in Hlabisa at 95% confidence. In Simdlangetsha, fertilizer costs for Pannar and Carnia are higher but not significantly different. Producers with two plots applied 247 kilograms of fertilizer per hectare on GM maize, which is significantly higher than 325 kilograms per hectare applied to non-GM maize plots.

Insecticide

Insecticide is similar to herbicide in that it provides damage abatement. In KwaZulu-Natal, the primary insect that causes damage to maize is the stock borer. Only 3 farmers used insecticide to control an insect other than stock borers. During the 2009-10 season little pest pressure from the stock borer existed, with 98% reporting that there were either “no worms” or “a couple worms.” 83% of farmers in post-season surveys reported “no damage” or “a little damage” due to stock borer (Table 3-17). Most farmers said that similar conditions of stock borer existed the previous year as well.

Table 3-17 Pest Infestation Rate and Insecticide Use

Site	SeedType	% Producers Who Reported "A Couple Worms"	% Producers Who Reported "Many Worms"	% Producers Who Applied Insecticide to Control Pests	Insecticide Applied (liters/ha)
Hlabisa	BR	.33	.00	.00	
	Pannar	1.00	.27	.00	
	RR	1.00	.00	.03	3.8
	Total	.90	.04	.02	3.8
Simdlangetsha	BR	.60	.00	.05	
	Bt	.56	.00	.00	
	Carnia	.91	.00	.68	1.9
	Pannar	.82	.00	.61	2.5
	RR	.80	.00	.60	1.7
	Total	.77	.00	.43	2.1

Note: N = 212; Hlabisa = 97; Simdlangetsha = 115; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

Farmers in Hlabisa used very few insecticides, most likely due to low pest pressure and the use of BR maize. In Simdlangetsha on the other hand, no insecticides were used in plots with Bt technology, while over 60% of farmers who planted varieties that were not resistant to stem borer sprayed insecticide, which cost around \$28 per hectare as seen in Table 3-18.

Table 3-18 Insecticide Price, Quantity, Labor, and Cost

Site	SeedType	Insecticide (\$/L)	Insecticide (\$/ha)	Insecticide (hrs/ha)	Insecticide Labor (\$/ha)	Total Cost (\$/ha)
Hlabisa	BR		0	0	0	0
	Pannar		0	0	0	0
	RR		0	1	1	1
	Total		0	1	0	0
Simdlangetsha	BR		1	0	0	1
	Bt		0	0	0	0
	Carnia	33	13	36	27	40
	Pannar	21	20	35	27	47
	RR	21	7	30	23	30
	Total	27	10	23	18	28

Note: N = 212; Hlabisa = 97; Simdlangetsha = 115; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

Harvest

Harvest labor is similar for different maize varieties, but significantly different between regions ($p = 0.000$). One explanation for this is that producers in Hlabisa are more efficient at harvesting maize. Maize harvest efficiency is defined as kilograms of maize harvested per hour,

and is calculated in two ways. First, harvest efficiency is calculated as total output divided by the total hours of harvest labor reported by producers. Second, producers were asked on average “how many bags of maize cobs do an adult male and female harvest in a day.” The answers were converted to reflect kilograms of maize harvested per hour as presented in Table 3-19.

Harvest efficiency (both calculated, male, and female) is significantly higher in Hlabisa using a one-tailed t-test ($p = 0.000$ for all three tests). The time it takes to walk to the maize plot appears to explain why farmers in Hlabisa are more efficient, which could suggest that these producers are more efficient in other activities as well.

Table 3-19 Maize Yield, Harvest Labor, Cost, and Efficiency

Site	Seed Type	Yield (kg/ha)	Harvest Labor (hrs/ha)	Harvest Labor Cost (\$/ha)	Harvest Efficiency, Calculated (kg/hour)	Harvest Efficiency, Male (kg/hour)	Harvest Efficiency, Female (kg/hour)	Time to Walk to Maize Plot (minutes)
Hlabisa	BR	1910	50	39	36	33	36	3
	Pannar	1788	60	46	30	25	32	3
	RR	1880	51	39	37	38	37	3
	Total	1870	52	40	36	35	36	3
Simdlangetsha	BR	1347	88	79	19	16	16	14
	Bt	1351	87	67	16	15	15	16
	Carnia	1227	87	66	18	17	16	16
	Pannar	1659	69	53	21	16	16	11
	RR	1953	75	58	26	18	17	9
	Total	1454	81	64	20	16	16	13

Note: N = 212; Hlabisa = 97; Simdlangetsha = 115; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

Most of the variation in maize price is between regions, not maize types. Farmers from Hlabisa received an average maize price of \$0.48 per kilogram¹², while farmers in Simdlangetsha received \$0.38 per kilogram of grain (Table 3-20). Green mealies is defined as cobs of maize that are harvested prior to drying. A high percentage of green mealies can be an indication of food insecurity if households are not able to wait until harvest to eat, but green mealies are also a part of households diets. The number of green mealies is included in the final maize yield¹³ (in Table

¹² Calculated at the exchange rate of 7.44 Rand per US dollar.

¹³ 100 green mealies = 16.7 kilograms of dry grain. Conversion from green mealies to dry grain is as follows: for 100 green mealies harvested, it was estimated that 3 green mealies is 1 kilogram. Therefore, 100 green mealies is

3-21). Producers of GM maize sold significantly more maize than non-GM producers ($p = 0.000$). Producers in Simdlangetsha harvested maize more than 20 days later on average than producers in Hlabisa, which could be attributed to weather patterns or farm characteristics, as farmers planted similar varieties in both regions.

Table 3-20 Maize Price, Percent of Green Mealies, Insecticide, Days to Harvest

Site	SeedType	Maize Price ^a	% of Total Yield		% of Producers		Days from Planting to Harvest
			Harvested as Green Mealies	% of Producers Who Sold Grain	Who used Post-Harvest Insecticide		
Hlabisa	BR	.48	5.9	.67	.00	164	
	Pannar	.48	12.8	.40	.07	165	
	RR	.48	5.4	.70	.00	165	
	Total	.48	6.6	.65	.01	165	
Simdlangetsha	BR	.38	1.1	.85	.90	192	
	Bt	.37	1.2	.61	1.00	190	
	Carnia	.38	1.3	.41	.88	186	
	Pannar	.38	1.6	.33	.85	187	
	RR	.38	.9	.40	1.00	182	
	Total	.38	1.3	.50	.90	188	

Note: N = 212; Hlabisa = 97; Simdlangetsha = 115; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77

^aAverage maize price of \$0.38 and \$0.48 per kilogram is equal to \$9.40 and \$12.19 per bushel respectively, 1 bushel = 56 pounds

Maize Yield

Maize yield was measured in kilograms of maize per hectare, as presented in Table 3-21. The mean maize yield across all farms was 1645 kilograms per hectare, with a range of about 350 to 4350 kilograms per hectare. In Hlabisa, the maize yield of BR, Pannar, and RR are not significantly different from each other. In Simdlangetsha, RR maize was significantly higher than Carnia ($p = 0.003$) and BR maize ($p = 0.047$).

33.33 kilograms including the cobs; since the cobs make up 50% of the weight, $33.33 \times 0.5 = 16.7$ kilograms (Gouse 2012).

Table 3-21 Maize Yield by Region and Maize Type (kilograms/hectare)^a

Site	SeedType	N	Mean	Median	Std. Deviation	Minimum	Maximum
Hlabisa	BR	15	1910	1953	615	631	2676
	Pannar	15	1788	1864	540	745	2586
	RR	67	1880	1988	577	512	3400
	Total	97	1870	1945	573	512	3400
Simdlangetsha	BR	20	1347	1174	663	569	2631
	Bt	18	1351	1056	892	345	4170
	Carnia	34	1227	1089	551	444	2763
	Pannar	33	1659	1298	1149	444	4362
	RR	10	1953	1864	909	753	3885
	Total	115	1454	1170	877	345	4362
Total		212	1645	1658	780	345	4362

^aAverage yield in Hlabisa and Simdlangetsha is 29.7 and 23.1 bushels per acre respectively where 1 bushel is equal to 56 pounds.

Comparing farmers who planted GM maize on one plot and non-GM maize on the other, removes uncertainty of farmer and farm characteristics, leading to a more concrete analysis. As Table 3-22 below shows, GM maize has a yield a little more than 100 kilograms per hectare, but this is not significantly different than non-GM maize.

Table 3-22 Maize Yield of Farmers with Two Plots (kilograms/hectare)

Seed Type	N	Mean	Median	Std. Deviation	Minimum	Maximum
BR	14	1406	1174	727	569	2631
Bt	7	1673	1111	1230	709	4170
Carnia	12	1333	1322	351	680	1872
Pannar	13	1628	1387	989	444	3684
RR	4	2116	1896	641	1620	3051
GM	25	1594	1355	885	569	4170
Non-GM	25	1487	1377	754	444	3684

Total Costs and Net Returns of Maize

Yield is important for producers in KwaZulu-Natal where a majority of maize is consumed at home. In comparing average maize yields of the five seed types, there was little significant difference between them. However, biochemical and labor use can have a large impact on total costs. GM maize typically has more expensive inputs such as seed or herbicide, while non-GM maize has more expensive labor costs. Each maize producer must make the

decision of how to allocate their resources between labor and biochemical inputs. The assumption is made that each producer will optimize resource use, allocating capital and labor to a variety of activities, including livestock, off-farm employment, leisure, or maize production. It is also assumed that producers are utility maximizers and will only produce maize if they consider it an optimal use of their resources. Examining net returns of the different maize types allows for a better understanding of optimal resource allocation among farmers.

Summary of Biochemical and Mechanical Input Costs

Biochemical and mechanical input costs, not including fixed costs such as land and depreciation of equipment, are presented in Table 3-23. In Hlabisa, GM maize plots had significantly higher seed and herbicide costs than non-GM maize, resulting in significantly higher total input costs. In Simdlangetsha, non-GM maize also has significantly higher seed costs, but total input costs are not significantly different. Insecticide costs are significantly higher on non-GM plots, which is expected since Bt and BR maize do not require insecticide.

Table 3-23 Biochemical and mechanical input costs (USD/hectare)

Site	Seed Type	Seed	Fertilizer	Herbicide	Insecticide	Oxen	Tractor	Total Inputs
Hlabisa	BR	185	98	216	0	32	0	531
	Pannar	124	121	22	0	30	0	297
	RR	169	87	187	0	16	0	458
	GM	172**	88	192**	0	19	0	471**
	Non-GM	124	121**	22	0	30	0	297
Simdlangetsha	BR	175	271	106	1	3	54	609
	Bt	151	259	124	0	7	64	600
	Carnia	131	307	123	13	5	65	642
	Pannar	111	280	76	20	3	64	549
	RR	159	247	68	7	11	66	556
	GM	163**	259	105	2	6	60	595
	Non-GM	121	290*	100	16**	4	64	596

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77; Hlabisa = 97; Simdlangetsha = 115
 **, * Indicates significantly higher at 1% and 5% respectively using a one-sided t-test.

Labor Summary

An even greater difference between GM and non-GM maize varieties is evident when comparing labor use by task (Table 3-24). Non-GM maize varieties use significantly higher labor than GM varieties except in planting and harvest labor.

Table 3-24 Labor by Task (hours/hectare)

Seed Type	Land Preparation	Planting	Weeding	Insecticide	Herbicide	Top Dress	Harvest	Total Labor
BR	27	64	0	0	24	31	72	219
Bt	17	75	23	0	57	68	87	327
Carnia	19	76	15	36	64	53	87	350
Pannar	43	86	127	24	29	44	66	421
RR	26	89	4	5	21	9	54	207
GM	25	80	6	3	27	23	63	227
Non-GM	33*	82	81**	29**	44**	48**	75	391**

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77; GM = 130, non-GM = 82

**, * Indicates significantly higher at 1% and 5% respectively using a one-sided t-test.

While it is evident that GM maize is labor-saving, Table 3-25 breaks labor into categories of family and hired labor in hours per hectare. Non-GM maize plots use significantly higher child, male, and female labor than non-GM plots in both Simdlangetsha and Hlabisa (Table 3-25). Hired labor is significantly higher in Hlabisa for non-GM maize and workgroup labor is significantly higher for GM maize. In Simdlangetsha hired and workgroup labor is not significantly different between GM and non-GM maize. The reason for higher family labor use may be that households with lower opportunity cost of time are more likely not to adopt labor-saving GM varieties of maize, but this assumption requires further research.

Table 3-25 Family and Hired Labor by Seed Type (hours/hectare)

Site	Seed Type	Child	Male	Female	Hired	Workgroup	Total Labor
Hlabisa	BR	2	37	62	39	47	187
	Pannar	18	153	177	68	20	437
	RR	2	41	52	22	76	194
	GM	2	41	54	25	71**	192
	Non-GM	18**	153**	177**	68**	20	437**
Simdlangetsha	BR	21	47	58	87	28	242
	Bt	42	70	122	39	54	327
	Carnia	55	93	115	42	45	350
	Pannar	75	96	121	59	62	414
	RR	48	77	103	39	33	300
	GM	35	62	91	59	39	286
	Non-GM	65**	94**	118*	50	53	381**

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77; GM = 130, non-GM = 82

**, * Indicates significantly higher at 1% and 5% respectively using a one-sided t-test.

Labor cost varies based on activity, as more labor intensive activities like land preparation and weeding labor are typically more expensive (Table 3-26). Previous research also suggests that spraying labor is also more expensive since spraying takes place during the Christmas period in KwaZulu-Natal when labor availability is low (Thirtle, Piesse and Gouse 2005). The wage rate was only available for 72 maize plots so the remaining plots simply received an average wage rate between \$0.79 and \$0.81 per hour¹⁴, depending on the region. Labor costs are slightly more than one third of total production costs, so their impact on net returns is still important. Hired labor is not significantly different between HT and non-HT maize plots. However, a two-sided t-test reveals that family labor is significantly different on HT maize plots (p = 0.000).

Table 3-26 Family and Hired Labor Costs by Region and Maize Type (USD/hectare)

Site	SeedType	Family Labor	Hired Labor	Total Labor
Hlabisa	BR	77	66	143
	Pannar	267	67	335
	RR	73	75	149
	Total	104	73	177
Simdlangetsha	BR	97	89	186
	Bt	179	72	251
	Carnia	202	66	268
	Pannar	224	93	317
	RR	175	55	230
	Total	184	78	262
	HT	87	75	162
Non-HT	215**	76	291**	

Note: N = 212; Hlabisa = 97; Simdlangetsha = 115; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77; HT = 112, non-HT = 100

**,* Indicates significantly higher at 1% and 5% respectively using a one-sided t-test.

Maize Input and Labor Cost Isoquant

As mentioned previously, there is a tradeoff between input and labor use. Producers of RR and BR maize appear to value the opportunity cost of labor high, and therefore substitute labor with herbicide, insecticide, or seed that allows them to use significantly less labor than other varieties. The assumption is made that maize yield is a function of inputs and labor,

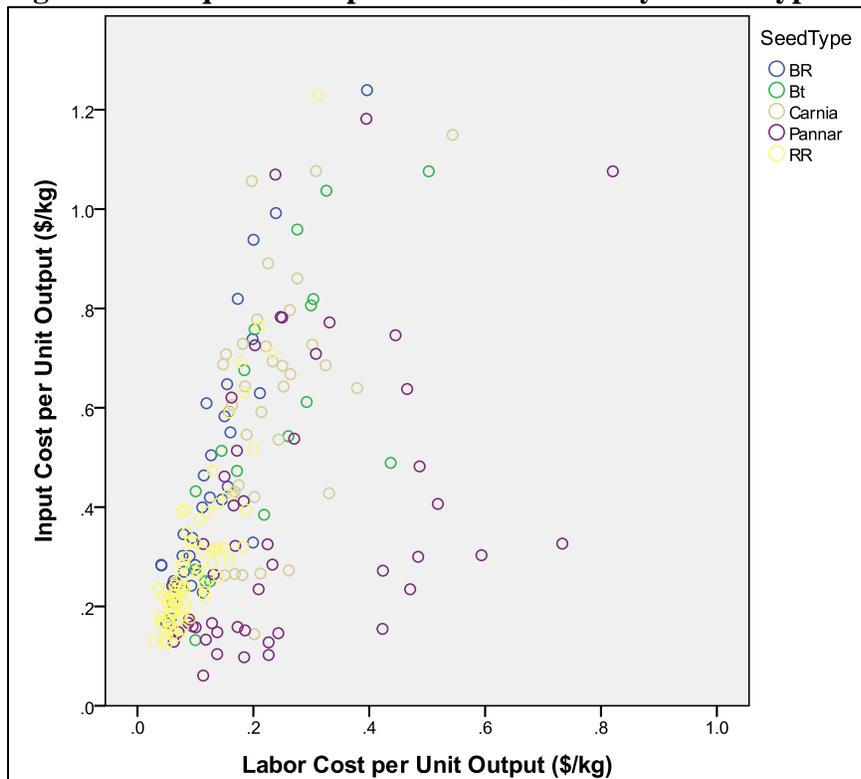
¹⁴ At the exchange rate of 7.44 Rand per US dollar.

$$\text{Maize yield} = \delta \text{Inputs}^{\alpha} \text{Labor}^{\beta}$$

similar to the Cobb-Douglas production function assumption that output is a function of capital and labor (Orazem 1998).

In order to create an isoquant, inputs and labor are normalized by USD per kilogram maize. The shape of the isoquant is apparent in Figure 3-3. Producers of BR and RR maize use relatively less labor than other producers which is why most of the RR and BR observations remain along the left side of the isoquant. Pannar producers on the other hand, are more strung out along the bottom, since they substitute labor for biochemical inputs in particular. The isoquant also shows producer efficiency; observations that are closer to the outer edges of the isoquant are more efficient. Many RR observations are clustered at the bottom along the left edge of the isoquant, while a group of Pannar observations are also clustered at the bottom of the isoquant, suggesting that these two varieties are very efficient at using biochemical inputs and labor respectively to increase maize output.

Figure 3-3 Isoquant of Input and Labor Cost by Maize Type



Maize Net Returns

The yield of HT maize was only slightly higher, and not significantly different than non-HT maize by region (Table 3-27). Since HT maize has higher biochemical costs and much lower labor costs than non-HT maize, net returns of HT maize in Simdlangetsha are significantly different than non-HT net returns ($p = 0.078$).¹⁵ RR maize out-performed all other varieties in both regions, due to high yields and low labor costs which outweighed higher seed and herbicide costs. BR performed second-best in Hlabisa for the same reasons, and Pannar performed second-best in Simdlangetsha due to lower input costs.

Table 3-27 Maize Revenue, Cost, and Net Returns across Region and Maize Type

	Seed Type	Yield (kg/ha)	Maize Price (\$/kg) ^a	Maize			Total Cost (\$/ha)	Net Returns (\$/ha)
				Revenue (\$/ha)	Input Cost (\$/ha)	Labor Cost (\$/ha)		
Hlabisa	BR	1910	.48	918	531	143	674	244
	Pannar	1788	.48	866	297	335	632	234
	RR	1880	.48	910	458	149	606	304
	GM	1885	.48	912	471**	148	619	293
	Non-GM	1788	.48	866	297	335**	632	234
Simdlangetsha	BR	1347	.38	512	609	186	794	-283
	Bt	1351	.37	502	600	251	851	-349
	Carnia	1227	.38	463	642	268	910	-447
	Pannar	1659	.38	640	549	317	866	-226
	RR	1953	.38	737	556	230	786	-48
	GM	1475	.38	555	595	219	814	-259
	Non-GM	1440	.38	550	596	292**	888**	-338
	Bottom 10%	586	.40	236	536	199	735	-499
	Middle 80%	1623	.43	713	529	223	752	-39
Top 10%	2827	.42	1173	493	246	739	434	

Note: N = 212; BR = 35, Bt = 18, Carnia = 34, Pannar = 48, RR = 77; Hlabisa = 97; Simdlangetsha = 115; GM = 130, non-GM = 82

**,* Indicates significantly higher at 1% and 5% respectively using a one-sided t-test.

^aAverage maize price of \$0.38 and \$0.48 per kilogram is equal to \$9.40 and \$12.19 per bushel respectively.

As stated previously, the assumption was made that producers will maximize net returns against the constraints capital, biochemical inputs, and labor. As can be seen in Table 3-27, the

¹⁵ Net returns are calculated as gross returns less total costs, excluding fixed costs such as land.

average producer lost money in Simdlangetsha. This is partly due to lower maize prices received by farmers in Simdlangetsha. It is also because the full wage rate is applied to both hired and family labor, even though non-pecuniary benefits to family labor may exist. Farmers in this study are not considered irrational; rather, some farmers may enjoy farming and receive a benefit from planting maize which is not captured in monetary units. This implicit price paid for family labor appears to have an impact on adoption of HT and non-HT maize (Table 3-26), warranting further research. However, the focus of this research is on net returns and attempting to capture this implicit labor price is beyond the scope of this study.

Producers with two plots also realized higher labor cost and greater loss on non-GM compared to their GM plots (Table 3-28). When comparing maize net returns, all GM varieties are significantly different than Carnia at 95% confidence level, but only RR is significantly different than Pannar at the 90% confidence level. When both regions are combined, GM maize net returns are significantly different than non-GM maize ($p = 0.000$) and that HT maize net returns are significantly different than non-HT maize ($p = 0.000$). This is not a fair assumption to make, however, since the number of GM or HT maize plots is not equally distributed between the two regions.

Table 3-28 Maize Revenue, Costs, and Net Returns of Producers with two plots^a

SeedType	Maize Revenue (\$/ha)	Total Inputs (\$/ha)	Total Labor Cost (\$/ha)	Total Cost (\$/ha)	Maize Net Returns (\$/ha)
BR	540	622	196	818	-278
Bt	623	588	221	809	-186
Carnia	502	724	309	1032	-530
Pannar	619	668	330	998	-379
RR	798	603	245	849	-51
GM	604	609	211	820	-216
Non-GM	563	695	320	1014	-451
Total	584	652	265	917	-334

^aAt the exchange rate of 7.44 Rand per US dollar

Results of the data overview reveal consistent differences between maize types. However, few conclusions can be made without further analysis. As stated earlier, the objective of this thesis is to test a set of three hypothesis; that GM maize has higher output, that GM maize reduces risk, and that GM maize has lower costs. The following section uses econometric techniques to test the first hypothesis that GM maize has higher output.

Chapter 4 - Production Analysis

The objective of Chapter 4 is to test the hypothesis that GM maize has higher output than non-GM maize. This chapter provides a technical approach by using econometric techniques to capture the variation in production, especially between RR and Bt maize varieties. The first section of this chapter provides the functional form and specification of linear and quadratic production functions, including a two-step least squares model which accounts for endogenous variables. Results of the analysis are presented in the second section, where the RR dummy variable stands out as significant and positive. For this reason, split regressions of RR and non-RR maize plots are used to calculate elasticities of output, which allows for the comparison responsiveness of maize output to input use.

Production Function Estimation

Production is defined as the process of turning a given set of inputs into outputs. The decision-making is in the hands of farmers, who must decide how to best allocate the limited inputs available in order to maximize output, using the information available to them. It is assumed that the production function is a representation of the farmers' technical knowledge; for example, farmers understand the effect that one more unit of fertilizer will have on maize output.

Functional Form

A short-run single-output production function as used in this research is represented as,

$$y = f(x_1, \dots, x_s | x_{s+1}, \dots, x_n) \quad (4.1)$$

where y denotes the quantity of output and x_1, \dots, x_s are variable production inputs and x_{s+1}, \dots, x_n are fixed inputs. Two functional forms, linear and quadratic, are used to describe the relationship between dependent and independent variables. This relationship can be described using either an ordinary least squares (OLS) or weighted least squares (WLS) regression.

Linear Model

The simplest form is the linear production function, which is specified as,

$$Y_i = \alpha_0 + \sum_{j=1}^n \beta_j x_{ij} + \sum_{d=1}^n \eta_d D_{id} + \varepsilon_i \quad (4.2)$$

where Y_i represents the total maize output in kilograms produced by the maize plot i , x_{ij} is a vector representing quantity of input j by maize plot i , D_{id} is a vector of dummy variables which includes location and maize seed type, α_0 , β_j and η_d are parameters and ε_i is an error term.

Elasticities of Output

One advantage of the linear model is that running split linear regressions (of RR and non-RR maize for example), allows for the calculation of elasticities of output. Elasticities of output, E_i , are measured as the percentage change in output, Y_i , associated with a one percent change in input x_j defined as

$$E_i = \frac{\partial Y_i}{\partial x_j} \cdot \frac{x_j}{Y_i} = \frac{MPP_i}{APP_i} \quad (4.3)$$

where MPP_i is the marginal physical product and APP_i is the average physical product, both of output i . Elasticities of output are especially useful because they are unit-free which allows the comparison of the marginal productivities of multiple inputs (Beattie, Taylor and Watts 2009). The summation of elasticities of output with respect to all the inputs is referred to as returns to scale, ϵ , also called the function coefficient, defined as

$$\epsilon = \sum_{j=1}^n \frac{\partial Y_i}{\partial x_{ij}} = \sum_{j=1}^n E_j \quad (4.4)$$

where Y_i represents the total maize output in kilograms produced by the maize plot i and x_{ij} is a vector representing quantity of input j by maize plot i . The function exhibits constant returns to scale (CRS) if $\epsilon = 1$. This indicates that the function is homogenous of degree one in inputs; if all inputs are doubled, output will double.

Quadratic Model

The quadratic model builds on the simplicity of the linear model, allowing for a more realistic representation of the relationship between the dependent and independent variables.

Squared and interaction terms between inputs allow for curvature in the production function. The quadratic model functional form is represented as follows,

$$Y_i = \alpha_0 + \sum_{j=1}^n \beta_j x_{ij} + \sum_{d=1}^m \eta_d D_{id} + \sum_{j=1}^n \sum_{k=1}^n \theta_{jk} x_{ij} x_{ik} + \varepsilon_i \quad (4.5)$$

where notation is the same as the linear production function (see equation 4.2) with the inclusion of a vector of interaction and squared terms, denoted by $x_{ij}x_{ik}$ representing quantity of input j and input l used on maize plot i . The quadratic equation also includes the additional parameter θ_{jk} which estimates the effect of the interaction and squared terms. To control for heteroscedasticity, a quadratic weighted least squares (WLS) regression is also provided.

Two-Stage Least Squares (2SLS)

Least squares models assume that inputs in the production function are exogenous, although this is typically not the case. Endogenous independent variables which are correlated with the error term are common when estimating production functions, and should be accounted for. The functional form of a least squares model which includes endogenous variables can be defined as,

$$Y_i = \alpha_0 + \sum_{j=1}^n \beta_j x_{ij} + \delta x_{ki} + \varepsilon_i \quad (4.6)$$

where x_{ij} is a vector representing all independent exogenous variables j , and x_{ki} represents the endogenous variables k which are correlated with the error term ε_i . In this case, the least squares models will produce inconsistent coefficients β and δ (Cameron and Trivedi 2009).

The two-stage least squares (2SLS) method is the most efficient instrument variable (IV) estimator, used for controlling for endogenous variables to provide unbiased estimates (Wooldridge 2002). First, variables can be tested for endogeneity using the Durbin-Wu-Hausman test. Once an endogenous variable is detected, instrumental variables defined by z_{il} , of plot i and input l , are used to correct for the endogeneity bias. Instrumental variables that are chosen must be correlated with x_{ki} and satisfy the assumption that $E(\varepsilon_i | z_{il}) = 0$.

The first step of the 2SLS procedure is to regress the endogenous variable x_{ki} on exogenous variables from the least squares equation and appropriate instrumental variables. The first-stage regression equation is defined as

$$\hat{x}_{ki} = \alpha_0 + \sum_{j=1}^n \beta_j x_{ij} + \sum_{l=1}^m \vartheta_l z_{il} + v_i \quad (4.7)$$

where \hat{x}_{ki} is the endogenous variable which is correlated with z_{il} , a vector of instrumental variables. The vector of exogenous variables is defined by x_{ij} and the error term is v_i . In the second-stage regression, the same variables as those in the original model are used, with the replacement of the endogenous variable, x_{ki} , with the predicted value of the endogenous variable, \hat{x}_{ki} (Cameron and Trivedi 2009, Wooldridge 2002).

Model Specification

The linear and quadratic production models presented in this section are based on a typical set of inputs. Maize output is a function of independent variables as presented in the following equation:

Maize output = *f(labor, fertilizer, herbicide, seed, land, land preparation cost, Hlabisa, Roundup Ready, Bt, assets, experience with herbicide, education)*

Inputs include labor, fertilizer, herbicide, seed, land, and land preparation cost. Since an increase in each of these inputs except for land preparation cost should lead to higher maize output, the value of the coefficient is expected to be positive. Dummy variables are used to capture differences based on region and maize type. To simplify analysis, and capture the effects of the RR and Bt technologies, only dummy variables for RR and Bt maize are included. Since BR maize includes both technologies, it is included in both dummy variables (Table 4-1). The remaining variables – assets, experience with herbicide, and education – are farmer characteristics which are used in the two-step least squares estimation as instrumental variables to reduce endogeneity bias of independent variables. Table 4-1 on the following page presents a description of variables used in the OLS, WLS, and 2SLS production models.

Table 4-1 Description of Variables Used in the Production Models

Variable	Description	Unit
<i>Maize Output</i>	Total kilograms of maize harvested	Kilograms
<i>Labor</i>	Total family and hired labor	Hours
<i>Fertilizer</i>	Total kilograms of fertilizer	Kilograms
<i>Herbicide</i>	The total liters of herbicide used both before and after planting	Liters
<i>Seed</i>	Total kilograms of seed planted	Kilograms
<i>Land</i>	The estimated area in hectares for each plot	Hectares
<i>Land Preparation Cost</i>	The total cost to prepare land, including the use or hiring of both oxen and tractors	US Dollars (2010)
<i>Hlabisa Dummy</i>	The dummy takes a value of one if the region is Hlabisa, and zero if the region is Simdlangetsha	1= Hlabisa 0= Simdlangetsha
<i>Roundup Ready Maize Dummy</i>	If the maize seed has the Roundup Ready trait, the dummy takes a value of one. This includes both RR and BR (stacked) maize	1= Roundup Ready maize 0= non-Roundup Ready maize
<i>Bt Maize Dummy</i>	If the maize seed is Bt, the dummy is one, including both Bt and BR (stacked) maize	1= Bt maize 0= non-Bt maize
<i>Assets</i>	Total assets of the household for each plot, a majority which is livestock assets such as cattle, goats, sheep, chickens, and donkeys. Also included are farm assets such as planters and plows	US Dollars (2010)
<i>Experience Using Herbicide</i>	The number of years that producers reported using herbicide to control weeds on maize plots in the past	Years
<i>Education Dummy</i>	Education dummy takes a value of zero if the head of household has had no formal education, and one if the head of household has had at least a primary education	1= Primary education at least 0= No formal education

The summary statistics presented on the next page in Table 4-2 reveal that there is a large variation in maize output and input use between the different maize plots. One of the reasons is that the plot size varies from 0.17 to 1.5 hectares, but there is also large variation in the amount of inputs that producers used on a per hectare basis (see Chapter 3).

Table 4-2 Descriptive Statistics of the Variables Used in the Production Models

Variable	Units	N	Mean	Median	Std. Deviation	Minimum	Maximum
<i>Maize Output</i>	Kilograms	212	754	637	526	89	4600
<i>Labor</i>	Hours	212	127	109	74	30	537
<i>Fertilizer</i>	Kilograms	212	93	100	59	0	500
<i>Herbicide</i>	Liters	212	4.5	4.0	2.5	0	10
<i>Seed</i>	Kilograms	212	7.9	5.0	3.8	3	25
<i>Land</i>	Hectares	212	.48	.37	.23	.17	1.50
<i>Land Preparation Cost</i>	US Dollars (2010)	212	21	20	19	0	101
<i>Hlabisa Dummy</i>	1= Hlabisa 0= Simdlangetsha	212	.46	-	-	0	1
<i>Roundup Maize Ready Dummy</i>	1= Roundup Ready maize 0= non-Roundup Ready maize	212	.47	-	-	0	1
<i>Bt Maize Dummy</i>	1= Bt maize 0= non-Bt maize	212	.25	-	-	0	1
<i>Assets</i>	US Dollars (2010)	212	8031	5735	7999	104	31931
<i>Experience Using Herbicide</i>	Years	212	3.5	4.0	2.0	0	10
<i>Education Dummy</i>	1= Primary education at least 0= No formal education	212	.67	-	-	0	1

Results

Estimation of Production Function using OLS and WLS

Table 4-3 presents the regression results using least squares estimates with maize output in kilograms as the dependent variable¹⁶. Both linear and quadratic models are used to explain the relationship between maize output and input use, while controlling for region and maize type using dummy variables. As seen in Chapters 4, RR maize appears to be the preferred variety by risk averse farmers; therefore, the RR maize dummy variable is of particular interest in this section.

¹⁶ A model with maize output per hectare was also run to reduce heteroscedasticity, but results were basically unchanged.

Table 4-3 Regression Results of Production for All Maize Plots

	OLS - Linear			OLS - Quadratic			WLS - Quadratic		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
<i>Intercept</i>	-336.32	***	109.6	-167.63		233.9	-52.32		202.3
<i>Labor</i>	3.26	***	0.5	2.73	*	1.6	1.77		1.4
<i>Fertilizer</i>	1.35	*	0.8	-0.58		2.4	-1.19		2.2
<i>Herbicide</i>	0.28		13.0	39.45		40.6	23.14		34.6
<i>Seed</i>	-26.16		20.6	-33.72		59.8	5.22		55.2
<i>Land</i>	993.56	***	324.1	1976.90	*	1024.8	1702.90	*	888.3
<i>Land Prep Cost</i>	1.27		2.6	-13.20	*	6.8	-15.28	**	6.0
<i>Hlabisa Dummy</i>	308.83	***	91.9	154.65		98.2	88.13		83.7
<i>RR Dummy</i>	217.27	***	74.6	137.45	**	80.6	131.61	*	69.8
<i>Bt Dummy</i>	-12.24		65.4	-4.90		56.6	5.39		48.4
<i>Labor</i> ²				-0.02	***	0.0	-0.02	***	0.0
<i>Fertilizer</i> ²				-0.02		0.0	-0.02		0.0
<i>Herbicide</i> ²				-4.72		4.2	-4.39		3.9
<i>Seed</i> ²				-7.13		9.0	-5.76		9.5
<i>Land</i> ²				-6420.40	***	2437.6	-4988.20	**	2352.5
<i>Land Prep Cost</i> ²				0.06		0.1	0.02		0.1
<i>Labor*Fertilizer</i>				0.02		0.0	0.02		0.0
<i>Labor*Herbicide</i>				0.49	***	0.2	0.48	**	0.2
<i>Labor*Seed</i>				-0.58	**	0.3	-0.56	*	0.3
<i>Labor*Land</i>				12.32	**	5.7	12.61	**	5.6
<i>Labor*Land Prep Cost</i>				0.11	**	0.0	0.10	**	0.0
<i>Fertilizer*Herbicide</i>				-0.08		0.3	-0.03		0.3
<i>Fertilizer*Seed</i>				0.49		0.5	0.32		0.6
<i>Fertilizer*Land</i>				-13.89		8.4	-13.08		8.9
<i>Fertilizer* Land Prep Cost</i>				0.11	*	0.1	0.13	*	0.1
<i>Herbicide*Seed</i>				-21.84	**	8.8	-19.62	**	8.9
<i>Herbicide*Land</i>				254.85		160.6	209.39		158.4
<i>Herbicide* Land Prep Cost</i>				-0.47		1.3	-0.18		1.2
<i>Seed*Land</i>				541.73	*	285.1	422.44		289.8
<i>Seed* Land Prep Cost</i>				0.33		1.4	0.92		1.5
<i>Land* Land Prep Cost</i>				-26.77		22.2	-33.57		23.3
<i>N</i>	212			212			212		
<i>R-squared</i>	0.47			0.68			0.87		
<i>Adjusted R-squared</i>	0.45			0.62			0.85		
<i>Breusch-Pagan</i>	138.8	***		25.1	***		4.6	**	
<i>F-value</i>	19.9			12.6			41.4		

***, **, * Indicates significantly different than zero at 1%, 5% and 10% respectively.

Interpretation of OLS Linear Model

The results of the OLS linear model show that labor, fertilizer, and land are all significant and positive; thus, they all have a positive marginal impact on maize output as expected. For example, for each additional hour of labor, it is estimated that maize output increases by 3.26 kilograms. The coefficients on the Hlabisa and RR maize dummy variables are also positive and significant, and are interpreted as follows; maize output on RR maize plots are expected to be 217 kilograms higher than non-RR maize output all else held constant.¹⁷ A one-sided t-test is used to determine if the output difference is positive. The null hypothesis, $H_0: RR = 0$, is tested against the alternative hypothesis, $H_1: RR > 0$. The null hypothesis is rejected, suggesting that RR maize plots have a significantly higher output than non-RR maize plots ($p = 0.002$). The Shapiro-Wilk W test for normality is required to run valid hypothesis testing, and is thus a good determinant of the robustness of these results. The null hypothesis of normal distribution rejected ($p = 0.000$), suggesting that the results of the hypothesis test are not robust. Even without normality, the OLS estimates are still unbiased, however, since an OLS regression only requires that the error term is identically and independently distributed (Chen, et al. 2003). The Bt dummy variable is not significant in any regression, which is because the benefits from Bt maize are realized when pest pressure is high (Gouse et. al 2006). In this production season, pest pressure appears to be very low as 98% of farmers reported that there were either “no worms” or “a couple worms.”¹⁸

Several statistical tests were performed to test the robustness of the linear model. The first test was to check for multicollinearity using the variance inflation factor (VIF). The VIF for the slope of coefficient j is simply $VIF_j = 1/(1 - R_j^2)$. The VIF reveals that the linear model has an acceptably low level of multicollinearity, since the VIF values for each coefficient were below 10. Next, the Breusch-Pagan test was used to check for heteroscedasticity with the null hypothesis that the variance of the residuals is homogenous. Using chi-squared distribution of the test statistic, the chi-squared value was 138.8 ($p = 0.000$) revealing heteroscedasticity in the model. Finally, the regression specification error test (RESET) was used to test for functional

¹⁷ 100 kilograms is equal to 3.93 bushels of maize at 56 pounds per bushel maize, and average yield is 29.6 bushels per maize plot.

¹⁸ A dummy variable for no-till was included in all three models, but is not presented as it does not contribute to the R-squared value and thus goodness of fit of the model. The p-values in all three models were 0.553, 0.268, and 0.616 respectively.

form misspecification. Since the linear model failed the test ($p = 0.000$) it is expected that the relationship between the independent variables and output is not linear, and a quadratic model may be more appropriate (Chen, et al. 2003, Greene 2003).

OLS Quadratic Model

The quadratic model has a higher R-squared value which shows that it better explains the relationship between maize output and the independent variables. The signs on the coefficients are once again as expected, except for land preparation costs which is negative. Labor is positive and significant, while labor squared is negative, showing diminishing marginal returns from labor. Labor interaction terms are mostly significant and positive.

An F-test was used to test the significance of the squared and interaction terms. The F statistic is 5.47, which shows that these terms are significant at the 1 percent level. This reveals that the squared and interaction terms help to better explain the relationship between maize output and the independent variables. The impact of the Hlabisa and RR dummy variables is smaller than the linear model, but still relatively large, positive and significant. Just as the linear model, the quadratic model failed the Breusch-Pagan test for heteroscedasticity ($p = 0.000$), indicating that it may be necessary to run a WLS model.

WLS Quadratic Model

To control for heteroscedasticity, a weighted least squares quadratic regression is used to provide more efficient coefficients. To determine which variable is causing heteroscedasticity, the residuals of the error term are plotted against the independent variables. A graphical representation shows that land is obviously the variable causing heteroscedasticity in the model; in other words, as land size increases, the variance in output also increases. The heteroscedasticity of the land term is explained by the assumption that small plots are easy to manage, and outputs are consistent. As plots get larger, they are either more difficult to manage or farmers are achieving higher outputs by specializing in maize production, creating greater variance in maize output. To control for heteroscedasticity, the model is weighted proportionally to the log of squared residuals of land and land squared; therefore, observations with smaller variance receive a larger weight and have a greater influence in the estimates (Greene 2003).

Although results show that the WLS quadratic model has a higher R^2 value, this is not particularly informative as the WLS model is not a great measure of goodness-of-fit. More

importantly, the WLS estimators are very similar from the OLS estimators, and many of the same coefficients are significant in both models. The WLS quadratic model also failed the Breusch-Pagan test for heteroscedasticity. In the presence of heteroscedasticity, coefficients in an OLS or WLS model are still unbiased or consistent. The null hypothesis, $H_0: RR = 0$, is tested against the alternative hypothesis, $H_1: RR > 0$ using a one-tailed t-test. The null hypothesis is rejected, suggesting that RR maize plots have a significantly higher output than non-RR maize plots ($p = 0.030$) in the WLS model as well.

Estimation of Production Function with Additional Variables

In this section, several additional variables which measure farmer characteristics are added to the production function to explain changes in output. The additional variables are assets, formal education, and experience using herbicide. Assets includes farm and livestock assets, and is a measure of farmers wealth or physical capital; it is expected that as a farmers wealth increases so does their ability to purchase inputs in larger quantities which lowers the total costs. Producers with higher education and more experience using herbicide have higher social capital, and are able to make a more informed decision when purchasing inputs. By including variables which capture assets, the model with additional variables provides a quasi-fixed long run approach to estimating a production function. Results are presented in Table 4-4.

Table 4-4 Regression Results of Production Function with Additional Variables^a

	OLS - Original			OLS - Additional variables		
	Coef.		Std. Err.	Coef.		Std. Err.
<i>Intercept</i>	-336.32	***	109.6	-608.52	***	125.61
<i>Labor</i>	3.26	***	0.5	3.60	***	0.54
<i>Fertilizer</i>	1.35	*	0.8	1.37	*	0.76
<i>Herbicide</i>	0.28		13.0	-10.09		13.02
<i>Seed</i>	-26.16		20.6	-30.45		19.91
<i>Land</i>	993.56	***	324.1	935.73	***	312.65
<i>Land Prep Cost</i>	1.27		2.6	1.39		2.55
<i>Hlabisa Dummy</i>	308.83	***	91.9	406.37	***	92.37
<i>RR Dummy</i>	217.27	***	74.6	183.88	**	74.03
<i>Bt Dummy</i>	-12.24		65.4	-47.34		63.67
<i>Assets</i>				0.01	**	0.00
<i>Experience using Herbicide</i>				37.42	**	15.28
<i>Formal Education</i>				168.55	**	65.27
<i>N</i>	212			212		
<i>R-squared</i>	0.47			0.52		
<i>Adjusted R-squared</i>	0.45			0.49		
<i>Breusch-Pagan</i>	138.8	***		109.2	***	
<i>F-value</i>	19.9			17.7		

***, **, * Indicates significantly different than zero at 1%, 5% and 10% respectively.

^aAverage output of 754 kilograms per maize plot.

Linear models are used for the purpose of simplicity. Several coefficients change in the model with additional variables. The Hlabisa coefficient increases and the RR coefficient decreases, but both remain highly significant. All three additional variables are significant at the 5% level, and all have a positive impact on maize output. For each additional \$1000 in assets, the model with additional variables estimates that maize output will increase 10.4 kilograms. The assets coefficient captures livestock including oxen, and farm machinery, both which increase productivity of the farmer and explain the additional output expected as assets increase. It is expected that farmers with more experience using herbicide and formal education are more efficient, or are timelier in the application of inputs, thus increasing output. The model with additional variables explains output slightly better than the original model with an adjusted R-squared or 0.49 compared to an adjusted R-squared of 0.45 in the original model. The VIF test reveals that there is not multicollinearity, but there is still heteroscedasticity with additional variables using the Breusch-Pagan test ($p = 0.000$).

Estimation using 2SLS to Control for Input Endogeneity

One issue of estimating the production function directly is that inputs are treated as exogenous. In reality, there could be endogenous variables for several reasons. First, farmers are deciding the level of input use; for example, a farmer may decide to apply herbicide midway through the maize production season if weed pressure is high. Second, farmer characteristics that are not observed such as include farmer motivation, education, experience, and access to services, could also have an impact on maize output.

Endogenous variables are independent variables which are correlated with unobserved determinants of the dependent variable that are in the error term. Endogeneity can be controlled by using suitable instrument variables, which are used to explain variation in the endogenous variable. If endogeneity is not severe, the least squares estimator is more efficient; however, it is important to test for endogeneity since it leads to biased and inconsistent coefficients (Shankar and Thirtle 2005).

Two-Stage Least-Squares (2SLS) Model

The Durbin-Wu-Hausman test is used to test for endogenous variables. The first step is to regress the expected endogenous variable on the instrument variables as well as the rest of the independent variables. The residual of the “endogenous” variable is then included in the original regression. The null hypothesis of no correlation between the “endogenous” variable and the error term is rejected if the residual term is significant. The next step is determining appropriate instrumental variables, which must be correlated with the endogenous explanatory variables but not the dependent variable (and thus the error term). Once suitable instrumental variables are determined (those which explain variation in the endogenous variable), a two-stage least-squares model will correct for the endogenous input. Since heteroscedasticity was present in previous models, the 2SLS models are presented with heteroscedasticity-robust standard errors (Cameron and Trivedi 2009).

Previous literature reveals that endogeneity is often a problem with pesticide use, since it may be applied in response to production shocks such as high weed pressure (Shankar and Thirtle 2005). The Durbin-Wu-Hausman test reveals that herbicide is an endogenous variable ($p = 0.005$). A learning curve is expected with farmers using herbicide, and thus as years of experience using herbicides increases, so does a farmer’s ability to more effectively control

weeds, leading to higher output. Years of experience using herbicide is shown to be a good estimator ($p = 0.000$), so it is used as an instrument variable in the two-stage least-squares (2SLS) model. Linear models were run for the sake of simplicity and to directly compare the impact of the 2SLS models on inputs. Results in Table 4-5 show that the adjusted R-squared value is 0.17 which is much lower than our OLS model and land is no longer a significant variable ($p = 0.275$). Instead herbicide is significant with a very large coefficient. The Hlabisa and RR dummy variables are still significant and larger than in the OLS model.

Table 4-5 Regression Results of 2SLS and OLS Production Functions^a

	OLS - Linear		2SLS – herbicide ^b		2SLS – labor ^c	
	Coef.	Std. Err. ^d	Coef.	Std. Err. ^d	Coef.	Std. Err. ^d
<i>Intercept</i>	-336.3 ***	109.6	-710.6 *	211.1	5.3	221.5
<i>Labor</i>	3.3 ***	0.5	4.9 ***	58.3	-0.4	2.1
<i>Fertilizer</i>	1.4 *	0.8	1.0	1.0	2.1	1.0
<i>Herbicide</i>	0.3	13.0	128.6 **	1.0	-26.3	20.4
<i>Seed</i>	-26.2	20.6	-56.4	28.3	-7.0	25.0
<i>Land</i>	993.6 ***	324.1	493.7	451.0	1360.9 ***	410.5
<i>Land Prep Cost</i>	1.3	2.6	2.9	3.2	0.1	2.9
<i>Hlabisa Dummy</i>	308.8 ***	91.9	371.0 **	115.2	215.9	113.6
<i>RR Dummy</i>	217.3 ***	74.6	332.0 ***	103.8	38.9	127.2
<i>Bt Dummy</i>	-12.2	65.4	-86.4	86.0	6.4	73.2
<i>N</i>	212		212		212	
<i>R-squared</i>	0.47		0.21		0.35	
<i>Adjusted R-squared</i>	0.45		0.17		0.32	
<i>F-value</i>	19.9 ***		13.94 ***		12.91 ***	

***, **, * Indicates significantly different than zero at 1%, 5% and 10% respectively.

^aAverage yield is 1645 kilograms per hectare or 29.6 bushels per maize plot as 100 kilograms is equal to 3.93 bushels at 56 pounds per bushel.

^bInstrumented variables for herbicide are; experience with herbicide

^cInstrumented variables for labor are: assets , formal education, and experience with herbicide

^dHeteroscedasticity-robust standard errors

Land is also expected to be an endogenous variable, whereas hectares of land increases output increases as well. It is predicted that total assets may be a proper instrumental variable, since it affects the ability of farmers to obtain credit to purchase inputs. Formal education (completing primary school) could also be an explanatory variable, as better educated farmers can read labels, gain knowledge more easily, and better manage larger plots of land which could all lead to higher output. Using the Durbin-Wu-Hausman test, it is determined that land is indeed

an endogenous variable ($p = 0.000$). An F test reveals, however, that assets and formal education are not good predictors of variation in output for land ($p = 0.668$). Since no proper instrumental variables are available, it is not possible to correct for the endogeneity problem for land.

Finally, labor is also expected to be an endogenous variable since farmers who use less labor may have a much higher return of output on their labor if they are spraying herbicide rather than weeding. Also, farmers can make the decision to invest more time in their maize plot during the production season in order to improve maize output. The Durbin-Wu-Hausman test indicates that labor is an endogenous variable ($p = 0.041$) and an F-test reveals that assets, and formal education, and experience using herbicides are all good instruments for labor ($p = 0.001$). Results of the two-stage least-squares (2SLS) model in Table 4-5 show that the adjusted R-squared is 0.32 which is lower than OLS regression and that many variables that were significant in the OLS model are no longer significant, aside from fertilizer and the Hlabisa dummy variable.

Estimation of Split Production Functions: RR and Non-RR Maize

Results of the previous models using the full sample show that the RR maize output is significantly higher than non-RR maize output. The interpretation of the difference between RR and non-RR maize is somewhat limited, however, since the RR dummy variable simply shifts the intercept (between 131 and 217 kilograms per maize plot). Splitting the regression by RR and non-RR maize plots shifts both the intercept and the slope, which reveals bias in the response of maize types to inputs. Results of the WLS and OLS models are presented in Table 4-6.

Table 4-6 Production Function Regression Results of RR and Non-RR Maize Plots

	OLS - RR		OLS - Non RR		OLS - RR		OLS - Non RR		WLS - RR		WLS - Non RR	
	Linear		Linear		Quadratic		Quadratic		Quadratic		Quadratic	
	Coef.		Coef.		Coef.		Coef.		Coef.		Coef.	
<i>Intercept</i>	157.9		-377.2		-692.0		55.8		-636.2		66.7	
<i>Labor</i>	3.7	***	3.7	***	-1.2		4.3	*	-1.9		3.2	
<i>Fertilizer</i>	-3.2	**	2.7	**	12.1		1.5		9.6		1.2	
<i>Herbicide</i>	-50.6		-6.9		217.4		106.2	*	202.0		82.0	
<i>Seed</i>	16.8		-15.8		-88.3		107.0		-50.0		99.0	
<i>Land</i>	1074.9	***	278.3		1265.8		-1609.5		1224.4		-447.9	
<i>Land Prep Cost</i>	-0.4		5.1		-7.0		-32.8	**	-6.8		-37.8	***
<i>Hlabisa Dummy</i>	187.9		261.4		487.3	**	143.2		456.1	**	53.0	
<i>Labor²</i>					0.0		-0.0	***	0.0		-0.0	***
<i>Fertilizer²</i>					0.1		-0.0	**	0.1		-0.0	*
<i>Herbicide²</i>					-39.1		-7.3		-36.9		-6.0	
<i>Seed²</i>					16.5		-35.7	**	17.5		-36.7	*
<i>Land²</i>					-6116.6		-19465.2	***	-5324.4		-16497.2	***
<i>Land Prep Cost²</i>					0.3		0.1		0.1		0.1	
<i>Labor*Fertilizer</i>					-0.0		-0.0		-0.0		-0.0	
<i>Labor*Herbicide</i>					0.4		0.5		0.5		0.4	
<i>Labor*Seed</i>					-0.3		-0.4		-0.6		-0.2	
<i>Labor*Land</i>					7.2		25.8	**	10.3		21.0	*
<i>Labor* Land Pre</i>					0.2		0.1		0.2	*	0.1	
<i>Fertilizer*Herbicide</i>					1.3		-0.5		1.6		-0.4	
<i>Fertilizer*Seed</i>					-2.1		1.6	*	-2.3		1.6	*
<i>Fertilizer*Land</i>					-10.0		-23.4		-6.3		-29.5	
<i>Fertilizer*Land Prep</i>					-0.0		0.3	**	0.0		0.3	**
<i>Herbicide*Seed</i>					-49.1		-23.7	*	-43.3		-18.5	
<i>Herbicide*Land</i>					638.7		701.0	***	515.6		625.4	**
<i>Herbicide*Land Prep</i>					-0.9		-5.5	**	-1.3		-5.6	**
<i>Seed*Land</i>					455.9		1426.4	**	372.7		1273.1	**
<i>Seed*Land Prep</i>					-1.0		-4.9		-0.1		-3.5	
<i>Land*Land Prep</i>					-13.2		120.4		-21.0		85.4	
<i>N</i>	112		100		112		100		112		100	
<i>R-squared</i>	0.41		0.54		0.57		0.8		0.62		0.97	
<i>Adjusted R-squared</i>	0.37		0.50		0.43		0.8		0.50		0.96	
<i>Breusch-Pagan</i>	10.6	***	70.9	***	22.7	***	9.4	***	26.8	***	0.82	
<i>F-value</i>	10.1		15.2		4.0		11.4		4.9		79.4	

***, **, * Indicates significantly different than zero at 1%, 5% and 10% respectively.

^aAverage yield is 33.0 and 25.8 bushels per plot for RR and non-RR maize respectively; 100 kilograms is equal to 3.93 bushels at 56 pounds per bushel.

Interpretation of OLS Linear Split Model

Table 4-6 contains the results the linear and quadratic models of RR and non-RR maize plots. Results of the linear OLS RR maize model show that labor and land increase maize output, but fertilizer negatively impacts output. On the other hand, in the non-RR model, both labor and fertilizer increase output. The VIF tests reveals that the RR linear model has an acceptably low level of multicollinearity, but in the non-RR model both land and seed have a VIF value of 14.30 and 10.25 respectively which is a higher VIF value than what is considered acceptable. This indicates that a quadratic regression may be a better fit for non-RR maize since it includes interaction variables. The Breusch-Pagan test for the RR and non-RR model have a chi-squared value of 10.61 ($p = 0.011$) and 70.86 ($p = 0.000$), revealing heteroscedasticity in both linear models. The regression specification error test (RESET) shows that the RR linear model is a good functional form; it is well specified with an F-value of 0.75 ($p = 0.526$) while the non-RR model is not a good fit as the F-value is 9.18 ($p = 0.000$).

Another advantage of running split models is that it allows testing to see if coefficients are significantly different between RR and non-RR maize plots. To test whether the coefficient of labor is significantly different between the two models, a new variable RR*labor is created. RR*labor tests the null hypothesis $H_0: \beta_{RR\ labor} = \beta_{nonRR\ labor}$ which is not rejected ($p = 0.264$) suggesting that labor does not have a significantly different impact on output between RR and non-RR maize plots. The same hypothesis test is used on all the coefficients, and only fertilizer is significantly different between the two models ($p = 0.005$).

OLS Quadratic Split Model

The RR maize quadratic model has a higher R-squared value but the only significant variable is the Hlabisa dummy variable. However, the added interaction and squared terms are jointly significant at the 10% level using an F-test ($p = 0.081$). In the non-RR model, many of the squared and interaction terms are significant, and an F-test reveals joint significance of the added terms ($p = 0.000$). Both the RR and non-RR quadratic model failed the Breusch-Pagan test for heteroscedasticity, with a p-value of 0.000 and 0.002 respectively.

As in the linear model, the null hypothesis $H_0: \beta_{RR\ labor} = \beta_{non-RR\ labor}$ is used to test whether coefficients are significantly different between the RR and non-RR regressions. Interaction terms are created for the labor squared and interaction terms, and a Wald F-test is used to test the joint significance. Somewhat surprisingly, the F-test fails to reject the null

hypothesis ($p = 0.192$) indicating that the coefficient on labor is not significantly different between the RR and non-RR models. While the linear regression found only fertilizer to be significantly different, the quadratic model shows that none of the coefficients are significantly different between the RR and non-RR models (Cameron and Trivedi 2009, Chen, et al. 2003).

WLS Quadratic Split Model

Due to heteroscedasticity in previous models, a weighted least squares (WLS) quadratic regression is used to provide more efficient estimates. Land is once again the variable creating heteroscedasticity; it is assumed that small plots are easy to manage, and output is consistent. As plots get larger, they are either more difficult to manage or farmers are achieving higher output by specializing in maize production, creating greater variance in maize output. Once again the model is weighted proportionally to the log of squared residuals of land and land squared, where observations with smaller variance receive a larger weight and have a greater influence in the estimates (Greene 2003).

Estimates in the RR model are similar to the OLS model with one more significant coefficient, but in the non-RR model there are several less significant variables. The F statistic testing the significance of the squared and interaction terms is 1.82 ($p = 0.029$) in the RR model and 5.18 ($p = 0.000$) in the non-RR model. The RR model fails the Breusch-Pagan test for heteroscedasticity as the chi-squared value was 26.78 ($p = 0.000$) while the non-RR model passes the test with a 0.82 ($p = 0.366$), revealing that there is not heteroscedasticity in the WLS non-RR model.

Elasticities of Output of RR and Non-RR Maize

In the RR and non-RR least squares models, it is not possible to compare the coefficients and their impact on output directly, since inputs are measured in various units such as hours, kilograms, and hectares. Elasticities of output on the other hand, which are calculated at the mean value of the independent variable, are unitless.

Table 4-7 Elasticities of Output Derived from OLS Linear Production Function

	RR		Non-RR	
<i>Labor</i>	0.41	***	0.82	***
<i>Fertilizer</i>	-0.35	***	0.44	**
<i>Herbicide</i>	-0.11		-0.14	
<i>Seed</i>	0.12		-0.20	
<i>Land</i>	0.61	***	0.33	
<i>Land Prep Cost</i>	-0.04		0.10	
<i>Returns to Scale</i>	0.64	***	1.36	***

***, **, * Indicates significantly different than zero at 1%, 5% and 10% respectively.

Note: N = 212; RR = 112, non-RR = 100

Elasticities of output presented in Table 4-7 are interpreted as follows: a 1 percent increase in labor on RR plots will result in a 0.41 percent increase in output. On non-RR plots, a 1 percent increase in labor will result in a 0.82 percent in output.¹⁹ The delta-method was used to calculate standard errors, which reveal that both output elasticities of labor are significant. This suggests that all farmers, but particularly those who are planting non-RR maize, are using less labor than they should in order to maximize maize output. This begs the question why farmers are not using more labor, especially with RR maize, if the expected returns to output are so high. The intuitive answer is that there is a labor constraint; either labor is not available or too expensive. This is an important issue that is investigated further when considering cost in Chapter 6.

The elasticity of output with respect to land for RR maize plots is 0.61, which suggests that RR maize producers should expand in size to optimize maize output. This can be expected, as RR maize requires less labor, and thus less time, allowing farmers to manage a greater area. The output elasticity of land for non-RR maize plots was 0.33, but not significant. The output elasticity of fertilizer is negative for RR plots, and positive for non-RR plots, suggesting that non-RR plots can increase maize output if they increase fertilizer use, while RR plots already receive enough fertilizer. This is somewhat surprising, as overall fertilizer use is well below the

¹⁹ Elasticities of output are calculated as $E = (\partial Y)/(\partial x) \cdot x/Y$, where both x is the input and Y is the output calculated at their mean values. Therefore, different mean input values between RR and non-RR maize will impact our results. The mean value of labor is 98 hours for RR maize and 159 hours for non-RR maize (Table 3-24). As the value of labor increases, the value of the elasticity of output with respect to labor also increases.

suggested level as reported in Chapter 3 (Mkhabela 2004, Manson n.d.). The elasticities of output presented in this research are estimated at the mean of the independent variables. Although ranges of elasticities may be more appropriate, concavity cannot be assumed. Therefore, the results are not largely applicable outside this study (Just 2000).

Returns to scale, called the function coefficient, is simply the summation of all elasticities of output. The function coefficient ε_{RR} for RR maize plots is 0.64 and significant ($p = 0.000$), which shows that returns to scale are decreasing (both average and marginal). The null hypothesis that $\varepsilon_{RR} = 1$ is rejected using a joint F-test ($p = 0.002$), suggesting that there is not constant returns to scale. A function coefficient value less than 1 and greater than zero suggests that maize is in stage two production, where increasing input use will increase maize output, but at a decreasing rate. The function coefficient ε_{non-RR} for non-RR maize plots is 1.36 which represents increasing average returns to scale while marginal returns to scale are increasing or decreasing. A joint F-test fails to reject the null hypothesis that $\varepsilon_{non-RR} = 1$ ($p = 0.488$), indicating constant returns to scale for non-RR maize producers. A function coefficient greater than 1 suggests that non-RR maize is in stage one of production. For example, if inputs are doubled on non-RR maize plots, output will more than double (Beattie, Taylor and Watts 2009).

Both function coefficients ε_{RR} and ε_{nonRR} are positive, indicating that maize producers should increase input use to maximize maize outputs. For RR maize, the elasticity of land is the largest positive value, so the best way to increase output on RR maize plots is to increase land size. For non-RR maize, labor is the most elastic input, indicating that increasing labor use is the best option to increase output for non-RR maize plots. Previous literature suggests that producers have access to an unlimited supply of land, while the labor supply is more constrained due to high levels of HIV/AIDS and migration of agricultural workers to urban centers (Gouse, Piesse, et al. 2009). Therefore, based on the results from the 2009-10 season, farmers using RR maize have the most potential to increase output by expanding the size of their maize plots.

Chapter 5 - Risk Analysis

Chapter 5 provides a more technical approach which compliments initial results in Chapter 3 which shows that producers of GM maize use significantly higher labor per hectare compared to non-GM maize, resulting in significantly higher costs in Simdlangetsha. This chapter tests the second hypothesis that GM maize reduces risk as compared to non-GM maize. In the first section, stochastic dominance techniques are used to compare maize yield and maize net returns of all five maize types in both regions. Then stochastic efficiency with respect to a function (SERF) compares the net returns of different maize types across a range of absolute risk aversion coefficients, assuming that producers are risk averse.

Motivation for this chapter lies in the supposition that maize production, not unlike other agricultural activities, is a game of risk. At planting, many uncertainties still exist for a farmer, such as rainfall, wind, temperatures, pest pressure, disease, and weed density, some of which cannot be controlled and all which have an impact on final production. For smallholders who lack risk mitigation tools such as insurance or their own safety net of cash reserves, the risk of failure is even greater. For smallholders who rely heavily on maize yield for consumption such as those in KwaZulu-Natal, failure to produce an ample harvest could mean inadequate caloric intake and reduced productivity, or inability to pay loans or send children to school. Therefore, risk assessment is vital for the long term success of any new agricultural technology, including GM maize.

Stochastic Dominance Analysis

The subjective expected utility (SEU) hypothesis states that to assess risky alternatives, it is necessary to know the shape of each decision maker's utility function. A risk averse decision maker will have a concave utility function while a convex function is indicative of a risk seeking individual. To precisely compare two or more risky technologies using SEU hypothesis would require the elicitation of utility functions, or risk preferences, from each producer. Elicitation of utility functions has been used in analysis of risk in agriculture previously using SEU hypothesis in the past, but with rather unconvincing results (Hardaker, et al. 2004). Since individual risk preferences are usually unknown and can be difficult to attain, approaches like stochastic dominance are frequently used. Stochastic dominance compares at least two risky alternatives

that are mutually exclusive and assumes that the distribution is representative of the entire population.

Methodology

The concepts of first-degree stochastic dominance (FSD) and second-degree stochastic dominance (SSD) were first introduced by Hadar and Russell (1969) and Hanoch and Levy (1969). First-degree stochastic dominance simply assumes that producers prefer higher net returns to lower net returns, and that decision-makers have absolute risk aversion with respect to wealth between the bounds $-\infty \leq r_a(x) \leq +\infty$ (Dillon and Anderson 1990, Hardaker, et al. 2004). Absolute risk aversion, $r_a(x)$, is defined as

$$r_a(x) = \frac{-U''(x)}{U'(x)} \quad (5.1)$$

where $U'(x)$ is the first derivative of the specified utility function, and $U''(x)$ is the second derivative of the utility function. If there are two probability functions $f(x)$ and $g(x)$, cumulative distribution functions (CDFs) $F(x)$ and $G(x)$ are created by ordering observations of both yield and net returns from smallest to greatest, and assigning cumulative probabilities from 0.0 to 1.0 to each observation. FSD occurs only if $F(x)$ always lies to the right of $G(x)$.

$$G(x) = \int_{-\infty}^{\infty} g(x)dx \geq \int_{-\infty}^{\infty} f(x)dx = F(x) \quad (5.2)$$

If $F(x)$ and $G(x)$ cross and no FSD can be determined, the integration of $F(x)$ and $G(x)$ is used to determine whether there is second-degree stochastic dominance. Second-degree stochastic dominance, like FSD, assumes that more is preferred to less. It is more restrictive in that it assumes that decision-makers are risk averse for all values of x , meaning the slope of their utility function is concave. Therefore, the absolute risk aversion with respect to wealth is bound between $0 \leq r_a(x) \leq +\infty$ (Hardaker, et al. 2004). This second assumption is to be expected in smallholder agriculture, where it is assumed that a majority of decision-makers are risk averse. Second-degree stochastic dominance occurs if the area under $F(z)$ is smaller than the area under $G(z)$ as presented in equation 5.3 (Moss 2010, Hardaker, et al. 2004).

$$G(z) = \int_0^{\infty} G(x)dx \geq \int_0^{\infty} F(x)dx = F(z) \quad (5.3)$$

Literature Review

Several studies compare yield distribution using stochastic dominance techniques. Shankar, Bennett, and Morse (2007) use stochastic dominance to determine the impact of Bt cotton yield and net returns on risk. Three years of data is analyzed from smallholders planting Bt and non-Bt cotton in Kwazulu-Natal, South Africa. Cumulative distribution functions are derived using the probability distribution of both yield and net returns for Bt and non-Bt cotton. In all three years, the CDF of Bt cotton yield is to the right of the non-Bt CDF, which confirms that Bt cotton is first-degree stochastic dominant, suggesting that Bt is a superior technology. The CDF of Bt cotton profits are also first-degree dominant in the first two years of analysis, but in the third year it is neither FSD nor second-degree stochastic dominant (SSD). Shankar concludes that while Bt cotton reduces the probability of very low-yield outcomes, it does not necessarily reduce it strongly enough to reduce the probability of very low-returns outcomes.

Barrett et al. (2004) uses stochastic dominance to compare yield distributions of traditional and intensive rice cultivation methods. The intensive cultivation method (SRI) is first-degree stochastically dominant to the conventional (SRT) method in both yield and labor productivity. However, the study concludes that stochastic dominance may be misleading since FSD assumes that any differences among alternatives is a result of only different technologies and chance, while farmer or plot characteristics may also influence final yield.

Shively (1999) uses stochastic dominance analysis to compare maize plots with and without hedgerows, which are used primarily to control erosion. The yield CDFs cross twice, eliminating the possibility of first-degree stochastic dominance, and failing to exhibit second-degree stochastic dominance. Shively concludes that differences in factors such as input levels, plot characteristics, or farming practices may provide a better explanation for differences in yield distributions, and must be controlled using econometric approaches.

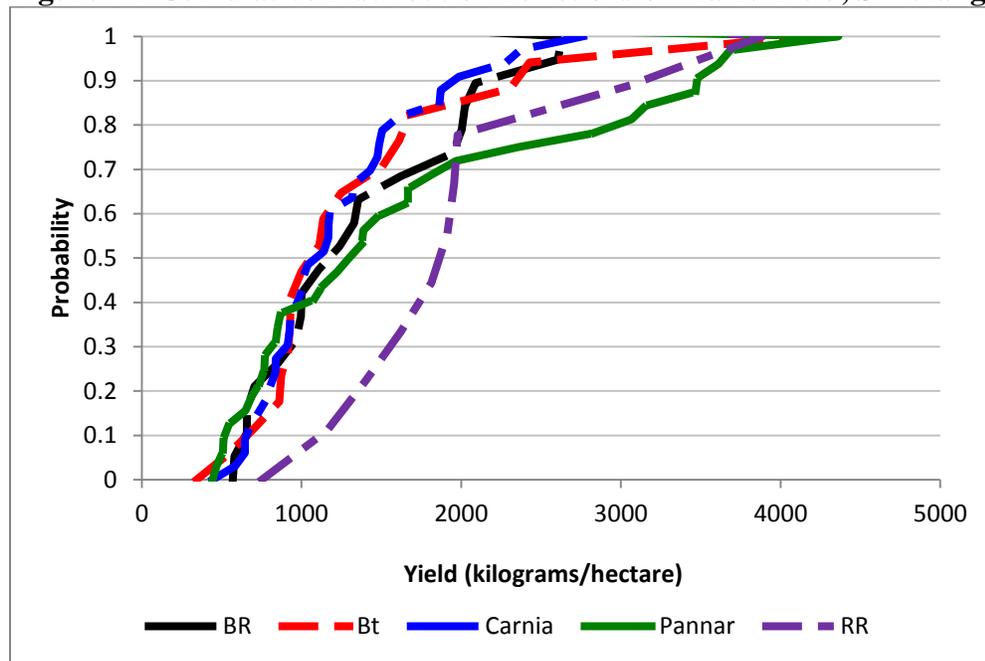
Results

Stochastic dominance compares at least two technologies that are mutually exclusive and assumes that the distribution is representative of the entire population. First-degree stochastic dominance is the least restrictive stochastic dominance analysis which only assumes that more is preferred to less and that differences between two alternatives come only from technological differences and chance.

Yield – Stochastic Dominance

Since the mean maize yield is significantly different between regions ($p = 0.000$), Simdlangetsha and Hlabisa are analyzed separately. CDFs were calculated from the probability distribution of yields of all five maize types using SIMETAR[®] developed by Schumann, Feldman and Richardson (2011). The CDF of RR maize is to the right of all other varieties until it crosses the CDF of Pannar at a cumulative probability of 0.7 where yield is approximately 1900 kilograms of maize per hectare (Figure 5-1). This is interpreted that RR maize has the highest yield 70% of the time, while Pannar has the highest yield 30% of the time. Most importantly to risk averse decision-makers, RR maize protects against low yields. Pannar on the other hand, appears to be the choice for more risk neutral or risk loving individuals, as it has the most potential for high yields. RR maize yield exhibits first-degree stochastic dominance (FSD) to Carnia since the CDF of RR maize is below and to the right of the CDF of Carnia at every point.

Figure 5-1 Cumulative Distribution Functions of Maize Yield, Simdlangetsha



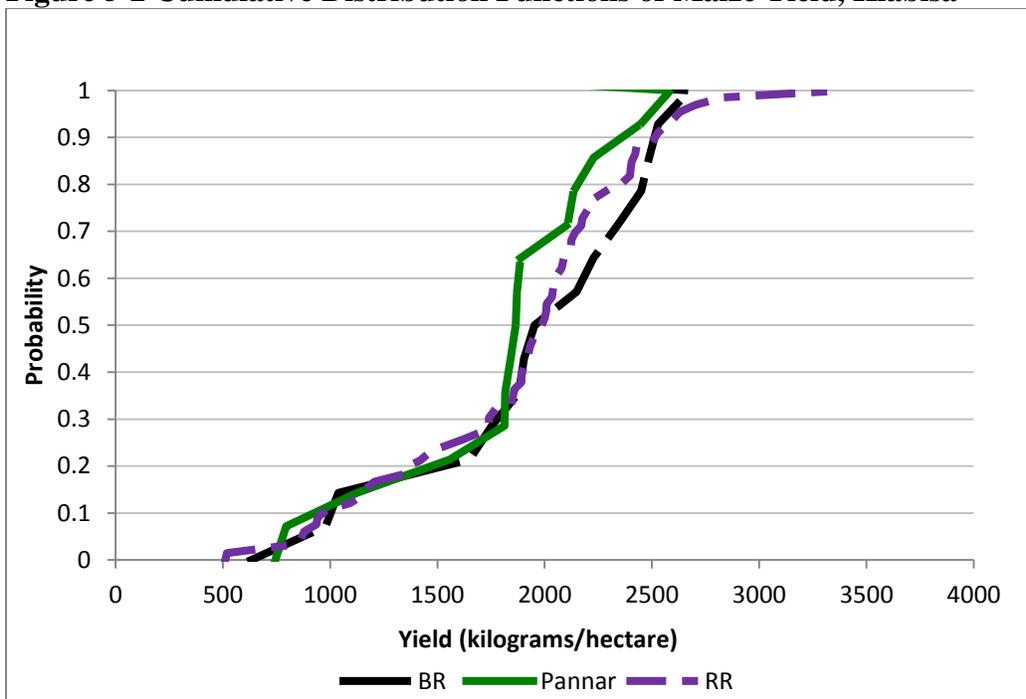
Note: N = 115; BR = 20, Bt = 18, Carnia = 34, Pannar = 33, RR = 10

Second-degree stochastic dominance, which offers a more restrictive analysis, assumes that more is preferred to less. It also states that all producers are risk averse, which is a reasonable assumption to make with smallholders (Shankar, Bennett and Morse 2007). RR maize

yield is second-degree stochastically dominant to every other maize type in Simdlangetsha (Figure 5-1).

In Hlabisa, only data on BR, Pannar, and RR was collected, and each variety exhibits neither first-degree nor second-degree stochastic dominance (Figure 5-2). Multiple crosses exist throughout the entire cumulative density function. As referred to earlier, differences in yield are not usually significant between maize varieties. There is a significant difference in the use of biochemical inputs and labor, however. For this reason, it is expected that net returns will reveal more variation between varieties.

Figure 5-2 Cumulative Distribution Functions of Maize Yield, Hlabisa



Note: N = 97; BR = 15, Pannar = 15, RR = 67

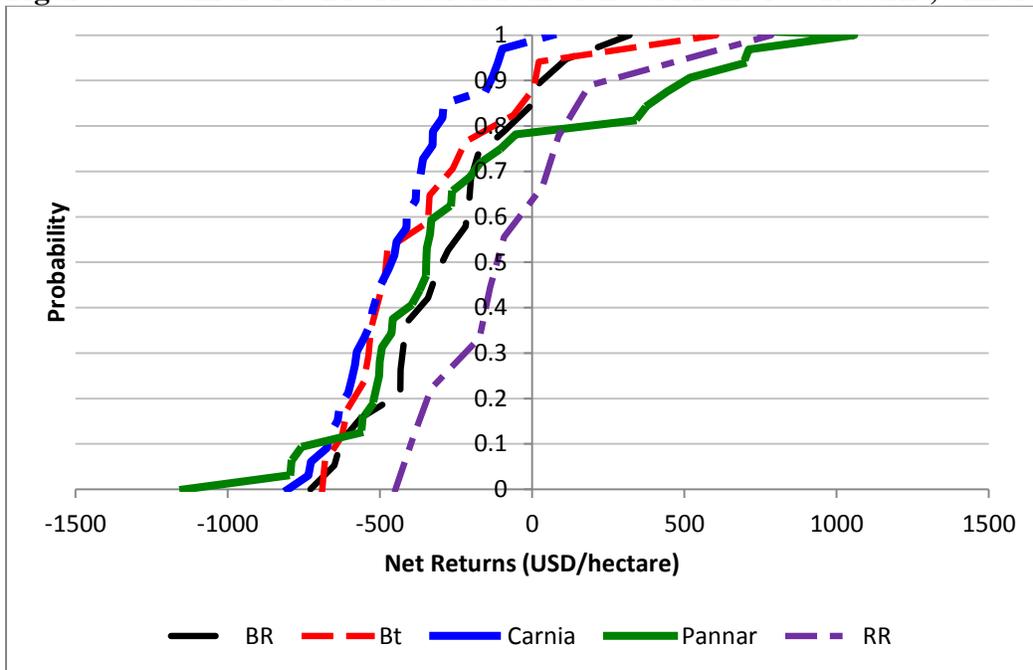
Net Returns – Stochastic Dominance

The usefulness of a comparison of yields between maize types is limited using stochastic dominance, since it does not take into account varying cost of biochemical inputs and labor. The tradeoff between RR and non-RR maize is especially important, since RR maize seed is more expensive, but RR also use significantly less labor by applying herbicide rather than weeding their maize plots. Therefore, the comparison of net returns is considered to be the most appropriate way to compare difference maize types.

First, maize revenues were calculated for each individual plot, multiplying maize output in kilograms by maize price. Since not all households sold grain, no price information was available. In that case, the average price from the region was used to calculate maize revenue. Then total costs, including inputs and labor, were subtracted from maize revenues to obtain maize net returns. Fixed costs such as land or machinery were not included in these estimates. Also, since no wage rate was available for family labor, the full wage rate of \$0.79 to \$0.81 per hour in Simdlangetsha and Hlabisa respectively, was used for both hired and family labor on all maize plots resulting in many negative net returns.

Results presented in Figure 5-3 are similar to yield in both locations, although they are more clear and easier to interpret in Simdlangetsha (Schumann, Feldman and Richardson 2011). RR maize has higher net returns more than 75% of the time, and Pannar has higher net returns about 25% of the time. Since RR maize is to the right of other varieties until a cumulative probability of 0.75 is reached, it appears to reduce the probability of low net returns even more than it reduces probability of low yields. This assumption is not certain, however, due to the general approach of stochastic dominance.

Figure 5-3 Cumulative Distribution Functions of Maize Net Returns, Simdlangetsha

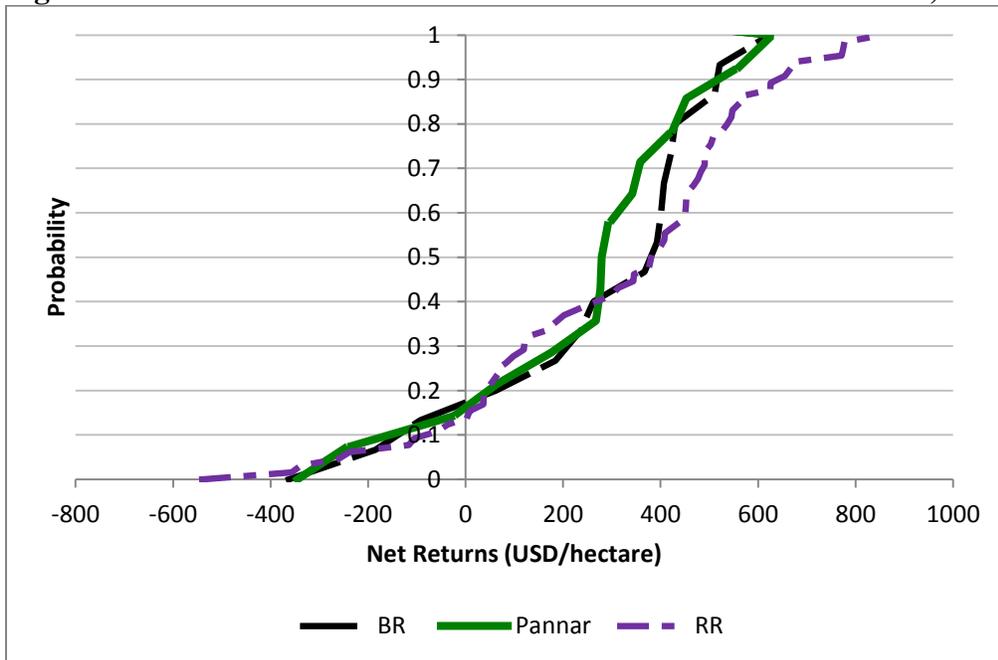


Note: N = 115; BR = 20, Bt = 18, Carnia = 34, Pannar = 33, RR = 10

RR maize indicates first-degree stochastic dominance for net returns to Bt, Carnia, and BR maize varieties. Another interpretation is that 63% of RR maize producers are expected to lose money producing maize, compared to almost 80% of Pannar producers, 90% of Bt and BR producers, and nearly 100% of Carnia producers. RR maize is second-degree stochastic dominant over all other varieties.

The shape of the CDFs of net returns for the three maize types in Hlabisa are also similar to yield but more difficult to interpret than results in Simdlangetsha due to a lower tail cross of BR, Pannar, and RR maize varieties (Figure 5-4). No variety in Hlabisa is either first-degree stochastic dominant or second-degree stochastic dominant. Until a cumulative probability of 0.40 is reached, the CDFs of all three varieties cross continually and stay very close together. RR maize has higher net returns at least 50% of the time. Producers that are very risk averse in Hlabisa will be indifferent, while producers that are moderately risk averse to risk neutral will prefer RR maize. Net returns are higher than \$450 per hectare 35% of the time with RR maize, but only 16% and 14% of the time for BR and Pannar maize respectively.

Figure 5-4 Cumulative Distribution Functions of Maize Net Returns, Hlabisa



Note: N = 97; BR = 15, Pannar = 15, RR = 67

While it can be assumed that farmers that are more risk averse will be more willing to adopt RR maize, stochastic dominance allows decision makers to have absolute risk aversion that is infinitely negative or positive, meaning that some decision-makers are so risk averse that a very small change in yield would result in an extraordinarily large change in utility (Hardaker, et al. 2004). Therefore, the more restrictive analysis which stochastic efficiency with respect to a function offers is necessary to allow more conclusive conclusions to be made.

Stochastic Efficiency with Respect to a Function (SERF) Analysis

Although first and second-degree stochastic dominance are useful methods for making general comparisons of risky alternatives, they are not very discriminating; for example, they allow for absolute risk aversion to be infinitely high, meaning that a minute change in yield at the lowest observation could be extraordinarily important. This extreme risk aversion is simply unrealistic. Stochastic efficiency with respect to a function (SERF) provides a more restrictive, and arguably more realistic approach to risk by putting lower and upper bounds on absolute risk aversion coefficients.

Methodology

Stochastic efficiency with respect to a function (SERF) simultaneously compares several alternative certainty equivalents (CE) across a range of absolute risk aversion, using graphs to show more transparent results.²⁰ The certainty equivalent is defined as the amount of net returns necessary to make the decision-maker indifferent to the risky alternatives. A higher CE is expected for alternatives with higher net returns, and is preferred to a lower CE. The value of the certainty equivalent is based on the risk preference of the decision maker, and is 0 for a risk neutral individual (Hardaker, et al. 2004).

The certainty equivalents are calculated using the inverse utility function. Any type of utility functions for which the inverse function can be calculated may be used, defined as

$$CE(x, r(x)) = U^{-1}(x, r(x)) \quad (5.4)$$

²⁰ Stochastic dominance with respect to a function (SDRF), introduced by Meyer (1977) sets lower and upper bounds on absolute risk aversion to $r_L(x) \leq r_a(x) \leq r_U(x)$. Since SDRF is a bit tricky to use, and does not discriminate well between alternatives, stochastic efficiency with respect to a function (SERF) was developed by Hardaker et. al (2004).

where x represents the level of net returns. A negative exponential utility function, which has concave slope, is used to characterize farmers since it is assumed that they are the risk averse. The certainty equivalents are calculated from the inverse of the negative exponential utility function, defined as

$$CE(x, r_a(x)) = \ln \left\{ \left(\frac{1}{n} \sum_i^n \exp(-r_a(x)x_i) \right)^{-1/r_a(x)} \right\} \quad (5.5)$$

where the negative exponential utility function assumes constant absolute risk aversion. At each level of absolute risk aversion, $r_i(x)$, the most utility efficient technology is that with the highest CE value. For a utility function $U(x)$, the absolute risk aversion coefficient is within lower and upper bounds, $r_L(x) \leq r_a(x) \leq r_U(x)$. These bounds are determined by the known relationship between absolute and relative risk aversion, $r_a(x) = r_r(x)/x$. Relative risk aversion, $r_r(x)$, is measured as a range between 0 and 4, where $r_r(x) = 0$ is risk neutral and 4 is extremely risk averse.

Then the risky alternatives, in this case $F(x)$ and $G(x)$, are integrated with the inverse utility function to determine each certainty equivalent

$$\int [G(x) - F(x)]U'(x)dx \quad (5.6)$$

where option $F(x)$ is preferred to $G(x)$, as long as the above expression is positive across all values of $r_a(x)$.

Risk premiums, which are used to compare risky alternatives, are defined as the minimum amount that a decision-maker must be compensated to switch from one alternative to another. Utility weighted risk premiums can be calculated by subtracting certainty equivalents from each other, defined as

$$RP_{1,2,r_i(x)} = CE_{1,r_i(x)} - CE_{2,r_i(x)} \quad (5.7)$$

where $RP_{1,2,r_i(x)}$ is the positive risk premium between alternative 1 and a less preferred alternative 2, at the given absolute risk aversion level of $r_i(x)$ (Hardaker, et al. 2004).

Literature Review

Hardaker, Richardson, Lien, and Schumann (2004) developed stochastic efficiency with respect to a function (SERF) in order to simultaneously compare several alternatives across

different levels of risk aversion. SERF is a type of stochastic dominance analysis with respect to a function that is developed as an alternative to stated expected utility (SEU) analysis which requires the elicitation of utility functions from respondents. SEU has been used in analysis of risk in agriculture, but with rather unconvincing results. Stochastic dominance analysis places fewer restrictions on the utility function, which leads to more general results; for example, first-order stochastic dominance allows decision makers to have absolute risk aversion with respect to wealth that is infinitely negative or positive, signifying that some decision makers are so risk averse that a very small change in wealth would result in an extraordinarily large change in utility. SERF uses an estimated utility function to calculate certainty equivalents. SERF then orders alternatives by levels of certainty equivalents over a range of relative risk aversion, which allows comparison of different alternatives based on decision maker risk preferences.

Williams et al. (2011) apply stochastic efficiency with respect to a function (SERF) analysis to determine the preferred strategy of wheat stubble management in south-central Kansas, using experiment station and price data from 1997 to 2006. Data was sorted into cumulative distribution functions according to the net returns of three different production systems used to control wheat stubble; no-till, reduced-till, and burning. Certainty equivalents (CEs) were then calculated using a negative exponential utility function, with relative risk aversion coefficients over a range of 0 to 4, representing risk neutral to extremely risk averse preferences of producers. The relative risk aversion coefficients were divided by net worth per acre to estimate absolute risk aversion coefficients. Risk premiums are then calculated by comparing CE values for each production system. Results show that the net returns between 2006 and 2010 are usually slightly higher for no-till systems than for burning. The highest risk premium required to encourage no-till instead of burning wheat stubble is only \$3.16 per acre, which suggest that only a small policy change could convince farmers to adjust practices.

Bryant et al. (2008) use stochastic efficiency with respect to a function (SERF) analysis to compare four types of cotton; conventional, Roundup Ready, Bollgard, and stacked gene varieties. Yield and production data is collected from field plots from 2001-03 in Southeast and Northeast Arkansas and used to calculate net returns, excluding seed costs and technology fees associated with the different cotton varieties. Net returns are used to create a cumulative distribution function, which is fit to a negative exponential function using absolute risk aversion coefficients (ARAC). The ARAC are calculated based on relative risk aversion values of 0.5 to

4.0, based on the average wealth for each alternative. Results show that in Southeast Arkansas, stacked cotton is preferred over other cotton varieties by at least \$34 per acre. In Northeast Arkansas, where pest pressure was low during the study period, Roundup Ready cotton was preferred to all other varieties. In both cases, the extra seed cost and technology fee is more than compensated by the gains in net returns, and widespread adoption of stacked and Roundup Ready cotton is expected in Northeast and Southeast Arkansas respectively.

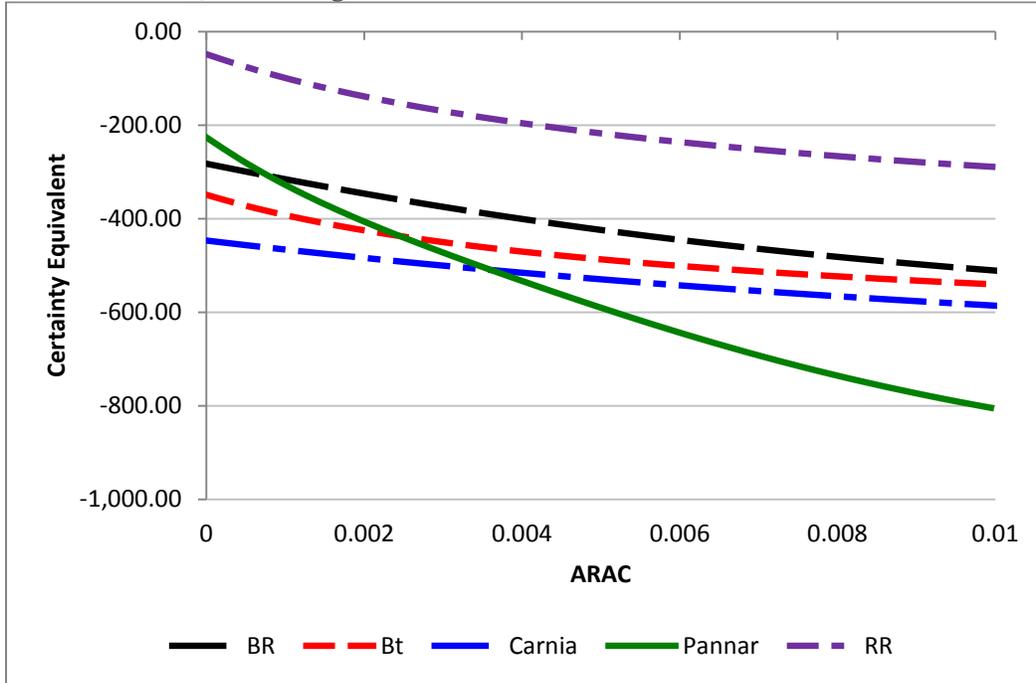
Results

Stochastic efficiency with respect to a function (SERF) analysis was carried out using SIMETAR[®] (Schumann, Feldman and Richardson 2011). The negative exponential utility function which assumes constant absolute risk aversion was used to calculate certainty equivalents, since it is assumed that smallholders are risk averse. It was assumed that producers range from risk neutral to very risk averse, with relative risk aversion values between 0 and 4 respectively.

Since SERF is based on utility, only results comparing net returns are derived. Due to regional differences mentioned previously, Simdlangetsha and Hlabisa are examined separately. In Simdlangetsha, the range of absolute risk aversion coefficients (ARAC) was calculated by dividing the relative risk aversion coefficients of 0.00 and 4.00 by the average net worth of producers. Net worth was calculated as farm assets such as plows and planters divided by total arable land per farmer (Table 3-2).²¹ Net worth, not including any outstanding debts, is calculated as \$465 per hectare, resulting in an upper bound ARAC of 0.0086. The range of ARAC corresponding to the relative risk aversion coefficients is 0.00 to 0.01 in Figure 5-5 to reveal the entire range of expected ARACs. The SERF results from Simdlangetsha show that RR maize always has a higher certainty equivalent, represented by the highest line. Since the highest CE is always preferred, RR maize is the superior choice, regardless of the risk preference of the decision-maker.

²¹ Not included in the estimate of wealth are non-farm assets like televisions and cell phones, and livestock, primarily cattle valued at an average of \$5380 per household.

Figure 5-5 SERF under a Negative Exponential Utility Function for Net Returns (USD/hectare), Simdlangetsha



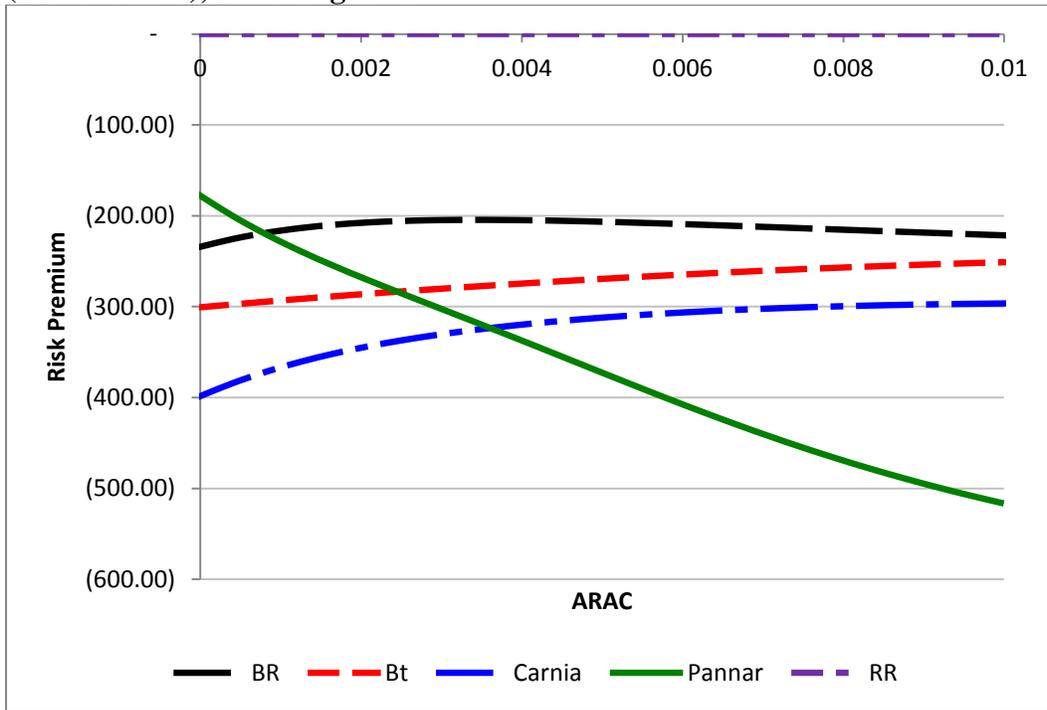
Note: N = 115; BR = 20, Bt = 18, Carnia = 34, Pannar = 33, RR = 10

The second most preferred choice depends on the risk aversion preference of the producer. The value of the risk aversion coefficient where the preference changes, was named the breakeven risk root (BRAC) by McCarl (Hardaker, et al. 2004). The BRAC point is where the CE curves of Pannar and BR cross, where $r_a(x) = 0.0008$ which is equal to a relative risk aversion value of 0.37, representing slight risk aversion. Thus, producers with a relative risk aversion value between 0.00 and 0.37 will prefer Pannar as their second choice of maize seed to plant, while producers who are slightly to extremely risk averse, with RRA values between 0.37 and 4.00, will prefer BR maize.

The difference in value between different CE curves is the risk premium. The risk premium is calculated by subtracting the CE of each variety from the CE of BR, the baseline variety. This value of each curve represents the amount of net returns that producers would have to be compensated to switch from BR to an alternative maize variety over a continuum of ARAC values. Figure 5-6 shows that producers of RR maize of all risk preferences would have to be paid over \$180 per hectare to switch to BR maize, and almost \$500 per hectare to switch to Carnia maize. Pannar is the most dynamic variety, as the risk premium varies depending on the

producers risk preference. As decision-makers become more risk averse, a higher risk premium will be required for them to switch to from RR to Pannar maize.

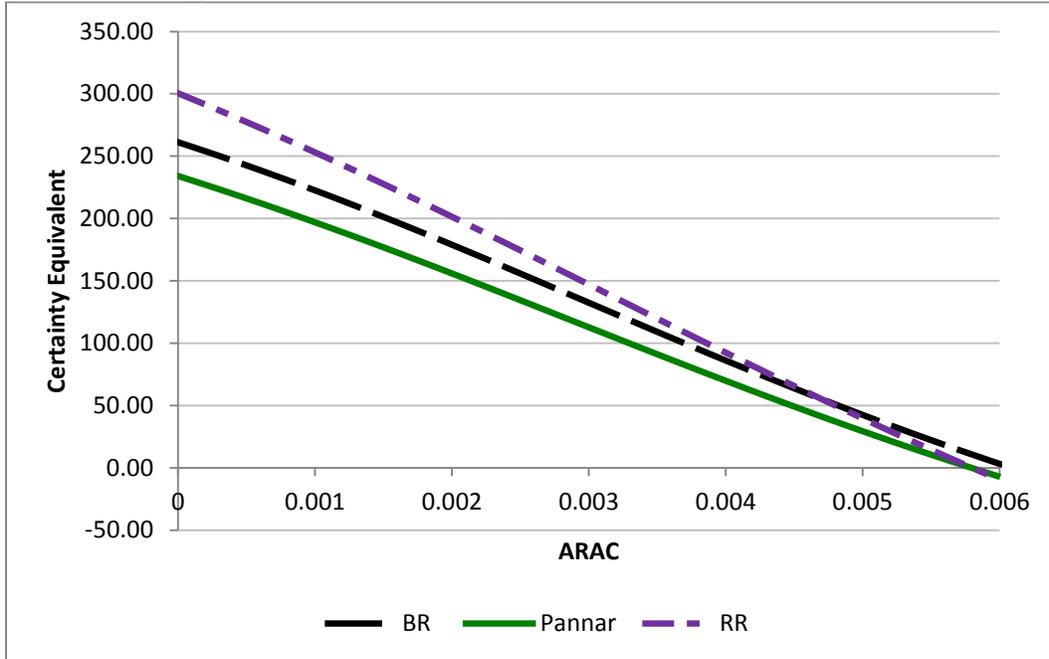
Figure 5-6 Negative Exponential Utility Weighted Risk Premiums Relative to RR maize (USD/hectare), Simdlangetsha



Note: N = 115; BR = 20, Bt = 18, Carnia = 34, Pannar = 33, RR = 10

Net worth for producers in Hlabisa is calculated as \$1607 per hectare, resulting in an upper bound ARAC of 0.0025. The range of ARAC corresponding to the relative risk aversion coefficients is 0.00 to 0.006 as seen in Figure 5-7. The SERF results from Hlabisa reveal that RR maize is once again the superior choice with a higher certainty equivalent, regardless of the risk preference of the decision-maker within our expected range of ARACs of 0.00 to 0.0025. However, extremely risk averse producers would prefer BR maize.

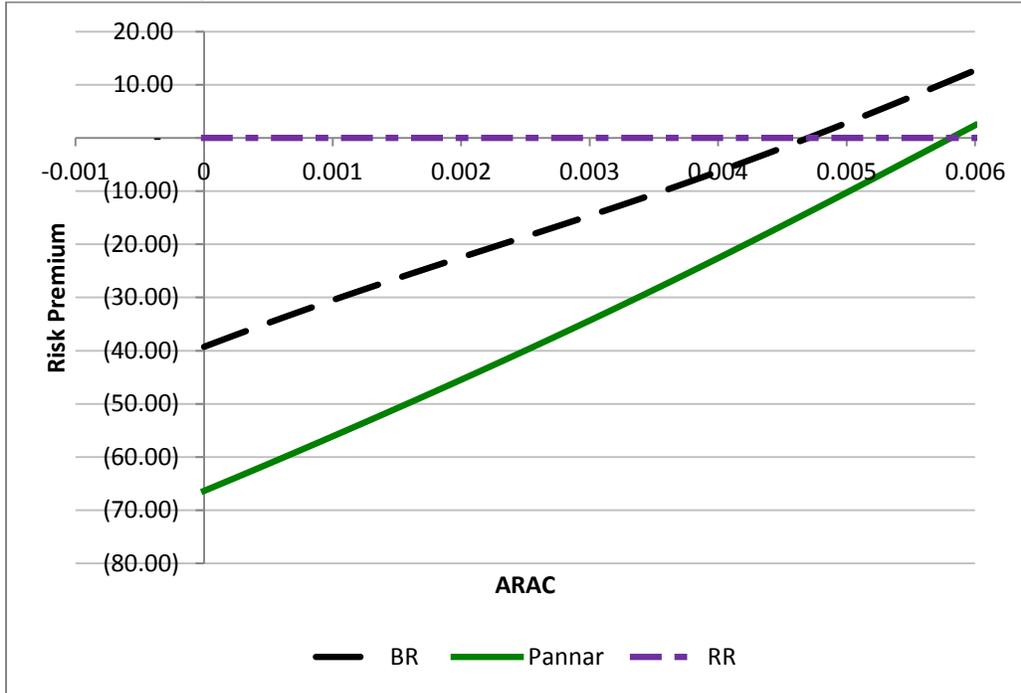
Figure 5-7 SERF under a Negative Exponential Utility Function for Net Returns (USD/hectare), Hlabisa



Note: N = 97; BR = 15, Pannar = 15, RR = 67

The risk premium, the value necessary to convince producers to switch varieties of maize, is much lower in Hlabisa as seen in Figure 5-8. Risk neutral RR producers would only have to be paid \$40 and \$65 per hectare to switch to BR and Pannar maize, respectively, but as farmers get more risk averse they must be paid less to switch varieties. RR producers that are extremely risk averse where $r_a(x) = 0.0025$, representative of a relative risk aversion value of 4.00, would require only \$18 and \$40 to switch to BR and Pannar maize.

Figure 5-8 Negative Exponential Utility Weighted Risk Premiums Relative to RR maize (USD/hectare), Hlabisa



Note: N = 97; BR = 15, Pannar = 15, RR = 67

SERF gives a clear picture of which varieties are preferred, and results are consistent across regions. In both Simdlangetsha and Hlabisa, maize producers prefer RR maize. The reduction in labor use clearly outweighs the extra cost of seed, according to the SERF. The race for second place is slightly less defined between BR and Pannar maize, but BR maize clearly holds an advantage for more highly risk averse producers in Simdlangetsha and for all producers in Hlabisa. It appears that certain types of GM maize reduce the risk of low yields and net returns, primarily RR maize, but the results are not completely conclusive.

Both stochastic dominance and SERF are fairly general approaches to analyze differences in yield and net returns of different maize varieties. They assume that differences between varieties are simply random or can be explained by the maize type. For example, while the stochastic dominance for net returns takes into consideration input and labor costs, it usually does not directly account for input quantities and prices or farmer characteristics which may lead to different results (Shively 1999). Econometric techniques are required to control for these differences. For this reason, the impact of different maize varieties using both production and cost function approaches is look at in the following sections.

Chapter 6 - Cost Analysis

The objective of Chapter 6 is to test the hypothesis that GM maize has lower cost than non-GM maize using an unrestricted cost function. One advantage of the cost function is that it uses input prices, eliminating endogeneity which is a persistent issue in the production function estimation in Chapter 4 (Binswanger 1974). The cost function also compliments Chapter 5 on risk since the cost function is more restrictive and technical than stochastic dominance and SERF, allowing for differences in cost between maize varieties to be teased out.

The first section of Chapter 6 provides the functional form and specification of a linear and quadratic cost function as well as a two-step treatment effects model, using a probit model to correct for selectivity bias. Finally, a nonparametric function using a kernel density estimator provides a more general graphical representation of the shape of total and average cost as maize output increases.

Cost Function Estimation

Using an unrestricted cost function, it is assumed that the production and consumption decisions of the household are independent. This assumption suggests that the households will seek to minimize cost subject to maize output which is held constant. Therefore, as input prices change which are out of the farmers' control, producers will use different input allocations to produce at minimum costs. As with the production functions, both linear and quadratic models are used to explain the relationship between total cost and input prices while controlling for region and RR and Bt maize types.

Functional Form

A short-run single-output unconstrained total cost function is represented as,

$$\tilde{C} = g(y, p_1, \dots, p_n) \quad (6.1)$$

where y denotes the quantity of output and p_1, \dots, p_n are the input prices of the variable production inputs x_1, \dots, x_n . The variable \tilde{C} is defined as the minimum cost producers will use to produce y kilograms of maize output, which is held constant (Beattie, Taylor and Watts 2009). As in the

production function analysis, both linear and quadratic relationships are used to describe the relationship between the dependent variable, total cost, and all other independent variables.

Linear Model

The linear cost function is specified as,

$$C_i = \alpha_0 + \gamma y_i + \sum_{j=1}^n \beta_j p_{ij} + \sum_{d=1}^m \eta_d D_{id} + \varepsilon_i \quad (6.2)$$

where C_i represents the total cost in US dollars to produce the output of maize plot i , y_i represents maize output of plot i , p_{ij} is a vector representing the price of input j by maize plot i , D_{id} is a vector of dummies which includes location and maize type represented by d of maize plot i , while $\alpha_0, \gamma, \beta_j$ and η_d are parameters and ε_i is an error term. Shephard's lemma allows for a direct interpretation of the cost function, defined as

$$\frac{\partial C_i}{\partial p_j} = x_j \quad (6.3)$$

where p_j is the estimated price of input j , and x_j is the conditional factor demand, or the input quantity that minimizes cost holding all else constant.

Quadratic Model

Since it is not expected that the cost relationship is linear, the quadratic model includes squared and interaction terms of inputs to allow for curvature. The quadratic model functional form is represented as follows,

$$C_i = \alpha_0 + \gamma y_i + \rho y_i y_j + \sum_{j=1}^n \beta_j p_{ij} + \sum_{j=1}^n \sum_{k=1}^n \theta_{jk} p_{ij} p_{ik} + \sum_{d=1}^m \eta_d D_{id} + \varepsilon_i \quad (6.4)$$

where C_i once again denotes total cost, and the other notation is identical to the linear cost function in the previous equation. The quadratic model also includes a vector of interaction and squared terms, denoted by $y_i y_j$ for output, and $p_{ij} p_{ik}$ representing the price of input j and input k used on maize plot i , along with the additional parameters ρ and θ_{jk} .

Treatment Effects Model

One hypothesis is tested in this research, is that RR maize has lower costs than non-RR maize. The previous equations estimated the effect of RR maize on total cost as follows,

$$C_i = \alpha_0 + \sum_{j=1}^n \beta_j x_{ij} + \delta RR_i + \varepsilon_i \quad (6.5)$$

where C_i represents total cost, and x_{ij} is a set of all variables (including dummy variables) except RR_i which is the dummy variable for RR maize. The parameter δ estimates the impact of RR maize. However, if the farmers adopting RR maize are better farmers, the parameter δ will overestimate the impact of the technology. The treatment effects model is the preferred method to correct for this bias. It is a type of Heckman's two-step estimation procedure, which first estimates a probit equation using maximum likelihood, followed by a least squares regression (Greene 2003). The treatment effects estimation uses the full sample which is available in our data set (both RR and non-RR maize plots). It assumes that there are only two groups of farmers, those which use RR maize and those which do not, and the selection of RR maize by farmers is not random (Maddala 1983).

The first step of the treatment effects model is the adoption decision model, estimated using a probit equation which controls for self-selection by estimating factors that influence RR adoption. It is assumed that farmers choose either RR or non-RR maize, whichever alternative minimizes cost at a given level of output. The probit model is defined by the equation

$$RR_i^* = \sum_{j=1}^n \gamma_j w_{ij} + u_i \quad (6.6)$$

where $RR_i = 1$ if $RR_i^* > 0$, and 0 otherwise. The vector of all explanatory variables is denoted by w_{ij} , γ_j is a parameter 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 ε_i are correlated.²² As a result, the expected impact of RR maize on total cost is determined by

²² The error terms are also assumed to have normal distribution.

$$\begin{aligned}
E[C_i|RR_i = 1] &= \sum_{j=1}^n \beta_j x_{ij} + \delta + E[\varepsilon_i|RR_i = 1] \\
&= \sum_{j=1}^n \beta_j x_{ij} + \delta + \rho\sigma\hat{\lambda}_i
\end{aligned} \tag{6.7}$$

where $\hat{\lambda}_i$ is the inverse Mills ratio²³ computed from the estimates of the probit model, γ_j (equation 6.6) defined as

$$\hat{\lambda}_i = \frac{\phi(a_i)}{\Phi(a_i)} \text{ if } RR_i = 1 \tag{6.8}$$

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, $\hat{\lambda}_i$, in the estimation. If $\hat{\lambda}_i$ is significant, it is effectively controlling for selectivity bias, and omitting $\hat{\lambda}_i$ from the previous least squares models will create biased estimators β_j and δ (Maddala 1983, Greene 2003, Key and McBride 2003).

Model Specification

The total cost models in this section are a function of input prices, dummy variables, and additional explanatory variables, as demonstrated in the following equation:

Total Cost = f(labor price, fertilizer price, herbicide price, seed price, land, land preparation price, maize output, Hlabisa, Roundup Ready, Bt, assets, experience with herbicide, education)

The value on coefficients for prices of labor, fertilizer, herbicide, seed, land, and land preparation are all expected to be positive, since an increase in input prices should lead to higher total cost. Dummy variables capture differences based on region and maize type, and variables

²³ The inverse Mills ratio is also called the Hazard rate in the treatment effects model.

which explain farmer characteristics are used to explain total cost, as well as adoption of various maize types.

Rather than using input quantities, the cost function uses input prices. This requires accurate price information which is not easy to collect. Information on prices is missing from several variables, including labor and land preparation cost. Labor price was only recorded from producers who used hired labor. Therefore, labor price information is only available for 40% of maize plots. To deal with the missing labor price, the average was calculated for each region. Price only varied slightly, between \$0.79 and \$0.81 per hour in Simdlangetsha and Hlabisa respectively. A similar approach was used to address the issue of missing prices of land preparation. In this case, producers who planted their maize no-till did not have land preparation prices, which includes only tractor and oxen use. The average price for land preparation of \$65 per hectare was used for these maize plots. Also, since no reliable price information was available for land, land area in hectares is used as a fixed factor instead. A description of variables used in the cost function is presented in Table 6-1.

Table 6-1 Description of Variables Used in the Cost Models

Variable	Description	Unit
<i>Total Cost</i>	The total cost of land, labor, and inputs	US Dollars (2010)
<i>Labor Price</i>	The price of labor, both hired and family	USD/Hour
<i>Fertilizer Price</i>	The price of fertilizer, including top dressing	USD/Kilogram
<i>Herbicide Price</i>	The price of herbicide per liter used both before and after planting	USD/Liter
<i>Seed Price</i>	The price of seed per kilogram	USD/Kilogram
<i>Land</i>	The estimated area in hectares for each plot	Hectares
<i>Land Preparation Price</i>	The price of land preparation is calculated as the total cost per hectare to prepare land for planting, including the use or hiring of oxen and tractors	USD/Hectare
<i>Maize Output</i>	Total kilograms of maize harvested	Kilograms
<i>Hlabisa Dummy</i>	The dummy takes a value of one if the region is Hlabisa, and zero if the region is Simdlangetsha	1= Hlabisa 0= Simdlangetsha

(Table 6-1 continued)

<i>Roundup Ready Maize Dummy</i>	If the maize seed has the Roundup Ready trait, the dummy takes a value of one. This includes both RR and BR (stacked) maize	1= Roundup Ready maize 0= non-Roundup Ready maize
<i>Bt Maize Dummy</i>	If the maize seed is Bt, the dummy is one, including both Bt and BR (stacked) maize	1= Bt maize 0= non-Bt maize
<i>Assets</i>	Total assets of the household for each plot, including livestock assets such as cattle, goats, sheep, chickens, and donkeys as well as farm assets such as planters and plows	US Dollars (2010)
<i>Experience Using Herbicide</i>	The number of years that producers reported using herbicide on maize plot to control weeds in the past	Years
<i>Education Dummy</i>	Education dummy takes a value of zero if the head of household has had no formal education, and one if the head of household has had at least a primary education	1= Primary education at least 0= No formal education

Table 6-2 presents descriptive statistics of the variables. All values are reported in US dollars, converted from South Africa Rand to US dollars (USD) at the constant exchange rate of 7.44 Rand per US dollar.

Table 6-2 Descriptive Statistics of the Variables Used in the Cost Models

Variable	Units	N	Mean	Median	Std. Deviation	Minimum	Maximum
<i>Total Cost</i>	US Dollars	212	343	313	156	107	1087
<i>Labor</i>	USD/Hour	212	.80	.79	.15	.39	1.60
<i>Fertilizer</i>	USD/Kilogram	212	.93	.75	.51	.55	5.03
<i>Herbicide</i>	USD/Liter	212	13.8	13.8	4.6	4.4	43.7
<i>Seed</i>	USD/Kilogram	212	9.0	9.7	2.2	3.2	14.6
<i>Land</i>	Hectares	212	.48	.37	.23	.17	1.50
<i>Land Preparation</i>	USD/Hectare	212	65	65	19	24	153
<i>Maize Output</i>	Kilograms	212	754	637	526	89	4600
<i>Hlabisa Dummy</i>	1= Hlabisa 0= Simdlangetsha	212	-	-	.50	0	1
<i>Roundup Ready Dummy</i>	1= Roundup Ready maize 0= Non-Roundup Ready maize	212	-	-	.50	0	1
<i>Bt maize Dummy</i>	1= Bt maize 0= Non-Bt maize	212	-	-	.43	0	1
<i>Assets</i>	US Dollars (2010)	212	8031	5735	7999	104	31931
<i>Experience Using Herbicide</i>	Years	212	3.5	4.0	2.0	0	10
<i>Education Dummy</i>	1= Primary education at least 0= No formal education	212	-	-	.47	0	1

It is expected that the independent variables will explain total cost better than independent variables in the production function. This is because it is assumed that more expensive seed and herbicide are also more effective. For example, Roundup, used on RR maize plots, is considered a more effective herbicide but it also costs about 50% more than 2, 4-D or Atrazine used by non-RR maize producers (Table 6-3). RR seed is also significantly more expensive. The hypothesis is that seed and herbicide will have a greater effect on total cost than they had on maize output, leading to even greater expected differences between RR and non-RR maize in the total cost model.

Table 6-3 Comparison of RR and Non-RR Seed and Herbicide Quantity and Price

	RR	Non-RR	Total
<i>Seed</i>			
Seeding Rate (kg/ha)	16.2	17.8	16.9
Price (\$/kg)	10.6	7.2	9.0
Cost (\$/ha)	171	127	150
<i>Post-emergence Herbicide</i>			
Quantity (L/ha)	5.8	7.5	6.5
Price (\$/L)	16.9	8.4	13.1
Cost (\$/ha)	98	62	84

Note: N = 212; RR = 112, non-RR = 100

Probit Model Specification

The first stage of the treatment effects model is an adoption decision model, which is estimated with a probit equation. The probit model estimates variables that influence RR maize adoption, and is described as follows:

$$\text{Prob}(\text{RR maize adoption}) = f(\text{Hlabisa dummy, assets, formal education, experience with herbicide, people in household, distance to maize plot, head of household above 60 years})$$

The value of the coefficients Hlabisa, assets, formal education, experiences with herbicide, distance to maize plot, and head of household above 60 years are all expected to be positive since it is believed that these factors increase the probability of RR maize adoption. The coefficient of people in household is expected to be negative. This is because as the number of people in the household increase, it is expected that more labor is available, thus discouraging producers from adopting RR maize which is labor-saving. The following Table 6-4 presents variables included in the probit model, the first step of the treatment effects model. All descriptive statistics of the variables used in the probit estimation are presented in Table 6-5 on the following page.

Table 6-4 Description of Variables Used in the Probit Model to Estimate RR Adoption

Variable	Description/ Expected Effect	Unit
<i>Hlabisa Dummy</i>	Location may capture attitudes towards GM crops, availability of RR maize seed, or farmer characteristics	1= Hlabisa 0= Simdlangetsha
<i>Assets</i>	Total assets are a measurement of wealth; as assets increase, farmers may be more likely to purchase RR seed and herbicide, which are more expensive than non-RR	US Dollars (2010)
<i>Education Dummy</i>	Producers with at least a primary education may be more likely to adopt a new technology such as RR maize	1= Primary education at least 0= No formal education
<i>Experience Using Herbicide</i>	As the number of years farmers use herbicide increases, it is expected that they become more comfortable with it, thus increasing the likelihood that they use RR maize which requires regular herbicide applications	Years
<i>People in Household</i>	RR maize requires significantly less labor; therefore, as the number of people in the household increases, the likelihood of RR adoption is expected to decrease	Number of People
<i>Distance to Maize Plot</i>	As the distance to the maize plot increases, it is expected that RR maize adoption also increases. This is because RR maize allows for no-till which should require fewer trips to the field	Meters
<i>Head of Household above 60 years</i>	All people above the age of 60 receive a pension of more than \$150 a month, a large amount of money relative to the prices of maize inputs. 51% of farmers used their pension to purchase maize seed; therefore it is expected that those receiving pension are more likely to purchase RR maize	1=Head of Household above 60 0=below 60

Table 6-5 Descriptive Statistics of the Variables Used in the Probit Model for RR maize

Variable	Units	N	Mean	Median	Std. Deviation	Minimum	Maximum
<i>Hlabisa Dummy</i>	1= Hlabisa 0= Simdlangetsha	212	.46	-	-	0	1
<i>Assets</i>	US Dollars (2010)	212	8031	5735	7999	104	31931
<i>Education Dummy</i>	1= Primary education at least 0= No formal education	212	.67	-	-	0	1
Experience Using Herbicide	Years	212	3.5	4.0	2.0	0	10
People in household	Number of People	212	6.2	6.0	2.1	1	17
Distance to maize plot	Meters	212	8.5	5.0	9.3	1	60
Head of household above 60 years	1=Head of Household above 60 0=below 60	212	.51	-	-	0	1

Nonparametric Regression Estimation

Parametric models require strong assumptions about functional form, homoscedasticity, correlation and distribution. For example, the least squares models used previously assume that total cost is generated with normal distribution where mean is zero and variance, skewness, and kurtosis are all one. Nonparametric models, on the other hand, abandon almost all of the assumptions held by parametric models. The result of removing these assumptions is that nonparametric models do not provide precise information such as statistical significance; however, the information they do provide is extremely robust. This is simply the tradeoff that exists between structured parametric and general nonparametric models (Just 2000). Examining both parametric and nonparametric models provides different perspectives and produces a more robust analysis (Greene 2003).

Kernel Density Estimation

The kernel density estimator is the most common nonparametric method, which fits a relationship between y which is maize output, and x , either total or average cost. The relationship is local, meaning that separate fitted relationships are determined for different levels

of x . A bandwidth parameter is used for smoothing. With regards to the cost function, it is expected that as maize output increases, total cost increases while average cost decreases. The relationship between y and x are represented by a nonparametric regression is specified as

$$y_i = \mu(x) + \varepsilon \quad (6.9)$$

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 $x = x^*$ is a local weighted average of y_i , where 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

$$\hat{\mu}(x^*) = \sum_{i=1}^n w_i(x_i, x^*, h) y_i \quad (6.10)$$

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, used to provide a smoother estimate of the conditional mean function, is defined as

$$\hat{\mu}(x_i, x^*, h) = \frac{\sum_{i=1}^n \frac{1}{h} K \left[\frac{x_i - x^*}{h} \right] y_i}{\sum_{i=1}^n \frac{1}{h} K \left[\frac{x_i - x^*}{h} \right]} \quad (6.11)$$

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 choice of a kernel function is not usually critical, whereas choosing bandwidth is the more important issue. The bandwidth parameter, which controls 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).

Results

In Chapter 3 it is revealed that non-GM maize has significantly higher labor cost. Therefore, it is expected that the reduction in labor will result in cost savings for RR maize that are even greater than the output advantage due to a relatively high wage rate in KwaZulu-Natal. This section provides results of the least squares models, the treatment effects model, and the nonparametric regression analysis.

Estimation of Cost Function using OLS and WLS

The results of the linear and quadratic least squares and the quadratic least squares total cost models are presented in Table 6-6, which includes all 212 observations. The variables assets, formal education, and experience with herbicide, which attempt to capture physical and social capital, are included in Table 6-7.

Table 6-6 Regression Results of Cost for All Maize Plots^a

	OLS - Linear			OLS - Quadratic			WLS - Quadratic		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
<i>Intercept</i>	-138.92	*	81.43	-2947.07	**	1287.73	-2839.86	**	1256.34
<i>Labor</i>	134.59	***	30.49	436.95		1207.51	290.77		1190.79
<i>Fertilizer</i>	237.79	**	117.88	6558.10	**	2700.18	6598.81	**	2621.50
<i>Herbicide</i>	2.91	**	1.40	-41.96		29.52	-39.81		29.35
<i>Seed</i>	14.64	***	3.24	79.49	*	46.93	75.83	*	43.89
<i>Land</i>	389.67	***	26.38	1630.07	***	557.54	1547.03	***	541.99
<i>Land Preparation</i>	-0.75	***	0.27	9.28	*	4.94	9.68	**	4.67
<i>Output</i>	0.05	***	0.01	0.69	***	0.22	0.61	***	0.23
<i>Hlabisa Dummy</i>	-168.77	***	14.40	-187.69	***	21.57	-170.97	***	21.18
<i>RR Dummy</i>	-63.83	***	17.62	-77.67	***	17.45	-69.60	***	16.50
<i>Bt Dummy</i>	6.57		10.60	4.51		9.59	2.90		8.30
<i>Labor²</i>				-28.53		114.71	20.22		117.78
<i>Fertilizer²</i>				-2497.82	**	965.04	-2617.35	***	940.96
<i>Herbicide²</i>				-0.02		0.12	0.05		0.12
<i>Seed²</i>				-1.02		0.85	-0.71		0.79
<i>Land²</i>				-334.78	**	131.05	-277.79	**	122.35
<i>Land Prep²</i>				-0.01		0.01	-0.01		0.01
<i>Output²</i>				0.00		0.00	0.00		0.00
<i>Labor*Fertilizer</i>				-802.17		2133.87	-724.69		2148.11
<i>Labor*Herbicide</i>				11.22		17.72	15.92		18.43
<i>Labor*Seed</i>				9.01		30.56	-4.16		28.76
<i>Labor*Land</i>				-110.37		205.27	-83.17		204.30
<i>Labor*Land Prep</i>				1.35		1.61	1.66		1.44
<i>Labor*Output</i>				-0.04		0.09	0.00		0.09
<i>Fertilizer*Herbicide</i>				38.66		47.11	25.31		47.03
<i>Fertilizer*Seed</i>				-139.56	**	67.29	-113.63	*	63.51
<i>Fertilizer*Land</i>				-1124.03		839.65	-1123.13		807.15
<i>Fertilizer*Land Prep</i>				-12.11		7.96	-13.97	*	7.65
<i>Fertilizer*Output</i>				-1.05	***	0.34	-0.99	***	0.35
<i>Herbicide*Seed</i>				2.64	***	0.77	2.26	***	0.74
<i>Herbicide*Land</i>				-6.86		7.90	-5.28		7.76
<i>Herbicide*Land Prep</i>				-0.04		0.11	-0.01		0.10
<i>Herbicide*Output</i>				0.00		0.00	0.00		0.00
<i>Seed*Land</i>				-7.16		15.03	-8.34		14.60
<i>Seed*Land Prep</i>				-0.07		0.14	-0.08		0.13
<i>Seed*Output</i>				0.00		0.01	0.00		0.01
<i>Land*Land Prep</i>				-2.07		2.02	-2.49		1.93
<i>Land*Output</i>				0.24	***	0.07	0.25	***	0.08
<i>Land Prep*Output</i>				0.00		0.00	0.00		0.00
<i>N</i>	212			212			212		
<i>R-squared</i>	0.85			0.91			0.93		
<i>Adjusted R-squared</i>	0.84			0.88			0.91		
<i>Breusch-Pagan</i>	60.96	***		39.16	***		34.90	***	
<i>F-value</i>	112.2			43.6			60.3		

***, **, * Indicates significantly different than zero at 1%, 5% and 10% respectively.

^aAverage cost is \$343 per maize plot

Interpretation of OLS Linear Model

Shephard's lemma allows for the direct interpretation of coefficients from the cost function. The values of the coefficients are simply the factor demands, conditional on output. For example, the coefficient on labor is 135, indicating that it should take 135 hours of labor in order to produce the optimal level of output.

The linear model has a R-squared value of 0.85 and an adjusted R-squared value of 0.84, suggesting that the independent variables explain total cost well. The sign on the independent variables in the linear model is positive for all input prices except land preparation price and can be explained as follows; as the price of labor, fertilizer, herbicide, and seed increases, so does total cost. Total cost also increases as land and output increase. Only the land preparation price is negative, which suggests that as farmers use more expensive methods of land preparation such as tractors, total costs decrease. This because initially investing in better land preparation, saves cost in subsequent production activities.

Only the Bt variable is not significant in the linear model. Similar to results from the production models, the coefficients on Hlabisa and RR maize dummy variables are significant and negative, indicating that farmers in Hlabisa and those which use RR maize have significantly lower costs. A one-sided t-test is set up to test the null hypothesis, $H_0: RR = 0$, against the alternative hypothesis, $H_1: RR < 0$. The null hypothesis is rejected, suggesting that RR maize plots have a significantly lower total cost than non-RR maize plots ($p = 0.000$).

The linear model passes the VIF test with values for each coefficient below 10, revealing an acceptably low level of multicollinearity. The Breusch-Pagan reveals heteroscedasticity in the model, with a chi-squared value of 60.96 ($p = 0.000$). Also, the regression specification error test (RESET) reveals that the model may be misspecified ($p = 0.000$). Similar to the production function, the Shapiro-Wilk W test for normality rejects the null hypothesis that distribution is normal ($p = 0.000$) in the OLS linear cost function.

OLS Quadratic Model

The quadratic model has an R-squared value of 0.91 and an adjusted R-squared value of 0.88, slightly higher than the R-squared values of the linear model. The signs on the coefficients are as expected, although several significant coefficients are large and have high standard errors. Both fertilizer and land have positive linear terms and negative squared terms, indicating decreasing marginal costs. The quadratic model also failed the Breusch-Pagan test for

heteroscedasticity, with a p-value of 0.000. The F statistic from the F-test is 3.76, which shows that these terms are significant at the 1 percent level. This reveals that the squared and interaction terms help to explain total cost.

WLS Quadratic Model

Next, a weighted least squares quadratic regression is used to provide more efficient estimates by controlling for heteroscedasticity. As in the production model, it is assumed that the land term is causing the heteroscedasticity but for a different reason. It is expected that costs are higher for small plots which purchase inputs in small quantities, while producers with larger plots of maize may purchase their inputs in bulk at lower prices, resulting in lower total costs. Therefore, the WLS model is weighted proportional to the log of squared residuals of land and land squared.

The WLS quadratic model has a high R-squared value of 0.93, but this is not a great measure of goodness-of-fit. On the other hand, the WLS estimators are very similar from the OLS estimators, and many of the same coefficients are significant in both models. The WLS quadratic model also failed the Breusch-Pagan test for heteroscedasticity ($p = 0.000$), although coefficients are still unbiased.

RR and Hlabisa Dummy Variables

Of particular interest in these models is the interpretation of the RR dummy coefficient. Results show that RR maize is significantly less expensive; from \$65 to \$78 cheaper per maize plot than non-RR maize while obtaining the same output (Table 6-6). Average plot size is one-half a hectare, or slightly more than one acre. These results are in agreement with results from both Chapter 3 and 4 which indicated that RR maize has lower costs than non-RR maize. Producing maize is also significantly cheaper in Hlabisa, from \$99 to \$161 per maize plot depending on the model. The reason for this large disparity is unknown, but could capture some unobserved regional differences such as soil type or rainfall, or farmer characteristics such as motivation.

Estimation of Cost Function with Additional Variables

The initial models only included variables which are expected to have a direct effect on total cost. Other variables, such as those that measure farmer characteristics, can also be used to

explain differences in cost. Several variables are added to the model; assets, formal education, and experience using herbicide. Assets includes farm and livestock assets, and is a measure of farmers wealth or physical capital; it is expected that as a farmers wealth increases so does their ability to purchase inputs in larger quantities which lowers the total costs. Producers with higher education and more experience using herbicide have higher social capital, and are able to make a more informed decision when purchasing inputs. Results are presented in Table 6-7.

Table 6-7 OLS Regression Results without and with Additional Variables^a

	OLS - Original		OLS - Additional variables	
	Coef.	Std. Err.	Coef.	Std. Err.
<i>Intercept</i>	-138.92 *	81.43	-131.96	82.18
<i>Labor</i>	134.59 ***	30.49	129.69 ***	30.55
<i>Fertilizer</i>	237.79 **	117.88	253.75 **	118.88
<i>Herbicide</i>	2.91 **	1.40	2.88 **	1.40
<i>Seed</i>	14.64 ***	3.24	15.13 ***	3.31
<i>Land</i>	389.67 ***	26.38	387.74 ***	26.80
<i>Land Preparation</i>	-0.75 ***	0.27	-0.75 ***	0.27
<i>Output</i>	0.05 ***	0.01	0.05 ***	0.01
<i>Hlabisa Dummy</i>	-168.77 ***	14.40	-177.33 ***	15.67
<i>RR Dummy</i>	-63.83 ***	17.62	-63.74 ***	17.60
<i>Bt Dummy</i>	6.57	10.60	6.51	10.74
<i>Assets</i>			0.00	0.00
<i>Experience using Herbicide</i>			0.04	2.44
<i>Formal Education</i>			-18.63 *	10.54
<i>N</i>	212		212	
<i>R-squared</i>	0.85		0.85	
<i>Adjusted R-squared</i>	0.84		0.84	
<i>Breusch-Pagan</i>	61.0 ***		62.2 ***	
<i>F-value</i>	112.2 ***		87.0 ***	

***, **, * Indicates significantly different than zero at 1%, 5% and 10% respectively.

^aAverage cost is \$343 per maize plot

Linear models were used for the purpose of simplicity. The two models are nearly identical, with R-squared and coefficient values that barely change. The assets and experience using herbicide coefficients are insignificant, while the coefficient on formal education is negative and significant and at the 10% level, which confirms our hypothesis that educated farmers have lower total costs. The VIF test reveals that there is not multicollinearity, but there is still heteroscedasticity with additional variables using the Breusch-Pagan test (p = 0.000).

Estimation of Cost Function using Treatment Effects Model to Control for Selectivity Bias

The previous models show that RR maize has significantly lower total cost. While it is expected that the lower cost is a result of the RR technology alone, this result could be biased if adopters of RR maize self-select. In other words, if RR maize producers are already better farmers than non-adopters, the resulting lower cost cannot be attributed only to the RR technology alone. The unobservable characteristics of better farmers would cause the RR dummy variable to be endogenous, thus overestimating the effects of the RR trait. It is well known that new technologies are not adopted evenly by different producers. Some farmers may have superior access to information or credit, or they may have positive (or negative) attitude towards GM maize (Croston, et al. 2007, Greene 2003).

The preferred method used to control for self-selection is to compare maize plots from producers that are planting both RR and non-RR maize, although this is not possible due to data limitations (only 18 farmers planted both RR maize and non-RR maize). Running separate OLS regressions for RR and non-RR maize does not fix the selectivity bias either, since estimators will still be inconsistent. The best way to control for selectivity bias with the data available for this research is a two-stage treatment effects model. The first stage of the model is an adoption decision model, estimated with a probit equation which takes into account factors that influence adoption of RR maize. The second stage is the impact model which estimates the impact of using RR maize on total cost (Fernandez-Cornejo and Li 2005, Maddala 1983).

Results from the probit analysis for adoption of RR maize are reported in Table 6-7. They show that the probability of adopting RR maize is both significantly and positively influenced by both location and experience using herbicide. The positive value of experience with herbicide indicates that as farmers gain experience using herbicide and become more comfortable with it, they are more likely to adopt RR maize. The signs on the other variables are as expected, but not significant.

Table 6-8 Probit Analysis Results: Estimation of the Probability of Planting RR Maize

Variable	Coef.		Std. Err.
<i>Intercept</i>	-1.44	***	0.49
<i>Hlabisa dummy</i>	1.90	***	0.29
<i>Assets</i>	0.00		0.00
<i>Formal education</i>	0.16		0.28
<i>Experience with herbicide</i>	0.23	***	0.06
<i>People in household</i>	-0.03		0.06
<i>Distance to maize plot</i>	-0.02		0.01
<i>Head of household above 60 years</i>	0.20		0.23
<i>Number of observations</i>	212		
<i>Likelihood Ratio test statistic</i>	99.64	***	

***, **, * Indicates significantly different than zero at 1%, 5% and 10% respectively.

In the second step of the treatment effects model, the inverse Mills ratio which was computed from the Probit estimates is included in the cost function. The treatment effects model is least squares estimation, and it uses the same variables used to estimate total cost in Table 6-6. Results are presented in Table 6-9.

Interpretation of the Treatment Effects Model

The first two models presented in Table 6-9 are simply the OLS and WLS presented earlier (Table 6-6) for comparison. The third model is a two-step treatment effects model, estimated to control for selection bias. The values of most of the coefficients in the least squares and treatment effects models are very similar. The herbicide coefficient is significant in the treatment effects model, and the Hlabisa dummy variable is slightly less but still significant. Most notably is the difference in the RR maize dummy variable, which is still significant but almost twice as large in the treatment effects model when selectivity bias is taken into account. Most importantly, the inverse Mills ratio is positive and significant at the 5% level. The fact that it is positive signifies that the previous models underestimated the impact of RR maize on reducing total cost. Significance of the inverse Mills ratio indicates that selectivity is an issue that needs to be corrected, and that it is being corrected for. The chi-squared value of the Wald test statistic was 1851.1 ($p = 0.000$), revealing that the model significantly explains the difference in total cost.

Table 6-9 Regression Results of Cost including the Two-Stage Treatment Effects

	OLS - Quadratic			WLS - Quadratic			Treatment Effects- Quadratic		
	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
<i>Intercept</i>	-2947.1	**	1287.7	-2839.9	**	1256.3	-2353.0	**	1131.5
<i>Labor</i>	436.9		1207.5	290.8		1190.8	32.0	**	1016.2
<i>Fertilizer</i>	6558.1	**	2700.2	6598.8	**	2621.5	5410.8	**	2356.1
<i>Herbicide</i>	-42.0		29.5	-39.8		29.4	-44.6	*	25.8
<i>Seed</i>	79.5	*	46.9	75.8	*	43.9	70.8	*	40.9
<i>Land</i>	1630.1	***	557.5	1547.0	***	542.0	1558.1	***	480.9
<i>Land Preparation</i>	9.3	*	4.9	9.7	**	4.7	8.8	**	4.3
<i>Output</i>	0.7	***	0.2	0.6	***	0.2	0.6	***	0.2
<i>Hlabisa Dummy</i>	-187.7	***	21.6	-171.0	***	21.2	-149.0	***	25.6
<i>RR Dummy</i>	-77.7	***	17.5	-69.6	***	16.5	-162.3	***	37.4
<i>Bt Dummy</i>	4.5		9.6	2.9		8.3	7.7		8.6
<i>Labor²</i>	-28.5		114.7	20.2		117.8	-56.1		99.1
<i>Fertilizer²</i>	-2497.8	**	965.0	-2617.4	***	941.0	-2243.7	***	836.6
<i>Herbicide²</i>	0.0		0.1	0.1		0.1	0.0		0.1
<i>Seed²</i>	-1.0		0.8	-0.7		0.8	-1.0		0.7
<i>Land²</i>	-334.8	**	131.1	-277.8	**	122.4	-332.2	***	114.6
<i>Land Preparation²</i>	0.0		0.0	0.0		0.0	0.0		0.0
<i>Output²</i>	0.0		0.0	0.0		0.0	0.0	**	0.0
<i>Labor*Fertilizer</i>	-802.2		2133.9	-724.7		2148.1	7.1		1771.3
<i>Labor*Herbicide</i>	11.2		17.7	15.9		18.4	2.2		15.2
<i>Labor*Seed</i>	9.0		30.6	-4.2		28.8	14.2		25.8
<i>Labor*Land</i>	-110.4		205.3	-83.2		204.3	-28.2		174.4
<i>Labor*Land Prep</i>	1.4		1.6	1.7		1.4	1.4		1.4
<i>Labor* Output</i>	0.0		0.1	0.0		0.1	0.0		0.1
<i>Fertilizer*Herbicide</i>	38.7		47.1	25.3		47.0	52.1		41.8
<i>Fertilizer*Seed</i>	-139.6	**	67.3	-113.6	*	63.5	-137.7	**	58.4
<i>Fertilizer*Land</i>	-1124.0		839.7	-1123.1		807.2	-1134.2		709.4
<i>Fertilizer*Land Prep</i>	-12.1		8.0	-14.0	*	7.7	-11.5		6.8
<i>Fertilizer* Output</i>	-1.1	***	0.3	-1.0	***	0.4	-0.9	***	0.3
<i>Herbicide*Seed</i>	2.6	***	0.8	2.3	***	0.7	3.0	***	0.7
<i>Herbicide*Land</i>	-6.9		7.9	-5.3		7.8	-5.7		7.1
<i>Herbicide*Land Prep</i>	0.0		0.1	0.0		0.1	-0.1		0.1
<i>Herbicide* Output</i>	0.0		0.0	0.0		0.0	0.0		0.0
<i>Seed*Land</i>	-7.2		15.0	-8.3		14.6	-11.2		13.2
<i>Seed*Land Prep</i>	-0.1		0.1	-0.1		0.1	0.0		0.1
<i>Seed* Output</i>	0.0		0.0	0.0		0.0	0.0		0.0
<i>Land*Land Prep</i>	-2.1		2.0	-2.5		1.9	-1.9		1.7
<i>Land* Output</i>	0.2	***	0.1	0.3	***	0.1	0.3	***	0.1
<i>Land Prep* Output</i>	0.0		0.0	0.0		0.0	0.0		0.0
<i>Inverse Mill's ratio¹</i>							49.77	**	
<i>N</i>	212			212			212		
<i>R-squared</i>	0.91			0.93					
<i>Adjusted R-squared</i>	0.88			0.91					
<i>F-value</i>	43.64	***		47.39	***				
<i>Wald test statistic</i>							1851.13	***	

***, **, * indicates significantly different than zero at 1%, 5% and 10% respectively

^a Average cost is \$343 per maize plot.

^b The inverse Mills ratio, lamda, is also called the Hazard rate in the treatment effects model.

This section uses several different cost functions to examine the impact of RR and Bt maize on total cost. First, least squares models are estimated which reveal a strong relationship between prices, output, and total cost. Little is added with the inclusion of additional variables to control for the impact of physical and social capital on total costs. The final cost function is estimated taking into account selection bias using a treatment effects model. When controlling for selection bias, which is present, the impact of RR maize on total cost increases.

Each of these cost functions requires assumptions to be made regarding functional form and distribution. One assumption is normality which is required for robust hypothesis testing; however, the previously mentioned cost functions fail the Shapiro-Wilk W test for normality. One way to deal with this situation is to use one final nonparametric approach to analyze the impact of maize seed type on total and average cost. The benefit of nonparametric analysis is that it discards most of the assumptions made previously by least squares estimations.

Nonparametric Regression: Total and Average Cost

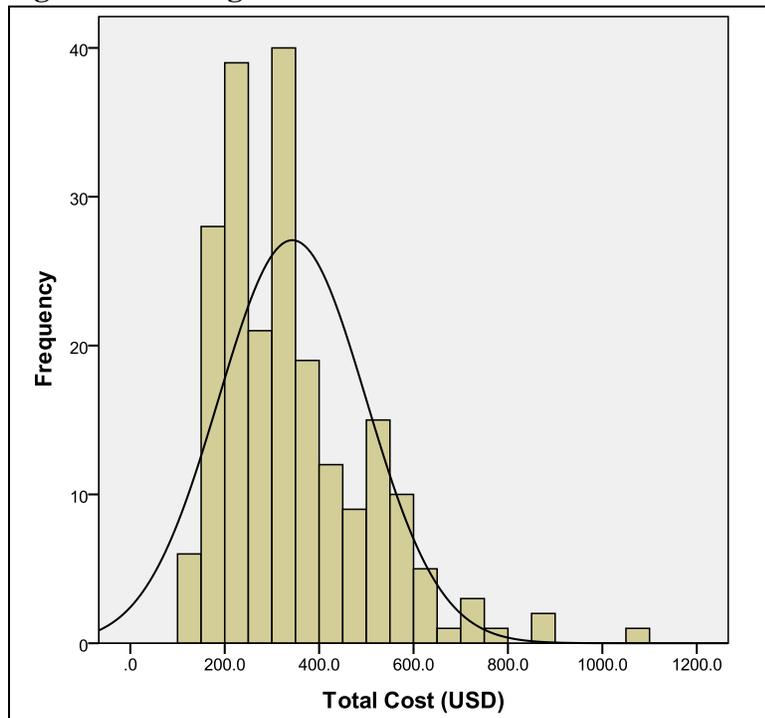
In this section, a nonparametric regression of total and average cost is examined using the Epanechnikov kernel density estimator. This provides a very open approach to analyze how total and average costs change as maize output increases. It allows the impact of maize seed type on total and average cost to be analyzed, while discarding the stricter assumptions of parametric least squares techniques.

Kernel Density Estimator

The kernel density estimator is a nonparametric estimation technique which abandons most assumptions about functional form and distribution. The nonparametric model shows the distribution of values that the random variable takes as opposed to a parametric model which produces estimates assuming normal distribution. The kernel density estimator is additive to this section since it provides a graphical representation of total and average cost. Regarding the cost function, it is expected that as output increases, total cost increases while average cost decreases.

The distribution of observed total cost has a mean value of \$343 and a median of \$313, meaning that the distribution is positively skewed. This is represented graphically by the histogram of total cost in Figure 6-1, which shows that the distribution of total cost is also bimodal. Histograms of RR and non-RR total cost also indicate bimodal tendencies (Figures A-1 and A-2).

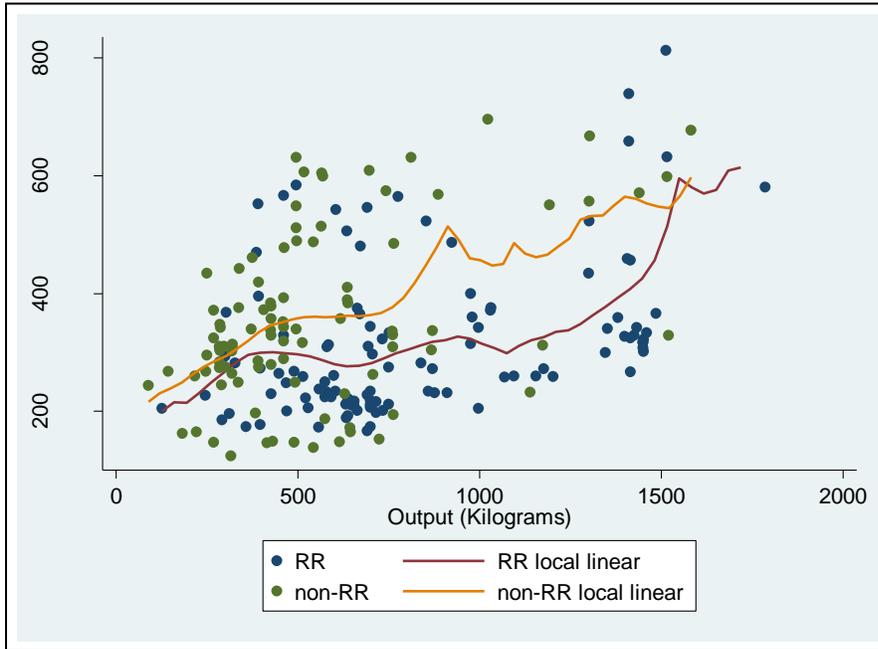
Figure 6-1 Histogram of Total Cost of All Maize Production (USD)



Bimodal distribution of total costs may occur because Bt farmers do not typically use herbicide, and non-RR producers do not always use herbicide. Accounting for censoring in econometric analysis using a Tobit model may reduce the bias created by the bimodal distribution (Mutuc, et al. 2012). However, a kernel density estimator eliminates the issue due to its lack of restrictions.

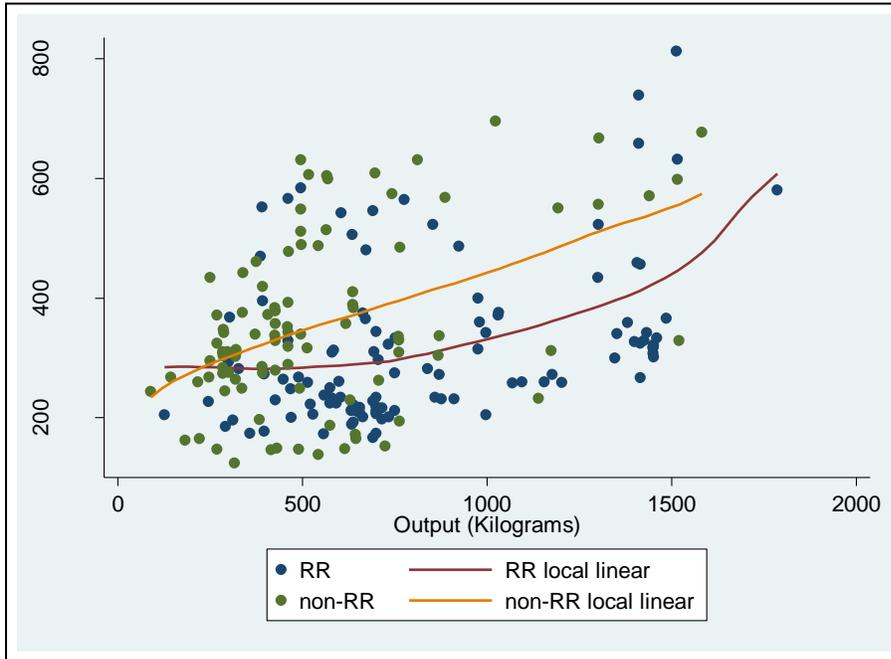
In order to estimate total cost nonparametrically, predicted values of total cost were first estimated from the split regression of RR and non-RR maize using the WLS quadratic regression weighted by land and land squared (Table A-2). Average cost was then calculated by dividing the predicted total cost by maize output. One important aspect of the kernel density regression is bandwidth, or the width of the bin. As bandwidth size increases so does bias, but variance decreases resulting in a smoother estimator. No method exists for determining optimal bandwidth; therefore, graphs of total cost and average cost include bandwidth sizes of 100 and 300 for comparison (Greene 2003).

Figure 6-2 Predicted Total Cost of RR and non-RR Maize using Epanechnikov Kernel Density Estimators, Bandwidth = 100



The results of the Epanechnikov kernel density estimators (bandwidth = 100) in Figure 6-2 show an expected general trend; as output increases so does total cost. The estimator of RR maize appears to follow cost function theory more closely, where total cost will increase at a decreasing rate until it reaches the inflection point (considered stage two in production) and then begin to increase at an increasing rate as output increases (Beattie, Taylor and Watts 2009). RR and non-RR maize total cost curves cross briefly at a output of approximately 1600 kilograms. In Figure 6-3, the bandwidth is 300 so the total cost curves are much smoother. It is less obvious that the total cost curves follow economic theory. Figure 6-3 reveals that RR maize has lower total costs than non-RR maize, except below a output of approximately 200 kilograms.

Figure 6-3 Predicted Total Cost of RR and non-RR Maize using Epanechnikov Kernel Density Estimators, Bandwidth = 300



Average cost is simply the total cost divided by output. Figure 6-4 reveals that as output increases, average cost decreases for both RR and non-RR maize, as is expected based on economic theory. Once again, both bandwidths of 100 and 300 are presented for comparison. In Figure 6-4, it appears that RR maize has overall lower output except at around 1500 kilograms where the kernel density estimator of RR and non-RR maize cross. Figure 6-5 is a smoother estimation since a higher bandwidth is used to determine the Epanechnikov kernel density estimator.

The results of the kernel density estimation do not provide precise information as presented in the total cost models. For example, it is not possible to determine how much lower cost are for RR maize at a given point. The results do, however, reaffirms previous results that indicated that RR maize has lower costs than non-RR maize. This allows for a visual interpretation of the difference between RR and non-RR maize, adding to the robustness of the findings in this research.

Figure 6-4 Predicted Average Cost of RR and non-RR Maize using Epanechnikov Kernel Density Estimators, Bandwidth = 100

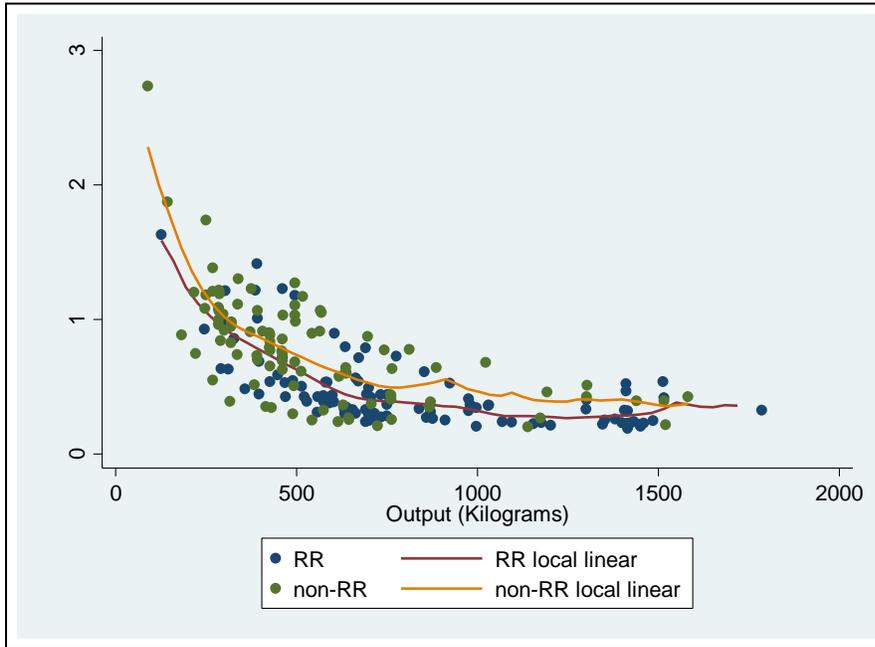
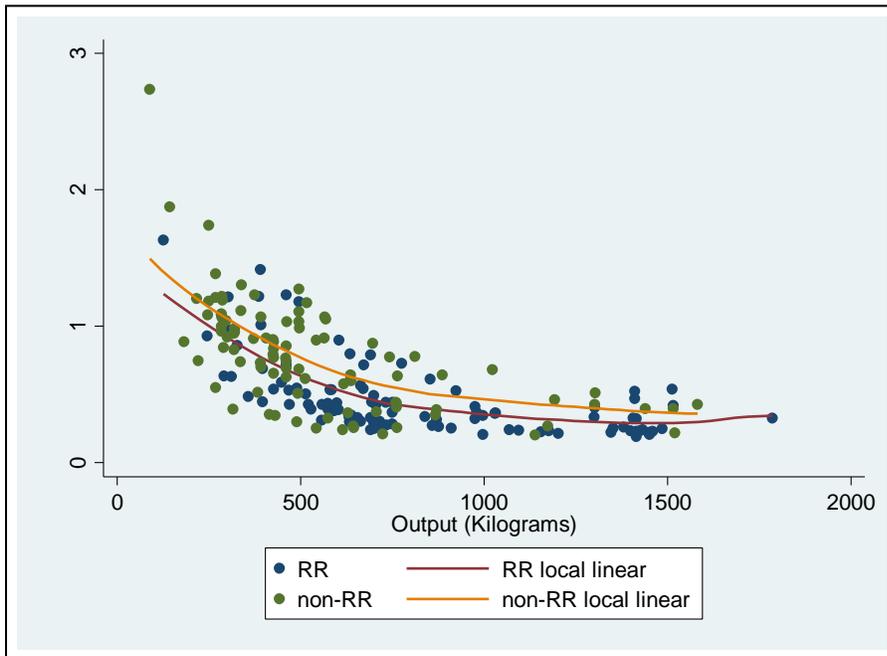


Figure 6-5 Predicted Average Cost of RR and non-RR Maize using Epanechnikov Kernel Density Estimators, Bandwidth = 300



Chapter 7 - Conclusion

The objective of this thesis is to examine the impact that GM maize has on risk, yield, and cost on small-scale farmers in two regions in South Africa. Smallholder farmers in Sub-Saharan Africa remain increasingly susceptible to food insecurity while agricultural productivity remains stagnant in the face of challenges such as environmental degradation and climate change. The development of pertinent agricultural technology which boost agricultural productivity and reduces risk for smallholder farmers must be of utmost importance in the strategy for reducing hunger and poverty in the region. The commercialization of GM crops is one with large implications for policymakers in Sub-Saharan Africa, where a majority of countries remain in limbo on the issue. The impact of GM crops in low-income countries, especially in Africa, is poorly researched, leading to assumptions that may or may not be true concerning the impact that GM crops may have on smallholders, especially regarding agricultural productivity and poverty reduction. Three primary hypotheses were tested: that GM maize leads to lower risk of low yield and net returns, that GM maize has higher yields, and lower cost.

The initial overview of data indicates that RR maize offers a technological benefit that is not provided by conventionally-bred hybrids. Producers of RR maize pay 47% more per kilogram of seed and use 44% less labor per hectare compared to other maize varieties. Due to a high HIV/AIDS rate and urban migration of agricultural workers, labor costs are relatively high in KwaZulu-Natal, South Africa. Therefore, RR varieties are still 25% and 40% more profitable than other varieties in the regions of Hlabisa and Simdlangetsha, respectively.

One of the objectives of this research is to examine the impact of GM maize technologies on smallholder risk. Several methods are used; first, stochastic dominance analysis compares net returns of all five varieties in both regions. RR maize is second-degree stochastic dominant to all other varieties in Simdlangetsha, while no variety is stochastically dominant in Hlabisa. The second method to examine risk is stochastic efficiency with respect to a function (SERF) analysis, which considers all maize producers to be risk averse. Results indicate that RR maize is the preferred variety for producers over the entire range of risk preferences in both regions. While average maize gross returns are \$713 per hectare, risk premiums between \$18 and \$221

must be paid to RR maize producers to persuade them to switch to the second-most preferred variety, depending on region and farmer risk preference.

Another objective is to examine the impact of GM maize on yields and profit. Econometric analysis, which uses a relatively restrictive approach, compares RR and non-RR maize using both production and cost functions. Results indicate that RR maize has a significantly higher yield of at least 8%, although the yield gain varies greatly when input endogeneity is taken into account. Elasticities of output are calculated from a split regression of both RR and non-RR maize. The elasticity of output with respect to land for RR maize producers is 0.61, indicating that RR maize producers should expand production onto new land in order to increase output. The largest elasticity of production for non-RR producers is labor, with a value of 0.82, suggesting that RR maize producers should increase labor use in order to increase output. Previous literature reveals an abundant supply of land in KwaZulu-Natal, while the labor supply is more constrained which suggests that RR maize producers in KwaZulu-Natal may be able to increase output the easiest (Gouse, Piesse, et al. 2009)

Next, a cost function analysis is used compare the cost of GM and non-GM varieties. Results reveal that total costs to produce the same output of maize are 19% lower when using RR maize as opposed to non-RR maize plots. The lower cost is most likely from the reduction of labor requirements of RR maize. The treatment effects model which controls for selectivity bias suggests that total costs for RR maize are up to 47% lower than for non-RR maize plots. Nonparametric kernel density estimation also reveals consistently lower total and average costs of RR maize, across most levels of output. Overall results reveal that GM maize, particularly RR maize, appears to hold strong benefits for smallholders. The benefits over non-RR maize include lower risk, higher yields and lower costs, although the results are not unambiguous.

Future Research

The use of GM maize in low-income countries among smallholder farmers has many implications that are not examined in this research. One area that should be examined in future research is the method used to estimate the impact of GM maize without overestimating its effect. This study reveals that controlling for selectivity bias using a treatment effects model leads to more consistent estimates. Mutuc, et al. (2012) takes it a step further, revealing that a Tobit model which controls for censoring should also be used so that the impact of GM maize at

the farm level is not overestimated. Future research should develop a more robust technique to remove this type of bias. One specific challenge is to determine a method to integrate the 25 farmers with both GM and non-GM maize plots into our econometric estimation.

In our study, it was revealed that maize producers planting GM maize used significantly less total labor, as well as significantly less child, male, and female labor, than producers of non-GM maize. Future research should provide more quantitative analysis to determine the extent that the labor supply is constrained. It should also consider how the adoption rates of GM maize are affected by the fact that RR maize is a labor-saving technology. Research should explore how RR maize will impact rural employment, and determine in which countries RR maize is most suitable for smallholder farmers as well as regions where the technology may not be appropriate.

Several factors also appear to influence the adoption of GM maize, warranting further research. The first is market constraints, as 22% of smallholders in this study were not able to get their first choice of seed, of 88% which preferred to buy GM maize seed. Future research should identify the source of these constraints, and their impact on adoption of GM maize. The second is the implicit price that farmers pay for labor, as non-RR producers use significantly higher amounts of labor leading to negative net returns. Assuming rational behavior by producers, this leaves some non-pecuniary benefits unaccounted for when estimating net returns which influence adoption of RR maize.

The results of this research indicate a strong preference for RR maize regarding yield, cost, and risk. However, previous research reveals that benefits of GM maize vary greatly depending on the year and location, which makes it a challenge to compare the benefits of the technology. For example, the average price of Roundup herbicide paid by farmers in the US dropped from \$42.80 in 2009 to \$16.80 in 2011, due to the flooding of generic versions of glyphosate (Roundup) on the market (National Agricultural Statistics Service 2011). Therefore, further investigation should look into the impact of GM technology on smallholder farmers over several years and within different regions.

Chapter 8 - References

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Appendix A - Additional Tables

Table A-1 Comparison of Average Prices of Herbicide, Fertilizer, Seed, and Maize in 2009

	<i>United States</i>	<i>KwaZulu-Natal, South Africa</i>
Atrazine (per gallon)	\$20.80	\$32.78
2, 4-D (per gallon)	\$19.30	\$30.69
Roundup (per gallon)	\$42.80	\$64.10
LAN (per ton)	\$307.00	\$486.00
% Premium paid for GM seed	69%	52%
Maize Price (per bushel May 2010)	\$4.16	\$10.92
<u>Average Yield (bushels/acre)</u>	<u>152.8</u>	<u>26.2</u>

Source: USDA; National Agricultural Statistics Service

Table A-2 Cost Function Regression Results of RR and Non-RR Maize Plots^a

	OLS - Linear RR		OLS - Linear Non-RR		WLS - Quadratic RR		WLS - Quadratic Non-RR	
	Coef.		Coef.		Coef.		Coef.	
<i>Intercept</i>	-208.74		-91.25		16212.80	***	-1944.76	
<i>Labor</i>	161.12	***	119.17	**	-8866.64	***	2687.39	
<i>Fertilizer</i>	375.85	*	149.62		-26490.83	***	16.03	
<i>Herbicide</i>	6.19	***	-2.63		207.00	***	84.57	
<i>Seed</i>	12.22	*	14.43	***	-336.83	*	1768.12	*
<i>Land</i>	312.15	***	450.83	***	-3171.96	**	15.54	*
<i>Land Prep</i>	-1.34	***	-0.30		-119.14	***	0.43	
<i>Output</i>	0.02		0.06	***	0.87	**	-134.89	**
<i>Hlabisa Dummy</i>	-207.56	***	-113.98	***	-226.41	***	185.07	
<i>Labor²</i>					0.56		-2503.30	
<i>Fertilizer²</i>					-11211.56	***	1.09	
<i>Herbicide²</i>					-1.53	***	0.71	
<i>Seed²</i>					-2.32		-402.66	*
<i>Land²</i>					-121.47		-0.01	
<i>Land Prep²</i>					0.04		0.00	**
<i>Output²</i>					0.00		4841.93	
<i>Labor*Fertilizer</i>					17736.90	***	-61.35	
<i>Labor*Herbicide</i>					-60.82	**	30.73	
<i>Labor*Seed</i>					-62.69		-259.04	
<i>Labor*Land</i>					-169.05		-4.36	
<i>Labor*Land Prep</i>					-1.50		-0.19	
<i>Labor*Output</i>					0.03		0.72	
<i>Fertilizer*Herbicide</i>					115.59		-186.23	
<i>Fertilizer*Seed</i>					842.63	***	-1175.12	
<i>Fertilizer*Land</i>					5576.60	**	-17.49	
<i>Fertilizer*Land Prep</i>					227.43	***	-0.45	
<i>Fertilizer*Output</i>					-2.42	***	-0.43	
<i>Herbicide*Seed</i>					-6.89	***	0.00	
<i>Herbicide*Land</i>					-26.52		0.14	
<i>Herbicide*Land Prep</i>					-1.33	***	-0.01	
<i>Herbicide*Output</i>					0.00		10.14	
<i>Seed*Land</i>					6.31		-0.11	
<i>Seed*Land Prep</i>					-0.38		0.01	
<i>Seed*Output</i>					0.07	***	-5.01	
<i>Land*Land Prep</i>					8.52	***	0.37	***
<i>Land*Output</i>					0.16		0.00	
<i>Land Prep*Output</i>					0.00		-1333.02	
N	112		100		112		100	
R-squared	0.85		0.89		0.96		0.99	
Adjusted R-squared	0.83		0.88		0.95		0.98	
Breusch-Pagan	80.77	***	22.44	***	0.46		0.76	
F-value	70.47		89.45		55.81		130.06	

***, **, * indicates significantly different than zero at 1%, 5% and 10% respectively

^aaverage cost is \$343 per maize plot

Figure A-1 Histogram of Total Cost of RR Maize Production (USD)

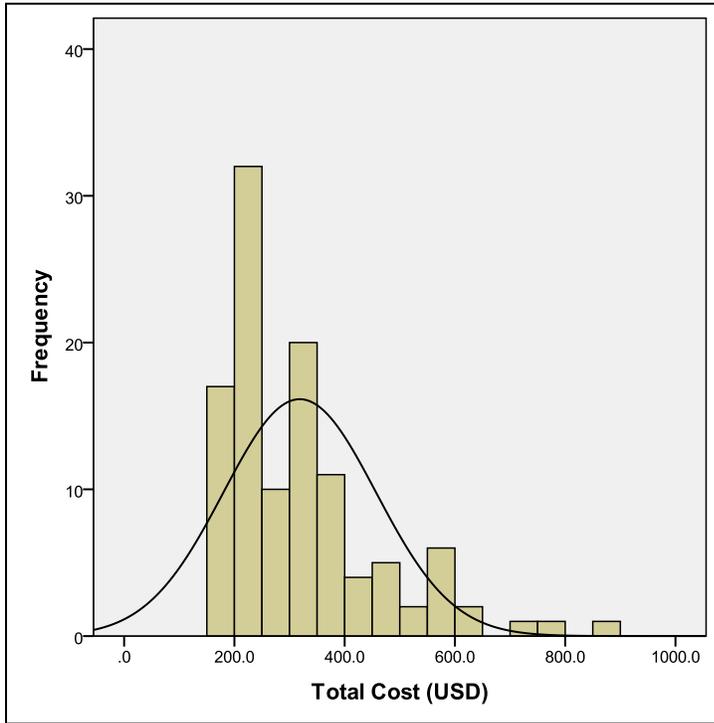


Figure A-2 Histogram of Total Cost of Non-RR Maize Production (USD)

