DETERMINANTS OF ADOPTION OF GENETICALLY MODIFIED MAIZE BY SMALLHOLDERS IN KWAZULU-NATAL, SOUTH AFRICA

by

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Abstract

Previous research on small-scale farmers in KwaZulu-Natal, South Africa indicates that certain genetically modified maize seed types improve production efficiencies and increase net returns (Regier 2012). Yet despite the substantiated advantages, not all farmers have adopted genetically modified maize. The purpose of this research is to identify the determinants of adopting certain types of genetically modified maize over traditional or conventional hybrid maize for 184 small-holders in two villages in KwaZulu-Natal, South Africa. Previous adoption studies use socioeconomic characteristics of the farmer as well as farm-level production characteristics to determine the probability that a farmer will implement an improved agricultural technology. While many studies employ a binomial approach to adoption, this study tests the probability of adopting three different GM varieties—the insect resistant Bt maize, the herbicide tolerant Roundup Ready® maize, and the stacked trait BR maize. Furthermore, the model is enhanced by farmers' open-ended explanations of their perceptions on genetically modified maize and of the major production constraints they face.

Following results from previous adoption studies, this research tests three hypotheses in a three different model structures. The first hypothesis tests whether farmers are more likely to adopt if they have greater financial means to cover higher expected production costs. This is tested by variables measuring off-farm employment and expected production costs. The second hypothesis tests whether farmers with less labor availability are more likely to choose maize with the herbicide tolerant technology, either the Roundup Ready® or stacked BR maize, which reduce the need for weeding. The final hypothesis is whether there are differences in the determinants of adoption that differentiate *GM adopters* into three distinct categories. These hypotheses are tested in three model structures that test the binary probability of adopting GM maize over non-GM, the probabilities of adopting each maize variety separately, and the intensity of adoption.

The first finding is that many non-adopters have greater access to income and are more likely to sell a portion of their yield than are many farmers who adopted, especially in comparison to those who plant RR maize. Also, BR farmers are more likely to report input expenses as a major constraint in their adoption decision. Results for the second hypothesis show that those who planted either RR or BR maize did in fact have less family labor available, used less total labor, and used a greater proportion of family to hired labor. Finally, there are differences in the determinants for geographic site, education, self-sufficiency in maize supply, number of family members working off-farm, and whether households planned to sell any of their maize yields. This indicates that adoption should be considered according to each genetically modified trait.

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Chapter 1 - Introduction of GM maize seed in South Africa

The Republic of South Africa was the first upper middle-income country to grow genetically modified maize and has been the testing ground for potential welfare gains for the rest of Africa and the developing world (Gouse et al. 2005). Starting in 1997, the first genetically modified maize grown was yellow maize, which is primarily used for livestock feed. Then in 2001, South Africa broke new ground by planting genetically modified white maize, the first GM food crop in a developing country (Fukuda-Parr 2007). The potential was great for improved yields and increased revenue for both seed companies and farmers alike. However, the introduction of GM maize was also a great gamble. There was no guarantee that farmers, wary from warnings against genetically modified foods, would purchase the seed. In the bigger picture, it was uncertain that the technology investment would improve the welfare of subsistence farmers and commercial farmers alike.

To date, three types of genetically modified maize are planted in South Africa and sold by a handful of seed companies. The first seed introduced is known as *Bt* maize. It carries a gene that produces a naturally occurring soil bacterium called *Bacillus thuringienisis* that kills maize stalk borers (*Busseola fusca* and *Chilo partellus*) within 72 hours of ingesting the maize. The Bt gene allows farmers to forgo spraying pesticides and prevents yield loss due to the pest, which ranges between 5 and 75 percent each year (Gouse, Pray, Kirsten, and Schimmelpfennig 2005). The second GM trait introduced was herbicide tolerant maize, often referred to as *Roundup Ready*® or *RR.* The herbicide tolerant technology allows farmers to spray the maize pre- and post-emergence and eliminate the need for weeding throughout the growing season (*Monsanto* 2011). Later, stack-gene varieties were introduced, which protect against stalk borers and herbicide damage. The third GM seed variety is thus referred to by a combination of the Bt and RR abbreviations, *BR (Monsanto 2011).* Table 1.1 presents the sources of gene codes and maize hybrids as well as the year of their approval in South Africa.

Table 1.1 Sources of Genes and Hybrids

Category	Source of Gene	Source of Hybrids	Year Gene Approved for Commercial Use	First Year Planting
Bt Yellow Maize	Monsanto	Monsanto	1998	1998
	Monsanto	Pioneer	1998	1999
	Monsanto	Pannar	1998	1999
	Syngenta	Syngenta	2003	2003
	Dow	Pioneer	future	future
Bt White Maize	Monsanto	Monsanto	1998	2001
	Monsanto	Pioneer	1998	2001
	Monsanto	Pannar	1998	2004
RR Yellow Maize	Monsanto	Monsanto	2003	2003
RR White Maize	Monsanto	Monsanto	2003	2003

Source: Gouse, 2005

In the first few years after *Bt* maize was introduced, the initial dissemination was slow and few farmers adopted the genetically modified maize. The book *Gene Revolution* proposes three reasons for this. First, the seed technology was transplanted from other countries and thus was not well adapted to South African soils and production conditions. Secondly, because farmers planted in years the stalk borer pressure was low, the *Bt* technology provided little benefit over traditional and conventional hybrid varieties. Finally, farmers feared that they would not be able to sell their output, as concerns about the safety of GM foods existed in both domestic and foreign markets. South African producers export to many GM-free markets such as Japan, Zimbabwe, Zambia, Malawi, Mauritius, Kenya, and Mozambique, so the concern was legitimate (Fukuda-Parr 2007).

After a few seasons of planting GM maize, these three barriers diminished. Many commercial seed producers incorporated the seed technology into local maize varieties so that the GM traits were better suited to South African soils and weather conditions. Now four main biotechnology companies in South Africa sell genetically modified maize. Pannar, a South Africa-based company, supplies 44 percent of the GM seed in the market. Monsanto bought the local company, Carnia, and supplies 23 percent. The other two multinational companies, Pioneer Hi-Bred and Syngenta, supply 18 and 16 percent of the market, respectively (Fukuda-Parr 2007). Table 1.2 summarizes the main seed types planted in South Africa.

Table 1.2 GM Maize Seed Types Used by Smallholders in South Africa

Category	Seed Name	Source	Variety
Bt	DKC 78-15B	Monsanto	white hybrid GMO
RR	Phb 30D04 R	Pioneer	white hybrid GMO
BR Stacked	DKC 80-40 BR	Monsanto	yellow hybrid GMO
Conventional Hybrid	Pan 6043	Pannar	white hybrid
	Pan 6611	Pannar	white hybrid
	Pan RO 413	Pannar	white hybrid
	CRN 3505	Monsanto	white hybrid
	CRN 3549	Monsanto	white hybrid
Traditional	Zama Star Afrigro		white OPV

Sources: Farmer reports of seed use
South Africa Variety List as Maintained by the Registrar of Plant Improvement

To address the second concern that using Bt holds little advantage over other varieties, the University of Pretoria has conducted research to explain the conditions of profitability for GM maize. One of the major findings is that the profitability of Bt depends on not only pest pressure, but also the weather. In low stalk-borer-pressure years, Bt seed offers little yield advantage over seeds without the technology, other conditions still warrant its use (Gouse et al. 2006). In wetter years with heavier pest pressure, researchers have shown that Bt technology does provide an advantage. They estimate that the African maize stem borer can damage between 5 and 75 percent of an entire maize crop, and South African farmers lose roughly an average of 10 percent of the annual crop to pests (Gouse et al. 2005). Later research indicated that since the initial 1998 season, adopters have increased their revenues over conventional hybrid and traditional varieties by saving on pesticides and by increasing yields (Gouse et al. 2008). To add to the benefit, Bt maize also reduces the need for pesticides and exposure to mycotoxins (Pray, Rheeder, Gouse, et al. 2009). This benefit is reflected in farmers' survey responses indicating that spending more time working in the fields makes them sick or gives them skin rashes. Beyond Bt, researchers estimate that herbicide tolerant maize outperformed conventional maize in terms of increased yield and reduced input costs (Gouse 2008). Because *BR* has not been available for long, there is little research on the profitability of stacked-gene maize locally.

The final concern—the potential difficulty of selling a genetically modified food crop—has also subsided. Since many domestic consumers were neither aware of nor concerned about GM foods, farmers have continued to sell their maize domestically with little change in demand. The premium that exists for exported non-GM maize has been absorbed by commodity trading companies more so than by producers (Fukuda-Parr 2007).

Dualistic Agriculture in South Africa

Because adoption studies are site-specific, understanding the prospective production and social environment is imperative. South Africa is different from other Sub-Saharan countries; consequently, findings from the present study cannot be generalized to other environments. Overall, South Africa is a middle-income country with rich natural resources; strong domestic and foreign trade markets; developed legal, communications, energy, and transport sectors; large urban cities; and well-developed infrastructure (CIA World Factbook 2011). South Africa exports maize, wheat, sugarcane, fruits, vegetables, beef, poultry, mutton, wool, and dairy products (CIA World Factbook 2011). However, as in other developed countries, agriculture in South Africa accounts for only two to three percent of the gross domestic product, much smaller in comparison to the industrial or services sectors. This is common among more developed countries.

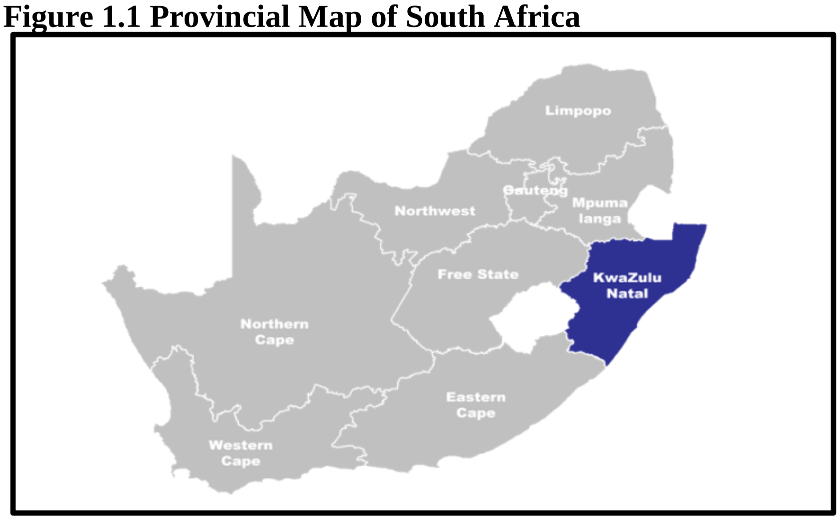
While the preceding description gives a positive overall outlook, the South African socio-economy is highly dualistic, and many South Africans are shut out of modern commercialism that accounts for the majority of agricultural productivity. Many of the poor who live in rural communities grow food for subsistence purposes, and the division in prosperity is mostly along racial lines. Of the total South African population, about 80 percent are black and ten percent are white. The other ten percent is comprised of other minority races (CIA World Factbook 2011). But while whites comprise such a small percentage of the total population, they hold much more land; 46,000 large white farm units hold about 87 percent of the agricultural land. By contrast, more than 240,000 black farms—many of which grow food for home consumption—support more than one million people on the remaining 13 percent of agricultural land (Fukuda-Parr 2007). Many of these subsistence farms are pushed to marginal lands with poor land quality and little rainfall (Organisation for Economic Cooperation and Development Review of Agricultural Policies: South Africa 2011). Though some subsistence farmers plant small plots—generally less than two hectares—of GM maize in KwaZulu-Natal, Mpumalanga, and the Eastern Cape, commercial farmers produce more than ninety percent of South Africa's total maize crop and plant most of the genetically modified maize in South Africa (Gouse et al. 2008).

Switching from conventional hybrid varieties to genetically modified maize affects commercial farmers differently than it does the small-holders who produce mainly for household consumption. Large-scale farms have a different objective and face a much different set of constraints than do subsistence farmers. The interest here is to examine the GM maize adoption decision-making process of the sub-population of small farmers in KwaZulu-Natal.

KwaZulu-Natal - Descriptive Statistics

KwaZulu-Natal is a province on the eastern coast of South Africa, bordered by the Eastern Cape, Free State, and Mpumalanga provinces, and the countries of Swaziland, Mozambique, and Lesotho. KwaZulu-Natal is the second most populated province in the country, with 10,259,230 inhabitants at the most recent count (Statistics South Africa, Community Survey 2007). Figure 1.1 illustrates where KwaZulu-Natal is situated within South Africa.

Figure 1.1 Provincial Map of South Africa



Source: http://www.platinumweekly.co.za/News%20KZN.html

The dual nature of the South African agricultural applies somewhat to the national society as well. The few comparative measures presented in Table 1.3 give only an idea of how KwaZulu-Natal measures against the country average. Characteristic of rural areas, family sizes in KwaZulu-Natal are larger at 4.5 people per household than the national average household size. The percentage of formal dwellings is lower than the national average (Statistics South Africa, Community Survey 2007). It is also important to note the extremely high levels of HIV infection and AIDS in KwaZulu-Natal; the provincial infection rate is considerably higher than the national average, especially among pregnant women (Statistics South Africa, Community Survey 2007). As expected from these numbers, residents of KwaZulu-Natal suffer high mortality rates, lower life expectancy, higher infant mortality, and low population growth rates (CIA World Factbook 2011).

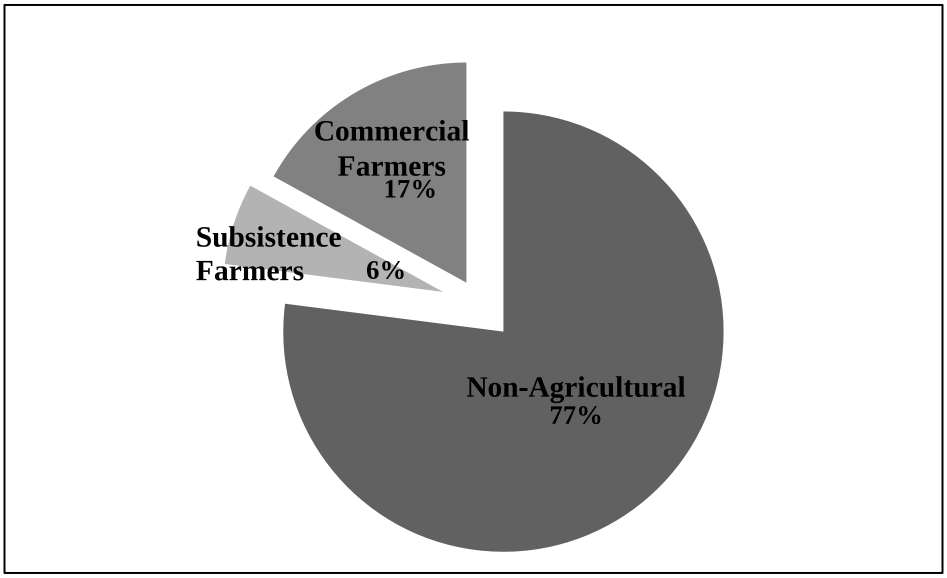
Table 1.3 Household Conditions: Size, Tenureship, HIV Rates

	KwaZul- Natal	*South Africa*
Number of households (2007)	2,234,129	12,500,609
Average household size	4.5 people	3.8 people
Percent living in formal dwellings	60.4%	70.5%
HIV prevalence, total population (2010)	15.8%	18.7%
HIV prevalence, prenatal women (2008)	39.5%	30.2%

Sources: Statistics South Africa: Community Survey, 2007
Avert International HIV & AIDS Charity

Agriculture is vital to the livelihoods of many in KwaZulu-Natal, with almost a quarter of its population participating in crop and livestock production. Agriculturalists are broadly defined in this context as anyone who works formally in the agricultural industry, or consumes or sells home produce (PROVIDE Project 2005). Figure 1.2 shows the portion of the KwaZulu-Natal population considered agriculturalists. Of the 23 percent that work in agriculture, 24 percent of those are subsistence farmers, or six percent of the entire population in the province.   The 24 percent of farmers who qualify as subsistence farmers is higher than the national average of 19 percent (PROVIDE Project 2005).

Figure 1.2 Percentages of KZN Population in Agriculture



Source: PROVIDE Project, 2005

Survey Data

Many of the farmers included in the survey have grown genetically modified maize rather consistently for eight production years, especially in the village of Hlabisa. The farmers in these villages are uncommon among small-holders in South Africa and should be considered a case study rather than a representative sample of small-holder farmers growing genetically modified maize, according to a researcher at the University of Pretoria. Since 2001-2002, researchers have been surveying farmers in both villages, though the sample population has evolved over the years. Researchers took a purposive sample of farmers and tried to maintain the sample group for panel data; however, too many farmers dropped out of the survey. GM seed technology adoption was not yet wide-spread enough for GM adopters to be adequately represented in the survey, so in the 2006-2007 season, farmers in the municipalities of Dumbe and Simdlangetsha were added to the survey frame, and the lead researcher and enumerators purposefully selected adopters and non-adopters based on seed sales lists and enumerators' knowledge of what local farmers were planting. The 2006-2007 sample has been maintained since and was used in the present study's 2009-2010 data. According to the researcher, the stratified sample includes about 80 to 100 percent of the GM adopters in the area, which allows the GM subgroup to be adequately represented in the sample population (Gouse 2012).

This study's 2009/10 survey asked farmers in KwaZulu-Natal, South Africa, a series of open-ended questions that evoked an unsolicited view of their production performance and the obstacles they faced. The survey prompted farmers to comment freely on, for example, why they chose a certain seed, the reasons they may not have been able to purchase their first choice, and production constraints such as labor requirements and availability. From these responses, it was possible to extract farmers' sentiments and code them into data that could be analyzed.

Research Purpose

Facing low agricultural productivity, high food prices, and scarce labor, the plight of small-holders in KwaZulu-Natal could improve with more efficient farming practices. Recent research using the same data set indicates that using Round-Up Ready maize varieties lowers labor requirement and costs, reducing the total cost of maize production and delivering higher net returns (Regier 2012). Further research in the region suggests that even after paying higher prices for the GM seed each year, adopters have an advantage in that they saved costs on inputs and increased yield per kilogram of seed planted (Gouse 2008). On average, about 75 percent of the maize grown is kept for household consumption or for animal feed, so increasing yield without increasing production costs will have two positive effects: it can reduce the dependence on purchased maize and maize meal; and provide farmers with surplus maize to sell for extra income (Baiphethi and Jacobs 2009).

If genetically modified maize increases input efficiency, yield, and net returns as research suggests, then all farmers should be expected to adopt GM maize (Regier 2012). Two possibilities have been proposed for why they have not. First, farmers may derive higher utility from planting traditional or conventional hybrids, either in order to follow with Zulu tradition, because they fear consuming GM maize, or that they will not be able to sell it. Secondly, farmers may face input constraints. For example, they may lack money or credit lines to purchase the more expensive seed or the associated inputs, they may not have enough land for test plots, or perhaps the seed was unavailable from their normal purchase venues. The addition of these *stated* perceptions and constraints to the classic adoption models captures a part of the *unobservable components* that affect farmers' utility.

The primary goal of this research, then, is to find the determinants of adoption of genetically modified maize that pertain specifically to subsistence farmers in KwaZulu-Natal, South Africa. The open-ended responses contribute to the discussion on attitudes toward and perceptions of genetically modified maize, but they can be further incorporated into the discrete choice model to estimate likelihoods of adoption.

Initial Hypotheses

Findings from previous studies motivate hypotheses that can be studied through descriptive statistics, explored in farmers' narratives, and tested in an econometric model. The first hypothesis is that farmers are more likely to adopt if they have greater off-farm income to cover higher expected production costs. Almost all adoption studies include some indication of financial well-being—off-farm income, full-time equivalent of household members working off-farm, remittances, net revenue from crop and livestock sales, savings or credit availability, and/or government pension. The variables used in this research measure off-farm employment and expected production costs. These serve as proxies for a farm household's ability to overcome the input cost constraint. Farmers are not concerned merely about the higher cost of GM maize seed as a one-time expense. Due to patent licenses, GM maize cannot be replanted from the previous year's seed, and farmers must purchase seed each year (Mueller 2004). Thus, farmers must have the financial means to purchase GM seed and the associated inputs year after year.

The second hypothesis is that farmers with labor constraints will adopt genetically modified varieties as a labor-saving technology. The labor force in KwaZulu-Natal is severely limited, so hired labor is scarce and expensive. An estimated 40 percent of the labor market is infected with HIV or AIDS, the highest HIV/AIDS infection rate in South Africa (Gouse et al. 2008). Most farmers surveyed responded that weeding was the worst task because it required so much time and spending time in the maize stalks caused rashes and sickness or made them tired. Fortunately, previous reports from South African farmers indicate that herbicide tolerant maize can reduce labor use (per unit of output) by up to fifty percent (Gouse et al. 2006). Subsequent benefits of the labor-saving technology may also include the following: reducing male family labor may allow more off-farm employment and income, and reducing child labor would allow children to attend school.

The third hypothesis is whether a "typology" of adopters can be formed from the model results. To this point, farmers have typically been referred to as "adopters" or "non-adopters." This research will first categorize farmers by seed type choice— non-GM, Bt, RR, and BR—

within the model, but will also test for differences in the intensity of adoption—non-adopters, partial adopters, and full adopters. Already it is hypothesized that "adopters" will have higher incomes and fewer labor-hiring options. However, crucial differences in the socio-economic traits or production attributes may set the three adopter types apart from each other and from those who plant only non-GM types. This final observation also uses elements of farmer perception to search for differences in other factors that induce a farmer to plant GM maize. If no significant differences among the three types of GM famers exist, then model results would substantiate previous research that assumes "adopters" share similar socio-economic and production-decision traits.

Chapter 2 - Literature Review

Adoption models have been used throughout the past three decades to describe farmers' decision making process, especially in light of emerging agricultural technologies. It is imperative to examine the variables commonly included in adoption models in order to advance the existing body of knowledge. Variables included in adoption models are generally characteristics of the farm, of the farmer, or of the attributes of each seed type, all of which are known to the farmer before making the adoption decision. Various studies have focused on different elements of the decision process and its constraints.

Adoption Model Theory

Farm Size

Farm size is one of the most frequently included variables in adoption studies for several well-founded reasons. Many adoption studies assume that if relative risk decreases as farm size increases, then the likelihood of adoption generally increases (Just and Zilberman 1983; Feder 1980). Some research finds a critical size threshold, under which farmers will not adopt (Feder and Umali 1993; Just et al. 1980). However, the roles of farm size and risk aversion are complex. The relationship between farm size and risk level is further dependent upon factors such as fixed costs, human capital, credit constraints, labor requirements, and tenurial arrangements (Feder, Just, and Zilberman 1982). Empirical studies, such as that by Floyd et al. (1992), suggest that lack of land negatively affects whether farmers will diversify their crop mix and adopt field crop, horticulture, livestock, and forestry technologies. Thus, the effects of farm size must be tested empirically in each case.

Education and Information Sources

Both education and experience in farming are shown to positively influence the likelihood of adoption, as they help farmers to adjust to the changes required for each new agricultural technology (Fernandez-Cornejo, Daberkow, and McBride 2001). Farmers with higher educations or greater access to agronomic information through extension agents or seed suppliers, for example, tend to adopt more quickly, allocate land more efficiently, and exhibit higher farm productivity (Feder et al. 1982). Education and improved information sources not only increase the probability of early adoption, but also reduce costs associated with adoption through more efficient farming practices (Wozniak 1987).

The age of the farmer is sometimes used to measure the "life cycle" of a farming career, which captures elements of human capital and risk. Older farmers tend to be less educated than younger farmers, more risk averse, and have shorter time horizons over which returns to investment can be realized, and thus are less likely to adopt (Fernandez-Cornejo 2002). While the effect is non-linear, most empirical studies report a negative correlation between age and the likelihood of adoption (Diagne and Demont 2007; Shiferaw et al. 2008; Fernandez-Corenjo, 2002).

Income Sources and Credit

Credit and off-farm income also play a role in a farmer's decision to adopt a new technology, especially if the new technology requires higher fixed costs (Feder 1982). Membership in credit clubs was found to relieve cash constraints on lumpy investments and increase the probability of adopting (Smale, Just, and Leathers 1994; Smale, Heisey, and Leathers 1995). However, credit availability is less crucial for capital that does not require great initial investment or for variable input costs (Feder et al. 1982). One caution when including credit availability is to note whether the farmer has *ever received* credit, as opposed to whether the farmer received credit *during the production season in question.* In an emerging credit market, the lack of credit may reflect a bad year and the farmer may have benefitted from credit in years prior (Doss 2003). Dummy variables for savings accounts are not included in adoption models because available financial services are not necessarily an indicator of credit or cash flow. In general, though, studies show that available credit—whether in the production season or prior—increases the likelihood of adopting high-yielding varieties (Feder 1993).

Farmers often offset increased farm expenses through off-farm income. This added income alleviates input cost constraints and also allows farmers to adopt higher-risk technologies that may otherwise endanger their required subsistence level (Feder et al. 1982). In addition to wage employment, off-farm income can also be attained through remittances or through government pensions. From any source, the off-farm income variable is most often positively correlated with the adoption decision.

Labor Availability

The labor available from either family or hired labor, relative to the labor requirement for each seed technology, likewise affects farmers' choice to adopt. Traditionally, agricultural households employ family members to work on the farm, so family (on-farm) labor availability greatly impacts the adoption decision. This is most often measured by the number of people living in the household, where household size positively influences the adoption decision (Diagne and Demont 2007). The total household size can be misleading, though, because not all family members necessarily work on the farm. Household labor should account only for the number of able workers, often measured as a dependency ratio. Off-farm employment of household members may also affect the adoption decision as it reduces labor availability. Off-farm employment would compete for managerial time and discourage labor-intensive technologies, and at the same time, it may be an incentive for labor-saving technologies (Fernandez-Cornejo 2002).

The availability and affordability of hired labor also affect the adoption decision. Depending on the labor requirement of the agricultural technology in question and the cost of labor, the effect on adoption plays out in one of two ways. Constrained labor markets increase the adoption of labor-*saving* technologies and decrease the adoption probability of labor-*intensive* technologies. In the case of incomplete labor markets or labor shortages, labor availability is unknown and is one of the major constraints during peak-season activities such as planting and harvesting (Feder, Just, and Zilberman 1982). When constrained labor markets make hired labor exceptionally expensive, labor-saving technologies likely become more attractive to farmers (Fernandez-Cornejo 2002). Conversely, a sufficient supply of relatively inexpensive hired labor positively affects a farmer's decision to adopt certain labor-intensive technologies (Doss 2003).

Market Constraints

Both input and product market constraints hinder the adoption decision. A farmer cannot adopt a certain innovation if it is not available in the input market. Likewise, farmers are less likely to adopt if the product is not marketable. Thus, it is rational to include market constraints in adoption models (Feder 1982; Fernandez-Cornejo 2002; Smale et al. 1994; Smale et al. 1995). Market constraints exist for not only the technology itself, but also the complementary inputs, such as fertilizer or herbicide. Market constraints can be measured as a binary variable—available or unavailable—or as a continuous measure of the amount of each input used. One particular study shows that imperfect markets create estimate bias, in that social returns are overestimated when innovations reduce the elasticity of the farm supply curve (Sundig et al. 2001).

Empirical Adoption Models

Classic Adoption Models

One of the first and most influential studies on adoption theory examined how farm size and risk aversion affect technology adoption decisions (Feder 1980). The study presented questions related to portfolio selection under uncertainty and credit constraints. It further provided equations and proofs for the optimal level of fertilizer for the new technology, the optimal land allocation, and implications of limited credit availability under varying degrees of risk. These questions were tested by maximizing expected utility of farms of various land sizes, first measuring utility under the traditional crop, and then under the modern crop. It found that the optimal fertilizer per acre rate is independent of risk aversion and farm size. However, the optimal fertilizer rate generally increased as the price of the modern crop increases. Next, it found that the land allocated to the modern crop decreases with increased risk aversion. Finally, for farmers with a binding credit constraint, the degree of uncertainty decreased the optimal land allocated to the modern crop, increased the optimal rate of fertilizer per acre, and decreased the total yield of the modern crop (Feder 1980).

Just and Zilberman followed with a study that more specifically looks at farm size as it relates to the adoption of new technologies in developing countries (Just and Zilberman 1983). Their rationale for studying the farm size effect was that fixed costs discourage adoption. In addition to farm size, they accounted for inter-farm variation and wealth, which also aid in determining risk preference. There was no empirical estimation in the study; instead, they maximized profit in net returns per hectare, and maximize expected utility for risk-averse farmers. They proposed that if the modern input is risk-increasing, larger farms will use less of the modern input per acre than will smaller farms, assuming relative risk aversion is decreasing. Second, if there is constant relative risk aversion, the amount of land allocated to the modern crop will be proportionate to farm size. Third, they report that if relative risk aversion is increasing, the relative proportion of land under the modern crop will decrease. Additionally, they asserted that there is a critical farm size under which farmers will not adopt if there are associated fixed costs or if relative risk aversion increases. They concluded that risk attitudes and the stochastic relationship of returns per hectare determine how important farm size is in the adoption decision (Just and Zilberman 1983).

Smale, Just, and Leathers (1994) built an empirical adoption model to find the optimal land allocation to high-yielding variety of maize (Smale et al. 1994). The studied tests four theories—safety first, portfolio selection, dynamic adoption, and incomplete markets—both individually and simultaneously for validity. The researchers surveyed 420 small-scale farms in Malawi during the 1989-90 production season and then use Heckman's two-step procedure to test nested models of simultaneous equations. The explanatory variables used to test the theories included fertilizer application rate for each type, a penalty for producing below subsistence level, the farmers' information set, expected yield, and a regional dummy variable. The likelihood ratio tests in the individual and combined approaches indicated that each theory is valid on its own but that the theories jointly give a better estimation. They reinforced this by explaining that "because explanations are not mutually exclusive, a finding that risk aversion may be a factor affecting adoption decisions does not eliminate the possibility that input fixity is also a factor, and vice versa" (Smale et al. 1994).

The following year, Smale and colleagues tested the same four theories again using data from the Malawi farmers and the same explanatory variables, but instead employed a simultaneous choice model using a tobit regression (Smale et al. 1995). In addition to the discrete adoption choice, the tobit model also revealed information on land allocation decisions and input use intensity. Ultimately, Smale concluded that subsistence requirements motivate farmers to plant traditional seeds rather than adopt modern varieties. The greater the survival strategy, the less likely they are to stray from traditional seeds. Also, the adoption model indicated a strong correlation with credit club membership and input availability but finds no significant correlation with input-output price ratios and cash availability. Furthermore, they concluded that because the subsistence crops were consumed at home rather than sold on the market, there were not price incentives for farmers to respond to, and as such, supply was relatively elastic (Smale et al. 1995).

To this point, all of the literature discussed has examined adoption decisions in small-scale agriculture, though some theoretical information can be taken from empirical studies in large-scale agricultural as well. A study released in 2012 used data from the USDA to 1) estimate the factors that influence the adoption of herbicide tolerant soybeans and corn, insect resistant corn, and precision agriculture in the United States and 2) contrast the relative factors for the four technologies with an emphasis on farm size (Fernandez-Cornejo, Daberkow, and McBride 2001). The study randomly selected farmers from the USDA's 1998 Agricultural Resource Management Study and included the following explanatory variables: farm size, farmer risk attitudes, education level of household head, experience, off-farm employment, land tenure arrangement, credit reserves, farmland typology, whether farmer uses contracting, the degree of pest infestation, and a regional dummy variable. This information was then tested in a two-limit tobit model, with each of the four technologies estimated individually. The tobit model allowed for an estimation of not only the influence of the explanatory of variable on the probability of adoption, but also the intensity of adoption. In this case, three possible scenarios can be gleaned from the tobit model: first, how probability of adoption changes among non-users of the technology (that is, the probability that a farmer will adopt for the first time ever); second, how probable it is that the proportion of land will change to the new technology among current users; and finally, how responsive the probability of having all acreage under the particular technology is to changes in farm size.

The study reported several findings. First, the adoption of herbicide tolerant soybeans was invariant to farm size because they are easily incorporated into current practices without much human or financial capital. Secondly, precision agriculture was more likely to occur on larger farms because farmers can lower unit costs by spreading fixed costs over larger area. Third, adoption of herbicide tolerant corn was most responsive to size in the initial innovation stage, but size becomes less important as diffusion becomes more wide-spread. Fourth, because stalk borer infestation varies by region, the benefit from the Bt trait was difficult to calculate across locations. Also, the only variable that was positively correlated with all technologies was contracting, because it is associated with price risk management. Finally, the education variable increased the likelihood of planting herbicide and insecticide tolerant corn and precision agriculture techniques, where experience in farming increased the adoption of herbicide tolerant corn and soybeans. This highlighted the fact that education and experience influence adoption rates in different ways (Fernandez-Cornejo et al. 2001).

Market Constraints

Diagne and Demont assert that traditional models fall short in that they do not consider whether a farmer is actually aware of the technology in question because it is not readily available on the market (Diagne and Demont 2007). Their general remark is that *non-exposure bias* occurs in models that do not account for technology awareness or availability, and that the best these models do is show the joint probability of exposure and adoption. Measuring the adoption rate among a population that includes non-exposed farmers will underestimate adoption rates, and studies should only measure exposed farmers. They tested these ideas using data from 1,500 farmers in Cote d'Ivoire and included the following explanatory variables: dummy variable for exposure, the number of varieties known in the village, contact with extension agencies, involvement in participatory variety selection (PVS) programs, whether the farmer practices upland rice cultivation, log of farm size, household size, age and gender of household head, off-farm employment, and a dummy variable for forest zone. They concluded that correcting for non-exposure bias provides more reliable results and that surveys should include an explicit question about awareness of the technology in question (Diagne and Demont 2007).

A more recent adoption model incorporated a constraint that captures the effect of an incomplete seed supply market. Shiferaw and his colleagues tested this constraint in an adoption model using data from 240 pigeon pea farmers in northern Tanzania. This study used the double hurdle model in order to account for farmers that had positive desired demand but were constrained by limited seed access and found market access to be the greatest determinant in the adoption decision. They further asserted that imperfections in labor, credit, land and input markets, as well as access to information, and availability of the technology are critical factors to be measured in future studies. The explanatory variables included are household wealth and assets, gender and education level of household head, participation in local variety selection groups, whether the household has a television, radio, or telephone (to measure information channels), saved seed effects, experiences through past involvement in seed exchanges, and transaction costs from transportation. The results of the estimation showed that the following variables are significantly correlated with adoption: involvement in PVS, initial amount of seed received in the past, transportation costs, and assets (Shiferaw, Kebede, and You 2008).

Farmer Perceptions of Technology Attributes

Farmers decide whether to adopt improved crop varieties based on not only a promised yield increase, but also other production and consumption attributes (Dalton 2004). Based on a survey of small-holders in western Ivory Coast, the implicit prices for technology and consumption attributes were derived using a hedonic price model. After farmers grew the new varieties, their stated willingness to pay was set as the dependent variable within the hedonic model. The hedonic model was then divided into production technology traits and consumption traits, which are tested in input characteristic models (ICM) and consumer goods characteristics models (CGCM), respectively. The results of the study showed that two of the four production attributes were significant, as were three of the eight consumption attributes. Yield, however, was not a significant factor. These findings imply that yield should not be the sole attribute determining which new varieties are considered valuable. Instead, researchers must identify the variety characteristics that farmers value in order to create and disseminate seed technologies that are desirable to farmers (Dalton 2004).

Using a study of rice farmers in Sierra Leone, researchers incorporated farmer perception of modern crops with the traditional explanatory variables to see how perception influences adoption decisions (Adesina and Zinnah 1993). More specifically, they measured the proportion of the total varietal portfolio of seed planted to traditional and modern varieties based on a vector of farm and farmer characteristics and then added a vector of farmer perceptions to a two-limit tobit regression model. The variables that captured farmer perceptions included information on taste preferences between traditional and modern varieties, yield, ease of cooking, tillering capacity, and ease of threshing. The author hypothesized farm size, extension, and experiences to be positively correlated with adoption, and age to be negatively correlated. All variables in the vector of farmer perception were positively correlated with adoption of modern varieties. The big picture result is that farmer perception plays a more significant role in determining adoption decisions than do the more traditional variables measured in adoption models (Adesina and Zinnah 1993).

Answers to open-ended questions can give great insight into farmers' perceptions of a technology relative to that of the current technology, even without a model to measure the quantitative effects. A study among rice farmers in India revealed the importance of farmer perception to agronomic research (Kshirsagar, Pandey, and Bellon 2002). In the study, farmers planted multiple traditional varieties in order to match varietal characteristics with different growing conditions, to reduce yield risk, and to avoid labor bottlenecks. Due to the limited adoption rate, Kshirsagar and colleagues could not measure the adoption determinants econometrically, so instead, they used open-ended questions to elicit farmers' perceptions of new, improved varieties compared to traditional. Specifically, farmers commented on market value traits, food consumption traits, and non-food production traits. They further offered their perception of the rice varieties' stress tolerance, the labor, input, and management requirements, and economic returns. They concluded that the adoption rate was low because, despite higher yields and profits, farmers perceived the improved varieties as inferior due to higher input costs and management requirements. Farmers listed cooking and visual qualities as most important over production traits (Kshirsagar, Pandey, and Bellon 2002). Had agronomic researchers known the demand for these traits, the improved varieties may have been more successful, consistent with work by Dalton (2004).

Chapter 3 – Data Overview

The following section provides descriptive information and a detailed overview of the farmers and their production environment. The initial information describes the farmers in a general context, following the socioeconomic variables that are commonly found in adoption models. This section also provides descriptive data regarding the first two hypotheses: that of farmer income, sourced through off-farm income and farm income, as well as family and hired labor.

Table 3.1 shows the varieties of maize that the surveyed farmers planted on the selected plots by region. There is a significant difference between the proportions of genetically modified maize planted between the two, where 83.5 percent of farmers in Hlabisa planted a GM variety and only 52.9 percent of farmers in Simdlangetsha did. The Roundup Ready seed was most popular in Hlabisa, but in Simdlangetsha, farmers opted most often to plant hybrid or traditional variety. The majority of farmers in Hlabisa—73 percent—planted only one variety, whereas most in Simdlangetsha—66 percent—planted more than one.

Table 3.1 Maize Seed Types Planted by Region

	Hlabisa		Simdlangetsha		Total
Selected Plot	*N*	%	*N*	%	*N*
Bt	1	1.0%	17	19.5%	18
RR	66	68.0%	14	16.1%	80
BR	14	14.4%	15	17.2%	29
non-GM	16	16.5%	41	47.1%	57
Total	97	100.0%	87	100.0%	184
	# varieties	frequency	# varieties	frequency	Total
Number of seed types planted in 2009/10	*1*	71	*1*	30	101
	2	23	*2*	46	69
	3	3	*3*	11	14
	Total	97	*Total*	87	184

The household was used as the level of analysis, but many questions are referenced toward one specific plot. Over the course of the four surveys collected during the 2009-2010 production year, farmers were asked to report on the different maize varieties they were growing and then to identify one selected plot for more specific questions. For the most part, if a farmer had planted a genetically modified seed on one plot and then either conventional hybrid or traditional seed on other plots, he or she listed the GM plot as the selected plot. Farmers also were differentiated by the intensity of adoption. Farmers who planted only traditional or conventional hybrids were classified as *non-GM*, while those who planted a plot of GM and a plot of non-GM are considered *partial adopters*, and those who planted only GM maize are *full adopters*.

Descriptive Statistics

The variables often included in adoption studies describe general aspects of the farmer as well as farm-level characteristics. The following descriptive statistics give a general idea of the average farmer in KwaZulu-Natal, but more importantly, they describe differences between farmers who plant the different maize varieties.

Differences in mean values of farmer and farm characteristics are apparent by inspection of contingency tables, but Pearson chi-square statistics will determine if the means between groups are significantly different. The main goal is to test whether any significant difference between groups of farmers exists. Special attention is given to variables that may answer the two hypotheses presented earlier: first, farmers are more likely to adopt if they have greater off-farm income to cover higher expected production costs and secondly, farmers with labor constraints will adopt genetically modified varieties as a labor-saving technology

Farmer Characteristics – by Selected Plot Seed Type

Table 3.2 gives a description of the variables common to many adoption studies which characterize the farm household heads, states the expected sign on the marginal effects coefficient if they are available from previous studies, and shows the most common response from the farmers in the survey. Because many of the variables are categorical, Table 3.2 describes how the variables were coded. Pearson chi-square test statistics that show the level of significant differences among categories of farmers who planted the various seed types are presented in Table 3.3.

Table 3.2 Head of Household Characteristics

Variable	Expected Sign	Description	N	Most Common Response
Site		0=Hlabisa, 1=Simdlangetsha	184	Hlabisa
Age	-	1=26-35, 2=36-45, 3=46-55, 4=56-59, 5=60-65, 6= >65	184	60-65
Highest Education Attained	+	1=no education, 2=primary, 3=grade 11, 4=grade 12, 5=diploma or higher	184	primary school
Gender		0=female, 1=male	184	female
Family Size	+	total number of people in family	184	7

The five variables were then cross tabulated by the four selected-plot seed categories, which are summarized in Table 3.3. In Hlabisa, more farmers planted non-GM or BR maize than they did Bt or BR. In Simdlangetsha, more farmers planted Bt and RR varieties than they did non-GM or BR. Interestingly, 17 of the 18 farmers who planted Bt maize live in Simdlangetsha. Farmers who planted RR maize tended to be a bit older on average than farmers of the other three maize types. On average, farmers in all four groups had only a primary education. However, further investigation reveals that farmers in the BR category have a slightly higher average education than the others, and those who planted RR maize have the lowest primary education. There were no significant differences in the gender and family size variables. There tended to be more female decision makers, and households in all categories averaged between six and seven family members.

Table 3.3 Average Household Characteristics by Seed Type

	Site	Age	Education	Gender	Family Size
	(% Hlabisa)	(mean)	(mean)	(% female)	(mean)
Bt	5.6	60-65	primary	50	6.33
RR	82.5	>65	primary	35	6.26
BR	48.3	60-65	primary	41.4	5.93
non-GM	28.1	60-65	primary	40.2	6.16

n=184

**=P<0.10, **=P<0.05, ***=P<0.01*

Food self-sufficiency is occasionally included as a positive factor in the adoption decision, as indicated in studies by Smale and colleagues (1994 and 1995) and Floyd et al. (1999). The cross-tabulation in Table 3.4 below indicates that 61 percent of those who have not yet adopted supply 50 percent or less from their own production. The other results follow the same correlation pattern, where the majority of adopters supply more than 75 percent of their own food supply. Specifically, BR farmers have the greatest self-sufficiency measure with 89 percent of BR farmers supplying 75 percent or more of their maize consumption, while 83 percent of Bt and 71 percent of RR farmers grow at least 75 percent of their maize supply. The opposite scenario reiterates this idea, where the highest percentage of farmers who purchased extra maize were those who planted RR or BR maize, and those who planted non-GM comprised the highest percentage altogether. Both measures of self-sufficiency show significant differences among seed type categories at the one percent level (P<0.01).

Table 3.4 Food Sources and Sufficiency

Percentage of household in each category	Bt	RR	BR	non-GM
Percentage consumed of own maize (as opposed to purchased)***				
Less that 20% own maize	0	7.5	0	15.8
About 25% own maize	0	6.3	0	19.3
About 50% own maize	16.7	15	10.7	26.3
About 75% own maize	22.2	52.5	35.7	12.3
More than 90% own maize	61.1	18.8	53.6	26.3
Total	100	100	100	100
Did household buy extra maize in last six months?***				
% of Households (1=yes)	44.4	16.3	10.3	49.1

n=184

**=P<0.10, **=P<0.05, ***=P<0.01*

Many farmers' willingness to adopt a beneficial seed technology is constrained by income and credit constraints, as illustrated by numerous studies. A farmer's ability to overcome the cost constraint can be illustrated in a number of ways: as a proxy of family members earning off-farm income, dummy variables that represent whether a household receives remittances or government pension, or as a cumulative value of the household's total income and assets. While none of these income sources guarantee that the seed cost constraint is fully relaxed, the results imply that a farmer has at least some income which potentially may be used for seed costs and associated inputs.

The number of family members who work off-farm within each household indicates that there is at least some non-farm income available, but also indicates that there may be fewer family members to work in the maize plots. These two factors lead to the assumption that families with more off-farm employment would adopt genetically modified seed because they have more cash available and because the labor-saving technologies alleviate on-farm labor constraints. Table 3.5 cross-tabulates the number of off-farm employment by seed type to see whether those who planted a GM variety have more family members working off-farm. The overall difference in off-farm employment between groups is significant (P<0.10). Farmers who planted the stacked BR variety have more family members working off-farm, where 24.1 percent have two or more people earning off-farm income. Those who planted RR maize have the lowest number of family members working off-farm, where 45 percent of those households had no family members working off farm.

Table 3.5 Full-time Off-Farm Employment by Seed Category

(% of respondents within category)		Bt	RR	BR	non-GM
*Number of family members working off-farm***	*0*	16.7	45	20.7	35.1
	1	66.7	41.3	55.2	47.4
	2	11.1	12.5	13.8	17.5
	3	5.6	1.3	10.3	0
	Total	100	100	100	100

n=184

**=P<0.10, **=P<0.05, ***=P<0.01*

Most farm households have non-farm income in addition to farm earnings. Table 3.6 shows that this is the case for the farmers in KZN, who receive income from off-farm employment, remittances, and government payments. The first result for off-farm income is the summed percentage of households that have one or more members working off-farm, which is compared within seed category to other sources of moneys. Among Bt farmers, off-farm employment is the most common source of income, followed by child grants and remittances and old-age pension. The majority of *all* farmers receive the South African government's old-age pension. However, the category with the highest rate of old-age pension is RR farmers, and they also have the lowest percentages of off-farm income and child grants, as shown in Table 3.3. BR farmers, on the other hand, receive higher percentages of off-farm income and remittances but receive less government grant money. Non-GM farmers, as expected, do not hold the highest percentage of any source of income. The categorical Pearson's chi-square statistic reveals that there are significant differences in three of the four income sources but also shows no significant difference in the percentage of households that received remittances. Many studies include a dummy variable for credit availability. For comprehensiveness, the table includes the percentage of households that have an active bank account and *stokvel*, an informal, cooperative savings account. There are significant differences between groups at the 5% level (P<0.05). However, these do not necessarily serve as credit lines from which farmers can borrow money to purchase seed.

Table 3.6 Off-Farm Income, Remittances, & Pensions

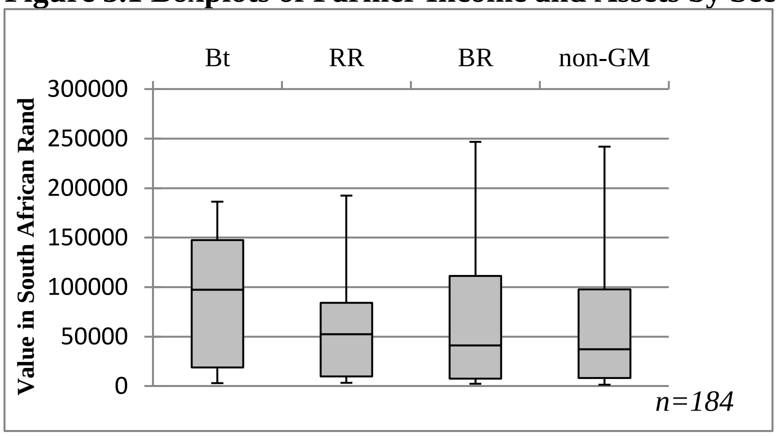
(% of respondents within category)	Bt	RR	BR	non-GM
*Off-farm income***	83.3	54.4	82.1	64.9
Remittances	66.7	62.5	82.8	52.6
*Child Grant****	75	43.4	64.3	64.3
*Old-Age Pension****	72.2	88.8	71.4	61.7
*Bank Account***	94.4	65	82.8	73.7
*Stokvel (informal savings)***	72.2	85	79.3	63.2

n=184
**=P<0.10, **=P<0.05, ***=P<0.01*

Those surveyed also reported the *value* of total household income, assets, and expenditures. Total income and assets are presented as boxplots in Figure 3.1. The black box represents the mean total income and asset value within each seed type category. The bottom half of the grey box represents the range of income and assets of 25 to 75 percent of farmers for each category, and the whiskers represent the ranges of income and assets for the bottom 0 to 25 percent and the top 75 to 100 percent of farmers. The values are calculated as a sum of total reported income (from crop and livestock sales and off-farm income), plus the total value of farm assets (machinery, livestock, etc.) and non-farm assets (televisions, cell-phones, vehicles, etc.). The major household expenses were then subtracted to give a cross-sectional measure of household wealth. Land value and remittance values could not be included in the measure. Farmers reported the total size of their farms, but the value of the land is not given. The average land size varies between one and three hectares and will be elaborated on in a subsequent section. Also, farmers reported the number of times they received remittances during the survey period, but the survey asked respondents to circle only the range of money that described their remittance value. The relevance of remittance value is briefly explored after the income and wealth section.

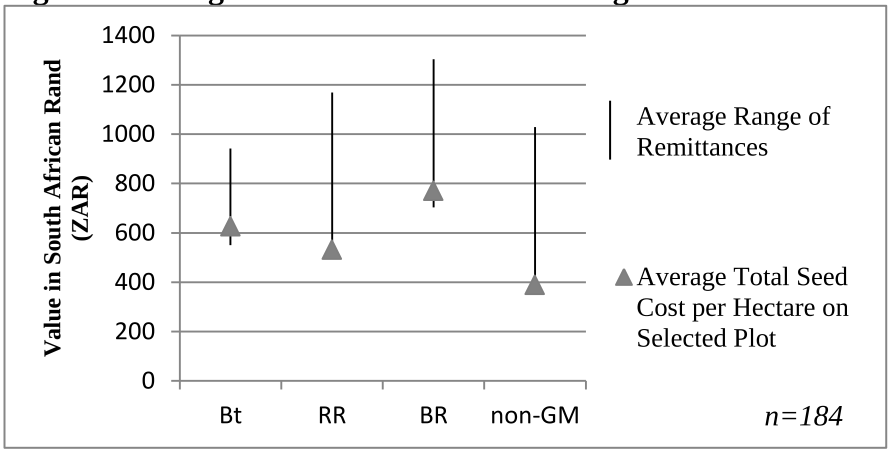
At first glance, the income and asset report in Figure 3.1 is somewhat surprising. Looking only at mean values of wealth, Bt farmers have the greatest mean “wealth,” followed by *BR* farmers, *non-GM,* and then *RR.* However, BR and non-GM farmers have higher maximum values and a broader distribution of values of ‘wealth’. The hypothesis that farmers with greater income and assets plant genetically modified maize does not appear to be satisfied by this table, as farmers who planted *RR* maize reported less income and assets than other farmers.

Figure 3.1 Boxplots of Farmer Income and Assets by Seed Category



Many farm households reported that they received money from family members who had moved away for work and sent back a portion of their income back as remittances. To conceptualize whether remittances account for a significant portion of income in the adoption decision, the average range of remittances are set against the average seed cost per hectare. Because the survey asked the farmer to circle the range that fit their remittance value, it was impossible to calculate an average remittance value. Instead, the lower ends and upper ends of each response were averaged for the final average range of remittance values in Figure 3.2. Also presented on the remittance ranges is the average seed cost for each seed category, shown by the small triangle. What is immediately evident is that in each case, farmers could purchase their seed with remittance money. By this argument, remittances are a very important part of the farmers’ incomes and could be considered a driving force of much of modern development. Even if farmers did not reserve remittance money specifically for their seed purchases, the average remittances are sufficient to cover average seed costs.

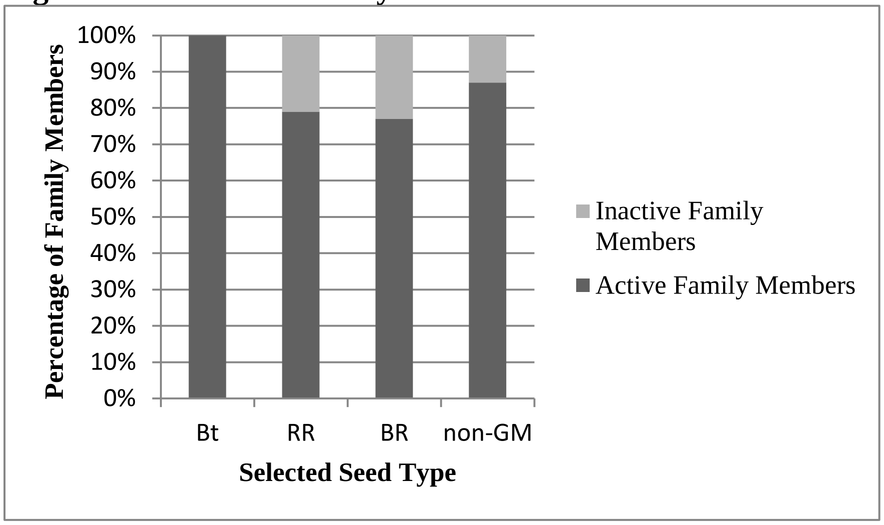
Figure 3.2 Ranges of Remittances and Average Seed Costs



While *off-farm* labor provides income vital to the adoption decision, perhaps even more crucial is the availability of *on-farm* labor. Tables 3.3 and 3.4 give measures that indicate the labor available from household members as well as the labor supplied by hired workers. Technically, the adoption decision should be modeled only by factors known a priori to the adoption decision, and data on actual labor use was collected after the adoption decision. However, the assumption is that farmers know how much family labor is available, the price of hired labor and the amount that they can afford, as well as the labor requirements for each maize seed type. Thus, labor availability presented in Figure 3.3 and the labor use by source in Figure 3.4 are used as proxies for "expected" labor availability and usage.

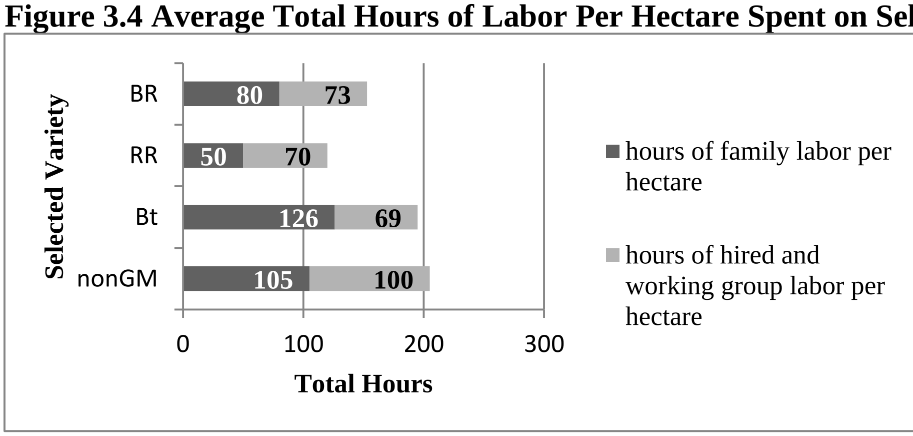
Rather than using the conventional measure to produce a dependency ratio, the ratio of family members active and inactive in maize production is an alternative method. Most frequently, the dependency ratio is calculated as the number of children and elderly divided by the number of adults, which is defined as those between the ages of 15 and 64. Figure 3.3 shows that on farms that planted Bt, all family members helped in some way with maize production. The data may have included extended family members who did not live in the household but who came to help plant or harvest. Farmers who planted BR maize had the largest percentage of dependents, followed closely by RR farmers and non-GM farmers. While Figure 3.3 illustrates the average number of *workers*, Figure 3.4 shows the average number of *hours* worked on the selected maize plot.

Figure 3.3 Portion of Family Members Active in Maize Production



The information in Figure 3.4 substantiates previous research that shows that Roundup Ready technology reduces total labor requirements, specifically by decreasing the need for tedious weeding. It is unclear if the information in this graph reflects the idea that farmers chose to utilize the Roundup Ready technology as a result of its labor-saving attributes or if the lower labor use is a result of the technological benefits. Realistically, both are likely correct to a degree. In any case, farmers who planted Bt used the most family labor—as expected from Figure 3.3—but non-GM farmers hired the most labor. In any case, the two categories of farmers who planted the herbicide tolerant varieties used the least amount of labor on the selected plot.

Figure 3.4 Average Total Hours of Labor Per Hectare Spent on Selected Maize Plot



Farm Characteristics – By Selected Plot Seed Type

Socioeconomic characteristics of the farm household alone are insufficient for drawing conclusions about the type of farm operations that choose to adopt certain seed varieties. As such, the following section details farm-level information such as farm size, rate of input use, and yield. Findings from previous studies on the effects of farm characteristics on adoption decisions—as discussed in the literature review—will be incorporated into the discussion.

The number of maize varieties planted and the average selected farm and plot sizes are outlined in Table 3.7. Empirical research by Aliou and Demont (2007) and Shiferaw, Kebede, and You (2008) both illustrated that farmers are more likely to adopt improved seed varieties if more varieties were available to plant. However, this finding does not necessarily correspond with the results in the Table 3.7, because the number of varieties planted by KZN farmers does not directly reflect the number of seed varieties available for purchase, only the number chosen. Recalling Table 3.1, farmers in Hlabisa overwhelmingly planted only one variety, while most farmers in Simdlangetsha planted two or even three. Table 3.7 also cross-tabulates the number of varieties planted by farmers grouped by selected plot variety, with significant differences between groups at the one-percent level ($P<0.01$). All farmers who planted Bt maize planted only Bt maize. The majority (79 percent) of RR farmers planted only one variety as well. Conversely, those with selected plots planted to BR and non-GM maize tended to plant multiple varieties, where only 41 and 39 percent, respectively, planted only one variety.

Numerous studies suggest that average plot or total farm size has a positive effect on the likelihood of adoption, though the farm size effect is often conditional on other factors. Just and Zilberman (1983) conclude that farm size is positive because risk-reducing inputs are used more heavily on larger farms. Other studies point to a lower or upper limit on the effect of land size. Just, Zilberman, and Rausser (1980) suggest that there may be a critical lower limit, below which famers can or cannot adopt the technology. In a model by Fernandez-Cornejo, Daberkow, and McBride (2011), the quadratic land size variable was concave, implying that the land size effect on adoption is negative after a certain point. For simplification, this study hypothesizes that land size has a positive effect on the likelihood of adoption of genetically-improved maize.

Looking at total estimated farm sizes, the hypothesis seems to hold in the cross-tabulation of land size and adoption of GM maize, except in the case of RR maize farms. Note first that the plot size cannot be compared as a percentage of the plot size, since the units are different between the two measures; instead, each can be compared only across seed type categories. The RR farms are smaller than even non-GM farms both in average selected plots size and total farm areas. Consistent with income and asset levels, Bt farmers have the largest total land holdings. BR farmers plant the largest selected maize plot. With each result, it becomes more evident that the groups of farmers should not be categorized as adopters and non-adopters, because those who plant Roundup Ready maize do not follow many of the same socio-economic and production trends as either Bt or BR planters.

Table 3.7 Land Size and Variety Diversification

	Bt	RR	BR	non-GM	Total
Number of varieties planted					
1	4	63	12	22	*101*
2	12	17	12	28	*69*
3	2	0	5	7	*14*
Average maize plot size[a]	0.57	0.45	0.6	0.48	*0.5*
Total estimated farm size[b]	2.86	1.22	2.45	2.07	*1.84*

n=184

[a] *measured by steps, farmer estimate*
[b] *measured in hectares, enumerator estimate*

The data presented in this chapter cannot yet confirm or reject the three hypotheses, but they do provide great detail which can be later compared with the model results. Without panel data, the question can be answered simply by analyzing the farmers' explanations of their decision process. The next chapter is a qualitative analysis of farmers' responses to open-ended questions, which will further these three hypotheses.

Chapter 4 Qualitative Exploration

In the survey, farmers provided many open-ended answers to explain their preferences and rationale for production decisions. The open-ended data add two contributions to the economic models. First, these responses can reinforce or contradict the initial hypotheses tested in traditional discrete choice models. Secondly, the open-ended explanations can be coded and incorporated into the logit model to capture additional elements of farmer perception.

Technical aspects of data processing

In order to transform the open responses into a form that could be analyzed and incorporated into a quantitative model, the data was cleaned in several phases of content analysis. Content analysis creates an objective coding scheme that systematically organizes open responses into data that can then be compared, counted, and analyzed. In open coding, content analysis first requires objective identification of response patterns for each survey response. These patterns are then sorted into a wide range of categories that preserve the original message of individual responses but allow them to be linked to other response categories. In each stage, the number of categories decreases and the responses become more inclusive. The art is in recognizing response phrase patterns; the science lies in consistent inclusion or exclusion of specific content (Berg 1998).

The main advantage of content analysis is that it allows for both qualitative and quantitative analysis of the respondents' viewpoints. For example, a farmer's description of his or her seed choice may be categorized along with similar responses so that something can be said of farmers' perceptions of the local seed market. The coding process requires consistent decisions on inclusion or exclusion. Once coded, these open-ended questions give further explanatory power to the variables that are added to the classic adoption model.

Attitude toward Maize Production

Open-ended responses to questions, such as attitudes on farming traditions, seed variety options, and their rationale behind certain production decisions, enrich the axioms of choice. These responses also reveal patterns among those who chose the same seed type. Table 4.1 gives farmers' statements on the primary reason they grow maize. The vast majority of those who planted BR or non-GM indicated that they grow maize because they could not afford to buy maize meal from the store all year long. While many of the Bt and RR farmers shared the same sentiment, the majority of these farmers grew maize because they prefer the taste and health qualities of home-grown maize.

Only the non-GM and BR farmers planted maize primarily to maintain their Zulu heritage. The only farmers who responded that they grow maize for economic rationale or for income grew non-GM or RR on their selected plots. If the seed varieties were considered on a scale from the least complex production traits and least costly to the most, one would not assume that non-GM and BR farmers would plant maize for the same general reasons. Despite the BR group's higher average income and assets, presented in Figure 3.1, many still claimed that they did not have the money to buy maize at the store or that they grew it out of tradition. And despite RR farmers' lower incomes and assets, most did not claim financial reasons for maize production.

Table 4.1 Farmers' Reported Reasons for Growing Maize

(% of respondents within category)	Bt	RR	BR	non-GM
Own maize meal has better taste	11	4	3	0
Own maize meal is more healthy	39	58	7	2
Cannot afford to buy meal all year	50	35	83	90
It makes economic sense as I have land and meal is expensive	-	-	0	2
It is part of Zulu tradition	-	-	3	2
Prefer to grow own mealies	-	-	3	2
Selling grain and mealies brings in cash	-	3	0	2

n=183

When asked if the farmers would grow maize if they could—all farm-level constraints removed—one hundred percent of Bt and BR farmers said they would like to grow more maize if they could. Two non-GM and six RR farmers said they would not. The main reasoning given by these eight farmers was that they already produce enough for the family and do not need any more. A couple farmers also specified that there was no market in which to sell output, so there was no point to increasing production beyond household subsistence.

Perception of Seed Varieties

Previous studies suggest that farmers' perceptions of the varietal characteristics play a significant role in the seed selection decision (Dalton 2004; Kshirsagar, Pandey, and Bellon 2002; Adesina and Zinnah 1993). The following section elaborates on the views that farmers hold about production characteristics, market conditions, and quality of maize yield. Table 4.2 explains why farmers favored a certain maize variety over the others. Overwhelmingly, the majority of farmers (51 percent) preferred the Roundup Ready maize as their first choice because they could use herbicide and reduce the labor required to weed. More farmers who favored insect resistance stated BR as their first choice (16 farmers) over Bt (4 farmers). All farmers who said that low cost was their top priority chose non-GM as their first choice. Of the 37 farmers who stated that yield as their major decision factor, the majority chose RR or BR as their preferred choice. Bt was the least preferred seed type. Seventeen farmers stated resistance to weather elements as their main reason for their seed choice.

Table 4.2 Farmers' First Choice in Maize Seed and Explanation

	Bt	RR	BR	non-GM	Total
Frequency of first choice by category:	8	94	52	30	184
Don't have to weed; can use herbicide	0	66	14	0	*80*
Not destroyed by stalkborers or insecticide	4	1	16	0	*21*
Less expensive than other seed	0	0	0	12	*12*
High yield	2	14	13	8	*37*
Good quality (tasty)	0	6	3	6	*15*
Not destroyed by weather (hot, dry)	2	7	5	3	*17*

n=182

Farmers were asked to indicate the top advantages and disadvantages of all seed types, even those they had never planted. In this question, the non-GM seeds were differentiated into traditional and hybrid varieties. Table 4.3 shows that more farmers were unfamiliar with the traditional and hybrid Pannar seed than the Roundup Ready seed, so unfamiliarity with improved seeds is not as substantial a hurdle as in some previous studies. BR was the newest and most unfamiliar seed, which may explain why more farmers were unfamiliar with it and perhaps, its lower adoption rate. In general, the non-GM varieties are recognized for the lower seed prices. GM varieties are recognized more often for having higher yield rather than for their GM technology traits. Only 31 farmers stated that insect resistance is the top benefit of Bt maize, only 16 farmers recognized herbicide resistance as the top benefit of RR maize, and only 5 recognized either GM trait as the top benefit of BR.

Table 4.3 Reported Benefits by Seed Type

	Bt	RR	BR	Traditional	Hybrid
Don't know this seed	23	2	60	8	23
Not expensive	1	2	2	165	118
High yield	92	104	107	2	38
Not/less affected by drought	33	53	9	1	
Maize is not affected by stalk borer	31	1	5		
Maize is not killed by herbicide		16			
Saves labor		3	1		
Saves on insecticide	3				
Maize grows fast		1			4
Get better price for green mealies				4	1
Get better price for grain				3	
Total	183	182	184	183	184

Similar sentiments are reflected in the perceived disadvantages of each seed, shown in Table 4.4. Traditional maize seeds are devalued primarily for their lower yield, and the major disadvantages for hybrid maize are its susceptibility to drought and stalk borers. The majority of farmers consider GM seeds to be expensive. Bt and RR seeds are also discounted for requiring the additional cost for fertilizer.

Table 4.4 Disadvantages by Seed Type

	Bt	RR	BR	Traditional	Hybrid
Don't know this seed	23	2	58	8	23
Expensive	107	117	123		
Not available when I want it	1	5			
Low yield				73	36
Easily affected by drought				28	57
Needs fertilizer	36	29	1		2
Maize is damaged by stalk borers	1	6		16	47
Maize is damaged by herbicide	6	8		21	8
Maize is affected by insects in storage	7	6			3
Have to buy herbicide	2				
Have to use insecticide for stalk borers		5		6	4
Maize grows slowly				32	
Maize cobs are damaged by rain		5	1		1
Low price for green mealies	1				
Total	184	183	183	184	181

**first response only*

Similar to the survey question captured in Table 4.2, which asked the primary reason a farmer preferred a certain seed type, farmers also were asked to rank the extent to which several attributes of the maize types affected their seed choice. Specifically, farmers were asked to assign a value—1 being very important, 5 ranking not important—to six seed attributes. Farmers' ranking of all six seed type traits can be found in Table 4.5. Some of the attributes apply to any seed type, such as price, yield, time to maturity, and drought tolerance. The other attributes are applicable only to the genetically modified varieties, that of herbicide tolerance and insecticide tolerance. The Pearson chi-square test statistic gives false confidence that significant differences exist; the reliability of the statistic decreases if there are many options (e.g. four seed types and five rankings) within the cross-tabulation.

The first two attributes, seed price and yield, did not reveal any extreme differences among the different seed varieties, and the difference between rankings of one and two is considered only as a minor difference. Nevertheless, the Bt category had the lowest proportion of farmers that ranked seed price as most important and BR the highest. Likewise, RR had the lowest proportion of farmers that ranked yield as most important and Bt the highest. The other two attributes that are not GM specific, drought tolerance and early maturity, have responses that range from one to five. To simplify analysis, a response of one or two can be considered 'important' and a response of three, four or five can be considered 'less important'. This binomial coding scheme is employed in the multinomial probit model later. In that regard, 85 percent of farmers who planted RR maize considered drought tolerance as an important factor in their seed choice, compared to only 6 percent of Bt farmers. Concerning early maturity, the majority of farmers in every category, 88 to 90 percent, considered early maturity to be an important factor.

Farmers also ranked the importance of the genetically modified seed attributes, even if those attributes were not present in the seed types they chose to plant. Interestingly, none of the farmers who planted Bt consider insect resistance as an important factor in their seed choice; however, 11 farmers who planted RR, 3 who planted BR, and 4 who planted non-GM indicated that it was. The results for herbicide tolerance are a bit more intuitive, where 65 of 78 farmers who planted RR and almost half of farmers who planted BR ranked herbicide tolerance as an important factor. Almost one third of non-GM farmers and one farmer who planted Bt also considered herbicide tolerance as important. It is apparent that farmers' stated priority attributes do not align always with the type they actually planted, especially regarding the genetically modified traits. For example, a farmer may have planted Bt maize on his or her selected plot, but did not rank insect resistance as an important factor in their maize seed decision. Further data show that some farmers were not able to plant the seed type of their preference, which may provide insight into these results.

Table 4.5 Farmers' Ranking of Most Important Attributes in Seed Choice Decision

	most important		somewhat important		least important	
Seed Price (chi^2=0.066)	1	2	3	4	5	Total
Bt	4	13	1	-	-	18
RR	36	35	8	-	-	79
BR	16	7	6	-	-	29
non-GM	28	24	3	1	-	56
Total Average (%) Within Seed Category	*46.2%*	*43.4%*	*9.9%*	*0.5%*	*0.0%*	*100%*
Yield (chi^2=0.029)	1	2	3	4	5	Total
Bt	17	1	-	-	-	18
RR	51	22	3	-	-	76
BR	24	2	2	-	-	28
non-GM	47	6	3	-	-	56
Total Average (%) Within Seed Category	*78.1%*	*17.4%*	*4.5%*	-	-	*100%*
Drought Tolerance (chi^2=0.000)	1	2	3	4	5	Total
Bt	1	-	7	6	3	17
RR	65	1	4	6	2	78
BR	14	2	6	6	1	29
non-GM	14	3	13	15	10	55
Total Average (%) Within Seed Category	*52.5%*	*3.4%*	*16.8%*	*18.4%*	*8.9%*	*100%*
Insect Resistance (chi^2=0.167)	1	2	3	4	5	Total
Bt	-	-	6	9	3	18
RR	2	9	42	22	3	78
BR	-	3	16	10	-	29
non-GM	-	4	24	22	6	56
Total Average (%) Within Seed Category	*1.1%*	*8.8%*	*48.6%*	*34.8%*	*6.6%*	*100%*
Early Maturity (chi^2=0.060)	1	2	3	4	5	Total
Bt	2	14	2	-	-	18
RR	39	30	8	1	-	78
BR	12	14	2	1	-	29
non-GM	16	33	7	-	-	56
Total Average (%) Within Seed Category	*38.1%*	*50.3%*	*10.5%*	*1.1%*	-	*100%*
Herbicide Tolerance (chi^2=0.000)	1	2	3	4	5	Total
Bt	1	-	7	4	6	18
RR	61	4	1	5	7	78
BR	14	-	3	2	10	29
non-GM	13	5	10	17	11	56
Total Average (%) Within Seed Category	*49.2%*	*5.0%*	*11.6%*	*15.5%*	*18.8%*	*100%*

Market & Production Constraints

Neither the seed planted on each farmer's plot nor his first seed preference is sufficient on its own to explain adoption decisions of genetically modified varieties. As previous studies indicate, market constraints may have prevented the farmer from planting his first choice. If the data includes only what the farmer planted, it assumes that the farmer did not instead want to plant another variety. Likewise, if it includes only the first preference, it assumes that the farmer was able to obtain the seed. Previous studies have addressed this issue by creating a dummy variable that accounts for this market failure (Aliou and Demont 2007; Shiferaw, Kebede, and You 2008). Other shortcomings—such as a binding credit constraint, labor availability or affordability, or access to land—may distort what adoption rates would have been under perfect market conditions. The following summarizes the market and production constraints as reported by the farmers in KwaZulu-Natal, South Africa.

As an overview, farmers were asked which two problems most affected their ability to increase maize production. Table 4.6 shows the sum of the top two constraints reported by farmers, organized by seed category. There are clearly three reported problems that stand out among the others: a land constraint, insufficient cash or credit to purchase seed and inputs, and no formal market to sell extra maize. These three are the main constraints for all seed type categories.

Table 4.6 Main Constraints to Increasing Maize Production

	Bt	RR	BR	Non-GM	Total
Not enough land	9	36	13	19	77
Not enough labor	3	9	4	9	25
Not enough money for seed or other inputs	9	39	8	21	77
Seed is not performing well	2	11	0	4	17
No market to sell extra maize	8	41	16	15	80
No good storage for extra maize	1	6	1	4	12
Problems with insects during production	1	1	0	0	2
Problems with insects after harvest	1	1	2	4	8
Low and unreliable rainfall	1	1	7	19	28

n=326

167 respondents listed their #1 reason, 159 listed their #2 reason

Seed Availability

Previous results indicated that in some cases, farmers' preferred traits do not match the seed they adopted. Table 4.7 cross-tabulates their seed choice by the seed they actually planted. Specifically, 41 of the 184 farmers, or 22 percent, were not able to obtain their first choice. Most often, farmers planted non-GM in place of their first choice. Roundup Ready maize was the most popular choice and 79 out of 94, or 84 percent, were able to purchase it. Bt maize was the least popular, and only one of the 9 that chose it was not able to purchase it. Farmers who preferred BR maize had the most difficult time obtaining it, as only 28 out of 52, or 54 percent, planted it. For clarification, it appears that one farmer did not get his first choice in non-GM seed. This farmer indicated that he preferred the taste of the traditional variety and was able to plant a plot of his first choice; however, he planted a GM variety as well, and so was considered as an adopter for later purposes. Because 22 percent of farmers did not get their first choice in maize seed, adding a dummy variable to account for this may significantly influence the adoption model.

Table 4.7 First Choice in Maize Seed Cross-tabulated by Actual Seed Planted

		First choice				
		Bt	RR	BR	non-GM	Total
Actual seed planted	Bt	8	3	7	0	18
	RR	0	79	0	1	80
	BR	0	1	28	0	29
	non-GM	1	11	17	28	57
	Total	9	94	52	29	184

n=184

Sources of Income and Maize Seed Money

Table 4.8 shows the main source of income for each category of farmers by seed type. The most important result of this table is that government payments are the main source of income for the majority of farmers. Crop and livestock sales do not support many farm households in these two areas, and more families rely on remittances than wages from local employment. A greater proportion of farmers who plant BR or Bt report earning off-farm income and receiving remittances as their main income source.

Table 4.8 Primary Income Sources by Seed Type Category

	Bt	RR	BR	non-GM	Total
Government Payment[a]	11	63	14	33	121
Remittances	3	2	4	7	16
Casual Employment[b]	0	3	0	8	11
Crop Production	1	5	4	0	10
Livestock Sales	0	1	3	0	4
Permanent Employment	3	6	4	9	22

n=184

[a] government payment includes 'child grant', 'pension', and 'other government payment'

[b] casual employment also includes 'other business'

While most farmers utilize their primary source of income for seed expenses, some farmers earmark income other than their main source of money to purchase seed. For example, four farmers who stated government payments as their primary source of income do not use it to purchase seed. Also, while 10 farmers claim that crop production is their primary source of income, only two farmers use that income to purchase the next year's seed. In the case of remittances and off farm-income, more farmers use those sources to purchase seed than claimed as their primary income sources. Another nine farmers use savings, presumably from various sources, to purchase maize seed.

Table 4.9 Source of Maize Seed Money

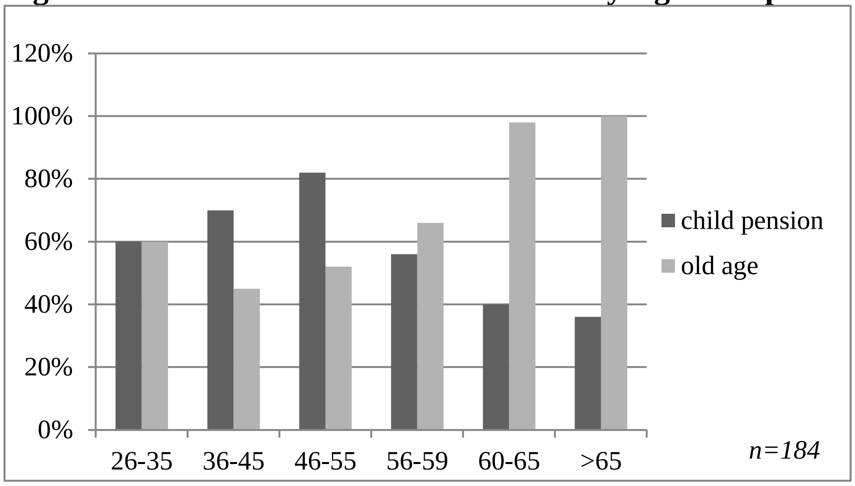
	Bt	RR	BR	non-GM	Total
Government Payment [a]	11	61	14	31	117
Remittances	4	3	3	9	25
Savings	0	9	2	3	14
Crop Sales	0	0	2	0	2
Livestock Sales	0	1	3	0	4
Wage Income	3	4	4	14	25

n=181

[a]government payment includes 'child grant', 'pension', & 'other gov't payment'

Because government payments constitute the most common source of household income and maize seed money, it warrants elaboration. First of all, there are significant categorical differences between those who receive old age pension and seed choice *($P<0.10$)*, but not between child grants and seed choice. Almost all older people receive government payments, where 98 percent of those 60 to 65 years of age receive it, and 100 percent over 65 years receive the pension, as can be seen in Figure 4.1. It could be further noted that 86 percent of those who receive the old age pension plant the Roundup Ready maize.

Figure 4.1 Government Pensions Received by Age Group



Other interesting aspects of the government payments are revealed in the open-ended explanations of how maize yield has changed as a direct result of the government payments, which were coded and summarized in Table 4.10. Of the 140 farmers who receive the old age pension, 65 said they used the money to increase their maize production, and the other 75 said it did not change or even decreased. The main reason it increased was that the money enabled them to have soil samples taken and then buy the necessary inputs to improve yield. The main constraints that prevented the others from increasing production were that the pension was the only form of income for the entire household, or that they did not have access to enough land.

Table 4.10 Explanation for Change in Production Due to Old Age Pension

	Increased	no change or decreased
Could afford better seed	6	---
Need more maize for household consumption	11	---
Soil samples taken and able to buy inputs	45	---
Don't have to weed	2	---
Plant extra and sell to the community	1	---
Could not afford good seed or inputs	---	8
Good seed not available	---	2
Pension only form of income for household	---	25
Not enough land	---	22
Too old or sick (labor constraint)	---	4
No market to sell surplus	---	9
Don't need any more for household consumption	---	5

n=140

The explanations for the child grants differ. There was a much lower response rate, and only one explained that they were able to purchase inputs and increase production given the child grant. Three households reported that they receive the child grant, but do not have children.

Ninety-seven farmers said that their maize production did not change or decreased after receiving the child grant, and 77 gave their reasons why. Table 4.11 presents coded explanations for changes in production. In general, child grants are used only for household, rather than farm, needs. The majority said that insects cause significant damage and their yield did not increase as a result. Many other farmers said that the child grant is used only for the children's needs, that the grant does not provide enough money to impact their maize production, or that it went to other household needs such as purchasing food. Household size also matters in this case: the average number of people in households receiving the child grant is slightly higher than household receiving the old age pension.

Table 4.11 Changes in Production Due to Child Grants - No Change or Decrease

Insects or another external factor	35
Grant is insufficient to increase maize production	21
Need to meet other household needs first	10
Insects or another external factor	4
Grow enough for household; don't want to buy	4
No market to sell surplus	2
Disease; no energy	1

n=77

Labor Requirements and Availability

Labor requirements and availability are crucial components of adoption decision. Only the labor factors that are known prior to purchasing the seed should be used in the model. There is not an obvious choice of proxy to measure family and/or hired labor, so several are explored in Table 4.12. The dependency ratio is a common method for measuring the demographic structure of the household and indirectly indicates the family labor availability, where the number of family members under the age of 15 or over 65 is divided by the number of able-bodied family members between 15 and 65 years. A higher value indicates more dependents. By this ratio, those who plant Bt have the most dependents and farms which plant RR have the fewest dependents per family. The problem with this is that responses from other survey questions indicate that children under the age of 15 and adults over the age of 65 are working in the maize fields. On the other hand, several farmers reported that they or other family members were inflicted with HIV infection, tuberculosis, or other unnamed diseases, many members between 15 and 65 are *not* able to work. One solution to this problem is to count the number of reported active family participants on each farm, and then divide it by the total number of family members in the household, so that higher numbers indicate more active family labor. The only issue here is how to interpret ratios with values higher than one (1). One possible suggestion is that other family members outside of the particular household came to help during certain labor activities. In this case, BR farmers report the most family labor, and non-GM farms have the lowest rate of working family participants. The final method is to calculate the total labor used on the maize plot – a sum of family, hired, and working group labor – and divide the family labor by the total, so that higher values indicate that more family labor is used. By this calculation, farmers who planted RR maize hired more labor than they used family labor, and Bt farmers used a greater proportion of family labor. The main problem with this proxy though, is that the number of hours of either family or hired labor is unknown at the time the adoption decision is made. However, it can be assumed that farmers know the approximate labor cost and availability. Thus, using the actual values can be justified as the approximate 'expected' labor use.

To summarize, there is no clear answer as to which method best captures labor availability without some empirical analysis. Looking first at labor availability and use by RR farmers, they have the lowest dependency ratio, but use the greatest proportion of hired labor. Conversely, Bt farmers had the highest dependency ratio but the lowest proportion of hired labor.

Table 4.12 Labor Availability Ratios

	Dependency Ratio [(<15 + >64)/ (15-64)]	# Family Participants / # Family Members	% Family Labor	% Hired Labor
higher values =	***less family labor***	***more family labor***	***more family labor***	***less family labor***
mean	0.84	0.84	0.56	0.44
median	0.67	0.75	0.57	0.43
st. dev.	0.77	0.66	0.27	0.27
95% C.I.	(0.5, 0.75)	(0.68, 0.77)	(0.52, 0.63)	(.037, 0.48)

n=184

As is already apparent from the previous table, family members did the majority of the work except for on farms that planted RR maize. In almost all cases, hired labor decreased in 2009-10 from the year prior. Those planting BR and Bt varieties hired the most labor, and non-GM farmers hired more than those who planted RR. Farmers in Simdlangetsha hired significantly more labor than those in Hlabisa, in which only 7.2 percent of all farmers in Hlabisa hired any non-family member to help with the maize crop in the 2009-2010 season.

Table 4.13 Reported Hired Labor in Current and Previous Production Year

(% of respondents within category)	Bt	RR	BR	non-GM	Hlabisa	Simdlangetsha
2009-2010 Season[a]	33.3	8.8	24.1	21.4	7.2	29.1
2008-2009 Season[b]	55.6	12.5	35.7	37.5	6.2	52.9

n=183[a], *182*[b]

Farmers reported on the worst maize production activity as well, and the open responses were coded into four categories, shown in Table 4.14. Weeding is the most disliked activity, because it requires so much time, is "too much work to do without help", or because the farmers are "too old or sick to weed". Since 60 percent of the respondents indicated that weeding is the worst activity, one would assume that either herbicide tolerant variety (RR or BR) would be the most popular to eliminate weeding. However, another aspect emerges in the rationale for disliking other activities; many of the farmers indicated that they are afraid of the chemicals' effects on their own health or on the maize. Many reported that pesticides caused skin rashes or other diseases. This may explain why some farmers were hesitant to plant genetically modified varieties that can be sprayed with herbicides.

Table 4.14 Farmers' Report of Worst Maize Production Activity and Reason

Why?	Land Preparation	Weeding	Herbicide Application	Pesticide Application	Harvesting
Time constraint	0	60	0	0	0
Afraid of chemicals' effects	0	3	7	23	34
Disease, old age	0	23	0	0	2
Difficult work to do by hand	1	14	0	0	0
Total	1	100	7	23	36

n=167

There seemed to be labor constraints in the two villages. The majority of farmers in Hlabisa, 62 percent, answered that labor is not easy to find due to a labor shortage. Recalling from Table 4.13, only 7.2 percent actually hired labor to work their maize fields in the 2009-10 season. Farmers in Hlabisa explained that other local farmers were busy in their own fields and did not have time to work as hired labor. The labor market is more active in Simdlangetsha, where 29 percent of farmers hired labor in the production season and only 29 percent said that labor was difficult to find. The main labor constraint reported in Simdlangetsha is that is "expensive". Farmers in both villages also explained that capital shortages also constrain the labor market. Reported capital shortages included mechanized or draft power for laborers to operate, or there was insufficient storage for the harvest.

Table 4.15 Hired Labor Availability

% of respondents within category	Hlabisa	Simdlangetsha
easy to find hired laborer	37.2	54.7
not easy to find hired laborer	62.8	29.1
don't know	0	16.3

n=164

Table 4.16 Reported Reasons on Why It Is Difficult to Find Hired Labor

(% of respondents within category)	Hlabisa	Simdlangetsha
Labor shortage	86.6	12.9
Hired labor is expensive	0	55.3
Lack of draft power, mechanized power, or grain storage	4.1	15.3
Laborers have disease, no energy	1	2.4
No one wants to do the job	8.2	14.1
Total	100%	100%

n=182

Land Accessibility

As reported in Table 4.6, 77 farmers reported that lack of access to land was one of the main constraints to increasing maize production. When cross-tabulated by seed type, however, there is a commonality between those who plant non-GM varieties and BR maize, where the majority of both said that it is easy to get new land; only about half of Bt and RR farmers said it was easy to attain new land. Table 4.16 shows the distribution of how farmers acquire new land. Most of the non-GM and BR farmers attain land by using their own land that is not already in production, and the greatest proportions of Bt and RR farmers ask the chief for more land. On average, those who planted no GM asked the chief for more land or used land that was not already under production, full adopters paid to rent land.

Table 4.17 Land Accessibility by Seed Type

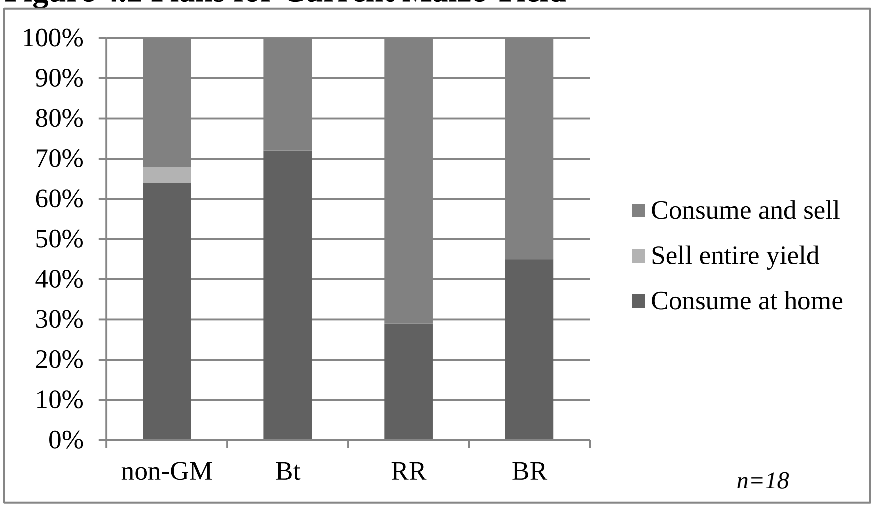
% of respondents		Bt	RR	BR	non-GM
How easy is it to get more land?***	*Easy*	50%	44%	86%	97%
	Not easy	50%	56%	14%	3%
How to get more land?***	*Ask the chief for more land*	44%	51%	31%	25%
	Use own land that is not currently used	28%	10%	55%	44%
	Borrow land without payment	22%	6%	7%	26%
	Rent land with cash or maize	6%	33%	7%	5%

n=184

Output Market

Many farmers reported that one reason they did not increase their maize production is that there was no market to sell their surplus. However, there is little discussion in the surveys concerning the output market. One question—whether they sold in the 2009-2019 production season—gives a good idea of the percentage of farmers who sold output. This is presented in Figure 4.2. Seventy percent of farmers who plant Bt planned to sell at least some maize, more than any other group of farmers. A later question in the survey revealed that 94 percent of respondents preferred to sell their maize to other people in the community, and the other six percent said they preferred to sell to the community miller.

Figure 4.2 Plans for Current Maize Yield



Concluding Remarks

Summaries from the open-ended responses revealed many aspects that could change or improve the adoption model beyond the classic model variables. First of all, Roundup Ready maize was the most popular first choice, most likely for its labor-saving qualities. However, 22 percent of all farmers were unable to obtain their first choice. Farmers appreciated genetically modified varieties for their higher yield more so than for their GM attributes, and they valued non-GM varieties mostly because they were less expensive. It follows, though, that GM adopters rank the GM attributes as more important when making their maize seed decision, and non-adopters usually consider price.

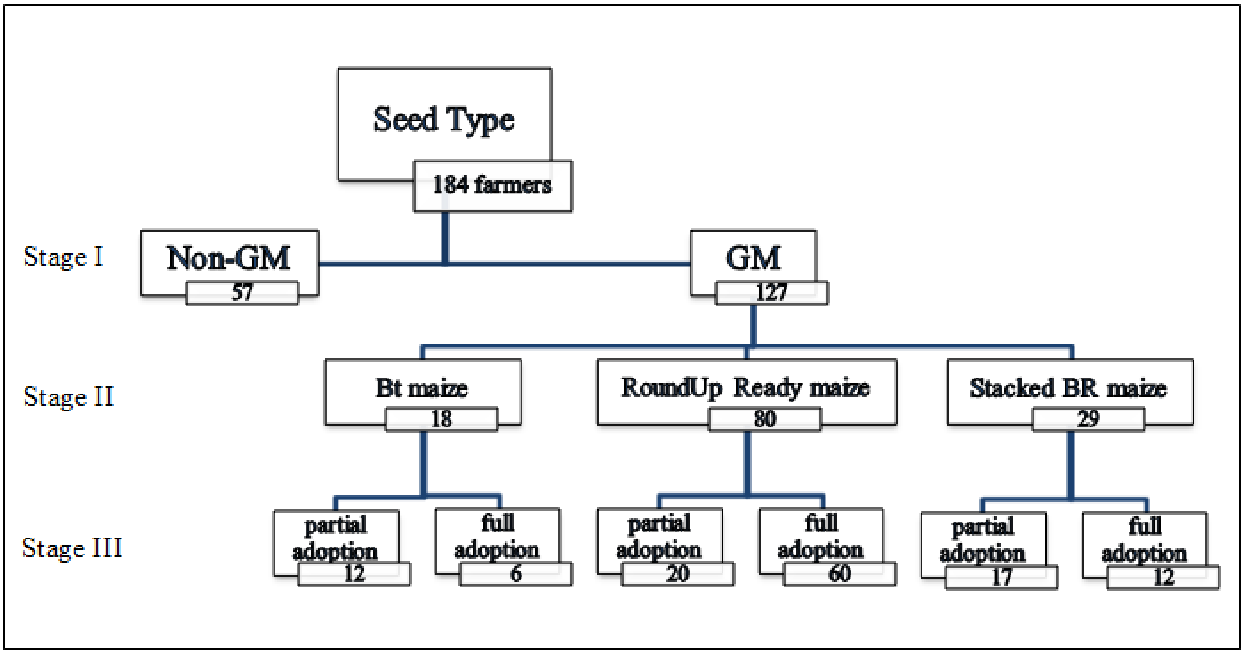
Farmers' preferences are reportedly constrained primarily by insufficient cash or credit, land constraints, and lack of market to sell maize. First, the majority farmers in all categories (66 percent overall) buy their maize seed using government pension, and the greatest proportion of pension users plant Roundup Ready maize. BR farmers purchase seed with money other than government pension, such as farm sales or wage income, more often than any other category of farmers. Second, the majority of farmers—especially those who planted BR or non-GM maize types—said that it was difficult to obtain more land. The most common method of obtaining more land was asking the chief for more land. Finally, many of the farmers said there was no market to sell their maize, and fewer than half of all households sold maize to other people within the community.

Chapter 5 Methods

Conceptual Decision Process

The seed choice decision process is multi-faceted, as farmers choose whether or not to plant a genetically modified maize seed, which specific production traits they wish to utilize, and how much of their land they want to plant to each particular seed. This entire decision process is conceptualized in Figure 5.1. Once a farmer had chosen to plant a genetically modified maize variety, the next choice was to decide between the Bt and Roundup Ready technologies or the combination of the two. The final decision was the intensity of adoption, which is captured by dummy variables for 'partial' or 'full' adoption. Partial adoption denotes that the farmer diversified by planting plots of both GM and non-GM maize, where full adoption indicates that the farmer planted his entire maize enterprise to the GM variety. In the choice set, the final decision is marked by non-GM, partial adoption, or full adoption. The off-set numbers indicate the number of farmers in each of the final decision categories; that is, 12 farmers planted at least one plot of their maize enterprise to Bt maize, and 6 planted their entire enterprise to Bt maize.

Figure 5.1 Full Decision Process



The conceptual model in Figure 5.1 describes a discrete choice which can be modeled empirically in a few different ways. Logit and probit are the most basic of the discrete choice models, but use only binary outcomes as the dependent variable (Train, 2009). A binary model cannot adequately capture the three-stage decision process. Optimally, each decision would be nested into the preceding decision, so that the intensity of adoption is nested in the GM technology choice, and the technology choice into the *GM* or *non-GM* choice. Unfortunately, the dataset is not large enough to accommodate such a model. Six observations of partial Bt adoption or 12 observations of full BR adoption will not give accurate model estimates. For necessity and simplicity, the model illustrated in Figure 5.1 is decomposed into three separate models, according to the three stages seen in the figure.

The first of three decisions is whether to plant a non-GM variety or a non-GM variety, depicted in Stage I. Many studies infer that there is a threshold, be it land size, credit availability, or human capital, which must be overcome in order for a farmer to decide to purchase and plant an improved seed type. Small-holders in KwaZulu-Natal had the choice of a few different traditional and improved hybrid varieties, which are aggregated into the 'non-GM' group. The goal of modeling this basic decision level is to check whether the results are consistent with expectations from previous binary studies.

The majority of the discussion will center on the second level, or the Stage II decision, which shows farmers' choice among the three GM seeds or non-GM. This model, which is more specific than the first, will calculate the determinants of choosing certain genetically modified traits. As previously mentioned, this model will reveal whether the different types of adopters share similar results. If the marginal effects of the three adopters result in opposite directions, then it would indicate that the binary choice model is insufficient.

The final level, Stage III, shows the intensity of adoption. Because the dataset only gives a cross-sectional look at the adoption process in KwaZulu-Natal, the intensity of adoption provides an important insight on where farmers are in the transition from conventional maize to improved GM varieties, from non-adopter to partial-adopter to full-adopter. The following section motivates the econometric models used to estimate the determinants of adoption.

Random Utility Model

The primary purpose of this research is to determine which factors significantly affect farmers' seed choice decisions. The most basic expectation is that farmers will choose the maize seed that provides the greatest yield for the lowest production costs. This, however, is not strictly the case. Farmers' decisions are inherently shaped by their perceptions and preferences for seed traits or limited by market constraints, as discussed in previous chapters. Thus, the decision process can be modeled as a discrete choice model, adapted from the random utility model as derived by Train (2009).

The goal of the econometric model is to maximize the utility of each farmer *n* obtained from seed type *j*. The decision-making process to maximize utility U_{nj} is unobservable, so in its place, the known, observable portion of utility, V_{nj}, is modeled. Modeling V_{nj} alone, given estimates of α and β and measures of the socioeconomic and production variables, the observed utility is greater from planting a GM variety than from a non-GM variety. Thus, modeling only observed production characteristics should result in all farmers planting the superior genetically modified variety. The equations below show the difference in observed utility between any GM maize *j* and non-GM maize *i* as an example.

(5.1) $$V_{nj} = Seed_{nj} = \alpha S_n + \beta X_{nj}$$ *for GM maize (j=RR, Bt, or BR)*

(5.2) $$V_{ni} = Seed_{ni} = \alpha S_n + \beta X_{ni}$$ *for non-GM maize*

However, there is a portion of random, unobserved factors in the decision process, which are captured by the term ε_j. The total observable and unobservable processes are then joined to form the random utility model, denoted:

(5.3) $$U_{nj} = V_{nj}(x_{nj}, s_n) + \varepsilon_{nj}$$

where s_n are characteristics of the farm household, and x_{nj} are attributes of the seed type. The probabilities for selecting either some GM maize *j* or non-GM *i* maize can be stated by

(5.4) $$P_j = Prob(\varepsilon_{ni} - \varepsilon_{nj} < V_{nj} - V_{ni})$$

(5.5) $$P_i = Prob(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj})$$

The dependent variable is set as the four seed varieties: non-GM, Bt, RR, and BR maize. For clarification, the seed types describe only the selected plot, and some farmers may have chosen to plant a secondary plot to reduce risk through diversification. However, the dependent variable must be mutually exclusive so that one seed category does not also incorporate another, exhaustive so that there is not another seed that does not fall into one of the four categories, and finite, or discrete (Train, 2009).

The resulting model calculates P_{nj}, the probability that the utility a farmer obtains from seed type *i* is greater than the utility from seed type *j*, or

(5.6) $$P_{nj} = Prob(U_{nj} > U_{ni}\ \nabla\ j \neq i)$$

where *U* is the sum of both observed and unobserved utility. Written in terms of observed and random portions of utility for both seeds *i* and *j*, the cumulative probability is:

(5.7) $$Prob(V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni})\ \nabla\ j \neq i$$

which can be arranged to show:

(5.8) $$Prob\left(V_{nj} - V_{ni} < \varepsilon_{ni} - \varepsilon_{nj}\right)\ \nabla\ j \neq i)$$

Integrating over the entire function in 5.8 gives the indicator function

(5.9) $$\int I\left(V_{nj} - V_{ni} < \varepsilon_{ni} - \varepsilon_{nj}\right) f(\varepsilon_n) d\varepsilon_n$$

The indicator function is equal to one (1) when *I* (.) is true, and equals zero (0) otherwise.

In any random utility model, there are *J* alternative choices and so there are *J* respective error terms, which allows for *J-1* differences. In this case of seed choice, farmers had the choice between four seed categories, so there are only three differences between seed choices, so that $\varepsilon_{nj} - \varepsilon_{ni}$ becomes ε_{nji} and the indicator function can then be written

(5.10) $$P_{ni} = \int I\left(V_{nj} - V_{ni} < \varepsilon_{ni} - \varepsilon_{nj}\right) f(\varepsilon_n) d\varepsilon_{ni}$$

(Train 2009).

Multinomial Probit Model
Methods

The random utility model is the basis of the probit model, modeling

(5.11) $$U_{nj} = V_{nj}\left(x_{nj} s_n\right) + \varepsilon_{nj}.$$

The important part to distinguish is that ε_n is distributed normal with mean vector of zero and, more importantly, a covariance matrix Ω. The density of ε_n is

(5.12) $$\phi(\varepsilon_n) = \frac{1}{(2\pi)^{\frac{J}{2}} |\Omega|^{1/2}} * e^{-1/2} \varepsilon'_n \Omega^{-1} \varepsilon_n$$

and the choice probability is the same as the multinomial logit model in Equations 5.6 and 5.8, where

(5.13) $$Prob(V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni})\ \nabla\ j \neq i$$

And the indicator function is the integral of the probability equation, rearranged.

(5.14) $$= \int I\left(V_{nj} - V_{ni} < \varepsilon_{ni} - \varepsilon_{nj}\right) f(\varepsilon_n) d\varepsilon_n$$

The indicator function essentially decides whether the statement in parentheses is accepted or rejected. The probability that alternative *i* is chosen then is the integral over all values of the error term. Then the set of error terms $\varepsilon_n$that result in the farmer choosing seed *i* be modeled as B_{ni} = ε_n subject to

(5.15) $$(V_{nj} + \varepsilon_{nj} > V_{ni} \ + \varepsilon_{ni})\, \nabla\, j \neq i,$$

which gives the probability

(5.16) $$P_{nj} = \int_{\varepsilon_n \epsilon B_{ni}} \phi(\varepsilon_n) d\varepsilon_n$$

The functional form of the probit model can be seen in Equation 5.17.

(5.17) $$F(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{\frac{-u^2}{2}} du$$

Since the difference between two normal error terms is normal, the density of the differences between errors is modeled by the equation below (Train, 2009)

. (5.18) $$\phi(\tilde{\varepsilon}_{ni}) = \frac{1}{(2\pi)^{\frac{J}{2}(J-1)} |\widetilde{\Omega}|^{1/2}} * e^{-1/2 \tilde{\varepsilon}'_n \widetilde{\Omega}^{-1} \tilde{\varepsilon}_n}$$

The most important feature of the multinomial probit model for this research is the covariance of the error term, which is normally distributed with mean zero and variance Ω ($\varepsilon_n \sim N(0, \Omega)$),. The covariance matrix is denoted by

(5.19) $$\Omega = \ I_j * \sum \text{ for j} = 1 \ldots \text{J}.$$

Here, I is an identity matrix and Σ is the covariance of ε_n. So for J= 4 for the four seed types, the Ω matrix

$$\Omega = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} \end{bmatrix}$$

should be a diagonal matrix so that the σ_{lj} elements are zero for j≠l and the diagonal elements of covariance are independent. Because the covariance matrix is normalized and structured so that all ε_{nj} are independent, the multinomial probit is not restricted by the same assumptions of the multinomial logit and fully relaxes the IIA assumption (Christiadi and Cushing, 2007).

Empirical Test for the Most Appropriate Discrete Choice Model

The seed choice can be modeled in a couple of discrete choice frameworks. Multinomial logit and multinomial probit are very similar. The multinomial logit model utilizes the logistic distribution and has a closed form solution, so is much simpler to derive. The multinomial probit is very similar, but assumes the normal distribution of the errors. Multinomial probit has no closed-form solution, but has an advantage in that it does not violate the assumption of independence of irrelevant alternatives (IIA). The output from both models is very similar, except that the parameter estimates are scaled differently. Because utility is not affected by scale, this point is not crucial. Each model is discussed more thoroughly in their respective methods sections.

The nested logit is another alternative to relax the violation of IIA that potentially occurs in the multinomial logit model. The nested logit model structures the seed choice as a decision process and would be optimal to model the stages illustrated in Figure 5.1. However, the nested logit requires both alternative- (seed-) specific and case- (farmer-) specific variables. This dataset does not provide sufficient alternative specific data to support the nested logit model.

The multinomial probit model was found to be the most appropriate framework to model the seed choice decision process. The remainder of the study derives and utilizes the multinomial probit model. The motivation of the multinomial probit model is in the appendix. Also, the methods and results for both the multinomial logit and the nested logit are presented in an appendix for review.

Goodness of Fit

The Stata program uses the Wald test as a fit statistic for tests of significance of individual coefficients and for overall significance of the model. The null hypothesis assumes all coefficients to be zero, and tests whether all coefficients in the model are significantly different from zero in the alternative hypothesis. Large values for the Wald test indicate a better fit. The result is significant and the null hypothesis is rejected if the *p*-value is less than 5 percent. The multinomial probit computes the Wald test, whereas the multinomial logit computes the likelihood-ratio test. The two tests are asymptotically equivalent under the null hypothesis, but the likelihood-ratio test is invariant under nonlinear transformations (Cameron and Trivedi, 2010).

The log likelihood ratio test statistic is a post-estimation test that, like the F-test, tests whether the additional variables in a set significantly improve the model. The log-likelihood ratio test requires computation of both the constrained and the unconstrained model. The likelihood ratio test compares the log likelihoods of both models and tests whether the difference is statistically significant. If the p-value associated with the test statistic is small (generally less than 0.05), then it the null hypothesis that the variables in the set are not simultaneously equal to zero and the model is improved (Institute for Digital Research and Education, 2013).

Coefficient Interpretation

A positive coefficient from the multinomial probit model means that as a regressor increases, the decision maker is more likely to choose alternative j (a GM variety) over the base alternative (non-GM variety). A more specific example gives clarification. Suppose the coefficient for land size in the BR seed category were equal to 0.043; then if a farmer were to increase his land holdings by one unit, then the multinomial log-odds for BR relative to non-GM would be expected to change by 0.043 times the original probability, holding all other variables constant in the model (UCLA Statistical Consulting Group, 2012). Alternatively, the original logit model can be transformed into odds ratio in the form of

(5.11) $$\frac{\Pr(y=j)}{\Pr(y=1)} = \exp(x'\beta)$$

which gives $e^{\beta_{jr}}$, the proportionate change in relative risk of choosing y=*j* over y=1 when x_{ir} changes by one unit (Cameron & Trivedi).

Average Marginal Effects

The average marginal effects show how the probabilities change as the regressors change by estimating $\frac{dP_{nj}}{dx_n}$. The signs of the coefficients do not necessarily give the signs for the marginal effects. Where coefficients give the change in the variables' respective units, marginal effects show the magnitude of change in probability as a result of an increase in the independent variable. Additionally, marginal effects are calculated for all dependent variable categories, so each of the four seed types are estimated independently. For all values of *x*, the marginal effect is positive if the estimated coefficient is greater than the mean estimate, $\beta_j > \bar{\beta}_j$ (Cameron & Trivedi). The equation form that shows the change in probability with a change in a regressor is found in equation 5.12 (Oaxaca, 2011).

(5.12) $$\frac{\partial p_{nj}}{\partial x_n} \begin{cases} = p_{ij}\left[\beta_j - \sum_{j=0}^{J} p_{ij}\beta_j\right] & \text{for } j \neq 0 \\ -p_{i0}\sum_{j=o}^{J} p_{ij}\beta_j & \text{for } j = 0 \end{cases}$$

Chapter 6 Results and Discussion

The discrete choice model is first constructed using variables commonly found in adoption models, utilizing proxies that capture the socioeconomic status of the farmers as well as farm-level production characteristics. This is referred to as Variable Set 1 in the following results and discussion. Then, following the work of Adesina and Zinnah (1993), Dalton (2004), and Kshirsagar et al. (2002), variables that capture farmers' perceptions of the seed varieties are added to the "traditional" variables for Variable Set 2. Finally, the main production constraints as reported by farmers are added to the traditional variables for Variable Set 3. Descriptions of the variables used in each of the three models are found in Table 6.1. Due to the limited number of observations and high number of possible parameters, the variables from all three models cannot be estimated simultaneously without overloading the model. The significant marginal effects and overall fitness of the models are given for comparison instead.

In addition to the various model specifications, changing the dependent variable allows for further investigation of the decision process. The first model shows the basic binomial choice between *non-GM* and *GM* maize seed, where 0 equals *non-GM* and 1 equals *GM* maize. This model captures the decision process shown in Stage I in Figure 5.1. More importantly, this model can be compared to expectations from previous binary choice studies and can then be compared to the results of the following multinomial model, to see which of the genetically modified seeds follow the same general pattern of binomial 'GM adoption' model. The second model utilizes the four seed categories as the dependent variable, which requires the multinomial probit model. This model assumes that the probabilities of adopting a Bt, RR, or BR over a non-GM seed are completely independent, as depicted in Stage II of Figure 5.2. The final model assesses which factors affect the intensity of adoption, where the dependent variables are non-GM, partial adopter, and full adopter. Because the cross-sectional data give only a snapshot perspective of GM adoption, this final model illustrates the differences in farm and farmer characteristics as seen in Stage III.

Following the results of previous literature that discussed market constraints, the model included two variables that described whether farmers were constrained by the seed input market. Variable Set 1 included a dummy variable that took the value of 1 if the farmer was able to plant his or her first choice, and 0 otherwise. Variable Set 3 included a dummy variable that took the value of 1 if famers reported seed access to be a major factor in his or her seed choice, and 0 otherwise. Unfortunately, the model would not converge with either of these variables, so they were subsequently dropped from the models.

Likelihood Ratio tests were run after Variable Sets 2 and 3 were added to the models. However, this post-estimation test measures whether coefficients are jointly significant, and the results tables present the marginal effects for the regressors. The Likelihood Ratio tests show that the new sets of coefficients do not significantly improve the model. However, there are several marginal effects that are significant, especially in Variable Set 3. Also, the overall fit of the model improves according to the Wald Chi-square statistic, and in many cases, more variables within Variable Set 1 become significant with the addition of the new variables. This may indicate that adding the perception and constraint variables do actually improve the model or that there may be omitted variable bias in the model containing only Variable Set 1.

Table 6.1 Variable Sets and Descriptions

Variable Set 1 'Traditional' Variables	*Site*	Dummy: 0 If Hlabisa; 1 if Simdlangetsha
	Age	Age Category of Farmer (1=26-35, 2=36-45, 3=46-55, 4=56-59, 5=60-65, 6=>65)
	Gender	Gender of Farmer: 0 if Female; 1 if Male
	HH Size	Number of People in Farm Household
	Sufficiency	Portion of HH Maize Consumption From HH Production
	Land	Total Land Size, in Hectares
	Input Cost	Total Cost of Seed and Inputs per Hectare, in Rand
	Employment	Number of Family Members Working Off-Farm
	Labor Ratio	Ratio of Total Hours Family Labor to Total Hours Hired Labor
	~~*First Choice*~~	~~Dummy: 0 If Did Not Get First Choice; 1 Otherwise~~
	Sell Portion	Dummy: 0 If HH Sells No Maize; 1 If HH Sells Some
Variable Set 2 'Traditional' Variables + Seed Choice Perceptions	*Seed Price*	Dummy: 1 If Seed Price Is Important; 0 Otherwise
	Yield	Dummy: 1 If Yield Is Important; 0 Otherwise
	Drought Tolerance	Dummy: 1 If Drought Tolerance Is Important; 0 Otherwise
	Insect Resistance	Dummy: 1 If Insect Resistance Is Important; 0 Otherwise
	Early Maturity	Dummy: 1 If Early Maturity Is Important; 0 Otherwise
	Herbicide Tolerance	Dummy: 1 If Herbicide Tolerance Is Important; 0 Otherwise
Variable Sets 3 'Traditional' Variables + Reported Constraints	~~*Seed Availability*~~	~~Dummy: 1 If Seed Availability Limits Production; 0 Otherwise~~
	Labor Constraint	Dummy: 1 If Labor Constraint Limits Production; 0 Otherwise
	Output Market	Dummy: 1 If Output Market Limits Production; 0 Otherwise
	Land Constraint	Dummy: 1 If Land Constraint; 0 Otherwise
	Input Money	Dummy: If Cash Constraint for Inputs; 0 Otherwise
	Insect Damage	Dummy: 1 If Substantial Insect Damage; 0 Otherwise
	Performance	Dummy: 1 If Reports 'Not Enough Rain' or 'Seed Does Not Grow Well'; 0 Otherwise

As discussed in the previous chapter, the multinomial probit model calculates a coefficient for which there is no straightforward interpretation. Marginal effects are much more useful because they calculate how the probabilities of choosing an alternative change as the regressors change (Cameron and Trivedi, 2010). The other advantage of reporting marginal effects is that they are reported for each category of the dependent variable, while only J-1 categories are reported for coefficients. For this reason, the marginal effects will be used to discuss the determinants of adopting genetically modified varieties of maize in South Africa.

There are two important points to reiterate before moving forward. First of all, the model shows correlation, but not necessarily causation. This leads to the second point that there are a few variables—yield, input cost, and labor use—which are actually ex-post metrics that are used as proxies for farmers' expectations.

Probit: Binary Decision between GM and Non-GM Seed Type

The first model uses only variables in Variable Set 1 in the binary probit model. Since the primary purpose is to compare expectations set forth by previous adoption models, only the "traditional" variables are used, as shown in Table 6.2. The Wald Chi-square test gives a joint significance of 54.13 and a log-likelihood value of -55.35. The significant marginal effects are found in Table 6.2. The first significant variable in the binary outcome is the *site* variable, which indicates that farmers are less likely to adopt in Simdlangetsha and more likely to adopt GM maize in Hlabisa, consistent with the cross-tabulation in Table 3.1. The significant *sufficiency* variable indicates a positive correlation between the proportion of their maize consumption supplied from their own production and the adoption of a GM variety. Next, the likelihood of adopting any of the GM seed varieties is positively correlated with higher input cost per hectare, where the probability of adopting a GM variety increases by 0.075 with every additional South African Rand spent on inputs. The model indicates that the likelihood of adopting GM maize increases as the ratio between family labor and hired labor increases. This variable does not measure the total hours of labor on the plot but does suggest that GM adopters are more likely to use a greater proportion of family labor than do non-adopters. The dummy variable that indicates whether a farmer got his or her *first choice* in maize seed is not significant in the probit model, but it is in the logit model. Only 8 of the 127 farmers who planted a GM variety did not get their first choice. The final significant marginal effect in the binary outcome is *sell portion*, which indicates that farmers were less likely to adopt a GM variety if they sold a portion of their yield.

Table 6.2 Choice of GM Maize Over Non-GM Maize

	GM		
	M.E.		**Std. Err.**
Site	-0.452	***	0.085
Age	0.007		0.022
Gender	-0.049		0.057
Education	0.021		0.027
HH Size	-0.003		0.012
Sufficiency	0.159	***	0.023
Land	0.020		0.037
Input Cost	0.083	***	0.030
Employment	0.033		0.035
Labor Ratio	0.245	**	0.111
No. Varieties	-0.006		0.061
Sell Portion	-0.214	***	0.077
N	184		
Wald Chi-square	54.90		
Prob > Chi-square	0.000		
Log Likelihood	-59.90		

*=P<0.10, **=P<0.05, ***=P<0.01

Multinomial Probit Model: Seed Type Selection

The primary interest is in the second model, which calculates the determinants of adopting each seed type individually, shown in Table 6.3. To summarize the significant marginal effects, the likelihood that a farmer will plant Bt maize increases if the farmer lives in Simdlangetsha, is more self-sufficient in maize supply, grows fewer varieties, and does not sell a portion of the maize yield. Conversely, a farmer is more likely to plant RR maize if he or she lives in Hlabisa, which was fairly evident in Table 3.1. The likelihood of planting RR maize decreases as the level of education increases by one level, from primary to secondary education, for example. Farmers were less likely to plant RR maize with every additional family member who worked off-farm and if the household sold a portion of the maize yield. Finally, the likelihood that a farmer plants BR maize increases for farmers who live in Hlabisa increases with greater self-sufficiency in maize supply and higher input costs per hectare similar to the probability of RR. However, the marginal effect is opposite in sign for BR compared to RR maize, where the likelihood of adoption increases with a one level increase in education and more family members employed off-farm. Finally, results for the non-GM category basically reiterate the opposite of the outcome for GM adopters in the binary model outcome. Farmers are more likely to continue with traditional or conventional hybrids if they live in

Simdlangetsha, are less self-sufficient in maize food supply, have lower 'expected' input costs, have a lower labor to hired labor ratio, and sell a portion of their maize supply.

Table 6.3 Selected Maize Type Using Traditional Variables Only

	Variable Set 1											
	Bt			RR			BR			Non GM		
	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.
Site	0.217	**	0.092	-0.256	**	0.112	-0.247	**	0.106	0.286	***	0.101
Age	-0.006		0.017	0.021		0.026	0.011		0.024	-0.025		0.024
Gender	0.043		0.051	-0.032		0.067	-0.055		0.062	0.044		0.063
Education	-0.016		0.027	-0.081	**	0.037	0.065	**	0.06	0.032		0.034
HH Size	-0.005		0.013	0.020		0.014	-0.011		0.012	-0.004		0.015
Sufficiency	0.050	**	0.023	0.006		0.032	0.068	*	0.036	-0.123	***	0.028
Land Size	0.012		0.027	-0.007		0.052	-0.002		0.039	-0.003		0.044
Input Cost	0.034		0.027	0.008		0.044	0.072	**	0.034	-0.114	***	0.038
Employment	-0.001		0.032	-0.102	**	0.045	0.079	**	0.034	0.024		0.041
Labor Ratio	-0.178		0.141	0.033	**	0.137	-0.019		0.119	-0.127		0.139
No. Varieties	-0.093	**	0.048	-0.080		0.083	0.094		0.067	0.079		0.069
Sell Portion	-0.122	**	0.059	-0.159	*	0.084	0.048		0.069	0.234	***	0.084
N			184									
Wald Chi-square			96.68									
Prob > Chi-square			0.000									
Log likelihood			-148.382									

*=P<0.10, **=P<0.05, ***=P<0.01

Next, the model is re-specified with the variables measuring seed choice perceptions in Variable Set 2. This model gives the highest value for the Wald Chi-square statistic of 96.4. The only significant finding within the new set of variables is the negative marginal effect for *herbicide tolerance* in the non-GM farmer category. The negative marginal effect for *herbicide tolerance* suggests that if a farmer ranks *herbicide tolerance* one level lower, then he or she is 0.097 units *more* likely to plant a non-GM maize variety. This result is not intuitive. One possible rationale is that these farmers prefer herbicide tolerant varieties but faced constraints which prevented them from adopting a seed type with the Roundup Ready trait. The same variables from Set 1 have significant marginal effects in this second specification as the previous: *site, sufficiency*, *input cost*, and *sell portion*. The only change in the Bt category is that the marginal effect for *site* is no longer significant. The only significant variable that is added in the RR category from Model 1 is that of household size, which indicates that for each additional family member, the farmer is more likely to plant RR maize. The outcome for the BR category is the same from the previous specification.

Table 6.4 Selected Maize Type Using Traditional Variables and Trait Preferences

	Variable Set 2											
	Bt			RR			BR			Non GM		
	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.
Site	0.046		0.19	-0.301		0.3	-0.244		0.27	0.499	**	0.251
Age	-0.012		0.018	0.041		0.028	0.004		0.026	-0.033		0.026
Gender	0.054		0.057	-0.075		0.067	-0.003		0.063	0.025		0.065
Education	-0.017		0.030	-0.073	**	0.039	0.062	*	0.033	0.028		0.036
HH Size	-0.007		0.014	0.030	**	0.015	-0.014		0.013	-0.009		0.016
Sufficiency	0.046	*	0.024	0.024		0.033	0.052		0.034	-0.116	***	0.03
Land Size	0.003		0.029	0.024		0.056	-0.014		0.042	-0.013		0.048
Input Cost	0.049	*	0.029	-0.010		0.044	0.073	**	0.038	-0.112	***	0.039
Employment	0.005		0.032	-0.117	**	0.047	0.113	***	0.036	-0.001		0.044
Labor Ratio	-0.116		0.138	0.313	**	0.135	0.007		0.121	-0.203		0.144
No. Varieties	-0.072		0.051	-0.113		0.084	0.092		0.072	0.092		0.071
Sell Portion	-0.117	**	0.060	-0.230	***	0.091	0.075		0.074	0.272	***	0.092
Seed Price	0.050		0.038	-0.081		0.062	0.036		0.048	-0.005		0.054
Yield	0.013		0.075	-0.068		0.065	0.012		0.058	0.043		0.085
Drought Tolerance	0.032		0.034	0.003		0.065	-0.059		0.053	0.029		0.052
Insect Res.	0.045		0.032	-0.042		0.044	-0.030		0.042	0.027		0.044
Early Maturity	0.008		0.037	-0.018		0.060	0.036		0.048	-0.026		0.054
Herbicide Tol.	0.014		0.028	0.014		0.058	0.064		0.049	-0.093	**	0.045
N			174									
Wald Chi-square			97.53									
Prob > Chi-square			0.000									
Log likelihood			-128.532									
LR Test			16.74									
Prob > Chi-square (18)			0.5414									

*=P<0.10, **=P<0.05, ***=P<0.01

The final multinomial probit model adds the reported production constraints from Variable Set 3. The constraints were coded as binary variables, so that 0 indicates that it was not a major constraint for the farmer, and 1 indicates that it was. Starting with the base non-GM category, the only addition from Variable Set 2 is the positive marginal effect for *production performance*. If a farmer reported poor seed performance, then it increases the likelihood of planting a non-GM variety. Next, there are two changes in the Bt category; the marginal effect for *number of varieties* is again significant and negative as it was in Variable Set 1, and the marginal effect for *money for inputs* suggests that if a farmer described insufficient money to purchase inputs as a major constraint, then the likelihood the farmer will plant Bt maize decreases by 0.107. The third category indicates that a farmer is more likely to plant RR maize if he or she lives in Hlabisa; a farmer is less likely to plant RR maize if he or she listed either *land* or *production performance* as a major constraint. Finally, the BR category loses *input cost per hectare* as a significant variable but gains *sufficiency* as a positive marginal effect, indicating that the likelihood of a farmer planting BR maize increases with maize self-sufficiency. The significant constraints for BR maize indicate that a farmer is more likely to plant BR varieties if he or she listed either *land* or *money for inputs* as the top constraints.

Table 6.5 Selected Maize Type Using Traditional Variables and Reported Constraints

	Variable Set 3											
	Bt			RR			BR			Non GM		
	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.
Site	0.242	**	0.109	-0.294	***	0.118	-0.179		0.114	0.232	**	0.109
Age	-0.008		0.017	0.006		0.026	0.016		0.024	-0.014		0.023
Gender	0.035		0.052	-0.013		0.068	-0.048		0.063	0.027		0.064
Education	-0.005		0.027	-0.099	***	0.037	0.063	**	0.031	0.041		0.033
HH Size	-0.011		0.014	0.027	*	0.015	-0.014		0.013	-0.003		0.015
Sufficiency	0.047	*	0.024	-0.025		0.035	0.071	*	0.038	-0.092	***	0.031
Land Size	0.009		0.026	-0.018		0.053	0.004		0.040	0.005		0.044
Input Cost	0.061	**	0.03	0.019		0.045	0.050		0.036	-0.129	***	0.039
Employment	-0.016		0.03	-0.102	**	0.046	0.097	***	0.034	0.022		0.041
Labor Ratio	-0.247		0.138	0.324	**	0.143	-0.002		0.121	-0.075		0.014
No. Varieties	-0.094	**	0.045	-0.065		0.080	0.086		0.064	0.074		0.067
Sell Portion	-0.260	***	0.087	-0.153	*	0.092	0.119		0.082	0.293	***	0.08
Labor Constr.	-0.020		0.058	-0.127		0.106	0.064		0.100	0.082		0.095
Output Market	0.087		0.064	-0.071		0.085	0.050		0.079	-0.067		0.083
Land Constr.	0.007		0.049	-0.209	***	0.071	0.106		0.072	0.089		0.066
Input Money	-0.119	**	0.054	-0.075		0.076	0.150	**	0.086	0.036		0.075
Insect Damage	-0.080		0.090	-0.009		0.140	0.061		0.143	0.021		0.143
Performance	0.048		0.046	-0.217	**	0.094	0.010		0.089	0.149	**	0.070
Storage	-0.071		0.092	0.079		0.129	-0.034		0.136	0.250		0.131
N			184									
Wald Chi-square			95.01									
Prob > Chi-square			0.001									
Log Likelihood			-134.192									
LR Test			28.38									
Prob > Chi-square (21)			0.1297									

*=P<0.10, **=P<0.05, ***=P<0.01

Multinomial Probit: Intensity of Adoption

The final models determine which variables significantly affect the intensity of adoption. These models use the multinomial probit and are specified with each of the three variable sets. The purpose of these final models is to examine the commonalities that describe non-adopters, partial adopters, and full adopters. Because the cross-sectional data give only a point-in-time perspective, this model captures the progression through the technology adoption process.

Table 6.6 presents the marginal effects for the multinomial probit using Variable Set 1. For the most part, the signs on the marginal effects for partial adopters follow the same direction as the marginal effects for full adopters, where the sign is in the opposite direction for non-adopters. The only significant sign that differs between adoption statuses is *number of varieties*, since partial adopters, by definition, must plant at least two seed types, and full adopters are not required to plant more than one. Each of the three model specifications will be discussed.

To summarize the significant marginal effects for the first specification, full adopters are more likely in Hlabisa and non-adopters in Simdlangetsha. Secondly, full adopters are much more likely to be self-sufficient in maize supply, and the likelihood of adopting declines for those with lower sufficiency measures. The next variable suggests that both partial and full adopters are more likely to have higher *expected* input costs per hectare than non-adopters; this is no surprise since the seed costs for GM varieties are much higher and generally require more expensive inputs. The significant marginal effects for *number of varieties* have been discussed. The final significant marginal effect follows suit with earlier findings that non-adopters are more likely to sell a portion of their maize yield.

Table 6.6 Intensity of Adoption Using Traditional Variables Only

	Variable Set 1								
	Partial Adopter			**Full Adopter**			**Non Adopter**		
	M.E.		**Std. Err.**	**M.E.**		**Std. Err.**	**M.E.**		**Std. Err.**
Site	0.067		0.103	-0.351	***	0.085	0.285	***	0.105
Age	0.037		0.024	-0.008		0.024	-0.029		0.024
Gender	0.040		0.064	-0.072		0.058	0.032		0.063
Education	-0.039		0.035	0.013		0.031	0.027		0.032
HH Size	0.015		0.014	-0.008		0.011	-0.007		0.015
Sufficiency	0.009		0.030	0.095	***	0.027	-0.104	***	0.028
Land	0.008		0.042	0.010		0.042	-0.018		0.043
Input Cost	0.057		0.037	0.069	**	0.034	-0.126	***	0.037
Employment	0.054		0.041	-0.079	**	0.039	0.025		0.041
Labor Ratio	0.198		0.132	-0.020		0.103	-0.178		0.132
No. Varieties	0.155	**	0.167	-0.255	***	0.065	0.100		0.066
Sell Portion	-0.140		0.079	-0.098		0.067	0.0238	***	0.085
N	184								
Wald Chi-square	96.67								
Prob > Chi-square	0.000								
Log Likelihood	-114.809								

*=P<0.10, **=P<0.05, ***=P<0.01

The number of significant marginal effects changes considerably in the second specification of the model, especially for partial adopters, found in Table 6.7. Again, this may indicated that there is omitted variable bias in the first model that includes only Variable Set 1. *Age* is significant for partial adopters, indicating that partial adopters are more likely to be older farmers. Partial adopters also are more likely to have more family members living in the *household*. The *sufficiency* and *total cost per hectare* measures tell the same story in this specification as in the model that uses only the "traditional" variables found in Table 6.6. Partial adopters are more likely to have more family members working off-farm, which is not a difficult connection to make since they typically have more family members available to work. The *family to hired ratio* variable suggests that the proportion of family labor decreases relative to hired labor for non-adopters, but is the opposite case for partial adopters, who are more likely to use a greater proportion of family labor. The only variable within the set of 'trait preferences' that is significant is *yield*, which suggests that farmers who ranked *yield* as important determinants are more likely to be partial adopters.

Table 6.7 Intensity of Adoption Using Traditional Variables and Trait Preferences

	Variable Set 2								
	Partial Adopter			Full Adopter			Non Adopter		
	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.
Site	-0.140		0.244	-0.243		0.267	0.383		0.256
Age	0.050		0.024	-0.008		0.026	-0.037		0.025
Gender	-0.044		0.065	-0.061		0.060	0.011		0.066
Education	0.024		0.038	0.019		0.036	0.017		0.036
HH Size	0.013	***	0.014	-0.011		0.012	-0.013		0.015
Sufficiency	0.002		0.033	0.089	***	0.030	-0.103	***	0.031
Land Size	0.045		0.044	0.032		0.045	-0.035		0.047
Input Cost	0.066		0.037	0.075	*	0.037	-0.120	***	0.038
Employment	0.265		0.042	-0.067	*	0.042	0.001		0.044
Labor Ratio	0.131	*	0.135	0.028		0.107	-0.237	*	0.140
No.Varieties	-0.156	**	0.066	-0.245	***	0.066	0.114	*	0.069
Sell Portion	-0.058	**	0.083	-0.121		0.077	0.278	***	0.094
Seed Price	-0.058		0.069	0.057		0.056	0.001		0.056
Yield	-0.170	*	0.100	0.067		0.066	0.103		0.087
Drought Tolerance	0.008		0.051	-0.056		0.065	0.049		0.056
Insect Resistance	-0.029		0.043	0.024		0.04	0.004		0.045
Early Maturity	0.021		0.052	0.007		0.051	-0.028		0.052
Herbicide Tolerance	0.063		0.042	0.003		0.046	-0.060	*	0.044
N	174								
Wald Chi-square	92.68								
Prob > Chi-square	0.000								
Log Likelihood	-101.48								
LR Test	11.28								
Prob > Chi-square (12)	0.5048								

*=P<0.10, **=P<0.05, ***=P<0.01

The final specification of the Intensity of Adoption model is summarized in Table 6.8. The only new finding in the non-adopter category is that the likelihood increases for farmers who report *production performance* as the top production constraint. Thus, non-adopters are more likely to report poor production as a major constraint. There are no new findings for partial or non-adopters that were not already discussed in the first two specifications. The overall fit of the model, as measured by the Wald Chi-square, is highest in the third specification of the Intensity of Adoption model.

Table 6.8 Intensity of Adoption Using Traditional Variables and Reported Constraints

	Variable Set 3								
	Partial Adopter			Full Adopter			Non Adopter		
	M.E.		**Std. Err.**	**M.E.**		**Std. Err.**	**M.E.**		**Std. Err.**
Site	0.082		0.101	-0.353	***	0.085	0.281	***	0.102
Age	0.029		0.024	-0.005		0.024	-0.025		0.024
Gender	0.061		0.066	-0.089		0.061	0.029		0.065
Education	-0.036		0.036	0.007		0.031	0.029		0.033
HH Size	0.018		0.014	-0.010		0.011	-0.008		0.015
Sufficiency	-0.015		0.032	0.094	***	0.029	-0.079	***	0.031
Land Size	0.009		0.043	0.010		0.044	-0.019		0.043
Input Cost	0.069	*	0.038	0.064	*	0.036	-0.132	***	0.038
Employment	0.066		0.042	-0.091	**	0.04	0.025		0.042
Labor Ratio	0.181		0.136	-0.053		0.112	-0.128		0.141
No. Varieties	0.142	**	0.068	-0.230	***	0.066	0.087		0.067
Sell Portion	-0.152	*	0.090	-0.114		0.078	0.266	***	0.099
Labor Constraint	-0.096		0.100	0.049		0.089	0.047		0.096
Lack Seller's Market	0.065		0.080	0.012		0.066	-0.053		0.081
Land Constraint	-0.011		0.065	-0.013		0.058	0.057		0.065
Money for Inputs	-0.011		0.075	-0.043		0.065	0.031		0.074
Insect Damage	0.108		0.133	-0.133		0.12	0.026		0.138
Performance	-0.017		0.077	-0.097		0.075	0.115	*	0.070
Storage	0.190		0.119	-0.161		0.106	-0.029	*	0.129
N	184								
Wald Chi-square	97.08								
Prob > Chi-square	0.000								
Log Likelihood	-109.19								
LR Test	11.23								
Prob > Chi-square (14)	0.6679								

*=P<0.10, **=P<0.05, ***=P<0.01

Summary of Model Results

After identifying three distinct variable sets and clarifying the appropriate discrete choice model, the dataset imparts significant findings. While each model finds significant determinants of adoption individually, it is also important to compare trends in results across models, among adopters of different seed types and among farmers at different stages of the adoption process. Similar findings among models substantiate the expectations built from earlier descriptive data and establish consistency in the results. Rather than revisiting each model sequentially, the concluding remarks will review each significant variable in order to avoid excessive repetition. Any further extrapolations will be saved for the final chapter, which will pull findings from previous chapters to illustrate the determinants of adopting a variety of genetically modified maize in KwaZulu-Natal.

The farmer characteristics constitute the majority of the differences in seed purchase decisions. The first significant variable in each model shows that non-GM and Bt farmers were more likely to live in Simdlangetsha, while the Roundup Ready and stacked BR farmers more frequently lived in Hlabisa. It follows then that full adopters live in Hlabisa and non-adopters in Simdlangetsha. The marginal effect for partial adopters indicated that partial adopters tended to be older. The education variable is significant and positive in the case of BR farmers, which suggests that the likelihood of adopting the BR variety increased with increased education, but significant and negative for farmers who chose RR maize. BR maize was introduced a few years after Bt and RR, so a time effect may and learning curve may be the reason that farmers with higher education are more probable to adopt this seed type first. The final farmer-specific variable is the measure of self-sufficiency in maize supply, which was significant and positive for all categories of GM maize farmers, so that an increase in sufficiency increased the likelihood of planting a GM variety. Only RR and BR farmers had significant marginal effects for the proxy measuring the number of family members working full-time off of the farm. The sign is opposite, indicating that as the number of working members increases, farmers are less likely to plant RR maize, but more likely to plant BR maize. The models show stark differences between GM and non-GM farmers. However, it is especially important to note that there are differences among the three categories of GM farmers in site, age, gender, education level, and full-time off-farm employment.

The remaining traditional variables describe the farm-level characteristics. There were fewer significant differences among the three GM adopters at the farm level. All three models showed a positive correlation between total cost per hectare and the adoption of GM maize types, whether the dependent variable was GM adopter, or Bt, RR, and BR, or partial and full adopter. The marginal effect for family to hired labor ratio was significant and positive for RR farmers and partial adopters, indicating a positive relationship among farms that utilized greater proportions of family labor and those who planted RR maize. It also follows the point that the majority of partial adopters planted RR maize rather than the other two GM seed types. An important point though is that the positive marginal effect does not in any way suggest that RR farmers used more total labor; it means only that they tend to employ a lower proportion of hired laborers. The final farm-level variable to discuss is the propensity to consume the entire maize yield or sell a portion of it. The result for this variable was consistent across models and, in fact, very interesting. The finding is that the farmers who did plan to sell maize were more likely to plant a non-GM variety. All of the marginal effects for Bt, RR, BR, partial, full, or GM adopters indicated that they were less likely to adopt if they planned to sell maize.

Several of the variables in Variable Sets 2 and 3 had individually significant p-values which merit some discussion. Looking first at the farmers' reports on factors that heavily influenced their seed choice, the models suggest that, for farmers who perceive yield as most important, the likelihood of being a partial adopter increases. As previously explained, the marginal effect is actually negative, but because 'most important' was coded as a 1 and 'least important' as a 5, lower numbers indicate that the factor is more important. Oddly, the significant negative sign on the marginal effect for herbicide tolerance suggests that non-GM farmers actually value the genetic trait for protection against chemical herbicides. The signs on the reported constraints are again intuitive, where the positive and negative signs actually signify 'more likely' and 'less likely', respectively. The variables were coded 0 for 'not a major constraint' or 1 for 'major constraint'. Model results showed that Bt farmers were less likely to be deterred by the money required for inputs, whereas BR farmers were. Farmers who planted Roundup Ready maize showed positive marginal effects for production performance, signifying that they did find poor growth to be a major constraint, whereas non-adopters had negative marginal effects. The production performance variable captured the sentiment that farmers were dissatisfied with their seed's poor performance, either for traits inherent to the seed or more specifically because it did not grow particularly well in dry conditions. Further conclusions could be extrapolated from the model results, which are discussed in the final conclusions.

Table 6.9 summarizes the differences in sign for all significant marginal effects between the 'GM Over Non-GM' binomial probit and the 'Selected Seed Type' multinomial probit models. There are four variables that differ among the three categories of genetically modified adoption. First, the sign on the site variable is opposite for Bt farmers from the other GM categories, which again points out that farmers are more likely to plant Bt maize in Simdlangetsha than in Hlabisa. The likelihood of planting Bt or non-GM in Simdlangetsha, as opposed to the greater number of farmers in Hlabisa who planted RR or BR maize, emphasizes the importance of seed availability in adoption models. Second, the education sign is opposite for RR and BR adopters, and is not significant in the binomial model. The reason for this difference cannot be explained. One possible explanation is that the stack-gene variety requires greater education or training to understand its complex production traits, and farmers with higher education generally have a greater capacity to learn. Employment was the third variable with differing marginal effects. Many adoption studies suggest that more family members working off-farm increases the likelihood of adopting an agricultural technology, especially if the technology saves labor and requires greater income to finance its use. The negative marginal effect then is counter to the expectation, but it may explain why more RR farmers use government pension to purchase the seed. Finally, the dummy variable that captures whether or not farmers sell any portion of their maize yield provides interesting discussion. The binomial model suggests that farmers are more likely to adopt if they sell maize, which generally follows expectations from previous literature. However, in the multinomial probit models, both Bt and RR categories exhibited negative marginal effects while non-adopters had significant positive signs. The marginal effect for BR farmers was not significant.

The over-arching point in this comparison is that the three categories of adopters are not a homogenous group but merely have opposing determinants of adoption. Thus, the binary 'adopter – non-adopter' dichotomy is insufficient, and the seed choice should be modeled individually for its own unique genetically modified traits.

Table 6.9 Comparison of Significant Marginal Effects from Binomial and Multinomial Models

	Binary Model	Multinomial Model		
	GM	Bt	RR	BR
Site	-	+	-	-
Education			-	+
HH Size			+	
Sufficiency	+	+		+
Input Cost	+	+		+
Employment		-	+	
Labor Ratio	+		+	
No. Varieties		-		
Sell Portion	+	-	-	

Chapter 7 Conclusion and Implications

The final chapter will summarize the findings and discuss the determinants of adoption of genetically modified maize in general, of adoption of particular GM technologies, and of the intensity of adoption. The site variable was significant in most of the models, which provides insight into the differences in the seed markets more so than into the choice decision. Thirty-six of the 37 farmers who did not get their first choice in maize seed lived in Simdlangetsha, which strongly suggests that the seed market is undeveloped in the region, and there is potential market space to increase the adoption of genetically modified maize. Consequently, the distribution of seed selection is very different between the two regions; the majority of farmers in Simdlangetsha planted either Bt or non-GM varieties and diversified by planting more than one variety, whereas most farmers in Hlabisa planted only one variety of either Roundup Ready or the stacked BR maize. Not all farmers who planted Bt maize should be considered intentional adopters, as many planted Bt as a consolation to their first choice, because it was available rather than desired. Only 8 of the 18 who planted Bt indicated that it was their first choice, and 17 of those farmers lived in Simdlangetsha.

The measure for self-sufficiency was the second most-frequently significant variable, suggesting that farmers are more likely to adopt if they supply more of their maize food supply from their own production. This has a few implications. First, many of the farmers reported that maize and maize meal is very expensive to purchase from the market, so supplying their own food source frees up money that potentially could be used for maize production. The second implication ties in with another significant determinant, which is that adopters are less likely to sell any of their maize crop. In each of the three dependent variable specifications, only the non-GM category had a positive marginal effect for selling maize.

The total input cost per hectare is commonly significant in each of the three models as well. The results for these marginal effects are more difficult to interpret though, because the proxy for 'expected prices' are actually ex-post data. In general, genetically modified seed types are more expensive than traditional or conventionally-improved hybrid varieties and usually are adopted along with a package of inputs that increase input costs. It is assumed that farmers are aware of the higher production costs, and the resulting total costs per hectare shows that farmers were willing to pay in advance the higher production costs in order to adopt. This assumption of informed expectations is justified by reports from some non-adopters that genetically modified maize is "too expensive."

Rather than looking at per-hectare costs, another way to view production expenses is to compare the total seed cost as a percentage of farmers' total income and assets. This reiterates that non-GM farmers report spending less than do other farmers, though the differences were not tested statistically. Specifically, RR farmers spent 0.83 percent of their total income and assets on seed, Bt farmers spent 0.97 percent, BR spent 1.0 percent, but non-GM farmers spent only 0.62 percent. On average, non-GM farmers have lower income and assets, holding only two thirds of what BR farmers have.

The source of maize seed money was not included in the model because a pre-model correlation table showed that it was not highly correlated with the adoption decision. However, it is interesting for future policy studies to note how farmers are financing their seed purchases. While non-GM farmers are more likely to sell a portion of their maize yield, none of the non-GM farmers reported that they buy seed using farm income. Instead, 54 percent of non-GM farmers use a government pension and another quarter say that they use money from off-farm employment to purchase maize seed. While the majority in all categories use government pension, the greatest proportion of farmers who use it were RR farmers, 78 percent of whom bought seed using government pension. Many farmers explained they used the government's old age pension because they had no other source of income.

In further regard to money sources, the farmer-reported input cost constraint was significant for both Bt and BR farmers; however, the effect was opposite. Bt farmers did not list the money required to purchase inputs as a significant production constraint, whereas BR farmers ranked it as one of the greatest constraints. Many of the Bt farmers did not choose the insect resistant seed as their first choice, and so it may be that Bt farmers either were less concerned or were less informed about the proper input mix for the seed. Also, the herbicide tolerance attribute in the BR seed implies that farmers had to purchase a particular type of herbicide in order to take advantage of the GM trait, which would have further increased input expenses. The ex-post measure of input expenses shows that BR farmers spent almost twice what Bt farmers spent on inputs. Therefore, it may not be higher seed prices alone that discourage adoption for non-adopters but the complementary inputs as well.

In their open-ended survey responses, labor use on the maize plots was a concern for many farmers, as indicated in the qualitative analysis. Model results produced positive marginal effects for RR farmers and for partial adopters and, to a lesser degree, for GM adopters in general. This positive result suggests that farm operations which employ a greater proportion of family labor are more likely to adopt, especially herbicide tolerant maize. This may likely be attributed to farmers with less total available labor—either sourced from family members or hired laborers—who need to overcome a labor constraint by planting an herbicide tolerant variety.

The three hypotheses studied in the current research provide insight into farmers' seed choice and open doors to further research. First, it is not necessarily the case that farming operations with greater amounts of assets and income are more likely to adopt. Model results showed that RR farmers were less likely to adopt based on more family members working off-farm, while the probability of adopting BR increased with greater off-farm employment. Likewise, it does not seem that income from selling the maize makes farmers more likely to purchase the more expensive GM maize seed; instead, only the probability of planting non-GM maize increased with the likelihood of selling any of the maize crop. Furthermore, non-GM farmers reported greater average wealth than RR farmers. It is important to note that the value of government pensions were not included in the income and assets measure. Finally, because the majority of farmers in all categories reported that they purchase seed using government pension—including old age pension and child grants—this could greatly alter the conclusion to the first hypothesis.

Secondly, it was hypothesized that farmers with greater labor constraints would adopt the herbicide tolerant maize varieties. The model indicated that those who planted Roundup Ready maize had greater family-to-hired labor ratios, though this does not mean that they used more hours of family labor. The marginal effect for the stacked BR maize was not significant. Earlier statistics showed that the farming households that planted RR maize did in fact have less family labor available and used far less hired labor. It must be addressed that the labor *use* is an ex-post metric, so the labor availability is actually the more pertinent indicator.

Finally, the model was to determine whether significant determinants could differentiate among the three genetically modified seed types. Differences in marginal effects surfaced more often in the socio-economic, farmer-specific data rather than in the production farm-level data. There were significant differences in site, age, gender, education, full-time employment, and money constraints. This indicates that the GM versus non-GM comparison is insufficient in addressing the adoption decision. Instead, the adoption decision for each specific genetically modified trait should be considered in future research.

Future Research

This research generates questions for future research opportunities. The open-ended responses enriched and substantiated the results from the economic models. Further research that incorporates farmers' thoughts into economic choice models may find otherwise. The results also suggest that future studies should extend beyond the dichotomous question of whether a farmer adopts, and consider the reasons why farmers choose specific traits expressed in different agricultural technologies.

One specific question that could not be adequately addressed in this research is the direct relationship between labor availability and the labor-saving herbicide tolerant maize. Many farmers explained that they preferred either the Roundup Ready or stacked BR maize because they did not have to weed. Unfortunately, the nature of their responses was difficult to model, because their preferences were constrained to the seed they could afford or obtain, which subsequently affected their labor and input use. The family to hired labor ratio was used in the model because correlation coefficient tables indicated greater correlation with seed type choice than did other measures of labor use. However, data which reflected labor availability and use both *before* and *after* the adoption may more accurately show the effects that labor requirements had on the adoption decision.

Another important aspect that should be explored in future research is the role of government payments in the adoption of genetically modified crops. The majority of farmers in all seed categories reported that they purchase seed using government payments, particularly old age pension. For the most part, those who received child pensions did not use the money for farm inputs, but rather explained that they put the money towards the children's education or other family expenses. Most of the farmers preferred to grow their own maize because, as they explained, it is more economical or has better taste and health qualities than purchased maize meal. Considering that genetically modified maize improves yield, net returns, and reduces labor costs, then the government payments are contributing to improved welfare of subsistence farmers. Research in this area could lead to policy decisions that further enable farmers to grow genetically modified maize.

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Appendix I: Empirical Tests for Appropriate Model

Multinomial Probit Model

Methods

The random utility model is the basis of the probit model, modeling

(1) $$U_{nj} = V_{nj}(x_{nj}s_n) + \varepsilon_{nj}.$$

The important part to distinguish is that ε_n is distributed normal with mean vector of zero and, more importantly, a covariance matrix **Ω**. The density of ε_n is

(2) $$\phi(\varepsilon_n) = \frac{1}{(2\pi)^{\frac{J}{2}}|\Omega|^{1/2}} * e^{-1/2}\varepsilon'_n\Omega^{-1}\varepsilon_n$$

and the choice probability is the same as the multinomial logit model in Equations 5.6 and 5.8, where

(3) $$Prob(V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni})\,\nabla\, j \neq i$$

And the indicator function is the integral of the probability equation, rearranged.

(4) $$= \int I\left(V_{nj} - V_{ni} < \varepsilon_{ni} - \varepsilon_{nj}\right) f(\varepsilon_n) d\varepsilon_n$$

The indicator function essentially decides whether the statement in parentheses is accepted or rejected. The probability that alternative *i* is chosen then is the integral over all values of the error term. Then the set of error terms $\varepsilon_n$that result in the farmer choosing seed *i* be modeled as B_{ni} = ε_n subject to

(5) $$(V_{nj} + \varepsilon_{nj} > V_{ni} + \varepsilon_{ni})\,\nabla\, j \neq i,$$

which gives the probability

(6) $$P_{nj} = \int_{\varepsilon_n \epsilon B_{ni}} \phi(\varepsilon_n) d\varepsilon_n$$

Since the difference between two normal error terms is normal, the density of the differences between errors is modeled by the equation below (Train, 2009)

. (7) $$\phi(\tilde{\varepsilon}_{ni}) = \frac{1}{(2\pi)^{\frac{J}{2}(J-1)}|\widetilde{\Omega}|^{1/2}} * e^{-1/2}\tilde{\varepsilon}'_n\widetilde{\Omega}^{-1}\tilde{\varepsilon}_n$$

The most important feature of the multinomial probit model for this research is the covariance of the error term, which is normally distributed with mean zero and variance Ω ($\varepsilon_n \sim N(0, \Omega)$),. The covariance matrix is denoted by

(8) $$\Omega = I_j * \sum \text{ for j} = 1 \ldots \text{J}.$$

Here, I is an identity matrix and Σ is the covariance of ε_n. So for J= 4 for the four seed types, the Ω matrix

$$\Omega = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} \end{bmatrix}$$

should be a diagonal matrix so that the σ_{lj} elements are zero for j≠l and the diagonal elements of covariance are independent. Because the covariance matrix is normalized and structured so that all ε_{nj} are independent, the multinomial probit is not restricted by the same assumptions of the multinomial logit and fully relaxes the IIA assumption (Christiadi and Cushing, 2007).

Multinomial Logit Model

Methods

The simplest approach for unordered discrete choice is the multinomial logit model (MNL), which uses case (farmer) specific data (Cameron & Trivedi, 2010). The probability that a farmer will choose the j^{th} seed variety, where J =4 is given by:

(9) $$Prob(y_i = j) = \frac{\exp(x'_i\beta^{nj})}{\sum_0^J \exp(x'_i\beta^j)} \qquad 0 < P_j < 1 \qquad \sum_0^J P_j = 1$$

where x is the row vector of k observations (x' is the transposed column) and β^j is k vectors of parameters.

Assume each unknown, unobserved portion of utility, ε_{nj}, is independently, identically distributed extreme value, or by the Gumbel distribution. The density for the unobserved portion is described by:

(10) $$f(\varepsilon_{nj}) = e^{-\varepsilon_{nj}} e^{-e^{-\varepsilon_{nj}}}$$

And the cumulative distribution is found to be:

(11) $$F(\varepsilon_{nj}) = e^{-e^{-\varepsilon_{nj}}}$$

The variance of the cumulative distribution is set to $Var[F(\varepsilon_{nj})] = {}^{\Pi^2}/_{6}$, which implicitly normalizes the scale of utility.

The difference between extreme value variables $[\varepsilon_{nj} - \varepsilon_{ni} = \varepsilon_{nji}]$ is distributed logistic, which is the definitive feature of the logit model over the probit, which is normally distributed. After normalization, the cumulative distribution of the differences between error terms is:

$F(\varepsilon_{nji}) = \frac{e^{\varepsilon_{nji}}}{1+e^{\varepsilon_{nji}}}$ These error terms are independent of one another. (Train 2009)

In logit models, normalization of error terms occurs automatically with assumptions on distribution. The overall scale of utility is irrelevant, since the scale parameter drops out in a ratio between two alternatives. As such, adding or multiplying the utility level does not change the decision-maker's choice. It is possible to normalize the scale of utility by normalizing variance of error terms by any term, λ so that $Var(\lambda\varepsilon_{nj}) = \lambda^2 Var(\varepsilon_{nj})$.

Due to the earlier restriction of *J-1* differences between choices, one limited dependent seed alternative is set to 0 as the base outcome, to which all other seed choice results will be compared. In most statistical software packages, the dependent variable with the most observations is set as the base category; however, by common sense, the non-GM dummy variable is overwritten as the base category. The previous probability statement can be re-written in terms of linear parameters $[V_{nj} = \beta' x_{nj}]$, so that the probability that farmer *n* chooses seed type *i* is divided by the sum of probabilities of all other seed types *J:*

(12) $$P_{ni} = \frac{e^{\beta' x_{ni}}}{\sum_0^J e^{\beta' x_{nj}}}$$

The model is only good as its predictive power. The probability that the model predicts that farmer *n* chooses the actual observed seed choice is modeled by the equation

(13) $$\prod_i P_{ni}{}^{y_{ni}}$$

Where y_{ni} is 1 if the prediction matches the observed seed choice, and is 0 otherwise. Thus, if the exponent is 0, then the probability equals one, so only the probability of correct predictions is calculated. After multiplying the probabilities of correct seed choice predictions for all farmers in the data set, the log-likelihood is written as

(14) $$LL(\beta) = \sum_{n=1}^N \sum_i y_{ni} \ln P_{ni}$$

The log likelihood function is found to be closed-form and globally concave, which makes model estimation and interpretation straightforward.

Goodness of Fit

There are several tests for overall model fitness. The pseudo R-squared test computes the amount of variation in seed choice explained by the x_i's, penalized for the number of explanatory variables included in the model, but is generally not the most accurate measure of fit. The R-squared is not exactly in the same manner as in an OLS regression, so its interpretation warrants great caution (UCLA Statistical Consulting Group, 2012).

Tests which check to see whether equations are jointly significant include the likelihood ratio chi-squared (LR-chi^2) & prob>chi^2 tests. First, the likelihood ratio chi-square test checks that for each of the equations for the three seed types (excluding the base category), at least one of the predictors' coefficients is not zero. The LR Chi-Square test is computed by -2 times the difference between the null model and the fitted model. The second test of joint significance, Prob>chi2, is the probability of getting a value as extreme as the likelihood ratio test, where a p-value less than or equal to the critical value of 0.05 indicates that at least one of the coefficients is not zero (UCLA Statistical Consulting Group, 2012).

The likelihood ratio index then measures how well parameters perform compared to model in which all parameters are 0. The likelihood measure from the estimated parameters is divided by the likelihood when when all parameters are set to 0, which is then subtracted from one (1) to give the index value. If the $\hat{\beta}$ parameters do no better than 0, then the ratio is equal to one and ρ is equal to 0, by equation (). Likewise, if the $\hat{\beta}$ parameters predict perfectly, then ρ is equal to 1. Unlike the R^2 statistic, there is no intuitive interpretation of ρ otherwise (Train, 2009).

(15) $$\rho = 1 - \frac{LL(\hat{\beta})}{LL(0)}$$

Independence of Irrelevant Alternatives

The logit model is susceptible to an error of independence of irrelevant alternatives, in which the probabilities are distorted by an immaterial difference between alternatives, when no real difference exists. For any two alternatives, the odds between the two choices depend solely on the respective x'_i and β of those two responses; they do not depend on the β vectors of any other alternatives. For example, the model may be specified so that farmers could have the choice between two conventional Pannar seed types and the three genetically modified seeds, Bt, RR, and BR. While minor differences exist between the two Pannar seeds, logically they are not enough different to set them apart against the GM seeds. For simplicity, if each seed had an equal chance of being selected, the probability for each of the five seed choices would be 0.20 each. The total probability of a farmer choosing a non-GM seed, then, is 0.40. This gives an incorrect measure of the probability that a farmer would choose a non-GM seed, because there are no real justifiable differences between the conventional seeds. Thus, the model is subject to independence of irrelevant alternatives.

The difference in probabilities in choosing seed i or seed j is given by a quotient which can be reduced to the difference in equation ():

(16) $$\frac{\Pr(y=i)}{\Pr(y=j)} = \frac{\exp(x\prime\beta^{i})}{\exp\left(x\prime\beta^{j}\right)} = \exp\left[x(\beta^{i} - \beta^{j}\right] \qquad \text{for } i, j = 1 \ldots J \text{ seed choices}$$

where β^i and β^j describe distinguishing characteristics of the seed.

Tests and Proposed Solutions for IIA

There are two tests for independence of irrelevant alternatives. In the first test, proposed by Hausman and McFadden (1984), the null hypothesis assumes that the parameter estimates obtained from a subset of alternatives will not be significantly different from estimates on the full set of alternatives. In other words, the results should not change between a subset and the full set of seed alternatives, since each result is a comparison between of each alternative compared to the base outcome. If there are differences in parameter estimates, then the model has violated IIA (Train, 2009).

The second test for IIA compares model results with the inclusion of cross-alternatives. After the model is run with a *subset* of alternatives, say *i* and *k*, then it can be re-run with an additional alternative, *j*. If the ratio of probabilities between *i* and *k* change with the inclusion of *j*, then it is proven that the attributes of alternative *j* have entered into the cross-alternatives of the other alternatives and significantly affect utility. McFadden (1987) proposed another method using the same cross-alternative concept, in which the dependent variables from the regression become the residuals of the original logit model, and explanatory variables are those of the cross-alternatives (Train, 2009).

Two possible solutions are proposed to relax the assumption of IIA. The nested logit partially relaxes the assumption of IIA by creating nests of alternatives in which the ratio of probabilities is independent from other alternatives within the nest. The second option is to run the model as a multinomial probit model, which fully relaxes the assumptions of IIA but further imposes the restriction of normally distributed error terms (Train, 2009)

Results: Multinomial Logit

Table 8.1 Selected Seed Type Using Traditional Variables Only

	Bt			Roundup Ready			Stacked BR			non-GM		
	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.	M.E.		Std. Err.
Site	0.18	*	0.1	-0.183		0.122	-0.167		0.107	0.169		0.113
Age	-0.006		0.016	0.017		0.027	0.016		0.025	-0.026		0.024
Gender	0.037		0.049	-0.04		0.067	-0.04		0.06	0.043		0.063
Education	-0.015		0.026	-0.08	**	0.037	0.062	**	0.029	0.03		0.032
HH Size	-0.009		0.012	0.023		0.014	-0.007		0.012	-0.007		0.015
Sufficiency	0.055	***	0.023	0.007		0.003	0.051		0.036	-0.113	***	0.03
Land	0.011		0.025	-0.015		0.053	-0.006		0.039	0.009		0.045
Input Cost	0.044		0.027	0.023	***	0.045	0.066	*	0.034	-0.133	***	0.053
Employment	0.013	*	0.03	-0.11	***	0.044	0.088	*	0.032	0.038		0.04
Labor Ratio	-0.13		0.032	0.307		0.131	-0.043		0.114	-0.134		0.136
First Choice	-0.284		15.44	0.666		58.72	1.5		104.1	-0.55		29.91
No. Varieties	-0.096	**	0.048	-0.083		0.082	0.094		0.064	0.084		0.07
Sell Portion	-0.12	**	0.057	-0.172	**	0.082	0.041		0.068	0.251	***	0.086
N		183										
LR Chi2		170.47										
Log Likelihood		-142.44										
Adjusted R-squared		0.37										

*=P<0.10, **=P<0.05, ***=P<0.01

Results for IIA Test

This first model gives clearer insight on how the explanatory variables affect the likelihood of adoption in each case. However, it may not be the most accurate way to model the determinants of adoption. To determine whether the multinomial logit is appropriate, the Hausman test measures whether the probabilities of choosing one seed variety changes if another is removed, as described in Chapter 5. The results of the tests are listed below Table 6.2, where Bt, Br, and non-GM categories are removed against the base outcome of RR. When either of the two GM types is removed, the test concludes that the model violates the assumption of IIA. However, when the non-GM category is removed, the test fails to reject the null hypothesis. The inconsistent test results are most likely due to the insufficient number of observations. In light of inconclusive test results, it is safe to run alternative models that relax the assumptions of IIA.

Table 8.2 Hausman Test for IIA

Test	Chi-square	Outcome	Conclusion
remove Bt	-11.14	reject H_0	violates IIA
remove BR	-0.25	reject H_0	violates IIA
remove non-GM	0.996	fail to reject H_0	does not violate IIA

**RR set as baseoutcome*

Nested Logit Model

Methods

An earlier section discussed the possibility that the multinomial logit model would violate the assumptions of the independence of irrelevant alternatives. Without empirically testing the MNL model, there is no way to intuitively tell which whether this violation will occur. In the case of such violation, the nested logit offers one way to relax the assumptions.

The first difference between the multinomial logit and the nested logit is that the mlogit uses only case- (farmer-) specific data, and the nested logit requires both alternative- (seed variety-) specific and case-specific data. The model works under the premise of the conceptual model presented in Figures 5.2, where the three genetically modified seed types are grouped into a nest due to their GM technology attributes. The idea behind this model is that the farmer makes the seed purchase decision sequentially, first to adopt a GM maize variety, and then which specific trait to choose. The model assumes the same random utility model as does the multinomial logit and is likewise estimated using standard maximum likelihood techniques. As such, the derivation of the nested logit will be much shorter than that of the multinomial logit (Train, 2009).

The benefit of the nested logit is that it is more general than the standard logit, specifically for situations in which the unobserved portions of utility are correlated and IIA does not hold. The nested logit is a generalized extreme value (GEV) model, which implies that the unobserved utility for all alternatives are jointly distributed as a generalized extreme value and allows for correlations over alternatives. If the correlation over alternatives is zero, that is, the error terms are in fact independent, then the GEV model collapses into a standard logit (Train, 2009). Using the same set-up for random utility, $U_{nj} = V_{nj}\left(x_{nj}s_n\right) + \varepsilon_{nj}$, the error term $\varepsilon_n = (\varepsilon_{n1}, \dots, \varepsilon_{nJ})$ has cumulative distribution

$$exp\left(-\sum_{k=1}^{K}\left(\sum_{j\in B_k} e^{\frac{-\varepsilon_{ij}}{\lambda_k}}\right)^{\lambda_k}\right) \tag{17}$$

which is one type of GEV distribution. The degree of independence in unobserved utility among alternatives within the nest k is given by parameter λ_k. The statistic 1-λ_k then can be interpreted as the level of correlation within the error terms. Moving forward from the distribution of the unobserved utility, the choice probability for alternative i within the choice set of nest B_k is given by

$$(18) \qquad P_{ni} = \frac{e^{V_{ni}/\lambda_k}\left(\sum_{j\in B_k} e^{V_{ij}/\lambda_k}\right)^{\lambda_k - 1}}{\sum_{l=1}^{K}\left(\sum_{j\in B_l} e^{\frac{-\varepsilon_{ij}}{\lambda_l}}\right)^{\lambda_l}}.$$

But because the denominator is the same for all choices within the nest, the probability can be written as a ratio between two alternatives *i* and *m* with the nest.

$$(19) \qquad \frac{P_{ni}}{P_{nm}} = \frac{e^{V_{ni}/\lambda_k}\left(\sum_{j\in B_k} e^{V_{ij}/\lambda_k}\right)^{\lambda_k - 1}}{e^{V_{nm}/\lambda_l}\left(\sum_{j\in B_l} e^{V_{ij}/\lambda_l}\right)^{\lambda_l - 1}}$$

If nests *k=l* so that *I* and *m* are in the same nest, then the explanatory factors cancel and the ratio of probabilities collapse into the following equation and the ratio is independent from all other alternatives.

$$(20) \qquad \frac{P_{ni}}{P_{nm}} = \frac{e^{V_{nj}/\lambda_k}}{e^{V_{nj}/\lambda_l}}$$

Ultimately, the nested logit probability can be expressed as the product of two logit probabilities. The given example is that the probability that alternative *i* is chosen as the probability that nest B_k is chosen, and then secondly that alternative *i* is chosen out of that nest.

$$(21) \qquad P_{ni|B_k}P_{nB_k}$$

The author further explains the three major shortcomings of the nested logit model. First, the standard errors in the upper model, which is the choice between GM and non-GM maize in this case, are biased downward. Secondly, some parameters may appear in several submodels. The total labor cost per hectare, for example, could be a characteristic of the seed variety, but could also reflect the labor efficiency or availability of the farmer. Finally, while estimating the decision process in a sequential manner provide consistent results, the estimation is not as efficient as simultaneous estimation (Train, 2009). Thus, a second possible model which relaxes the assumption of IIA is discussed.

The rationale for the two-stage decision process was described earlier in Chapter 5. The decision can be considered by a farmer deciding first whether he is capable of overcoming the threshold between non-GM and GM maize production, and then deciding which GM variety best suits his production needs. Because the nested logit is an extension of the conditional logit rather than the multinomial logit, the variables are required to be alternative-specific rather than case-specific (Stata Quick Reference and Index: Release 12). Unfortunately, the vast majority of the farm-level questions that farmers answered in the survey were targeted only towards their selected plot. Even when reporting information on maize plots, such as seed price per kilogram or total labor costs per hectare, they answered only for their selected plot, which does not allow for any variation among alternatives. The only possible survey questions that qualify as alternative-specific, then, are farmers' perceptions of the benefits and disadvantages of each seed variety. The broad results of the question are cross-tabulated in Tables 4.3 and 4.4. The two most frequent response categories are of yield and expense. These two attributes are coded into a binary variable and used in the level one equation of the nested logit model. Variables from Variable Set 1 are included in the level two equation, based on their higher correlation with the selected plot variety. The outcome of the nested logit is presented in Table 6.3.

Results: Nested Logit

Unfortunately, the data does not support the nested logit model. Because some farmers listed all zeros (not expensive or does not exhibit high yield) or all ones in the benefits and disadvantages questions, the model reports an error for lack of variation across alternatives. Additionally, the dissimilarity parameters calculated in the nested logit are greater than one, which measure the degree of correlation of random shocks and indicates that the model is inconsistent with the Random Utility Model (Stata Quick Reference And Index: Release 12). The nested logit, then, is discarded for a second alternative to relax the assumption of IIA: the multinomial probit.

Table 8 3 Nested Logit: Seed Choice

Seed Type			**Coef.**		**Std. Err.**
		High Yield	0.867	*	0.526
		Expensive	-0.478		0.519
Selected Variety			**Coef.**		**Std. Err.**
	non-GM	*(base)*			
	GM				
		Sufficiency	0.475	***	0.189
		Total Cost per Hectare	0.479	*	0.258
	Family Hired Ratio		1.454	*	0.785
	First Choice		2.045	***	0.47
	Sell Portion		-0.84		0.516
Seed Type Equations			**Coef.**		**Std. Err.**
	non-GM	*(base)*	0		0
	Bt	*Intercept*	4.467		5.622
	RR	*Intercept*	1.546		2.18
	BR	*Intercept*	9.365		7.178
Dissimilarity Parameters					
	Non-GM		1		3.461
	GM		2.827		46158.1
N			732		
Cases			183		
LR test for IIA			>1		
Chi-square			0.7		
Prob > Chi-square			0.7059		

*=P<0.10, **=P<0.05, ***=P<0.01

Testing for Differences Between MLogit and MProbit

The multinomial probit model fully relaxes the assumptions of IIA that are imposed in the multinomial logit model. The multinomial probit model is the simplest way to relax IIA, but is only an appropriate replacement if the model estimates are similar to the multinomial logit model. The information presented below the model in Table 6.4 show the test results of the stored model statistics, which indicate that there are no substantial differences between the two. The Log-Likelihood from the model differ only by 1.12, where M1 reports a Log-Likelihood of -149.04 M2 gives a Log-Likelihood of -147.92. The values for the AIC and BIC post-estimation tests are likewise similar. The more important finding here is that the multinomial logit can be discarded in favor of the multinomial probit and any concerns about the independence of irrelevant alternatives are immaterial.

Table 8.4 Comparison of Multinomial Logit and Multinomial Probit

Model	N	Log-Likelihood (null)	Log-Likelihood (model)	df	AIC	BIC
1	183	-227.68	-149.04	39	376.083	501.25
2	183		-147.92	39	373.839	499.01