FARMERS' VALUATION AND ADOPTION OF NEW GENETICALLY MODIFIED CORN SEEDS: NITROGEN-FERTILIZER SAVING AND DROUGHT TOLERANCE TRAITS

By

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To my family: Dad, Mom, Patty, Ivancho, Ferni, Belen, Chivi, Joaquin, Pau, and Nanitos; and to my grandfather Papa Guci and uncle Paco, may they rest in peace

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Abstract of Dissertation Presented to the Graduate School
of the University of Florida in Partial Fulfillment of the
Requirements for the Degree of Doctor of Philosophy

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We used a double bounded (DB) Contingent Valuation (CV) methodology on a sample of 345 farmers from Minnesota and Wisconsin to obtain estimates of farmers' willingness-to-pay (WTP) for corn seeds with fertilizer saving (FS) and drought tolerance (DT) traits. Two versions of each trait were presented for farmer valuation – one obtained by genetic modification (GM) and one obtained via traditional breeding (nonGM). This allowed comparison of factors affecting WTP for a nonGM version with those affecting WTP for a GM version.

The objective was to study adoption potential and understand which farm and farmer characteristics affect farmers' WTP for these traits. In total, four traits were considered: FS-GM, FS-nonGM, DT-GM, and DT-nonGM. The estimated mean WTP's, in dollars per acre, were $17.25, $19.72, $18.73, and $20.87, respectively. In both FS and DT traits, farmers are willing to pay more for the nonGM version compared to the GM version – $2.47 and $2.14, respectively. At prices lower than $20 per acre, nonGM versions showed better adoption potential.

Farmers specialized in nonGM corn showed willing to pay less for GM versions. Otherwise, factors affecting adoption of nonGM and GM versions were similar. The largest positive effect was observed for early adopters whom showed willing to pay between $9.61 and

$14.96 per acre more than other adopters. Also, farmers were willing to pay 6 cents more for the FStraits for each extra dollar they spend on fertilizer. Seed traits (GM or nonGM) seem to be regarded by farmers as imperfect *ex ante* substitutes (i.e., less than dollar per dollar). Results also suggest farmers see the DT trait as a substitute for crop insurance.

Being a nonGM specialist also asymmetrically affected (reduced) the probability of participation in the CV market exercise – a larger non-response rate was observed for CV questions regarding the GM versions. We estimated a DB-Dichotomous Choice Sample Selection model and found no evidence of sample selection. Therefore, we hypothesize the reason for a lower participation rate was lack of familiarity with GM crop production practices and subsequent inability to construct valuations.

CHAPTER 1
STRUCTURE OF THE THESIS

The focus of this dissertation is to study farmer adoption decisions regarding new genetically modified (GM) seed technologies. In specific, we consider two new promising traits that are in the R&D pipelines of major seed companies, these are: (i) a drought tolerance (DT) and (ii) fertilizer saving (FS) trait. The dissertation is organized as follows.

Chapter 2 presents an overview of the GM crop industry. The chapter is intended to provide the reader with the “big picture” surrounding GM seed technologies. The potential benefits of GM crops are outlined emphasizing the relevance of the technology to utmost important welfare improvement goals set by world consensus regarding poverty alleviation, reduction of world hunger, and environmental sustainability. The controversial facets of the technology are not left out as we discuss several different concerns voiced by different segments of the population. At the end of the chapter, the current situation of the GM crop industry is summarized, and the two GM traits that are the focus of our study are introduced – a FS and a DT trait.

Chapter 3 reviews the relevant theory for the non-market approach used in this thesis to examine the adoption of GM traits. A non-market approach is necessary because the traits we study have not reached the market yet. The key concept of willingness-to-pay (WTP) and Contingent Valuation (CV) methods are discussed in detail. The reader unfamiliar with CV methods should find this chapter very helpful.

Chapter 4 builds on the theoretical concepts considered in the previous chapter and adapts them to the context of technology adoption, in order to empirically analyze the value of the GM traits to farmers and their adoption potential. A sample of farmers from the states of Minnesota and Wisconsin is used to obtain estimates of farmer’s willingness-to-adopt corn seeds with

FSand DT traits. Farmers were asked to consider two different versions of the same trait – one obtained via conventional selective breeding (i.e., nonGM) and another by recombinant ribonucleic acid (RNA) techniques (i.e., GM). This amounts to a total of four traits: (i) nonGM, (ii) FS-GM, (iii) DT-nonGM, and (iv) DT-GM. One question we ponder is whether farmers value the agronomic aspects of the trait or focus more on the nonGM vs. GM aspect, and whether we can disentangle both aspects of the valuation. The results obtained show the differences in adoption potential between traits. They also provide estimates of the effects of farm and farmer characteristics on the WTP for each trait. Valuable insights are gained by comparing different versions of a same trait. The results should prove valuable both for policy makers interested in overseeing desired adoption rates and for seed companies interested in developing efficient pricing programs.

Chapter 5 explores the possibility that sample selection bias may be affecting the estimates of farmer's WTP for the GM traits that we obtained in Chapter 4. The application of a sample selection model was motivated by the observation, in our sample, of a considerably larger number of non-respondents to the CV questions concerning the GM version of a trait compared to the number of non-respondents to CV questions concerning the nonGM version of the same trait. This observation led us to consider the possibility that failure by the farmer to respond to GM questions could be systematically related to his WTP. If that were the case, it would imply underlying sample selection problems. Testing for sample selection in our results from Chapter 4 is important because if detected it would suggest we have inconsistent estimates for the parameters of the population initially targeted. On the other hand, if no sample selection is detected, it would provide more reliability to our findings.

Chapter 6 gives an analysis of GM crops under the state contingent paradigm initiated early by Arrow (1953, 1964) and Debreu (1952). The uncertainty inherent in GM crop adoption has traditionally been oversimplified and sometimes even neglected. Analogously, the analysis of crop production in general, models uncertainty using a stochastic production function which is simply a production function with a random error term added to it. The state contingent model of production developed by Chambers and Quiggin (2000) as an alternative to the traditional stochastic production framework, presents a different and intuitively appealing view of farming under uncertainty. While the chapter is not intended to fully develop and implement a new theory, the discussion hopes to shed some light on the GM crop farmer adoption scenario.

CHAPTER 2
GENETICALLY MODIFIED CROPS

Crop plants are constantly being improved to maintain a secure and sustainable supply of food in order to meet demand from current and future generations (OECD 1993). A most valid recent example of this is the use of selective breeding techniques to develop the high yield varieties (HYVs) (or "miracle seeds") that formed the basis for the Green Revolution – a large scale technological diffusion phenomena that sprouted dramatic increases in food production and averted widespread famine in Asia during the 1940's and 1960's.

The interplay between food production and global population has intrigued many brilliant minds for centuries. In the 1700's, Malthus hypothesized that hunger and famines would ceaselessly plague humanity as population growth, driven by fertility rates, would inevitably exceed food production growth. Gregory Clark (2007) has recently formalized Malthus' ideas in a mathematical model showing technological advances can, at best, support larger quantities of individuals, but cannot improve the long run level of material wellbeing. If fertility rates run amuck, showing a large and sustained increase, the short run material wellbeing may drop drastically and very high death rates may ensue. Many places across the globe today, particularly in poor developing countries, present fertility and death rates that are not far from this scenario.

One of the most important challenges for the coming decades will be to find ways to achieve a sustainable increase in food production in order to alleviate world hunger and eliminate extreme poverty (United Nations 2008), while at the same time recognizing: (i) that in the most likely scenario human population will continue to grow until it reaches a supposed peak of 9.2 billion in 2050; (ii) that most of this increase in population will happen in developing countries which are already the most affected by hunger, malnutrition, poverty, and disease; and (iii) that, given the state-of-the-art, the current scale of economic and agricultural activity is already causing important destruction and changes in the environment that threaten our ability to achieve an increase in food production that is sustainable.

A growing consensus exists in the global development and scientific community that the current state-of-the-art based on conventional breeding technologies will not suffice to achieve the increase in food production needed to meet future demand in 2050. In his lecture as a Nobel Peace Prize recipient, Norman Borlaug – known as one of the fathers of the Green Revolution – has expressed his view that the Green Revolution has only won us a temporary success in man's war against hunger, one that may be sufficient only for the three decades succeeding it. Genetically modified (GM) crops[1], improving upon conventional breeding techniques in terms of precision, scope, and speed of seed improvements, present themselves as a promising new technology that could complement selective breeding techniques in our search for future sustainable food security.

GM crops, however, like many other innovative technologies, are not without controversy. Many uncertainties surround the GM crop topic. Opponents of biotechnology do not discard the claimed benefits of GM crops, but argue that not enough is known about the environmental safety and health risks associated with these foods and that they should be more rigorously controlled (U.S. General Accounting Office 2002). Other opponents have ethical concerns about manipulating the genetic material of living beings. A last variety of opponents, believes in the benefits of GM crops, but holds some doubts about how these should be produced, by whom (private or public), and what the net effects will be for poor developing nations.

In spite of all controversies, many still believe biotechnology and GM crops will be essential in augmenting our chances of securing adequate levels of food production in the future

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[1] Also known as biotech crops or transgenic crops.

while at the same time minimizing further stress to the environment. Most proponents of biotech crops cite enhanced crop yields, more environmentally friendly food production, and more nutritious food as the major benefits and reasons to move forward (U.S. General Accounting Office 2002). Borlaug calls for the need of a second Green Revolution and endorses the use of biotechnology to develop the new "miracle seeds" that will be necessary (Monsanto 2005; Schattenberg 2009).

This chapter provides the reader with an overview of GM crops: their discovery; their definition and the concepts from biology used to describe them; their relevance, potential benefits, and controversial facets; the motives for regulating their development and the different observed approaches to regulation; their history as a new and growing industry; the current situation of such industry; and a glimpse into two particularly important biotech traits that may start being marketed in the near future and that are the focus of this dissertation – a fertilizer saving (FS) trait and a drought tolerance (DT) trait (in corn seeds).

From Naïve Crop Selection to Biotech Crop Engineering

The invention of agriculture some 10,000 years ago was followed by a long period of naïve crop selection that lasted thousands of years. The first experimenters in crop selection had to actually separate edible crops from poisonous and non-edible ones. As sad a picture as this might be, early hunter-gatherers and proto-farmers probably relied on trial and error methods to do this.[2] The second wave of crop selection, after sorting out all edible crops, had the objective of selecting crops with higher yields and resistance to disease and pests. For centuries, naïve trial and error remained the exclusive method. Early farmers would plant different seeds and hand-

[2] In practice this brought some advantages, specifically, trial and error practices helped early hunter-gatherers and proto-farmers develop an extensive knowledge about the qualities and potential uses of the local flora. This point has been argued by Jared Diamond (1999) in his Pulitzer Prize winning book "Guns, Germs, and Steel" (who supported his argument on several studies in the area of Ethnobiology).

pick those which resulted in individuals with the most desirable traits. Improvements in crop genetic traits during this period happened at a very slow pace.

It was not until the turn of the 20th century, when the experiments on inheritance of an Austrian monk named Gregor Mendel (1822-1884) were rediscovered by the German botanist Karl Erich Correns (1864-1933), that crop selection took its first big turn. Understanding the rules of inheritance allowed for a more systematic approach to breeding based on the probabilistic processes that were found to govern the passing of genes from one generation of crops to the next. Simple trial and error was substituted by calculated trial and error. With this, genetic improvements could be obtained in a faster manner by design and analysis of plant breeding experiments. The discovery led to the era of modern plant breeding characterized by the production of thousands of improved varieties at a relatively accelerated pace.

The importance of such innovation to global stability and human advancement cannot be overly emphasized. The Green Revolution, led by the Rockefeller Foundation along with the Ford Foundation and other major agencies during the 1940's and 1960's, was largely driven by the use of selective breeding for the rapid development of HYVs. The Green Revolution was mainly a diffusion phenomena, it spread technologies that already existed in the industrialized world (in particular pesticides, irrigation technologies, and fertilizer) into the developing world. HYVs were better suited than existing indigenous varieties to exploit the large potential increases in productivity of using these technologies. HYVs had a higher nitrogen-absorbing capacity compared to indigenous varieties but were less resilient to other pressures of the indigenous ecosystems and so they had to be bred and adapted to tailor the particularities of each environment – modern selective breeding was the key. The novel technological innovation of the Green Revolution were these so called 'miracle seeds'. Today, the consensus among many scientists is that the Green Revolution allowed food production to keep pace with global population growth and thus it helped us avoid the Malthusian catastrophe.[3]

By the end of the Green Revolution in the late 1960's, Nobel Prize scientists Francis Crick and James Watson discovered the molecular structure of deoxyribonucleic acid (DNA). Their groundbreaking research and findings led to the development of biotechnology which allows scientists to identify desirable genes in one living organism and transfer it to another without mating them. The application of this knowledge to crops and foods resulted in the birth of biotech crops also known as GM crops. Biotechnology tremendously increased the potential benefits of crop improvement compared to selective breeding, taking a huge leap not only in terms of speed but also in the scope and precision with which crop improvement could be obtained.

Prior to biotechnology, when only conventional selective breeding was possible, only intra-species genes could be transferred from one generation to the next via "natural" reproduction (including sexual and vegetative). With current biotechnology-based techniques, not only can desirable genes from one species be inserted into other unrelated species but the process is also sped up by artificial means of "production" such as gene guns or *Agrobacterium tumefaciens*. In biotechnology, crop selection has evolved to its current form more accurately described as a "crop engineering" or "crop production" process rather than crop selection per se. Some have termed this post-Green Revolution era the Gene Revolution.

Genetic Engineering and Genetically Modified (GM) Crops

GM crops[4] are produced from natural crops that have been conferred a specific desired trait by introduction of pre-isolated gene(s) via genetic engineering methods. It is well

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[3] However, some critics of the Green Revolution argue that while impeding a food shortage in the short run, it has set us on a long-run path of population growth that is inconsistent with the Earth's carrying capacity.

understood, in genetics, that different genes (genotype) are responsible for the expression of different physical characteristics or traits (phenotype) in all living organisms. Gene transference is possible due to the ubiquity of DNA in all living cells. The DNA molecule stores all the genetic material and information necessary for correct metabolic functioning of the organism. Genes are segments of DNA that encode necessary information for production of a specific protein. Produced proteins then function as catalytic enzymes regulating metabolism, or as storage units, and contribute to the expression of a specific trait. Decoding of the information in DNA by the cell requires its transcription into messenger ribonucleic acid (mRNA) molecules which then produce proteins by a process called translation. These two processes (transcription and translation) are regulated by a complex set of mechanisms so that production of a particular protein is activated only when and where it is needed (Department of Soil and Crop Sciences 2004). Thus, traits are physical characteristics conferred, in part, to the organism by its genetic material.

The term genetic engineering applies to scientific laboratory methods that involve direct manipulation of an organism's genes. The engineering process generally involves five basic steps: (i) isolation, (ii) insertion, (iii) transfer, (iv) transformation, and (v) selection. In GM crop engineering, a final (vi) breeding step is added to produce marketable seeds and evaluate gene stability.

During the isolation stage a naturally occurring gene of interest is identified that is responsible for the expression of a desired trait in a donor organism. The engineer then proceeds to insert the isolated gene into an adequate vector such as a plasmid (i.e., *Agrobacterium tumefaciens*). Once the vector is obtained, it can be reproduced to produce copies of the gene and

[4] Alternative commonly used names include bioengineered or biotech foods (or crops) or transgenic foods (or crops).

then used to transfer the gene and transform the target organism. Alternatively, the use of gene guns eliminates the need for vectors by transferring the genes directly into the target organism. The final step in the engineering process entails the selection and separation of the successfully genetically modified organisms from those that failed to take up the gene. In the case of GM crops, the resulting GM organism is usually crossed into other crop lines (via regular cross-hybridization methods) that have desired commercial traits. Besides its obvious objective of producing a final seed product, this final step allows for the engineer to evaluate the genetic stability of the newly introduced gene.

Genetic engineering provides three main advantages over traditional selective breeding – increased precision, increased speed, and increased possibilities. First, the engineering techniques avoid one of the major problems encountered by traditional crop breeders that use cross-hybridization – no unwanted genes are introduced. Second, sexual reproduction used in conventional breeding requires the plant to reach sexual maturity before each cross is made. Genetic engineering works with individual cells and does not require mature plants. Thus genetic engineering increases the speed at which a new variety with the desired traits can be obtained. Finally, genetic engineering increases the pool of possible traits that can be transferred since it allows for gene transfer between unrelated species.

While it remains impossible to account for all possibly transferable traits and genes; we can present categories for those traits that have shown the most popularity among researchers and developers (James and Krattiger 1996), these are: bacterial resistance (BR), fungal resistance (FR), insect resistance (IR), herbicide tolerance (HT), marker (M) genes, male sterility (MS), quality characteristics (Q), and virus resistance (VR). Promoter (P) genes should also be considered. Most of these categories are self-explanatory. Quality traits include physical and agronomic characteristics of the plant or fruit, like for example, delayed ripening (tomato), or production of a wanted chemical substance (beta-carotene in rice), or pigment production (in flowers). The use of M genes and P genes is illustrated in the following subsection by using the development of Bt-crops as an example.[5]

Bacillus thuringiensis, commonly known as Bt, is a gram-positive bacteria that occurs naturally in soil. Early in the 20th century, the entomologist Ernst Berliner isolated a novel bacterium that had the capacity to kill the larvae of Mediterranean flour moths in the German province of Thuringia (Pueppke 2001). The new bacterium was dubbed *Bacillus thuringiensis* or Bt. Bacteriologists then became aware that different strains of Bt are able to kill different insects. Bt produces proteins (known as Cry proteins or δ-endotoxins) which, when ingested by the insect, adhere (bind) to its gut and disrupt its digestive system resulting in eventual starvation and death. Research has helped in determining which strains affect which insects. Cry proteins have been categorized (Höfte and Whitley 1989) into major classes with their respective susceptible insect families (e.g., CryI: *Lepidoptera,* CryII: *Lepidoptera* and *Diptera*, CryIII:*Coleoptera,* CryIV:*Diptera*). No binding sites for Cry proteins exist in the intestines of mammalian species, therefore, livestock and humans are not susceptible. Bt had long been used as a pesticide before it was even considered for use in GM crops. Commercially produced first in 1927, Bt based pesticides were popularized and released for large scale sale by Sandoz Corp. as "Thuricide" (Feitelson 2001). Bt was registered for use in the U.S. in 1961.

With the discovery of genetic engineering, it became possible to develop insect resistant crops by transferring the gene that produces the Bt toxin. First, a Bt strain that attacks the desired

[5] Some material is drawn from Krattiger (1997)

insect is identified and the implicated *cry* gene[6] isolated. Expression of the desired protein is usually low in these genes. P-genes are usually included as part of the transformation package in order to obtain desired expression levels. P-genes act like switches that turn on the production of the desired protein. M-genes, used to identify successfully modified cells, are also part of the transformation of plants at the tissue culture phase. These M-genes can confer modified cells with resistance to antibiotics (e.g., kanamycin) or herbicides, or express certain chemicals for visual identification. For example, the plant cells in tissue culture modified with kanamycin resistance can be treated with antibiotics resulting in death of non-modified cells and survival of only transformed ones. As mentioned earlier, the gene transformation can be done via *Agrobacterium tumefaciens* or with biolistic methods such as gene guns. Finally, once successfully transformed cells are identified, they are grown into full plants for seed production and further testing. Major Bt genes include *cryIA(b)*,*cryIA(c)*, and *cryIII(a)*.

Relevance, Potential Benefits, and Potential Risks

This section intends to illuminate some of the key issues in the "benefits versus risks" debate surrounding GM crops. It does not attempt to resolve such debate, but rather to inform the reader about the reasons why GM crops and the ensuing debate are relevant to poverty reduction, hunger reduction, environmental conservation, human health, and different human religious and ethical beliefs. The subsections on potential benefits and risks presented in this section are also overviews of the issues, as such, they do not present a comprehensive evaluation of the benefits and risks of GM crops which is beyond the scope of this chapter and could only be adequately pursued in a case by case basis (per trait, per region of the world). We start by discussing the

[6] Cry is used to denote the protein, while "*cry*" is used to denote the gene. Cry stands for crystalline reflecting the appearance of the δ-endotoxins.

relevance of GM crop technologies to hunger reduction, poverty reduction, and environmental conservation.

The magnitude of current and future human impact on the environment depends on three main factors: (i) population, economic activity, and technological state of the art. In the following we argue that sustained population growth and increasing human economic activity are likely to increase human impact on the environment. The most viable avenue for reducing such impact comes from the development and adoption of highly sustainable technologies.

The human impact on the environment can be summarized in the I-PAT equation: $I = PxAxT$. In this equation I represents the magnitude of human impact, P represents total population, A represents income (or output) per person, and T represents the technological state-of-the-art measured by the environmental impact per dollar of income. A high T implies the current state-of-the-art is not environmentally friendly. Highly sustainable technologies may be defined as those showing high values of S, where $S = 1/T$. The I-PAT equation clearly shows that, given our preceding discussion about the presence of pent up economic growth in the world, there are two viable strategies for averting further damage to the environment: (i) population controls and (ii) the development and diffusion of new technologies that are high-S.

The relevance of GM crops, whether we consider ourselves advocates or skeptics, becomes evident when we identify that one of the most important challenges for the coming decades will be to find ways to achieve a sustainable increase in food production in order to alleviate world hunger and eliminate extreme poverty (United Nations 2008), while at the same time recognizing: (i) that in the most likely scenario human population will continue to grow until it reaches a supposed peak of 9.2 billion in 2050; (ii) that most of this increase in population will happen in developing countries which are already the most affected by hunger, malnutrition, poverty, and disease; and (iii) that, given the state-of-the-art, the current scale of economic and agricultural activity is already causing important destruction and changes in the environment that threaten our ability to achieve an increase in food production that is sustainable.

The global human population in 2007 is estimated at 6.6 billion (World Bank 2007). Under the assumption that fertility rates continue to decline, the United Nations (UN) Population Division estimates world population will reach 9.2 billion in 2050 (United Nations 2007).

The UN Population Division puts forward four variants of the TFR evolution and the corresponding population forecasts (See Figure 2-1). Population forecasts developed by the UN Population Division depend mostly on the evolution of total fertility rates (TFR) – the average number of children per woman during her reproductive years. A TFR=2 means the population stabilizes and stops growing.[7] The medium-decreasing variant of TFR is considered the most likely.[8] All four TFR variants published by the UN Population Division, except the constant variant, assume that the TFR converges toward the replacement rate as we move towards 2050.[9]

[7] A TFR of 2 is called the replacement rate. At a TFR of 2 each woman has two children, most likely one boy and one girl. The girl will grow up to give birth to a boy and a girl (in average) and thus replace herself and her brother in the population.

[8] In addition, a slowly-decreasing fertility variant and a rapidly-decreasing fertility variant are published. The fourth and final variant assumes the TFR remains unchanged (i.e., business as usual). In the medium variant, world population reaches its peak of 9.2 billion in 2050. It is considered a peak since in this scenario all nations reach a TFR 2 by midcentury.

[9] The current TFR rate for the world as a whole is estimated at around 2.58 (CIA 2008). If the TFR remains constant instead of converging to the replacement rate, we would reach a population of 11.8 billion by 2050. On the other hand, even if a miracle event were to instantly drop world TFR down to the replacement rate, we would still observe an increase in population of about 1 billion, reaching 7.5 billion in 2050. While it may seem contradictory, an increase in population even after reaching the replacement rate is warranted by what is called population momentum. Population momentum happens because of the pyramidal (triangular) age structure of populations that have maintained a high TFR prior to reaching the replacement rate. In these nations the majority of the population is of young age with only a small percentage of elderly people. Even if the young grow to only replace themselves in the population (TFR=2) this would increase population because such replacement would mean an increase compared to the small number of elderly people leaving the population (being deceased). For a detailed explanation see Sachs (2008).

Besides driving growth rates, the TFR also influences the age structure in the population. Nations with high TFR (i.e., TFR>2) will replace each aging individual with more than one young individual thus gradually concentrating the age structure at young age categories. On the other hand, nations that maintain the TFR at the replacement rate or lower (TFR ≤ 2) will tend to have aging populations with higher concentrations of older people.

A generally recognized and observed pattern is that most developed nations have TFR ≤ 2 while many developing nations have TFR>3 (See Figure 2-2). Thus aging populations and low TFR's in developed nations mean those populations are stable and won't contribute to the expected increase in population. This means most of the 2.6 billion increase in population will happen in developing nations which are also the most affected by poverty, disease, malnutrition and hunger.

The World Bank estimates show about 1.4 billion people living below the international poverty line of $1.25 a day in 2005 (Chen and Ravalion 2008). Even though the globe's population is steadily urbanizing, the largest share of poor still live in rural areas and depend on agriculture. According to new evidence 75 percent of the poor, living on less than $1 per day in developing nations, still reside in the countryside (Ravallion, Chen, and Sangraula 2007). Their livelihoods depend largely on the natural provision of resources by the environment.

Experts argue that the current scale of human economic activity is already causing environmental destruction at unprecedented levels. Deforestation and other human-related impacts now threaten and affect almost every single ecosystem in the globe. Ocean fisheries are being depleted of fish. Water is becoming more and more scarce: for both drinking and irrigation. Climate change, among other important impacts, is causing huge changes in weather and agricultural production: reducing rainfall levels in many places and increasing rainfall variability in general. The level of human economic activity is only expected to grow. A simple exercise making the reasonable assumption that all regions of the globe join the convergence club[10] in the coming years is developed in Sachs (2008), it is shown there that global Gross Domestic Product (GDP) is expected to rise by a factor of six times by 2050.

More than a century ago, in his famous 1798 publication *An Essay on the Principle of Population,* Thomas Malthus warned us about the imminent danger of human population growing faster than food production. He argued that human population growth, depending only on human's will to reproduce, has no bounds and happens at a geometric rate. On the other hand, food production growth is bounded by the stock of natural resources and by the technological state-of-the-art, and happens only at something closer to an arithmetic progression.

In his time, Malthus could not have foreseen the improvements man would achieve in the efficiency of food production due to incredible advances in agricultural production technologies. About two centuries after Malthus presented his catastrophic hypothesis, two German chemists named Fritz Haber and Carl Bosch, discovered what is known as the Haber-Bosch process. This process is used to fixate nitrogen from the air for industrial scale production of nitrogen fertilizer (N-fertilizer) – essential for plant growth. Both scientists were awarded the Nobel Prize (1918 and 1931) for their breakthrough.

In 1970, Norman Borlaug, known as the father of the Green Revolution, received the Nobel Peace Prize for his work in the development and diffusion of HYVs of dwarf wheat in India and Pakistan. The extensive development of HYVs and the earlier discovery of the Haber-Bosch process formed the technological basis for the Green Revolution – a large scale

[10] Convergence describes the process by which the poorer countries (regions) catch up with the richer countries. Convergence occurs when per capita income of a poorer country grows more rapidly in percentage terms than per capita income in the richer regions.

technological diffusion phenomena that sprouted dramatic increases in food production and averted widespread famine in Asia during the 1960s.

Malthus also could not have foreseen the currently slow but still apparent convergence (among high-income nations) in fertility rates towards the replacement rate. As mentioned, at the replacement rate; zero population growth is achieved.

Skeptics of the Malthus hypothesis use these two factors (advances in technology and convergence in fertility rates) to argue that no such catastrophe is imminent. However, even if we agree with the relevance of these two factors, this is not to say that Malthus was wrong. It simply means that the basic Malthusian thesis, as such, applies to a world with a fixed level of technology and unchecked population growth rates. Therefore, the Malthusian catastrophe is in fact imminent unless we keep on with advances in technology and population controls that are necessary to avoid it. Clark (2007) has recently formalized Malthus' ideas in a mathematical model showing technological advances can, at best, support larger quantities of individuals but cannot improve the long run level of material wellbeing. This is because, in a dynamic world, larger quantities of better quality food and material living standards will give rise to healthier individuals and in particular healthier female populations which should increase fertility rates. The result is a decrease in death rates and an increase in population that drops material well-being back to its fixed long run level. If fertility rates run amuck, showing a large and sustained increase, the short run welfare may drop drastically and very high death rates may ensue.

Evidence from recent human history seems to support Clark's argument that, given a fixed and exogenous birth rate, technological advances may provide a short run increase in material well being, but in the long run it will only increase the number of people we can support at subsistence material wellbeing levels.[11] As Borlaug (1970) puts it in his Nobel Prize Lecture, the technological advances diffused during the Green Revolution, have "won us a temporary success in man's war against hunger […] it has given man breathing space […] sufficient for […] three decades [if fully implemented]. But […] human reproduction must also be curbed."

More than three decades have passed since only a partially implemented[12] Green Revolution took place. Despite major advances in agriculture and growth in food production, the twentieth century saw famine after famine kill millions of people across the world. It is evident that sizes of human populations in several places have reached a point where they have outstripped the local environment carrying capacity, at least with currently deployed technologies (Sachs,2008).

A growing consensus exists in the global development and scientific community that the current state-of-the-art based on conventional breeding technologies will not suffice to achieve the increase in food production needed to meet future demand in 2050. Many believe biotechnology and GM crops to be essential in augmenting our chances of reaching this objective and at the same time minimizing further stress to the environment.[13] Development and deployment of biotechnology crops is becoming more and more relevant. Among those that support this view is Norman Borlaug, who calls for the need of a second Green Revolution and endorses the use of biotechnology to develop the new "miracle seeds" that will be necessary (Monsanto 2005; Schattenberg 2009). If appropriately diffused, biotech crops have the potential

[11] Technology advancements may be able to increase material wellbeing in the long run if the fixed birth rate assumption is relaxed and we assume that birth rates may be brought down.

[12] Many rural places across the globe, where very rustic agricultural practices predominate, remain unreached by the technologies of the Green Revolution. See Duflo, Kremer, and Robinson. (2006) for an interesting view of why some of these communities have failed to adopt agricultural technologies.

[13] "The international scientific and development community now recognizes that doubling or tripling of world food, feed and fiber production by the year 2050 to meet the needs of an 11 billion global population cannot be achieved without biotechnology." (James and Krattiger 1996).

of improving food security across the globe and minimizing impact on the environment through rapid improvements in local and global crop productivities per unit of input (i.e., land, water, fertilizer, pesticides, labor or other inputs).

The following subsection presents an overview of the most cited benefits attributed to GM crops. After this we finish this section by presenting an overview of the most cited potential risks.

Potential Benefits of Biotech Crops

Scientists and researchers have the ability to genetically modify agronomic traits and quality traits. Agronomic traits are traits that determine crop's suitability to its specific environment. Scientists modify these traits to produce the following benefits: (i) improvements in productivity and easiness[14] of food production, (ii) lower production costs, and (iii) achieving greater consistency of production (i.e., reducing uncertainty).

Quality traits refer to those conferring specific physical or chemical desirable characteristics to the commercialized portion of the crop. Scientists modify quality traits to obtain benefits like improving the quality and nutritional contents of foods.

With respect to agronomic traits, some of the different strategies being investigated to increase crop output per unit of input are: (i) attacking the causes of crop losses, for example, pests (e.g., insects, virus, disease) or competitors for soil nutrients (e.g., weeds); (ii) improving plant's own efficiency in using inputs (e.g., N-fertilizer saving); and (iii) improving plant's ability to grow under harsh conditions (e.g., salinity, drought, frost resistance) (Pew Initiative on Food and Biotechnology 2001).

Examples of biotech agronomic traits are:

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[14] Ease of use may be particularly important for farmers that have limited access to education and extension services.

- Resistance to pests and disease – (e.g., Bt-corn) (marketed)
- Tolerance to chemical herbicides – (e.g., Roundup Ready varieties) (marketed)
- Tolerance to drought – (in last stages of research and development (R&D) pipeline)
- Improved absorption of soil nutrients – (e.g., N-fertilizer saving) (R&D pipeline)
- Tolerance to adverse soil and other physical conditions – (e.g., salinity, frost)

The second type of beneficial traits corresponds to those that improve quality and nutritional content. During its early years, most genetic modifications of plants were aimed at increasing or protecting crop yields. These early modifications, the so called first generation GM crops, usually involved parts of the plant not consumed directly by humans (i.e., cornstalks). The beginning of the 21st century saw a new wave (second generation) of potential modifications involving changes in the composition of foods to enhance their quality and nutritional value.

For example, Golden Rice was created by transforming rice with two beta-carotene biosynthesizing genes: psy (from daffodil) and crt1 (from soil bacterium *Erwinia uredovora*) (Ye et al. 2000). Beta-carotene, a precursor of Vitamin A, is produced and made available by the plant in its endosperm (the edible part of rice). Vitamin A deficiency (VAD) is an important nutritional problem in the world (World Bank 1993). VAD is frequent among the poor in Asia whose diet is based mainly on rice which does not contain Vitamin A precursors. Supplementation of carotenoids in deficient populations has shown to reduce morbidity and mortality in children (Sommer 1997). Dawe, Robertson, and Unnevehr (2002) compare the costs of Vitamin A supplementation via Golden Rice with supplementation by other methods such as health programs. The evidence shows that modifying the nutritional content of staple foods of the poor, like rice in this case, holds huge potential benefits in terms of reducing the costs of nutritional supplementation.

Other examples of traits that improve quality and nutritional contents of food are:

- Foods that exhibit improved processing traits
- Foods that have improved ripening, texture, or flavor

- Foods that show improved nutritional contents besides carotenoids
- Foods that hold lower concentrations of allergens, toxins, or antinutrients

In addition to the benefits presented above, some important environmental benefits may be realized by rapid and widespread diffusion of modified crops. For example, higher yields on current agricultural fields may prevent further deforestation. Better absorption of N-fertilizer by crops may reduce losses to environment (by leaching, ammonia volatilization, denitrification) that have negative effects such as eutrophication and climate change. Drought tolerance traits could reduce irrigation needs in areas with limited water supplies.

Potential Risks of Biotech Crops

Opponents of biotechnology do not discard the claimed benefits of GM crops, but argue that several potential risks associated with these crops might outweigh the potential benefits. Opponents argue that not enough is known about the environmental safety and health risks associated with these foods and that they should be more rigorously controlled (U.S. General Accounting Office 2002). Other opponents have ethical concerns about manipulating the genetic material of living beings. A last variety of opponents, believes in the benefits of GM crops, but holds some doubts about how these should be produced, by whom (private or public), and what the net effects will be for poor developing nations.

Some potential risks to the environment include:

- Risk of GM crops becoming weeds or invasive species
- Impact on non-target organisms (i.e., Bt effect on monarch butterflies)
- Birth of a “super weed” by accidental cross-pollination with wild relatives (“gene flow”)
- Exposure of insect pests to insect resistant crops may induce insect resistance to the pesticides.

In addition, many argue that while increases in yield due to biotech traits may reduce the pressure on land, traits that expand the range of environments in which crops can be grown may affect previously unthreatened ecosystems. As we can see, both the potential benefits and potential risks to the environment are plausible, which is why the debate goes on. An important counterargument made by supporters of GM crops, is that these environmental risks, to some extent, are not exclusive to biotech engineering.

Potential risks to human health from consuming GM crops also enter the debate. GM crops have been consumed widely for many years with no conclusive confirmation of serious harmful effects on human health (Pew Initiative on Food and Biotechnology 2004). Some of the less serious potential risks debated, such as risk of toxicity and allergenicity, are continuously being controlled by government regulation of the seed development process. These risks, again, are not exclusive of GM crops, and may happen in crops developed by conventional breeding (i.e., glycoalkaloids in potatoes). One important setback, however, in the early evolution of the industry due to a mistake in the regulation process was the negative event associated with StarLink™ corn. In May 1998, the U.S. Environmental Protection Agency (EPA) granted a limited license to Aventis Crop Science for the production of StarLink™ corn. StarLink™ corn was engineered by isolation and incorporation of the gene responsible for synthesizing the Cry9c protein, occurring naturally in *Bacillus thuringiensis* subspecies *tolworthi* bacteria, and responsible for expressed crop resistance to several insect pests (including European corn borer (ECB), cornstalk borer, and corn earworm). The granted limited license allowed for production of animal feed, industrial nonfood uses, and seed increase; but proscribed its use in food intended for human consumption because the Cry9c protein shared several molecular properties with proteins that are known food allergens (i.e., stability to heat, acid, and enzyme degradation). Nevertheless, in September 2000, Cry9c-DNA was detected in taco shells, proof that the variety had either intentionally or inadvertently been introduced to the food supply chain. The ensuing media coverage resulted in large recalls of implicated processed products. This was followed by reports to the Food and Drug Administration (FDA) of adverse health effects from consumers who had eaten potentially contaminated corn products. In addition, the U.S. Department of Agriculture (USDA) reported that mixing of all corn after harvest, including StarLink™ corn, was a common practice in the industry suggesting the leak had happened unintentionally. In June 2001, the Center for Disease Control (CDC) presented a report (Center for Disease Control 2001) to the FDA which had analyzed serum collected from 28 individuals reporting valid allergic reactions apparently associated with the Cry9c protein. Additional serums were collected from individuals identified as being highly sensitive to a variety of allergens. The individual serums where tested for presence of antibodies to the Cry9c protein using an FDA-developed Enzyme Linked Immunosorbent Assay (ELISA) type method. Based on negative results from the serums to the ELISA tests, the study concluded evidence was insufficient to link the allergic reactions to the Cry9c protein. Regardless, the whole event had large and lasting repercussions on the consumers' perceptions about GM foods and on GM markets worldwide.

Opponents argue that, even though no harmful effect has been confirmed as of yet, there exists the risk of unintended health effects in the long run. This claim may be impossible to prove a priori (U.S. General Accounting Office 2002).

A third point of controversy involves ethical beliefs of different social and religious groups. The term "ethically sensitive genes" has been used to refer to genetic transformations that may raise ethical concerns from specific human groups (Aldridge 1994). For example, the transfer of human genes to animals or crops used for feed or food, the transfer of genes from animals whose consumption is forbidden to certain religious groups, and the transfer of animal genes into crops which may raise concerns among vegetarians. The debate here focuses on whether genes, when taken out of the cell, remain part of the organism or may be simply considered as chemical molecules made of nucleic acids.

So far we have discussed potential risks to the environment and to the consumer. The last group of opponents focuses on market and economic issues of GM crop introduction. A main concern is whether GM crops will become an effective tool to fight world hunger and benefit farmers in developing nations. This depends, partially, on whether GM crops are tailored to meet the needs of small farmers (i.e., drought tolerance) in developing countries. It also depends on how these technologies are diffused, distributed, and marketed. The debate focuses on whether public or private (or public-private partnerships) should take on the task. As far as the private sector goes, some are doubtful that the market demand from poor-small farmers in developing nations is insufficiently large to create the necessary incentives to invest in research and development. In addition, deficient intellectual property right laws and inadequate regulatory capacity in these nations increase market (and environmental) risks and may deter market supply. A final point of concern among governments in developing countries, is whether granting of property rights to multinational seed companies and guaranteeing enforcement will increase incentives but also result in GM crops been sold at prices unaffordable to small farmers. In the light of these issues, it appears the development of GM crops tailored to meet the needs of small farmers in developing nations, and their effective supply, will probably require participation from universities, governments and international research centers. Public-private partnerships may have a better chance of success in developing and supplying such GM crops at prices that are affordable to farmers and profitable to private enterprises.

Finally, some other market related issues have been raised on the introduction of GM crops that are not exclusive to small farmers. For example, the StarLink™ corn event resulted in segregation costs that reduced the revenue that U.S. corn producers would have received in 2000/2001 in the absence of the event (Schmitz, Schmitz, and Moss 2005). Segregation costs were the costs incurred in separating GM from nonGM corn throughout the supply chain in order to meet Japan's stringent import tolerance levels following the StarLink™ event.

The potential risks and potential benefits presented here are not an exhaustive list, but hopefully they have given the reader a broad view of the major points around which the debate is centered. We have not attempted to give a concluding assessment of the net effect GM crops will have in the long run, however, it is evident that the technology is relevant for many reasons.

Brief History of Early Commercialization of GM Crops

Successful commercial production is the final phase in the biotech crop development process. The process begins with a first phase in which scientists in government or private laboratories and greenhouses investigate potential genetic traits to be transferred. Once a promising trait has been identified and successfully transferred into the target crop, the next step is testing it under real life conditions in field trials in a second phase. The third phase involves securing regulatory approval for commercialization for feed or food. The fourth and final phase is widespread commercialization and market acceptance.

Most steps in the process involve some degree of regulation, for example, the second phase requires regulatory approval for environmental release.[15] Why regulate? The justification is largely based on unfamiliarity (Dale 1995; OECD 1993; James and Krattiger 1996). Different regulatory schemes predominate in different regions (See Appendix A for a more complete description of GM crop regulatory schemes).

[15] For a more detailed description of the development process see http://www.monsanto.com/pdf/pipeline/pipeline_2009_phase.pdfu.

The first GM food to be commercially produced and marketed in the U.S. was FLAVR SAVR™ Tomato from Calgene Inc., approved by the FDA in May 1994.[16] The tomato had been genetically engineered to remain firm for a longer period of time after harvest compared to other tomatoes. Regular tomatoes are normally harvested while still green in order to avoid crushing during transportation through the marketing chain. They are later ripened artificially in ethylene gas chambers. The formation of Polygalacturonase (PG), an enzyme naturally occurring in ripening tomatoes, breaks down pectin in cell walls and causes ripe tomatoes to soften. Synthesis of PG is suppressed in FLAVR SAVR™ tomatoes allowing the farmer to leave the fruit on the vine longer than its conventional (nonGM) counterpart. This particular attribute allows the tomato to ripen and reach full flavor before harvest, eases transportation, and results in tomatoes that remain firm for longer periods after reaching the final market (Food and Drug Administration 1994a). FLAVR SAVR™ was approved by FDA to be marketed without any special labeling (Food and Drug Administration 1994b). Consumer acceptance was positive (James and Krattiger 1996); however, competition from conventionally bred longer shelf-life tomatoes created profitability problems and prevented FLAVR SAVR™ from successfully penetrating the market (Martineau 2001).

The production, approval, and marketing of one single GM food (FLAVR SAVR™) in 1994 was just the tip of the iceberg when it came to investments and R&D on GM food technologies that had begun in 1971 when the first GM organism was developed (James and Krattiger 1996).[17] During the period 1986-1996, more than 3,500 field trials were conducted on

[16] The first country to commercialize GM crops worldwide was China in the early 1990s (virus resistant tobacco and virus resistant tomato).

[17] According to Monsanto (2009), the first plant cell modification was achieved in 1982 by scientists working at Monsanto. However, a website published by the Department of Soil Sciences at Colorado State University (2006) identifies four groups that, working independently, simultaneously achieved the first modification of a plant cell: (i) a Washington University Group (antibiotic kanamycin resistance into Nicotiana plumbaginifolia); a Belgium group

more than 15,000 sites, in 34 countries with at least 56 crops (James and Krattiger 1996). Commercialization of more GM crops would soon follow. Several more GM foods that had been waiting in the R&D pipeline followed FLAVR SAVR™ into the market shortly after. By year-end 1995, 20 petitions had been granted to commercially grow 9 transgenic crops only in the U.S. (James and Krattiger 1996).

By 1996, the major crops approved in the U.S. included: tomato with delayed ripening qualities, cotton (herbicide tolerant), cotton (insect resistant), soybean (herbicide tolerance), maize (herbicide tolerant), maize (insect resistant), canola (modified oil quality), potato (insect resistant), and squash (virus resistant) (James and Krattiger 1996). Table 2-1 shows a list of GM crops approved for sale in the U.S. in the initial years of the GM crop industry. In all countries (except China and Australia) all approvals up until 1996 were granted to the private sector (James and Krattiger 1996).

Current Status of GM Crops

The International Service for the Acquisition of Agri-Biotech Applications (ISAAA) publishes year to year briefs concerning updates in the global status of commercialized GM crops. The last report corresponds to the year 2008 (James 2006, 2008). This section draws heavily from statistics and key issues presented in these reports.

Many of the brand names introduced in the first years of GM commercialization remain as star products today (e.g., RoundupReady™, YieldGard™, LibertyLink™), although they have been improved in several ways. After an initial period in which several new traits were introduced, the advances focused not in more new traits, but in producing stacked-trait hybrids by cross-breeding those initially marketed star products. Monsanto, for example, produced a

(antibiotic kanamycin resistance into tobacco plants); a Monsanto group (antibiotic kanamycin resistance into petunia plants); and a Wisconsin group (bean gene into sunflower plant).

stacked hybrid variety of corn that was resistant to the ECB and tolerant to glyphosate by hybridizing two GM mother lines: NK603 (RoundupReady™) and MON810 (YieldGard™). Since the GM mother lines in these stacked trait hybrids had already been approved for commercialization, no further approval was needed.

More recently, seed companies have started producing stacked varieties that are not obtained via hybridization but by simultaneous "multiple" genetic modification. Monsanto has developed its trademark *Agrobacterium*-mediated process for multiple trait insertion called VecTran™. The advantages of using direct multiple-trait transformation are: (i) the process is sped up since no cross breeding is necessary, and (ii) better control over the transformation process, for example, guaranteed better promoter genes. These two advantages result in stacked varieties that can be produced in a more time-efficient manner and that produce more consistent results.

As far as companies go, acquisitions and divestures have been more of a rule than an exception in the industry. For example, Syngenta was created by the merger between Novartis and AstaZeneca in 2001. Novartis itself was the result of a merger between Ciba and Sandoz in 1996. Monsanto started buying interests in Calgene in 1996 and finalized acquisition by 1997.

Global adoption of GM crops has occurred at a rapid pace. As of 2008, the number of countries planting biotech crops has soared to 25. Cumulatively, the total number of acres planted with biotech varieties in all years since the first biotech crop was commercialized in 1996, reached the billion-mark in 2005. In 2008, only three years later, the 2 billion-mark was reached. In hectare terms, 2008 showed a total area of 125 million hectares dedicated to GM crops; this meant a strong growth of 10.7 million hectares over the 114.3 million hectares observed in 2007. Figure 2-3 shows the areas planted (in millions of hectares) with GM crop varieties by the top eight GM producers in the globe in 2006. Six out of the major GM players (Argentina, Brazil, India, China, Paraguay, and South Africa) are listed by the IMF as emerging or developing economies.

Four major crops have reached the market to date: soybean, cotton, canola, and maize. Figure 2-4 presents the global planted area (GM+nonGM) and the total GM planted area in 2006 for each of these four GM crops. For soybean, about 91 million hectares were planted globally in 2006, of which 58 million (or 64%) were GM varieties[18]. Cotton was planted in an area approximating 35 million hectares, of which 13 million (or 38%) were GM varieties. Canola, observed a global planted area of 27 million hectares, of which 5 million (or 18%) where GM. Finally, corn was planted at a global scale in some 148 million hectares, of which 25 million (17%) came from GM seeds. These numbers are considerably large considering 2006 marked only the first decade of GM commercialization.

The frequency with which they are mentioned in GM forums may lead some to believe that these four crops are practically the only GM crops out there. However, this is not the case. Other GM crops, such as papaya, tobacco, and squash have also been approved for commercialization in the U.S. Many more GM crops have been commercialized with varying market acceptance: tomatoes, rice, potatoes, melon, and peppers. If we consider crops that have not yet reached commercialization phase, but that have been subject to field and laboratory trials, the list expands. In a report prepared for the Council of Biotechnology Information, Runge and Ryan (2004) surveyed all biotech crop research and trials being conducted worldwide identifying fifty-seven plants under investigation: 16 field crops, 14 vegetables, 16 fruits, and 11 miscellaneous.

[18] In Argentina, 99% of the soybean produced comes from GM seeds.

Since the beginning of GM crop commercialization in 2996, the most widely adopted trait has been herbicide tolerance. James (2008) estimates that herbicide tolerant varieties account for 63% of the global total of 125 million hectares planted with GM crops in 2008.

In 2008, a new biotech crop, RR®sugar beet was commercialized in U.S. and Canada. The success of this crop's launch poses a good omen for sugar cane biotech traits which are at advanced stages of development in several countries.

Fertilizer Saving and Drought Tolerance Traits

Two new promising traits are in the R&D pipeline of major seed companies, these are: (i) a DT and (ii) FS trait. Monsanto, for example, has a first generation DT corn seed in Phase IV.[19] They also have a N-efficiency corn trait (i.e., N-fertilizer saving trait) in Phase II.[20]

The relevance and potential benefits of the DT trait are obvious. As they say "Water is life". This simple biological fact by itself explains the importance of water. However, in a complex global society, water means many other things. Deficient quantities and quality of water supplies may be linked to livelihood insecurity, health risks, hunger and poverty, and social conflict.

Nature's water supply is unpredictable and is becoming more so due to climate change. In many places, climate-related water events (e.g., floods, droughts) are becoming more frequent and more severe (United Nations 2009). Supplementation of locally deficient natural supplies via water projects is, in many cases, limited by financial and social factors.

Water is an important input in many industries, but more so in agriculture. Every acre of corn, even on irrigated fields, suffers some degree of water stress at some point during the

[19] Phase IV is the last stage prior to market launch. The first three stages are Phase I: Discovery and Proof of Concept, Phase II: Early Development and Compilation of Pre-Regulatory Data, Phase: 3 Advanced Development, Field Testing, and Data Generation. As mentioned before, these two traits are the focus of this dissertation.

[20] See http://www.genuity.com/Innovation/Explore-The-Pipeline/Print-The-Pipeline.aspx.

growing season. Agriculture accounts for the largest share of human water use – about 70% of freshwater withdrawals are destined to irrigated agriculture (United Nations 2009). The demand for water has increased substantially mainly because of population growth, but an important factor has also been growing incomes and the ensuing changes in dietary habits. Grains and cereals are usually seen by consumers as inferior goods compared to beef and other meats. As global incomes grow, the demand for beef follows closely. The UNs' World Water Assessment Programme (2009) estimates that meat production requires 8-10 times more water than cereal production.

The case for the N-fertilizer saving trait can be made too. Nitrogen is one of the most intensively-used inputs in crop production – especially in U.S. corn production. Among the major field crops produced in the U.S., corn uses the most fertilizer (Huang, McBride and Vasavada 2009). While natural provision of nutrients is less variable and much more predictable than the natural provision of water, the price of N-fertilizer is not so. Recent volatility of fertilizer prices has shown the potentially large negative impacts on crop profitability these fluctuations may have (Huang, McBride and Vasavada 2009). Price volatility in fertilizer is closely tied to fuel price volatility. This is because natural gas is used in producing ammonia – the main ingredient in many N-fertilizers. That future fuel prices will stabilize is a scenario hard to picture.

In summary, the need to feed growing populations in a sustainable manner; the upcoming increase in demand for water coupled with the increased variability in natural supplies; and the intensive use of fertilizer in crop production coupled with an increased variability in fertilizer prices; suggest that widespread adoption of the DT and the N-fertilizer saving traits holds potentially large benefits for farmers, consumers, governments, and society in general. These two traits, and the factors affecting (increasing or decreasing) their adoption potential at the farm level, are the focus of this dissertation.

Table 2-1. Summary of genetically modified (GM) crops approved for commercial growing in the U.S. in 1996

Product	Company	Altered trait	Approved for sale	Commercial name
Tomato	Calgene	Delayed ripening	1994	Flavr Savr™
Cotton	Monsanto	Resistance to bollworms & budworm (Bt toxin)	1995	Bollgard™
Soybean	Monsanto	Resistance to herbicide glyphosate	1995	Roundup Ready™
Maize	Ciba-Geigy	Resistance to corn borer (Bt toxin)	1995	Maximizer™
Cotton	Monsanto	Resistance to herbicide glyphosate	1996	Roundup Ready™
Canola	Calgene	Altered oil composition (lauric acid)	1995	Laurical™
Cotton	Calgene	Resistance to herbicide bromoxynil	1995	BXN Cotton™
Potato	Monsanto	Resistance to Colorado potato beetle	1995	New Leaf™
Squash	Asgrow	Resistance to viruses	1995	Freedom II™
Tomato	DNA Plant Technology	Delayed ripening	1995	Endeless Summer™
Tomato	Monsanto	Delayed ripening	1995	
Tomato	Zeneca/Peto Seed	Thicker skin, altered pectin	1995	
Maize	DeKalb	Resistance to glufosinate	1996	
Maize	AgrEvo	Resistance to glufosinate	1996	Liberty Link™
Maize	Plant Genetic Systems	Male sterility	1996	
Maize	Monsanto	Resistance to corn borer (Bt toxin)	1996	YieldGard™
Maize	Northup King	Resistance to corn borer (Bt toxin)	1996	
Cotton	Dupont	Resistance to herbicide sulfonylurea	1996	
Tomato	Agritope	Altered ripening	1996	
Potato	Monsanto	Insect Resistance	1996	

Source: James and Krattiger (1996).

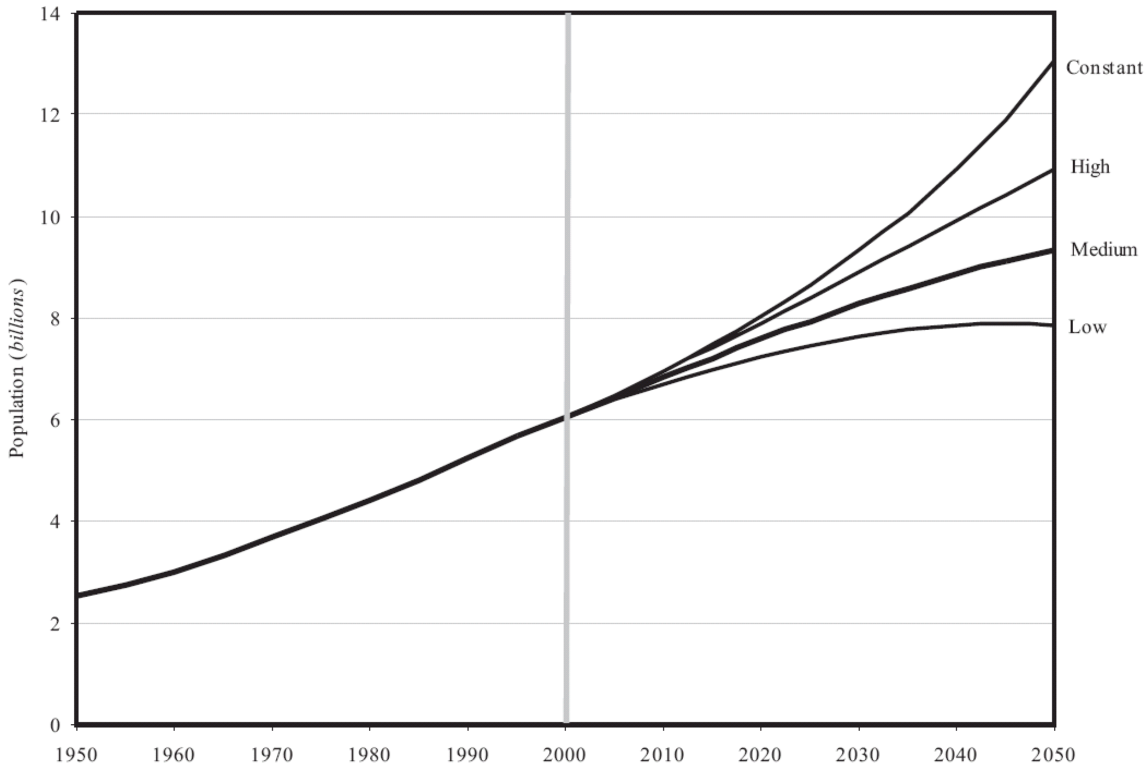

Figure 2-1. Estimated and projected population of the world by projection variant, 1950-2050. (Source: United Nations 2007).

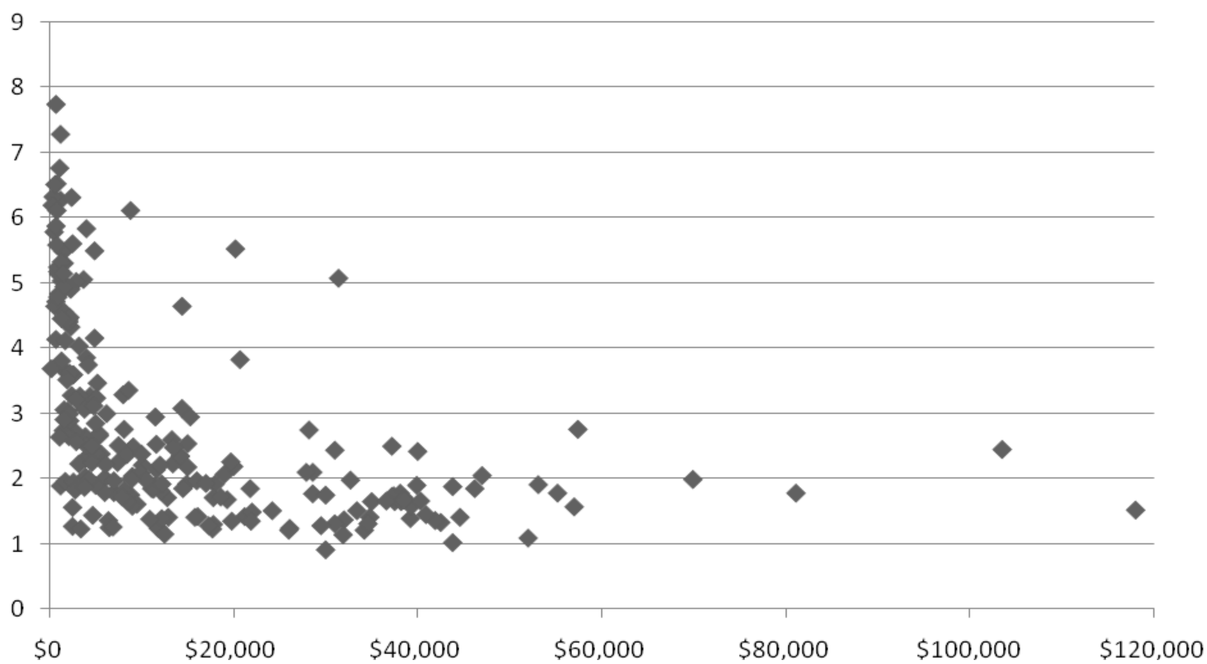

Figure 2-2. Total fertility rates (TFR) in 2008 (estimates). (Data Source: CIA World Fact Book 2008).

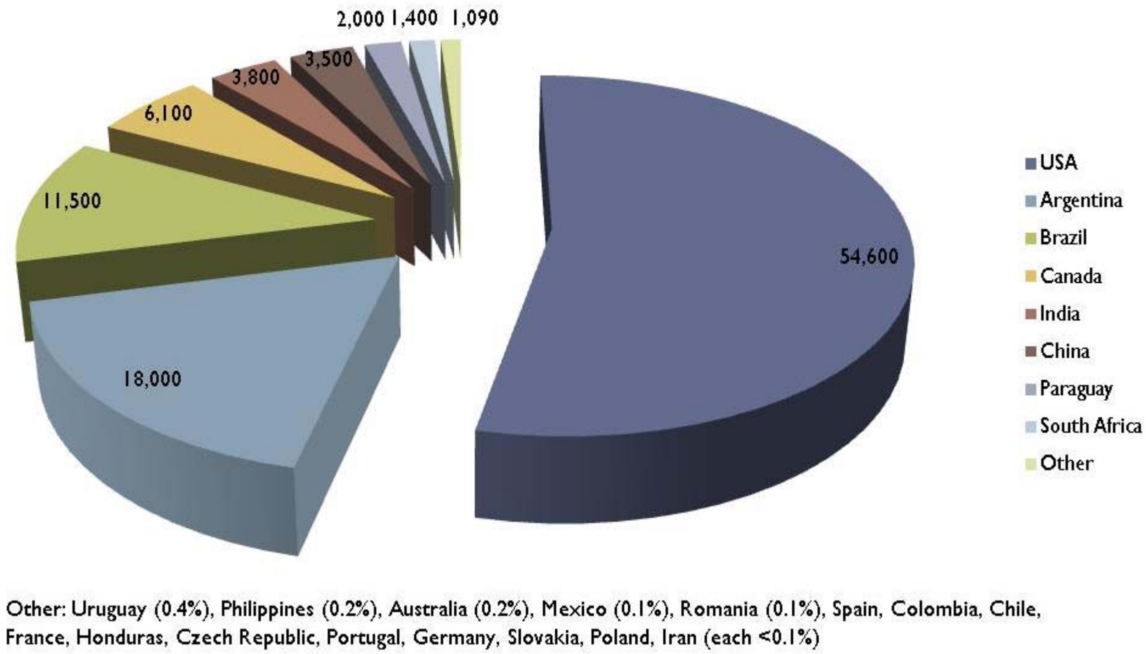

Figure 2-3. Participation in total genetically modified (GM) crop planted area, by country, 2006. (Data Source: Argenibio 2006; James 2006).

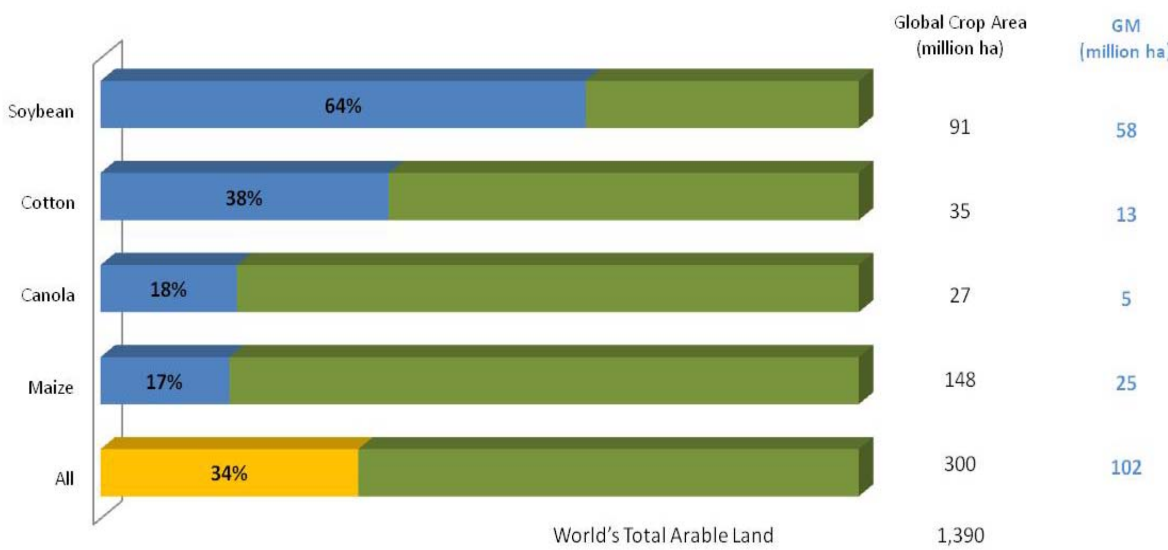

Figure 2-4. Global GM crop planted areas, for four major GM crops, as a percentage of their global planted area. (Data Source: Argenbio 2006; James 2006).

CHAPTER 3
THEORY AND KEY CONCEPTS

The main focus of this dissertation is to obtain estimates of farmers' willingness-to-pay for, and to study the adoption potential of, two genetically modified (GM) corn seed traits: a fertilizer saving (FS) trait and a drought tolerance (DT) trait. A nonmarket valuation approach is used due to the fact that these traits have not yet reached the market. This chapter presents an overview of the economic theories relevant to the nonmarket valuation pursued in this study. The chapter is divided in the following two sections.

The first section begins by presenting the concepts of Equivalent Variation and Compensating Variation which form part of the theory of welfare measures of price change pioneered by Dupuit (1844) in the nineteenth century and developed by contributions of Marshall (1930), Hicks (1941, 1943, 1956), Willig (1976), and others[1]. The adaptation of these exact welfare measures to changes in quantity space, owed mainly to seminal contributions by Mäler (1974), Randall and Stoll (1980), Hanemann (1991), and others; is also presented in this section. This adaptation to quantity space forms the theoretical basis for methods used in nonmarket valuation theory. The section finishes by presenting the formal definition of the key economic concepts of willingness-to-pay and willingness-to-accept.

The second section in this chapter presents an overview of the theory and key issues underlying the Contingent Valuation method. The Contingent Valuation method is recognized in the U.S. *Federal Register* as one of three methods recommended for measuring value in nonmarket situations. The core of the section begins by describing the Contingent Valuation method and goes on to describe (i) the predominant elicitation methods used in the literature (i.e., open ended, iterative bidding, single bounded, and double bounded), (ii) its microeconomic

[1] See Just, Hueth, and Schmitz (1982) and Just, Hueth, and Schmitz (2004).

foundations, and the (iii) appropriate statistical models to be used with the two predominant elicitation methods (i.e., single bounded and double bounded). The section finishes with (iv) a brief presentation of the "Stated Preference vs. Revealed Preference" debate in the Contingent Valuation literature, and (v) a discussion of Krutilla's(1967) concept of existence value (or non-use value).

The two sections in this chapter are intended to present the reader with some basic concepts that are used in the type of nonmarket valuation pursued in the remaining chapters of this study. The concepts in this chapter are presented at a very abstract level to facilitate exposure. The reader familiar with these basic concepts may want to skip to the next chapters where the concepts presented here are adapted to the specific situation of technology adoption.

Willingness-to-Pay (WTP) and Willingness-to-Accept (WTA)

Monetary measures of welfare value for different goods are necessary to conduct appropriate benefit-cost analysis in welfare economics. Traditionally, benefit-cost analysis has played a key role in informing policymakers' decisions with respect to the potential net benefits associated with the price changes (e.g., taxes, subsidies, etc) implied by different policies.[2]

The two exact measures of welfare impacts due to price changes were proposed by Hicks (1941, 1943, 1956) based on the areas under the Hicksian demand curve[3]; one which holds indirect utility at the initial level (u_0) as the reference point called the Compensating Variation (C), and another one that holds indirect utility at the posterior level (u_1) as the reference point called the Equivalent Variation (E). Formally, the C and E measures are defined by:

[2] Even though measures of welfare change due to price changes are not directly relevant to this study, we present them first because they may result more familiar to the reader, and to emphasize the difference with measures of welfare change in quantity space which are of our direct interest and which are presented later in Equations 3-3 and 3-4.

[3] The Hicksian measures are defined as the area under the Hicksian demand curve and above the price line.

$$u(p^1, \mathbf{q}, y - C) = u(p^0, \mathbf{q}, y) \qquad (3\text{-}1)$$

$$u(p^1, \mathbf{q}, y) = u(p^0, \mathbf{q}, y + E) \qquad (3\text{-}2)$$

where u represents indirect utility, $\mathbf{q}$ is the utility maximizing vector of goods, p^0 is the initial price, p^1 is the price after the change, and y is the income level.

In many cases one may be more interested in the effects on welfare of quantity changes as opposed to price changes. This usually is the case of policy makers aiming to evaluate the benefits and costs of proposed projects or programs or the welfare effects of provision vs. non-provision of a good. These have been popular objectives in the nonmarket valuation theory where no market behavior data on prices or quantity is available.

Karl-Göran Mäler (1974) was maybe the first to show that the concepts of C and E could be adapted from price change effects to measures of welfare impacts due to quantity changes. At this point, it is useful to define C and E for a change in quantity in a formal manner. We restrict our attention to a change in a single commodity[4], q , which could represent the supply of a public good (or bad), could be an index of quality, or could be a new technology product which is not yet in the market – this final one being our case.

Let $\mathbf{p}$ and y unchanged, and consider valuing the effect on welfare from a change in a situation "without" to one "with" the single commodity q . Let us represent this change as a change from q^0 to q^1. The individual's utility thus changes from $u^0 \equiv v(\mathbf{p}, q^0, y)$ to $u^1 \equiv v(\mathbf{p}, q^1, y)$; with $u^1 > u^0$ if she considers the change an improvement, $u^1 < u^0$ if she considers it for the worse, and $u^1 = u^0$ if she is indifferent about the change. Following

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[4] Having quantity change in more than one good does not change the results but makes the calculations and discussion much more complicated.

Hanemann's (1991) notation, the welfare measures C and E in quantity space are formally defined as:

$$u(\mathbf{p}, q^1, y - C) = u(\mathbf{p}, q^0, y) \tag{3-3}$$

$$u(\mathbf{p}, q^1, y) = u(\mathbf{p}, q^0, y + E) \tag{3-4}$$

That is, C and E are the monetary values that make the individual indifferent between a situation where they have the good (q^1) and a situation where they do not have it (q^0). The C measure takes indirect utility at the initial situation where the individual is "without the good" as the reference point, while the E measure uses the indirect utility in the situation "with the good" as the reference point.

The usual measures of individual value are the willingness-to-pay (WTP) and willingness-to-accept (WTA). In a market exchange situation these correspond, respectively, to the buyer's best offer and the seller's reservation price.

The notational convention in Equation 3-3 and Equation 3-4 is used so that $sign(u^1 - u^0) = sign(C) = sign(E)$. Therefore, if the change is an improvement: $u^1 - u^0 > 0$, $C > 0$, and $E > 0$. In this case, C is the individual's maximum WTP^C to secure the change, and E is her minimum WTA^E to forego it. On the other hand, if the change is for the worse: $u^1 - u^0 < 0$, $C < 0$, and $E < 0$. In that case, C measures the individual's minimum WTA^C in compensation to endure the change, and E is her maximum WTP^E to avoid such change. Notice that WTA is not always the C measure and WTP is not always the E measure.

In the case of quantity changes, methods have been developed to directly estimate WTP and WTA. One of the most popular and most extensively used of these methods is the Contingent Valuation method which will be discussed in the following section.

Contingent Valuation (CV)

The Contingent Valuation (CV) method is a stated preference approach that has been extensively used to obtain estimates of WTP in nonmarket situations such as the case of environmental goods. Cameron and James (1987b) suggested that the CV method can be equally useful in pre-testing new market goods.

The CV method is recognized in the U.S. *Federal Register* as one of three methods recommended for measuring economic value in nonmarket situations. The CV method was first recognized in the *Federal Register* as a valid method for evaluation of project benefits in the "Principles and Standards for Water and Related Land Resources Planning" guidelines published by the U.S. Water Resources Council (1979). It is also named as an approved method in the Comprehensive Environmental Response, Compensation, and Liability Act of 1980 (Superfund) (U.S. Department of Interior 1986).

The CV method uses especially designed surveys to directly elicit from respondents their individual's preferences for a given commodity by querying them for their WTP (or WTA) to secure (forego) a positive change in the level of provision of that commodity.[5] The ultimate aim of a CV survey is typically to obtain an accurate estimate of the benefits (or costs) of a change in the level of provision of some good (Mitchell and Carson 1989).

In a CV survey the individual is presented with a hypothetical "constructed" market and is asked to give responses stating her preferences (in terms of dollar amounts he is WTP or WTA) regarding different scenarios in which the quantities of the good are changed.[6] The respondent's

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[5] Mitchell and Carson (1989) provide a comprehensive overview of the issues involved in the design and analysis of CV surveys, and Bateman et al. (2002) provide a useful manual for the practitioner.

[6] If the change in case is an improvement, CV measures the WTP to secure the change and/or WTA to forego it. If the change is for the worse, the method measures the WTP to avoid the change and/or WTA to endure it.

answers are said to be “contingent” on the details of such hypothetical market as put forth by the survey.

In essence, the CV method is seen as having four distinctive advantages: (1) the CV method represents a tool to estimate the effects on welfare of changes in the quantity of some commodity when market data on prices and quantities exchanged is not available (e.g., public goods, new unmarketed products), (2) its hypothetical nature gives it more flexibility than observed behavior methods allowing for evaluation of scenarios that haven’t actually happened but may be very interesting, (3) the CV method obtains the actual Hicksian measures of welfare (WTP and WTA); and (4) the WTP measures obtained by use of the CV method include Krutilla’s (1967) existence value and Weisbrod’s (1964) option value.

The remainder of this section on CV is organized as follows. First we present the predominant elicitation formats used in the literature and discuss their relative merits and shortcomings. Second, we present the microeconomic foundations of CV and develop the appropriate statistical models to be used with the two most relevant elicitation formats (single bounded and double bounded). After this we briefly illustrate the “Revealed Preference vs. Stated Preference” debate that surrounded the early years of CV research and how such debate has today shifted towards a more holistic view where revealed and stated methods are seen to complement rather than compete against each other. We finish this CV section by discussing Krutilla’s (1967) concept of existence value framed in a description of alternative (other than CV) indirect revealed preference methods that are used in the literature to perform nonmarket valuations.

Elicitation Formats, Statistical Efficiency, and Starting Point Bias

There are several ways in which one can query the respondent about her WTP. Two distinct elicitation formats predominate in the CV literature: (i) the open ended (OE) format and

(ii) the dichotomous choice (DC) format (or closed-ended format). In the OE format one asks the respondent:"How much are you willing to pay (accept) for a change from q^0 to q^1?" Suppose the answer given is $Bid, then $Bid is taken as that individuals measure of C (of E). The DC format asks: "Would you be willing to pay (accept) $Bid for a change from q^0 to q^1?" In this case, the respondents answer is dichotomous – "yes" or "no".

A major stimulus to the development and refinement of CV methods was the enactment of U.S. laws that allowed for recovery of monetary damages for injuries to natural resources (Superfund). The key event was the Exxon Valdez oil spill where the state of Alaska claimed for damages based on estimates obtained using CV methods[7]. Following the spill, an aggressive campaign was launched by oil companies that had several studies published which left CV methods in bad light (See Hausman 1993). At the same time, on the other side of the debate, the U.S. National Oceanic and Atmospheric Administration (NOAA) convened a Blue Ribbon panel co-chaired by two Nobel Prize laureates (Arrow et al. 1993) to make a comprehensive assessment of CV methods. The now famous NOAA report endorsed CV and in particular endorsed the DC elicitation format.

Critics of the OE formulation of CV have referred to it as the "Silly Question Method" or "Pick a number" and have characterized it as: "Suppose one approached people in a shopping mall, made them put their bags down for a moment, and asked them what was the most they would be willing to pay for conservation of a sea otter in Alaska or an expanse of wilderness in Montana". The DC format is generally agreed to give better results because it provides respondents with a more market-like situation.

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[7] CV method was used by the state of Alaska because it is the only method that measures existence value. Existence value refers to the value people assign to things just from knowing they exists, even if they do not plan to consume them. In contrast, use value is what economists are used to and refers to the value derived from consumption of things.

There exist several variations along the lines of DC elicitation: (i) single bounded (SB), (ii) iterative bidding (IB), and (ii) double bounded (DB).

The SB format was first implemented by Bishop and Heberlein (1979) who estimated the WTP for duck hunting permits. In the SB-DC approach, respondents are presented with randomly assigned bids and are asked in a single yes/no question whether they would pay or refuse to pay the offered bid to secure being provided with the good.[8] Several early studies were produced using the SB-DC method, popularized by Hanemann (1984) who demonstrated the economic theory underpinning such method using a random utility framework and an indirect utility approach. The SB approach, since it provides less information about the magnitude of WTP,[9] requires a larger number of observations compared to the OE format to achieve similar levels of statistical efficiency.

The IB method (Davis 1963a; Randall, Ives, and Eastman 1974) lies at the other end of the spectrum. The IB method is simply a series of sequenced DC questions. In the bidding method a $Bid offer is made; if the respondent answers is "no" the offer is sequentially and gradually decreased until a "yes" is obtained; if the initial response is "yes" the offer is sequentially and gradually increased until a "no" is obtained. The value of $Bid at which the respondent switches her answer is used as the dependent variable in regression models that estimate WTP. The IB method, while achieving greater statistical efficiency compared to SB method, results tiring to the respondent and is known to be greatly affected by what is termed "starting point bias".

Starting point bias is concerned with the initial offer being used by the respondent as an anchor or focal point. ''Confronted with a dollar figure in a situation where he is uncertain about

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[8] If instead of WTP we want to elicit WTA, then this changes to "whether they would forego the good for the offered bid". From here on our discussion will be about WTP.

[9] Open-ended format elicits the actual magnitude of WTP while dichotomous choice obtains only a "yes" or "no" bound.

an amenity's value, a respondent may regard the proposed amount as conveying an approximate value of the amenity's true value and anchor her WTP amount on the proposed amount'' (Mitchell and Carson 1989). Therefore, her first answer will derive from her prior WTP distribution while subsequent responses in the bidding process will only be updates to this prior based on information obtained by each offer (Herriges and Shogren 1996). Ideally, we would want each answer to be based on the same distribution, that is, each answer should be independent because in each answer the respondent should query her preferences and not her prior answers to provide her personal response.

Hanemann (1985) and Carson (1985) proposed the DB format which can be thought of as a compromise between the SB and IB methods: (i) improving upon the low statistical efficiency of SB and (ii) ameliorating the effects of starting point bias of IB. We can think of the SB format being at one end of the spectrum, and the IB method at the other, with DB lying in the middle. In the DB method respondents are asked one initial question and one single follow-up question. In the initial question an initial $Bid offer is made, if the respondent's answer is "no" a second lower offer is made in the follow up question, if the initial answer is "yes" a second higher offer is made in the follow up question. The bidding process consists only of these two offers. Hanemann (1985) and Carson (1985) first proposed this method to improve efficiency of discrete choice questionnaires.

Hanemann, Loomis, and Kanninen (1991) demonstrated the large efficiency gains from using DB instead of SB methods. Cooper and Hanemann (1995) showed that only small gains in efficiency, which do not justify the extra mathematical complications, could be obtained by adding a third or further follow ups.

The DB method, as part of a larger category of iterative elicitation formats, is not completely free of starting point bias problems.[10] Several different models to control for these problems have been proposed (See Cameron and Quiggin 1994; Herriges and Shogren 1996; Alberini, Kanninen, and Carson 1997; Whitehead 2002; DeShazo 2002) but results from these models show the gain in efficiency of the DB method is lost when controlling for the starting point bias.[11]

Statistical Models for Single Bounded and Double Bounded CV Data

One must avoid being careless in modeling CV responses to different elicitation formats. Each elicitation format warrants a specific statistical model. In this subsection we first present the appropriate statistical model to be used with the SB elicitation format while emphasizing its microeconomic foundations. Hanemann (1984) made the link between SB-CV survey responses and the utility-maximizing agent of economic theory by specifying a Random Utility Model (RUM). We follow his discussion. We then present the two available approaches to model the WTP distribution. Hanemann (1984) proposed an Indirect approach to modeling the WTP distribution which remained the only way until Cameron and James (1987a) proposed the more tractable Direct Approach. At the end of this subsection we extend the SB statistical model to be coherent with a DB elicitation format.

Hanemann (1984) starts by setting up the individual's indirect utility. The individual derives utility from consumption of a good q through $u(\mathbf{p}, q^j, y; \mathbf{x})$; $j = 0,1$; y denotes income, $\mathbf{p}$ represents a vector of prices, and $\mathbf{x}$ are other observable individual attributes that might affect

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[10] Some of the alternative explanations for starting point bias are the: (i) anchoring effect, (ii) shift effect, and (iii) framing effect.

[11] Flachaire and Hollard (2005) have recently proposed an alternative method that seems to correct starting point bias without losing the efficiency gains of DB.

her preferences (e.g., sex, age, etc)[12]. The individual's indirect utility can be considered as being composed by a deterministic portion and a stochastic portion:

$$u(q_j, y; \mathbf{x}) = v(q_j, y; \mathbf{x}) + e_j \quad , \quad j = 0,1 \tag{3-5}$$

where $v(p,q,y)$ is the portion of indirect utility which is explicitly defined in the model, $j = 0$ if q is not provided, $j = 1$ if q is provided, and e_1 and e_0 are i.i.d. random variables that represent everything else that is not observable to the researcher in the jth state of the world. The addition of a random term is usually justified by arguing that, while the decision making process of rational maximizing agents is not random to the individual herself, there are elements involved in the decision-making process that are not observed by the researcher. The RUM approach enables economists to estimate a distribution for WTP.

Single bounded model: two approaches reconciled

As described earlier, in the SB-CV method the respondent is asked the single question: "Would you be willing to pay \$Bid for a change from q^0 to q^1?". An individual will be willing to pay for a given good if and only if after paying \$Bid and acquiring the good her utility remains the same or is increased compared to the initial situation of not paying and not having the good. Because of the assumed stochastic nature of the indirect utility, we can define the probability of an acceptance to pay to secure provision of a good as:

$$\Pr_1 \equiv \Pr\{\mathit{individual\ willing\ to\ pay}\} = \Pr[v(q^1, y - Bid; \mathbf{x}) + e_1 \geq v(q^0, y; \mathbf{x}) + e_0] \tag{3-6}$$

$$\Pr_0 \equiv \Pr(\mathit{individual\ not\ \ willing\ to\ pay}) = 1 - \Pr_1 \tag{3-7}$$

[12] For notational simplicity we do not always write utility as a function of prices in what follows, this has no bearing on the theoretical results since all changes in quantity of good q assume that prices are held fixed. We include **x** to emphasize that the parameters of the estimated distribution are a function of **x.**

Let $\eta = e_0 - e_1$ and let F_η be the cumulative distribution function (cdf) of η, then we can solve the brackets in Equation 3-6 to obtain:

$$\Pr_1 = F_\eta(\Delta v) \tag{3-8}$$

$$\Delta v \equiv v(q^1, y - Bid; \mathbf{x}) - v(q^0, y; \mathbf{x}) \tag{3-9}$$

Equation 3-8 defines the probability that the individual is willing to pay the offered price \$Bid and purchase the good; and depends on quantities q_0 and q_1, on y and on the offered price, Bid. Typically, F_n is assumed to be either the normal or logistic distributions obtaining the probit and logit binary choice models, respectively.

The link between the individual's WTP, given by the theoretical measure C, and the empirical survey responses to an offer (\$Bid) is made by motivating the binary choice model in a different way. When asked to chose whether or not he would pay \$Bid to secure a given change in q, the individual will accept to pay (respond "yes") only if $C \geq$ \$Bid and refuse otherwise (respond "no"). Thus the acceptance probability defined in Equation 3-6 and Equation 3-8 can be expressed in an alternative manner as:

$$\Pr_1 = \Pr(C \geq Bid) \equiv 1 - G_C(Bid) \tag{3-10}$$

By comparing Equation 3-10 with Equation 3-8 we can see:

$$1 - G_C(Bid) \equiv F_\eta(\Delta v(Bid)) \tag{3-11}$$

so that fitting the binary choice model $F_\eta(\Delta v(Bid))$ is tantamount to estimating the parameters of the distribution of $1 - G_C(Bid)$, the distribution of WTP.

Two different approaches exist in the literature to model the distribution of WTP. We refer to these as the Direct Approach and the Indirect Approach. The Indirect Approach was initially proposed by Hanemann (1984), the Direct Approach (Cameron and James 1987a) came later.

However, we discuss them in inverted chronological order to make the point that both approaches can be shown to be equivalent (dual).

The Direct Approach, proposed by Cameron and James (1987a), is to specify the mean of $C = \mu_C$ (i.e., the population mean WTP) directly and add a white noise stochastic term: $C = \mu_C + \upsilon$. The mean can then be assumed to depend on some covariates. Typically a linear specification is assumed, $\mu_C = \gamma\mathbf{x}$, thus WTP is modeled as:

$$C = \gamma\mathbf{x} + \upsilon. \quad (3\text{-}12)$$

This model may be estimated as a linear regression in the case of an OE elicitation format, or by some discrete choice model if the DC format is used.

The Indirect Approach, proposed by Hanemann (1984), uses the formal definition of $\Delta v(Bid)$ derived in Equation 3-9. In this approach the distribution of C is not directly specified but instead an assumption is made about the functional form of $v(q^j, y; \mathbf{x})$, $j = 0,1$. For example, the linear specification is given by the following form:

$$v(q^j, y; \mathbf{x}) = \alpha_j + \beta y \quad (3\text{-}13)$$

$$u(q^j, y; \mathbf{x}) = v(q^j, y; \mathbf{x}) + \varepsilon_j \quad (3\text{-}13b)$$

To obtain $\Delta v(Bid)$ we use the definition in Equation 3-9,

$$\begin{aligned}
\Delta v &= v(q^1, y - Bid; \mathbf{x}) - v(q^0, y; \mathbf{x}) \\
&= \alpha_1 + \beta y - \beta Bid - \alpha_0 - \beta y \\
&= \alpha_1 - \alpha_0 - \beta Bid \\
&= \alpha - \beta Bid
\end{aligned}$$

$$\Delta v(Bid) = \alpha - \beta Bid \quad (3\text{-}14)$$

where only $\alpha = \alpha_1 - \alpha_0$ and β can be identified. The statistical choice model for the SB format presented in Equation 3-11 then becomes,

$$P_1 = 1 - G_C(Bid) = F_\eta(\alpha - \beta Bid) \tag{3-15}$$

From this approach we could solve our model to get our expression for C. This is done first by solving Equation 3-13b for $y \equiv m(q^j, u(q^j, y))$ to obtain:

$$m(q^j, u(q^j, y)) = \frac{v(q^j, y)}{\beta} - \frac{\alpha_j}{\beta} - \frac{\varepsilon_j}{\beta} \tag{3-16}$$

We can then plug Equation 3-16 into the Compensating Variation Function as follows,[13]

$$\begin{aligned}
C \quad &= y - m(q^1, u(q^0, y)) \\
&= y - \left(\frac{v(q^0, y)}{\beta}\right) - \frac{\alpha_1}{\beta} - \frac{\varepsilon_1}{\beta} \\
&= y - \left(\frac{\alpha_0 + \beta y + \varepsilon_0}{\beta}\right) - \frac{\alpha_1}{\beta} - \frac{\varepsilon_1}{\beta} \\
&= \frac{\alpha_1 - \alpha_0}{\beta} + \frac{\eta}{\beta} \\
&= \frac{\alpha}{\beta} + \frac{\eta}{\beta}
\end{aligned} \tag{3-17}$$

This shows that the ratio of parameters estimates α/β obtained via estimation of Equation 3-15 gives us an estimate of WTP. Moreover, if we let α/β depend linearly on $\mathbf{x}$ through a regression such as $\alpha/\beta = \gamma\mathbf{x}$ and write $\upsilon = \eta/\beta$, we obtain back Equation 3-12 which is the Direct Approach. This reconciles the two approaches for specifying a functional form for $\Delta v(Bid)$. In essence, the Direct Approach models WTP directly while the Indirect Approach models the indirect utility function to obtain estimates that can be algebraically manipulated to obtain WTP estimates. McConnell (1990) showed the two approaches are dual or equivalent. "In

[13] See Hanemann (1991) for a formal derivation of the Compensating Variation function.

general, for any given regression formulation of a WTP distribution, one can always find a RUM formulation which generates this distribution. In this sense, any given WTP distribution can be derived using either approach" (Carson and Hanemann, 2005). However, the Direct Approach has become the most popular due to its tractability and the easiness with which one can obtain the marginal effects of individual characteristics on WTP.

We finish deriving the appropriate statistical model for the SB elicitation method under the Direct Approach framework. Going back to our linear specification under the Direct Approach we rewrite Equation 3-12 for individual i:

$$C_i = WTP_i^C = \mathbf{x}_i'\gamma + \upsilon_i \tag{3-12}$$

where $\mathbf{x}$ denotes a set of individual characteristics thought to have an effect on WTP. In practice, each respondent receives a randomly chosen threshold bid offer, Bid_i. Her response depends on the magnitude of her WTP which is not observed, we observe only a dichotomous "yes" or "no" answer, y_i;

$$y_i = \begin{cases} 1 = yes & if\ WTP_i^C > Bid_i \\ 0 = no & if\ WTP_i^C < Bid_i \end{cases} \tag{3-18}$$

using Equation 3-12, her probability of accepting (i.e., answering "yes") the offer is given by

$$\begin{aligned} \pi_i^y = \Pr(y_i = 1 \mid \mathbf{x}_i) \quad &= \Pr(WTP_i^C > Bid_i) \\ &= \Pr(\mathbf{x}_i'\gamma + \upsilon_i > Bid_i) \\ &= \Pr(\upsilon_i > Bid_i - \mathbf{x}'_i\gamma) \\ &= \Pr(z_i > (Bid_i - \mathbf{x}'_i\gamma)/\sigma) \end{aligned} \tag{3-19}$$

here we assume $\upsilon \sim N(\mu_\upsilon, \sigma_\upsilon)$ so that z_i is distributed standard normal, this results in a probit model given by,

$$\pi_i^y = 1 - \Phi((Bid_i - \mathbf{x}'_i\gamma)/\sigma) \tag{3-20}$$

$$\pi_i^n = \Phi((Bid_i - \mathbf{x}'_i \gamma)/\sigma) \tag{3-21}$$

While a regular probit yields parameter estimates only up to a factor of proportionality (i.e., γ/σ), Cameron and James (1987a) show that the variability in Bid_i (due to its random assignment across the sample) allows us to identify and estimate γ and σ separately. The estimation technique resembles an ordered probit with given cutoff points (also known as interval data estimation).

Double bounded model

We now develop the appropriate statistical model for the DB elicitation method. The model presented here forms the basis for the models used throughout this study. The model is an extension of the SB model. In the SB case we had a dichotomous (1=yes, 0=no) dependent variable, y_i in response to a single bid offer, Bid_i. In the DB methodology a second question is asked with a higher offer, $Bid_i^H > Bid_i$, if the response to the first question is yes and a lower offer, $Bid_i^L < Bid_i$, otherwise. Combining the answers to both questions we obtain four different possible scenarios,

$$d_i = \begin{cases} 1 & no, no \\ 2 & no, yes \\ 3 & yes, no \\ 4 & yes, yes \end{cases}$$

If we assume the utility maximizing respondent queries his preferences to answer each of the questions, we can derive the formulas for the respective likelihoods (See Hanemann, Loomis, and Kanninen 1991) of each outcome. The likelihood for individual i giving a $d_i = yes, yes = 4$ response is,

$$\begin{aligned}\pi_i^{yy}(Bid_i, Bid_i^H) &= \Pr\{Bid_i \le WTP_i \text{ and } Bid_i^H \le WTP_i\} \\ &= \Pr\{Bid_i \le WTP_i \mid Bid_i^H \le WTP_i\} \cdot \Pr\{Bid_i^H \le WTP_i\} \\ &= \Pr\{Bid_i^H \le WTP_i\} \\ &= 1 - G(Bid_i^H; \theta) \qquad (3\text{-}22)\end{aligned}$$

since by definition $Bid_i^H > Bid_i$ so that $\Pr\{Bid_i \le WTP \mid Bid_i^H \le WTP_i\} \equiv 1$; where G is a cumulative distribution function with estimable parameters θ. Similar reasoning is used to derive the remaining likelihoods,

$$\pi_i^{yn}(Bid_i, Bid_i^H) = G(Bid_i^H; \theta) - G(Bid_i; \theta) \qquad (3\text{-}23)$$

$$\pi_i^{ny}(Bid_i, Bid_i^L) = G(Bid_i; \theta) - G(Bid_i^L; \theta) \qquad (3\text{-}24)$$

$$\pi_i^{nn}(Bid_i, Bid_i^L) = G(Bid_i^L; \theta) \qquad (3\text{-}25)$$

We can then write the log likelihood for the DB model as;

$$\begin{aligned}\ln L(\theta) = \sum_{i=1}^{N}\{&d_i^{yy} \ln \pi_i^{yy}(Bid_i, Bid_i^H) \\ &+ d_i^{yn} \ln \pi_i^{yn}(Bid_i, Bid_i^H) \\ &+ d_i^{ny} \ln \pi_i^{ny}(Bid_i, Bid_i^L) \\ &+ d_i^{nn} \ln \pi_i^{nn}(Bid_i, Bid_i^L)\} \qquad (3\text{-}26)\end{aligned}$$

Where $d_i^{yy}, d_i^{nn}, d_i^{ny}$ and d_i^{yn} are binary-valued indicator variables for each outcome. Using the linear specification for the Direct Approach (Equation 3-12) to model WTP and assuming a normal distribution for υ_i, we obtain the log-likelihood for the DB elicitation format,

$$\begin{aligned}\ln L(\theta) = \sum_{i=1}^{N}\{&d_i^{yy} \ln[1 - \Phi((Bid_i^H - \mathbf{x}_i'\gamma)/\sigma)] \\ &+ d_i^{yn} \ln[\Phi((Bid_i^H - \mathbf{x}_i'\gamma)/\sigma) - \Phi((Bid_i - \mathbf{x}_i'\gamma)/\sigma)] \\ &+ d_i^{ny} \ln[\Phi((Bid_i - \mathbf{x}_i'\gamma)/\sigma) - \Phi((Bid_i^L - \mathbf{x}_i'\gamma)/\sigma)] \\ &+ d_i^{nn} \ln[\Phi((Bid_i^L - \mathbf{x}_i'\gamma)/\sigma)]\} \qquad (3\text{-}27)\end{aligned}$$

Which is maximized for $\theta = [\gamma, \sigma]$. The estimated $\hat{\gamma}$ are directly interpreted as the marginal effects of x on WTP.

Stated vs. Revealed Preferences

Economists distinguish between revealed (or observational) preference (RP) methods and stated preference (SP) methods to study individual behavior. RP methods (i.e., revealed preference theory) are heavily relied on by economists for estimating parameters to explain demand for market goods. In RP methods consumers reveal information about their tastes and preferences through their behavior in real markets. Consumers' preferences are "revealed" in the market by the quantities they choose to consume at different prices.

Because environmental goods seldom reach any market, environmental economists were pioneers in pointing out the data availability limitations of the RP approach and the possibilities inherent in the SP approach to tackle this. For economists to be able to estimate the value of non-market goods or new unmarketed products, for example, it usually becomes necessary to reach into the realm of SP methods such as CV where the value the consumer associates to the good (WTP and WTA) is directly elicited from her through survey questionnaires about some hypothetical market situation. Schelling (1968) makes the point quite clear by saying that while the price system is one way to find out what things are worth to people, another way is to ask them directly.

Proposed early by the famous environmental economist Ciriacy-Wantrup (1947), who wanted to measure the dollar benefits of soil conservation, SP methods have been of interest in the academic world since the late 1940's. In his book *Resource Conservation: Economics and Policies*, Ciriacy-Wantrup (1952) advocates for the use of the "direct interview method" to measure the values related to natural resources. In a contemporaneous contribution Bowen

(1943) reached the same conclusion when studying the welfare benefits of beautification of landscapes, and suggested the use of polls. It was Robert K. Davis (1963b) who was first to use CV methods in his doctoral dissertation at Harvard.

Regardless of the potential advantages associated with embracing SP methods, their use has borne some antagonism from traditional RP economists for several reasons. Economists usually shy away from SP approaches in favor of RP economics. One reason is that many economists believe that SP methods may spur strategic behavior from respondents and as a result what people say they would do in a market during an artificial market session is not necessarily what they actually do in the real world situation. Samuelson (1954) makes this point in his seminal paper: "It is in the selfish interest of each person to give false signals, to pretend to have less interest in a given collective activity than he really has." Milton Friedman also contributed to the debate with his famous analogy of the professional pool player not knowing the underlying physics behind the shot. In his view, maximizing agents might behave as such even without consciously knowing they do so, as a result their survey responses are meaningless (not linked to their behavior).

The debate between RP supporters and SP supporters has lasted more than three decades. At a beginning, attempts were made to validate CV results by comparing them to WTP estimates obtained via RP methods (e.g., Hanemann 1978; Cameron 1992; Adamowicz, Louviere, and Williams 1994). In Resource Economics, the most commonly RP methods used for valuation and comparison are the hedonic pricing and the travel cost method. Results from such comparisons have been inconclusive, showing convergence in some cases and divergence between RP and SP methods in others.

More recently, a different approach has become popular which views both SP data and RP data as flawed in differing aspects. In this view SP and RP methods are seen as complimentary to each other rather than as opposing and mutually exclusive. Both methods are thought as containing important but incomplete information about the preference structure of consumers. As such, each method has its relevance and applicability. Under this paradigm, the convergence tests applied in studies mentioned above make no sense since both methods are imperfect and one cannot arbitrarily pick one or the other as a benchmark. A result of this late conceptualization is the production of studies that combine SP and RP data to formulate a more complete picture of consumers' preference structures (Azevedo, Herriges, and Kling 1993; Cooper 1997; Hubbell, Marra, and Carlson 2000; Qaim and DeJanvry 2003).

Existence Value and Alternative Methods to Obtain WTP Measures of Non-Market Goods

This subsection presents some of the alternative methods that are commonly used to obtain estimates of WTP for non-market goods. In some cases, regardless of observable market data unavailability, economists are still able to estimate part of the value of nonmarket goods by using specialized indirect-observed behavior methods such as hedonic pricing (Rosen 1974) or the travel cost method (Clawson and Knetsch 1966). For example, a hedonic pricing study would estimate the value of a nonmarket good such as air quality by modeling the price of real estate as a function of: characteristics of the property, air quality, and other attributes of the housing zone which may or may not be pure public goods (i.e., non-market valuated goods). The idea is that the value people assign to real state is composed by the value of the property per se, plus the value of nonmarket attributes of the housing zone surrounding the property (e.g., air quality, crime rate, parks and recreation area, closeness to main roads, etc); as such, the parameter estimate associated with the air quality variable in our example is interpreted in hedonic pricing studies as the component value of real state assigned to air quality by the "purchasing" individual. As opposed to direct market data on air quality prices which is inexistent, market data on real estate prices is readily available. A second example would be the travel cost method which is typically used to estimate economic "use value" associated with recreational parks or natural ecosystems. The method estimates individuals' WTP (or WTA) using data on the number of trips made to visit the park at different trip distances and different travel costs. The idea is that the cost of the trip provides evidence of the value the individual assigns to the nonmarket good, in this case the natural park. Other examples of alternative indirect RP methods used to estimate the value of nonmarket goods include the household production model and the averting expenditure method (Freeman 1993).

All of these methods suffer from the same limitation, as we have tried to emphasize in the preceding discussion by using quotation marks, these methods are able only to measure what is known since Krutilla (1967) as the "use value" of nonmarket goods. Krutilla's contribution was influential in that it argued, quite convincingly, for the importance of "non-use values" (or existence value) and defined them clearly enough to distinguish them from conventional "use values".

Non-use value covers situations in which individuals who do not use, nor plan to use, a commodity would nevertheless feel a loss if the commodity would cease to exist. Many individuals, for example, would assign a dollar value to things such as the existence of the Amazon Rainforest even if they do not have plans of ever visiting or using it. From an economist perspective, the total economic value (TEV) of a commodity is the sum of its use value (UV) and its non-use value (NV):[14]

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[14] Kerry Turner (2002) argues that a broader categorization of values which encompasses TEV=UV+NV as part of what he calls Anthropocentric Instrumental Value can be done by including four categories based on whether the valuer is a human being or not; and whether the value assigned is of instrumental or intrinsic type. The categories are: (1) Anthropocentric Instrumental Value, (2) Anthropocentric Intrinsic Value, (3) Non-Anthropocentric

$$TEV = UV + NV \tag{3-28}$$

Since market price data is inevitably tied to a decision to consume, market prices hold only information about the use value consumers give to things; lacking information about existence values. Thus, in general, indirect-RP methods based on market data are only able to obtain estimates of the relevant use values while unable to obtain existence values. Therefore, it may be argued that if the non-use portion of value is quite large market-data driven methods obtain defective TEV estimates.

There are some indirect RP methods that can, under certain circumstances, obtain estimates of non-use value. Analysts can switch attention from the market system towards the political system and, for example, estimate demands for local public goods using the collective choice method (Oates 1994). Collective choice models make use of the theory of the median voter proposed initially by Duncan Black (1948). In this approach, by assuming simple majority voting, the results of an election are shown to be equivalent with the preferences of the median voter. Candidates adjust their policy stances to match median voter's preferences as closely as possible in hopes of being the winning ticket. Therefore, the quantities offered of a public good in a given municipality can be thought of as points in the demand function of a single voter with median preferences. In other words, we can obtain price and income elasticities of public goods by simply treating quantities offered of the public good in different municipalities as the dependent variable, and using median income and tax share of median voter as the independent variables (we can also include other socio-demographic variables as long as they are

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Instrumental Value, and (4) Non-Anthropocentric Intrinsic Value. The UV is bounded by the NV which in his view is also anthropocentric since it is composed of (i) intragenerational altruism (i.e., vicarious consumption) , (ii) intergenerational altruism (i.e., bequest value), and (iii) stewardship motivation; which are all human motivations that require a human valuer (i.e., are Anthropocentric).

representative of the median voter).[15] What the method essentially is suggesting then is taking an observed outcome in a community and associating it with a point on the demand curve of a decisive voter; then, each jurisdiction serves as a unit of observation (Oates 1994). The potential limitations in gathering the data needed for this type of study become obvious when we think of obtaining only one observation per jurisdiction; in some cases the logistics and costs associated might prove impossible.

All of the methods mentioned so far are popularly used in the environmental valuation theory. There is another group of non-market valuation techniques worth mentioning, these are known as Conjoint Analysis (or choice modeling) methods (Green and Rao 1971). They are SP techniques that are more commonly used in the marketing community. Even though these methods were not pursued in this study, it is worth mentioning them so as to have a more complete picture of the methods available to perform economic valuations in non-market situations.

Conjoint Analysis (CA) techniques are very similar to CV; they are in essence a multiple attribute valuation exercise.[16] CA and CV, however, differ in their origins. CA techniques hold their origins in the psychometric literature and their development in the marketing literature. CV grew out of the need to valuate non-market environmental goods in the resource economics literature. Both CV and CA, however, share their statistical foundations in the development of discrete choice models.[17]

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[15] The method also allows for estimation of the grade of "publicness" of the good via a single parameter (See Borcherding and Deacon 1972; Bergstrom and Goodman 1973).

[16] For an introductory text on Conjoint Analysis see Orme (2005).

[17] See for example Luce (1959), Marschak (1960), and McFadden (1974) for the logit model.

In a CA exercise the respondent is presented with an array of hypothetical potential products showing different combinations of previously selected salient attributes. Depending on the exact type of CA method being used, the respondent is asked to rank or to express their preferred choice among the presented products. In Rank CA, for example, the individual is presented with profiles of products with varying prices and attributes and is asked to rank them or rate them. In this way the researcher is able to obtain estimates of latent utilities (part-worths) that emulate choice behavior. In Choice Based Conjoint (CBC), on the other hand, the individual is asked to choose their preferred product, as opposed to ranking every single product presented. CBC is in essence a multinomial choice CV (i.e., where the choice set has more than one good).

One problem with Full Profile CA is that even a small number of goods, prices, and attributes gives rise to a large number of alternatives which increases costs of carrying this type of study and may overwhelm the respondent. Adaptive CA (ACA) improves on this by using classic Experimental Design methods to eliminate unnecessary alternatives (Johnson 1974). An improvement on CBC and ACA is possible by using Hierarchical Bayes estimation methods (Allenby, Arora, and Ginter, 1995).

We have discussed the methods used in non-market valuation studies and some of their advantages and disadvantages. Many of the methods presented here are not applicable to our case of pre-testing market technologies and studying their potential for adoption. The discussion, however, illustrates the concept of existence value (or non-use value) and some of the reasons why CV is preferred in many situations. Two distinct groups are identified: those that can obtain existence values and those that cannot (See Figure 3-1). In general, SP methods obtain existence values, while RP methods do not.[18]

[18] In Figure 3-1, Rank CA, CBC, and ACA are listed under "choice modeling" as "contingent ranking", "choice experiments" and "paired comparisons", respectively.

Among SP methods (which are in fact applicable to our case), two groups or methods, one derived from the marketing literature (i.e., CA) and another derived from the resource economics literature (i.e., CV) were discussed. CA methods are a powerful tool for obtaining simultaneous valuations of multiple attributes, but are prone to large implementation costs.

CV methods are a better fit for the scale and for the “attribute by attribute” valuation targeted by this study, plus they allow for capturing any potential existence values. Non-user (or non-adopter) valuation of GM crops is important because of the controversial facets and uncertainty associated to the technology (See Chapter 2). The total value that farmers associate with a GM crop may be in part given by its use value (i.e., profitability) but also may be affected by its existence value (i.e., a negative penalization due to uncertainties and controversial aspects of the technology or a positive additional value associated with non-market benefits such as “ease of use”).

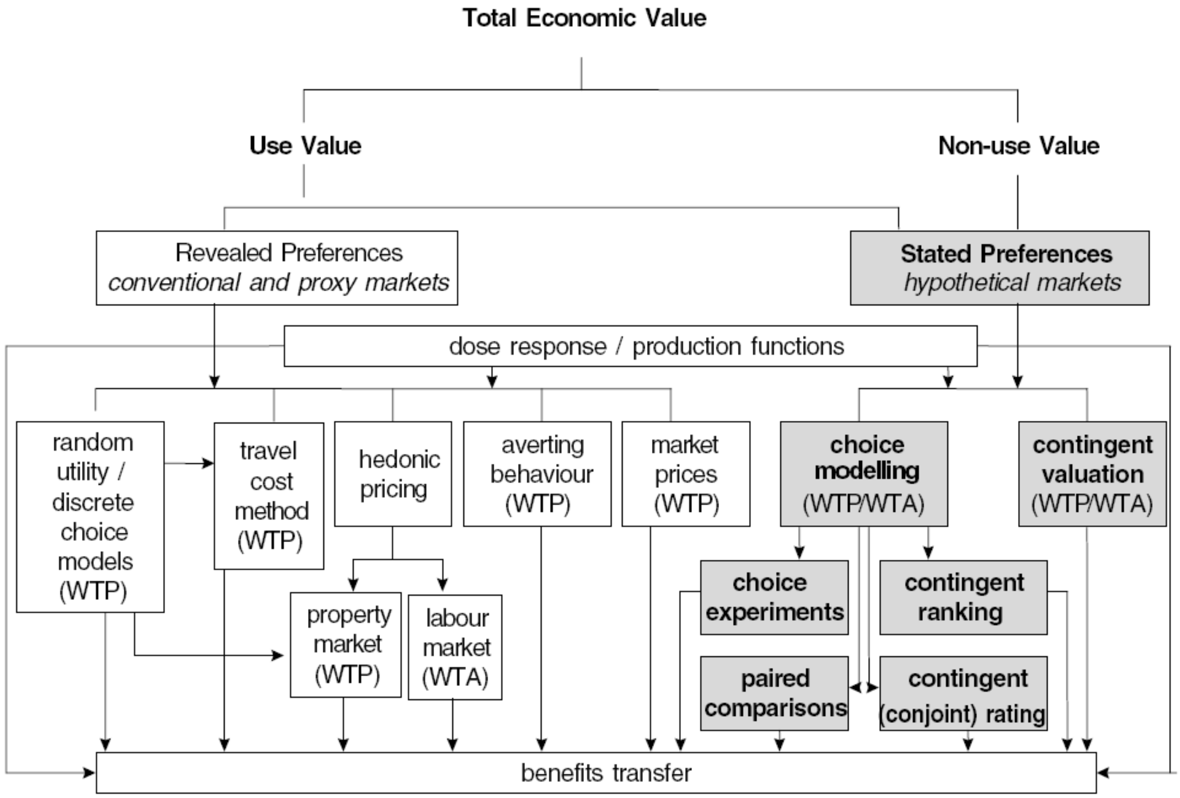

Figure 3-1. Total economic value and valuation techniques. (Source: Pearce and Özdemiroglu 2002).

CHAPTER 4
ESTIMATING PRODUCERS' WTP FOR CORN SEED TRAITS NOT YET IN THE MARKET

In Chapter 2 we presented an overview of genetically modified (GM) crops and the GM crop industry. From our discussion there, the relevance of GM crops to international policy is evident. GM crops have the potential to increase our chances of success in utmost important goals we have set regarding reduction of world hunger and protection of the environment. The use of biotechnology presents an opportunity to develop highly sustainable (high-S)[1] seed technologies that, if properly diffused, have the potential of improving food security for future growing populations while at the same time minimizing impact to the environment. On the other hand, the controversial facets and uncertain long-term outcomes that many associate with using the technology also call for the attention of policy makers.

Several GM crops have already been developed and marketed. Where made available, these technologies have observed widespread adoption.[2] The four most widely adopted GM crops have been: soybeans, corn, cotton, and canola. In terms of GM traits, the two most widely adopted have been the herbicide tolerance trait and the insect resistance trait. Many other are at different stages of the development process.

Two important GM traits currently in advanced or medium stages of development are: (i) a trait that increases the crop's tolerance to drought, and (ii) a trait that reduces inefficiency in nitrogen fertilizer (N-fertilizer) applications by increasing the crop's N-absorption efficiency. These two traits and their application to corn seeds are the focus of this dissertation.

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[1] High-S technologies are defined in Chapter 2. The I-PAT equation is commonly used to measure human impact on the environment. I represent such impact, while P represents population, A represent output per capita, and T represents the technological state-of-the-art measured by the environmental impact per dollar of income. A high T technology is deemed not environmentally friendly. If we define S as 1/T, we can define a sustainable technology as a high-S technology.

[2] See section "Current state of the GM crop industry" in Chapter 2.

In specific, we focus on studying the adoption potential and valuation of these traits by corn farmers in Minnesota and Wisconsin. In order to make a true assessment of the benefits and global adoption potential of these traits, it would be ideal to obtain farmers' valuation on a region-by-region basis (i.e., developed vs. developing; by continent; or by country). Such task, however, results prohibitively expensive for a single study. Our intention here is not to make a complete assessment on a global scale; rather, the main contribution and goal of this study is to obtain results at the local level that provide valuable insights which may guide further studies evaluating adoption of these traits on other regions. Also, the results we obtain for U.S. corn farmers may serve as a benchmark for comparisons with future valuation studies.

On a more practical and more immediate level, a better understanding of the adoption potential and of farmers' valuation for these forthcoming GM seed products should prove valuable both to the private and public sectors for several reasons.

The effective and timely development of innovative GM crop technologies necessitates participation from both the private and public sectors. Given appropriate incentives, the market will respond to the demand for agricultural innovations. However, without the existence of a patent system and the appropriate enforcement of intellectual property (IP) laws that ensure appropriate incentives are in place, the market will fail to respond and will invest too little in research and development (R&D). This fact is well known in economics, being a result of the public good characteristics of pure scientific knowledge. In essence, a granting of a patent confers monopoly power to the recipient; the prospects of being able to charge monopoly prices to recover R&D costs and observe a gain are what motivate the inventor to engage in the long and costly process of innovation. Thus patent systems play an important role in securing adequate investments in R&D and promoting the creation of innovations in the market. The implementation of a patent system for the case of GM crops, while observing some initial resistance from some groups, has been successful in promoting R&D investments and producing seed innovations. In fact, the existent GM crops, including those already in the market and those in process of gaining market approval, have almost exclusively been developed by private companies as a result of large investments made by these companies in R&D.

In practice, the patent system, although effective in setting appropriate incentives, may restrict access to scientific information and thus prevent the creation of further innovations that develop on existing patented innovations. This observation has led to public investment in R&D at the basic science level to complement patent systems. The basic knowledge produced by public investment in R&D is then freely available to firms and efficiently used by the market to produce a myriad of practical innovations.[3,4]

Beyond the issues of innovation development, there is the issue of adoption and diffusion. Developing a new high-S technology is one thing, to have it adopted on a widespread basis is another completely different thing. For true success, a technological development must be followed by its adoption and widespread diffusion. Final adoption is not determined in the science laboratory, but in the market.

From the supply side, a key factor in determining adoption rates is sale price. The functioning of patent systems implies that in order to recover their R&D investments and observe gains, it is reasonable to believe that private innovators in the GM crop industry will pursue

[3] Of course, this last point depends on disclosure policies and patent structures at the public sector level. However, information sharing and disclosure should in general be higher in public research because it is financed by public funding.

[4]As discussed in Chapter 2, even when appropriate patent systems are in place, public-private research partnerships may still play a role in developing innovations that may improve the lives of many but whose effective demand is hindered by low levels of income. Such is the case of developing GM crops tailored to the needs of small poor farmers in developing countries. In these places, public-private partnerships may have a better chance of success in developing and delivering such GM crops at prices that are affordable to farmers and profitable to private enterprises.

monopolistic pricing strategies. In welfare economics, if a product is desirable, aggregate welfare will be maximized when the product is sold at competitive prices. Monopolistic pricing above the competitive price level will increase seller surplus and reduce buyer surplus. In terms of adoption, prices above the competitive price will result in lower relative adoption rates. This is of concern to policy makers who may want to oversee appropriate diffusion which may be hindered in the market by overly aggressive monopolistic pricing.

From the demand side, customer preferences play a big role in adoption decisions. The maximum amount an individual is willing to pay for a given quantity of a product is termed his willingness-to-pay (WTP). An individual's perceived value for a product is embodied in his WTP. It is the interaction between WTP and sale price that ultimately determines adoption in the market place. An individual will adopt (purchase) a GM crop technology if his WTP exceeds the sale price; otherwise, he will refuse to adopt.

Setting the right sale price for a product is maybe the most important and also the toughest task for a company.[5] Under the non-competitive setting conferred by patent systems, private firms are able to exert some control over pricing. Avoiding excessive pricing is of interest not only to policy makers overseeing adoption, but also to the seed companies that sell the innovation. In the absence of an adequate instrument to provide them with the necessary knowledge, firms may overestimate customer perceived value and set excessive prices at levels incompatible with customers' WTP. In this case adoption may be so low that profits obtained are less than optimal. This danger is particularly true for seed companies, which have little experience in pricing of GM crops (Hubbell, Marra, and Carlson 2000). This is evident, for example, in the early years of Bt cotton marketing. Bt cotton was initially marketed in 1996 at a

[5] Price is the only element in the marketing mix that generates income; all the other elements (advertising, placement, packaging, etc) generate costs. More so, price is the element that is most easily adjusted.

small premium over conventional seeds plus a technology licensing fee of $38/acre. In 1997, the second year of marketing, a discount pricing offer of $10/acre for the first 50 acres planted by new adopters was introduced to improve on prior adoption rates. Still, the adoption rate that would occur at the discounted price level was overestimated by seed companies who had prepared seed for planting 7.5 million acres but sold only seeds for 5.5 million acres (Hubbell, Marra, and Carlson 2000). In any case, logic tells us that innovations in general, which by definition are new in the market and new to firms and customers, are initially difficult to price.

Besides low adoption and inefficient profit levels, failure to understand the consumer from the part of seed companies may result in failure to recognize opportunities for segmenting the market. Missing such market-segmenting opportunities and failing to identify different types of customers and what they value will also result in flawed pricing strategies.

In marketing theory, firms are considered to hold two distinct approaches to pricing: (i) the value-based approach, and (ii) the cost-based approach. In the value-based approach companies base their pricing decisions on information about customers' perceived values. The company first estimates the customers' perceived value for the product. After this, the decisions about product design, costs incurred in its development, and pricing, are simultaneously based on the firms improved knowledge about the customers' perceived value. In contrast, in the cost-based approach, the product is first developed and price is set by deciding some desired profit margin above of incurred costs. A working value-based pricing strategy, being based on more and better information, holds the potential for higher efficiency and larger profits compared to the cost-based approach (Monroe, 2003).

Besides informing pricing strategies, knowledge of farmers' valuation for different traits may help companies decide which seed products are worth developing. Given the large costs associated with the development of each seed product (i.e., trait), mainly R&D costs incurred in identifying and testing product concept, it would be valuable for seed companies to have information about the value that farmers associate with a given trait before incurring such costs. In other words, it would be valuable to have an idea of the adoption potential of each seed product on a trait-by-trait basis at the early stages of product development, before investing large sums in it.

Valuation on a trait-by-trait basis is possible due to recent trends in market differentiation strategies of GM seed products. Crop seeds and primary agricultural products have been traditionally considered commodities with little space for differentiation. Commodities are products for which there is a demand but which are marketed with no qualitative differentiation. With the advent of biotechnology, the line separating such crop seeds into undifferentiated commodities rather than as differentiable goods seems to be fading. Seeds today are conferred traits that are advertised in marketing programs designed to differentiate them as a product. The market for corn seeds today is filled with numerous differentiated seed brands (e.g., Monsanto's RoundupReady and YieldGard product lines, Dow AgroScience's Herculex seeds). Differentiation seems to have occurred at two levels: by trait and by type. Differentiation by trait has been facilitated by the increasing popularity of asexual methods in seed production. Recombinant ribonucleic acid (RNA) and tissue culture techniques allow seed companies to create a seed product that is more consistent in its attributes (traits) than what conventional breeding allows. Differentiation by type, into GM and conventional (nonGM), has also been apparent.

This chapter hopes to inform the decisions of both policy makers and seed companies by developing estimates of farmers' mean WTP (in $ per acre) for two corn seed traits that are not yet in the market but appear as potentially profitable to private companies and are highly relevant to the global search for future food security and environmental sustainability. We compare two different versions of the two traits, one version in which the trait is obtained by conventional selective breeding (i.e., nonGM) and another version in which RNA recombinant techniques are used (i.e., GM).

The two specific traits considered are: (i) a trait that "maintains same yield but reduces N-fertilizer requirements by one third", and (ii) a trait that "increases the crop's DT so that under severe drought conditions it would still yield 75% of the normal yield." In all of the following we will refer to these two as fertilizer saving (FS) trait and drought tolerance (DT) trait. To the best of our knowledge, no other formal study, as of yet, has considered valuation or adoption of the traits studied here.

In addition to estimating mean WTP, the methods used in this chapter allow us to understand what farm or farmer characteristics have an effect on farmers' WTP for these traits, what is the direction of that effect, and what the size of that effect is. Estimating WTP for both a nonGM and a GM versions provides us with the opportunity to gain some valuable insights (or confirm those found in the literature) with respect to these effects. We also show how the estimates obtained on farmers' WTP for a given technology can give us some idea of its adoption potential. Finally, we compare the estimated adoption potential of the different versions (nonGM and GM) of each trait.

Theoretical Model

Since no market choice data is available for these, as of yet, unmarketed technologies, we use a Contingent Valuation (CV) method to estimate farmers WTP for each trait. CV is a stated preference (SP) approach that has been extensively used to obtain estimates of WTP of nonmarket goods in the environmental economics literature. Cameron and James (1987b) suggested that the CV method can be equally useful in pretesting new market goods. The CV method obtains WTP estimates of goods in nonmarket situations.[6]

A similar approach to the one taken here was also used by Hubbell, Marra, and Carlson (2000) in estimating adopters' and non-adopters' WTP for Bt Cotton among farmers in the United States, and similarly by Qaim and DeJanvry (2003) in estimating farmers' WTP for Bt Cotton in Argentina. In those studies the use of CV was warranted because market data is not available for the non-adopters that those studies aimed to include in their models.

In our study, the double bounded (DB) dichotomous choice (DC) elicitation format was selected over other possible formats for several reasons. In the DC format the individual is presented with a price scenario and asked about her purchasing decision –"yes" or "no". This approach has been shown to better resemble a real market situation compared to the alternative OE format which asks directly to the respondent "How much would you pay?" As a result, DC formats are considered to give more valid estimates than open ended (OE) formats. Federal guidelines (U.S. Department of Commerce, 1993) recommend using the DC approach.

Several types of DC formats are available: single bounded (SB), double bounded (DB), and iterative bidding (IB).[7] These elicitation formats differ in the number of price scenarios and therefore in the number of DC questions asked. The SB-DC approach considers one single price scenario and asks one single "yes" or "no" question. The IB-DC gradually increases (decreases) the price asked if the respondent answers "yes" ("no"), and stops when the respondent's answer switches to "no" ("yes"). The DB-DC asks one initial and only one follow-up question. The price scenario presented in the follow up question is higher (lower) if the individual answers "yes"

[6] See Chapter 3 for a more complete presentation of the CV method.

[7] See Chapter 3 or Chapter 5 for a detailed description of each of these DC elicitation formats.

("no") to the initial question. The DB-DC approach is usually preferred over the SB-DC method since it provides much larger statistical efficiency for same sample sizes (Hanemann, Loomis, and Kaninnen 1991). The gains obtained from adding a third (or further) question to the DB-DC method are insufficiently large to justify the added mathematical complications (Cooper and Hanemann 1995).

Willingness-to-Adopt

In this section, the abstract theories (WTP, random utility model (RUM), and CV) presented in Chapter 3 are applied and adapted to the case of technology adoption, which is the situation concerned by this study. In the case of technology adoption, the individual faces two possible actions: adopting the technology or refusing to adopt. In this case, a WTP measure makes more sense than a willingness-to-accept (WTA) measure.[8]

An individual will be willing-to-pay for the technology a price per unit of P and adopt such technology if her utility with the profit (net of the technology cost) provided from adopting the technology minus the cost of the technology is at least as high as her utility without the technology. Formally, the individual will adopt a new technology if[9]

$$u(q^1, y_1 - P; \mathbf{x}) \geq u(q^0, y_0; \mathbf{x}) \qquad (4\text{-}1)$$

where q^1 indicates adoption, q^0 indicates non-adoption, y_1 and y_0 are profits (net of technology costs) with and without the technology, respectively, and $\mathbf{x}$ are individual characteristics and characteristics of the production unit.

Given that utility is only partially observable to the analyst we use the RUM approach

[8] It would be awkward to ask the individual how much he would be willing to accept (in monetary terms) to disadopt a given technology.

[9] We make a slight switch in notation from Bid to P to better reflect the technology adoption situation (See previous chapters).

$$u(q^j, y_i; \mathbf{x}) = v(q^j, y_i; \mathbf{x}) + \varepsilon_j \ , \qquad j = \{0,1\} \tag{4-2}$$

where $v(q^j, y_i; \mathbf{x})$ represents the observable portion of utility associated with technology situation j and ε_j is a stochastic zero mean term representing the respective unobserved portion of utility. In this RUM framework, the decision to adopt (Equation 4-1) may be re-expressed as;

$$v(q^1, y_1 - P; \mathbf{x}) + \varepsilon_1 \geq v(q^0, y_0; \mathbf{x}) + \varepsilon_0 \tag{4-3}$$

Following the Indirect Approach (See Chapter 3) a linear specification, common in CV studies, may be assumed for the individual's indirect utility

$$v_j = \mathbf{x}'\beta_j + \alpha(y_j - P) \tag{4-4}$$

where α represents the marginal utility of income. Applying Equation 4-4 to Equation 4-3 and solving for $\varepsilon = \varepsilon_0 - \varepsilon_1$ gives

$$\varepsilon \leq \mathbf{x}'\beta_j + \alpha(\Delta y - P) \tag{4-5}$$

where $\beta = \beta_1 - \beta_0$ and $\Delta y = y_1 - y_0$. The change in profits (Δy) is unfortunately unobserved, not even for the individual himself, since it belongs to the counterfactual world. An assumption is necessary in our application, that the expected change in profits $\Delta\bar{y}$ can be explained by some of the individual and farm characteristics contained in $\mathbf{x}$, so that $\Delta\bar{y}$ is implicitly included in $\mathbf{x}$. Measuring v in monetary terms means that $\alpha = 1$. Thus we may express the probability of adoption as

$$\Pr(adopt) = \Pr(\varepsilon \leq \mathbf{x}'\beta - P) \tag{4-5b}$$

In the DB-DC format, individuals in the sample are randomly assigned an initial price scenario P_i. Based on their answer to the initial price scenario, they are offered a higher price

P_i^H or a lower price P_i^L in the follow-up question. In any given price scenario, a given individual will answer "yes" and adopt the technology only if his WTP is larger than some asked price P_i^* (i.e., $WTP_i \geq P_i^*$). Four possible answer sequences to the initial and follow-up questions are possible

$$d_i = \begin{cases} 1 & no, no \\ 2 & no, yes \\ 3 & yes, no \\ 4 & yes, yes \end{cases} \tag{4-6}$$

The likelihood of an individual giving a response sequence $d_i = yes, yes = 4$ is given by

$$\begin{aligned} \pi_i^{YY}(P_i, P_i^H) &= \Pr(P_i \leq WTP_i \;\; and \;\; P_i^H \leq WTP_i) \\ &= \Pr(P_i \leq WTP_i \mid P_i^H \leq WTP_i) \cdot \Pr(P_i^H \leq WTP_i) \\ &= \Pr(P_i^H \leq WTP_i) \end{aligned} \tag{4-7}$$

where we have used $\Pr(P_i \leq WTP_i \mid P_i^H \leq WTP_i) \equiv 1$. The term π_i^{YY} represents the likelihood of adoption by individual i at some offered price $P_i^* \geq P_i^H$. Assuming ε is distributed $N(0,\sigma)$ this likelihood may be expressed (using Equation 4-5b) as

$$\begin{aligned} \pi_i^{YY}(P_i, P_i^H) = \Pr(P_i^H \leq WTP_i) &\equiv \Pr(\varepsilon \leq \mathbf{x}_i'\beta - P_i^H) \\ &= \Phi\left(\frac{\mathbf{x}_i'\beta - P_i^H}{\sigma}\right) \\ &= 1 - \Phi\left(\frac{P_i^H - \mathbf{x}_i'\beta}{\sigma}\right) \end{aligned} \tag{4-8}$$

Let π_i^{YN}, π_i^{NY} and π_i^{NN} represent the likelihoods of the remaining possible answer sequences shown in Equation 4-6. For example, the likelihood of adoption by individual i at a price $P_i^* : P_i < P_i^* \leq P_i^H$, is given by π_i^{YN}. Applying a similar reasoning to that shown in Equation 4-7 and Equation 4-8 to these remaining likelihoods, the log-likelihood function of our willingness-to-adopt model for a sample of N individuals is given by

$$\begin{aligned}\ln L(\theta) = \sum_{i=1}^{N} \{ & d_i^{YY} \ln[1-\Phi((P_i^H - \mathbf{x}_i'\beta)/\sigma)] \\ & + d_i^{YN} \ln[\Phi((P_i^H - \mathbf{x}_i'\beta)/\sigma) - \Phi((P_i - \mathbf{x}_i'\beta)/\sigma)] \\ & + d_i^{NY} \ln[\Phi((P_i - \mathbf{x}_i'\beta)/\sigma) - \Phi((P_i^L - \mathbf{x}_i'\beta)/\sigma)] \\ & + d_i^{NN} \ln[\Phi((P_i^L - \mathbf{x}_i'\beta)/\sigma)]\}\end{aligned} \tag{4-9}$$

where $d_i^{YY}, d_i^{YN}, d_i^{NY}$ and d_i^{NN} are binary-valued indicator variables for each answer sequence. Estimation of Equation 4-9 is made using maximum-likelihood methods to obtain estimates of $\theta = \{\beta, \sigma\}$. The estimated β may be directly interpreted as marginal effects of $\mathbf{x}$ (in dollars per additional unit of x) on WTP.

Empirical Application

We apply CV methods to the case of technological adoption of new GM corn seeds (DT and FS traits) by farmers in Minnesota and Wisconsin.

Using a DB-DC elicitation format, corn farmers in Minnesota and Wisconsin were asked about their WTP (in $ per acre) for having a FS trait added to their current most-used corn seeds. WTP was elicited for two different versions of the same trait. In the first version of the trait the farmer was told that the trait was to be added to the seed by conventional selective breeding methods (i.e., nonGM), in the second version the farmer was told that the trait was to be conferred to the plant via genetic modification (i.e., GM).

A second trait was also considered in a separate DB-DC question. In this second CV question farmers were asked about their WTP for having a DT trait added to their current most-used corn seeds. Two different versions of the trait (nonGM and GM) were also presented for this second trait. Table 4-1 shows the four different traits that were presented for farmer evaluation. The CV questionnaire portion of the survey used to elicit WTP for both traits and both versions may be seen in Figure 4-1.

Data and Surveys

The data for this study was mainly provided by two separate interview-based surveys: (i) the 2006 Corn Poll (CP06) and (ii) the 2007 Corn Poll (CP07). Both surveys were administered to corn farmers in the states of Minnesota and Wisconsin by the University of Madison-Wisconsin – Program on Agricultural Technology Studies (PATS). The CP06 (conducted in 2006) contained sections of questions asking 945 randomly selected corn farmers about their individual demographics, farm characteristics, purpose of corn production (i.e., grain, silage, sweet corn, or other), and previous experience with GM-corn varieties.

The CP07 (conducted in 2007) was administered to 451 randomly selected farmers and was in essence a short CV survey designed to complement the CP06 and find out which corn seed technologies farmers are using and how they value certain traits. The CP07 also yielded data on production practices, insurance practices and, most importantly, it provided the CV responses per se.

The CP07 listed 9 different seed codes that identify each of the corn varieties planted in the two states. Seed codes and varieties are listed in Table 4-2. Farmers participating in the survey were asked to identify the seed code with highest acreage in their farm. Data on production practices (i.e., yield and costs) and CV responses was gathered with reference to this highest acreage seed code.

The CV questionnaire had four different versions (A, B, C, and D) each presenting a different initial price scenario and also varying in the subsequently presented follow-up price scenarios – this is typical of CV surveys. Table 4-3 shows the different versions and their respective price offers. For example, version A first asked "would you pay $P_i = \$10$ dollars for the seed"; if the respondent answered "yes" to this initial question the survey then asked "would you pay $P_i^H = \$15$?"; if the respondent's answer to the initial question was "no" he was instead asked "would you pay $P_i^L = \$5$?" In contrast, version B asked a different initial price of $P_i = \$15$ instead of the $P_i = \$10$ asked in version A; and it also asked different follow-up prices of $P_i^L = \$15$ and $P_i^H = \$25$.

The 451 randomly selected farmers who participated in the CP07 were randomly assigned one of each of the different versions of the survey. This randomization is made to avoid possible bias in the estimation. Also, the produced variation in P_i is what allows us to identify β instead of only being able to identify β / σ (Cameron and James 1987a).

Farmers in the CP06 were assigned a unique identification number. The same identification number was maintained for each farmer in the CP07. This allowed us to merge both data sets and obtain a data set containing only those farmers that were randomly selected to participate in both surveys. Out of the 451 total farmers participating in the CP07, only a total of 345 farmers also participated in the CP06. These 345 farmers form the base sample for this study.[10]

Factors Affecting Adoption and WTP

We should clarify that the focus in this study is adoption as opposed to diffusion. In the technological adoption literature, adoption studies focus on "if" and "to what extent" the technology is adopted by a given farmer at a given point in time (Does the farmer adopt the

[10] Since both surveys were administered randomly, we have no reason to suspect any bias is created from reducing the sample size to 345 farmers when merging both polls.

technology? If so, on how many acres does he use it?). Diffusion studies, on the other hand, focus on the dynamic evolution of aggregate adoption through time in a given social unit.

Static (Griliches 1957) and Dynamic (Knudson 1991; Fernandez-Cornejo, Alexander, and Goodhue 2002) diffusion models are the most popularly used when studying the diffusion phenomenon. Choice models based on farmer profit comparisons (Qaim et al. 2006) or expected utility comparisons (Payne, Fernandez-Cornejo, and Daberkow 2002) and willingness-to-adopt models (Hubbel, Marra, and Carlson 2000; Qaim and DeJanvry 2003) are some of the approaches that have been used to study adoption decisions.

Among the factors influencing adoption, an innovation's profitability over the profitability of traditional alternatives has long been considered a key factor (Griliches 1957; Sunding and Zilberman 2001). Besides profitability, most studies in the literature also acknowledge the role of farm and farmer heterogeneity in explaining adoption decisions (Feder, Just, and Zilberman 1985; Khanna and Zilberman 1997; Fernandez-Cornejo and McBride 2002).

Before continuing, let us clarify that our model holds two interpretations of how farm and farmer attributes influence the adoption decision. Taken literally, the linear specification in Equation 4-4 implies that profitability (y) is one factor influencing adoption decisions, but final adoption decisions are made based on comparisons of utilities that are also shaped by variables affecting consumption decisions such as farm and farmer attributes $\mathbf{x}\beta$. This non-separability of production and consumption decisions is usually couched on assumptions of missing markets. When markets are missing, variables that affect consumption decisions may also affect production decisions (Vakis, Sadoulet, DeJanvry, and Cafiero 2004). In lieu of missing markets for the externalities associated with GM technologies, the farmer in our model may be thought of as internalizing these into his adoption decision. That is, the farmer may see the hypothetical market as an opportunity to express his value for the trait as a producer and as a consumer of GM crops.

Alternatively, a different interpretation of Equation 4-4 takes farm and farmer attributes as proxies for expected changes in utility from adoption. At any given point in time, the farmer has adopted the technology (in which case we observe profits under adoption, y_1) or has not adopted the technology (in which case we observe profits under no adoption, y_0). The two parallel realities (adoption and no adoption) cannot possibly be observed simultaneously for a given farmer; therefore, the change in profits ($\Delta y = y_1 - y_0$) is unobservable. The farmer, however, most certainly holds expectations about the change in profits. In the absence of a known change in profits the farmer should base his valuation of the technology (i.e., WTP) and his adoption decision on his expected change in profits, $\Delta\bar{y}$. Arguably, the farmer develops this expectation based on what he is currently able to do without the new technology (i.e., current production practices) and what he thinks he could do (given his individual and farm characteristics) if given the chance to try the new technology.[11] Accordingly, we may suppose that the farmer's expected change in profits from adoption is implicitly explained by his individual and farm characteristics, and his current production practices.

To the best of our knowledge, no other study, as of yet, has considered valuation or adoption of the traits studied here. There is an extensive literature, however, focused on adoption and valuation of GM traits already in the market; namely, herbicide tolerance and insect resistance. This literature offers some guidance as to what farm and farmer attributes may have significant effects on adoption and the possible explanations of those effects.

[11] Alexander, Fernandez-Cornejo and Goodhue (2003a) write:"The decision to adopt a new technology depends on its expected profitability. The expected profitability of an innovation depends on the suitability of the innovation, given its characteristics, for a specific farmer and farm, given their characteristics."

A list of the explanatory variables used in our models with their descriptions is presented in Table 4-4. We work only with complete observations. For the FS trait we have a subsample of 175 complete observations to estimate producers WTP for the nonGM version of the trait and a subsample of 155 observations for the GM version of the trait. For the DT trait we have a subsample of 149 complete observations for the nonGM version of the trait and a subsample of 137 observations for the GM version.

We ran a series of difference in proportion tests to see if the reductions in sample size affected the randomization of the different CP07 versions. Table 4-5 presents the results of these tests for both traits and both versions of the traits. Calculation of the statistic z is based on differences in sample proportions, where $z \sim N(0,1)$. No evidence of changes in sample proportions due to the reduction in sample size is observed for any of the subsamples.

We also ran a series of t-tests for differences in means between each subsample and the base sample of 345 farmers for each of the explanatory variables. These tests check if individuals in the subsamples differ significantly in observable characteristics from individuals in the base sample. The results of these tests and summary statistics for each variable are presented in Table 4-6a and Table 4-6b. In all of the four subsamples we find no important differences in means.[12]

Farm and farmer characteristics

The literature identifies farm size, education, age and off-farm employment as among those farm and farmer characteristics that are likely to affect adoption decisions. Almost every study of GM crop adoption includes farmer's age and education as possible explanatory variables. These factors are considered to represent the farmer's physical and managerial abilities (i.e., human

[12] The statistically significant difference in mean education indicates that if education influences WTP values, then WTP estimates will be biased (Whitehead, Groothuis, and Blomquist 1993). As we shall see, the effect of education is not significant and relatively small in all of our estimated models. In any case, one possible correction for the bias would be to use the population mean instead of the sample mean to calculate the average WTP (Whitehead, Groothuis, and Blomquist 1993).

capital). Average age among farmers in the CP06 is 54 years. As far as education, the average farmer in the CP06 has at least some college instruction.

Farm size has been a central focus of many studies of technological adoption (Feder, Just, and Zilberman 1985). The literature offers mixed results. Farm size was the main focus of a USDA study of GM crop adoption (Fernandez-Cornejo and McBride 2002) in which the direction of the estimated effects suggest a positive but decreasing influence of farm size on adoption (not all estimates were found to be significant at the 0.1 level). Positive effects are seen as evidence of scale dependency of the technology. Hubbell, Marra, and Carlson (2000) find a negative and not statistically significant effect of farm size (i.e., cotton acres) for a subsample of Bt cotton non-adopters and a positive significant effect when the full sample is considered. Fernandez-Cornejo, Hendricks and Mishra (2005) find a negative and significant effect of farm size on adoption of herbicide tolerant soybean among U.S. farmers. Other studies find no significant effect of farm size on adoption of GM crops (e.g., Alexander and Von Mellor 2005). Daberkow and McBride (2003) use income from farm sales as a measure of farm size. However, farm size and farm income need not be correlated. Alexander, Fernandez-Cornejo, and Goodhue (2003b) include both farm size and farm income as possible explanatory variables of farmer acreage allocation between GM and nonGM varieties. They find farm income has a significant and positive effect while the effect of farm size is negative and not statistically significant. We follow this latter approach and include both measures. The correlation between farm size and farm income is only $\rho = 0.11$ in our base sample of 345 famers. Farms in the CP06 vary largely in size with an average size of 338 acres and a standard deviation of 565 acres. The average farmer in the CP06 has income somewhere between \$60,000 and \$79,999.

Facilitated in part by the adoption of labor saving technologies, off-farm employment and off-farm income have grown steadily in importance over the past decades in U.S. farming (Mishra et al. 2002). Fernandez-Cornejo, Hendricks, and Mishra (2005) find significant positive correlation between off-farm household income and adoption of herbicide tolerant (Ht) varieties for U.S. soybean farmers. The observed positive correlation is believed to be consistent with the notion that ease-of-use and management-time saved by Ht varieties allows farmers to increase their off-farm activities and income. However, such positive effect is not guaranteed. The argument may be tuned on its head where, depending on its degree of importance, off-farm employment and income may take the farmer's focus away from the farm (i.e., hobby farming). Off-farm employment may constrain adoption if it competes with on-farm managerial time. In a different study, Payne, Fernandez-Cornejo and Daberkow (2002) find a negative correlation between off-farm job hours and adoption decisions and attribute this finding to the possibility that off-farm occupied farmers may be less informed about new GM technologies. In our estimations we include a binary indicator =1 if the farmer reported having an off-farm job and =0 otherwise. A large proportion of farmers in the CP06 reported having some kind of off-farm employment (42%).

Production data

Production data is also included in our model. One important factor determining WTP for a FS trait should be current fertilizer costs. The larger a farmer's fertilization costs are (per acre), the more he should value a trait that reduces such costs. Qaim and DeJanvry (2003) apply a similar reasoning to the case of Bt cotton in Argentina and find that higher current insecticide costs increase the farmers WTP for the Bt seed.[13]

[13] Fertilizer costs ($52/acre) represent the largest expense in the CP07 sample followed by seed costs ($46/acre).

As noted by Qaim and DeJanvry (2003), the direction of the effect of each input cost on WTP will depend on whether the farmer considers the input as a substitute or a complement for the trait in case. Estimate values smaller than one in absolute value are interpreted as the farmer seeing the trait and the input as imperfect substitutes (or complements). We also consider yield per acre; average yield in the CP07 was 149 bushels per acre.

Purpose of production

An indicator for purpose of production is included in the FS trait models. Different purposes of production may entail different fertilizer requirements. For example, a good field of corn silage can yield 20-25 tons of wet forage per acre. A 20-ton yield will remove approximately 150 pounds of nitrogen per acre. In comparison, a 100-bushel corn crop will only remove 100 pounds nitrogen (Bates 2009). This difference derives from two agronomic facts: (i) Nitrogen is used by the plant for vegetative growth, that is, for production of biomass, and (ii) when producing for silage the purpose is to build up biomass whereas producing for grain entails maximizing grain production (i.e., reproductive growth).

The CP07 included a section where farmers were asked about the acreage they destined to different purposes: (i) grain, (ii) silage, (iii) sweetcorn, and (iv) other. We used this data on acreage to construct binary choice indicators that classify farmers into the following categories: grain, silage, sweet corn, other, or diversified (i.e., in purpose). Farmers were first assigned into a given category, for example grain, if they dedicated the largest acreage (>50%) to that purpose compared to other purposes. Some of these farmers were found to plant the same acreage for two purposes (i.e., 50% grain, 50% silage), these farmers were reclassified as diversified. A similar criteria was used to also reclassify the following farmers as diversified: (i) produced for two purposes and had at least 40% acreage on each purpose; (ii) produced for three purposes and had at least 30% dedicated to each purpose; and (iii) produced for four purposes and had at least 20%

dedicated to each purpose. A high proportion of farmers (76%) in the original CP06 survey were specialized in grain with the next largest category being silage (10%)[14]. For the sake of parsimony, in our estimations we group farmers into only two groups creating an indicator =1 if corn is grown mainly for grain purposes, or =0 if corn is grown for other purposes (other=silage+sweetcorn+other).

Early adopters and familiarity

Several studies of adoption have found perceived risk and lack of information about a new technology to be important barriers to adoption (e.g., Dufflo, Kremer, and Robinson 2006; Conley and Udry 2007). Understandably, farmers who are familiar with a similar technology will be more likely to adopt the new technology. Payne, Fernandez-Cornejo, and Daberkow (2002) find that likelihood of adoption of corn rootworm resistant GM corn varieties (Bt-CRW) among U.S. corn farmers is significantly and largely increased by prior experience with GM corn varieties resistant to European corn borer (Bt-ECB) measured in a binary dummy variable. We adopt a similar dummy that tells us whether the farmer was an early adopter of a recently introduced corn variety: Bt-CRW corn. Our measure of familiarity differs from the one used by Payne, Fernandez-Cornejo, and Daberkow (2002) in that it identifies familiarity and also early adoption of a recent GM seed technology. Early adopters, in marketing theory, are thought as having attributes different from other types of adopters (e.g., more education, less risk averse, more exposure and better access to information) (Rogers 2005). They are usually a small subgroup of the population (Sunding and Zilberman 2001). Our binary indicator takes a value =1 if the farmer adopted Bt-CRW corn varieties in their first year in the market; and takes a

[14] Not reported in Table 4-6a.

value =0 otherwise.[15] According to this measure, 4.7% of the farmers in the CP07 sample are considered early adopters. This indicator may also be interpreted as a measure of habit formation.

NonGM farmers

One important farm characteristic that has been overlooked by the literature is the current seed type being planted. Almost every single study of adoption recognizes that the farmer bases his adoption decision on comparisons between the new technology and his current technology. A farmer's expected yield (profits) should be expected to depend on the characteristics of his current seed technology. Most certainly, in any given sample of farmers, there will be heterogeneity in terms of the seed type currently being used. In order to capture the effects of this heterogeneity, we include an indicator of whether the farmer is currently producing only nonGM varieties. Under the non-separability scenario, this measure could help capture differences in attitudes towards GM crops between nonGM specialists and other types of farmers. A total of 24% of the farmers in the CP07 sample produced exclusively nonGM varieties.

Drought measures

Probability of severe drought is hypothesized to have an effect on farmers' WTP for a DT trait. We used historic weekly data from the Drought Monitor Index archives (National Drought Mitigation Center 2006) to calculate a measure of the probability of severe drought in each of the counties in the two states (Minnesota and Wisconsin) for 2006. The Drought Monitor Index is produced by a partnership consisting of the U.S. Department of Agriculture (Joint Agricultural Weather Facility and National Water and Climate Center), the National Weather Service's Climate Prediction Center, National Climatic Data Center, and the National Drought Mitigation

[15] An alternative measure was also used which included not only the first but also farmers that adopted in the second year. No significant changes in the results were observed.

Center at the University of Nebraska Lincoln. Advice and information from many other sources is incorporated in the index, including virtually every government agency dealing with drought.

The Drought Monitor Index identifies four (D1, D2, D3 and D4) different types of drought areas by intensity. D1, D2, D3 and D4 indicate moderate, severe, extreme and exceptional drought, respectively. D0 are "drought watch" areas that are either heading for drought or are recovering from drought but not yet back to normal. The four drought categories are based on six key indicators and numerous supplementary indicators. Table 4-7 shows the definitions for each of the drought categories and the different drought indicators used to construct them. Since the ranges of the various indicators often don't coincide, the final drought category tends to be based on what the majority of the indicators show. The Drought Monitor reports the county's percentage area under each drought category.

The CV questionnaire asked the producer to consider a trait that produced 75% of its normal yield under severe drought; therefore, we base our measure on D2. The data reported by the Drought Monitor for D2 may be summarized by $D2_{ct}$ where c indicates county and t indicates time in weeks. Famers in the CP06 and CP07 were geographically identified at the county level. The exact measure we use is the county yearly average $\overline{D}2_{c.}$; this measure is included in the model as a proxy for the farmer's subjective probability of drought. Figure 4-2 shows a graphical summary of our drought measure $\overline{D}2_{c.}$.

Insurance costs

For the DT models we include insurance costs as a factor hypothesized to affect WTP for the trait. Data on insurance costs in dollars per acre were collected as part of the CP07. The average cost paid by farmers in our base sample of 345 farmers is $10.86 per acre.

Results

Fertilizer saving trait

The estimation results for the two versions (nonGM and GM) of the FS trait are presented in Table 4-8. The likelihood ratio test[16] of the global null hypothesis that all coefficients are equal to zero is strongly rejected at the 1% level in both models. A Likelihood Ratio Index[17] of 0.62 and 0.55 for the nonGM and GM versions, respectively; seems to indicate good explanatory power.[18]

A higher farm income (*f_income*) results in higher WTP for both the nonGM and GM FS traits. In contrast, farm size (*farmsize)* as measured in acres has no effect. We take this as evidence that the technology has no scale dependency per se. This seems to make sense because a seed input is perfectly divisible. The positive effect of farm income suggests that "scale dependency" may be more related to cash flow constraints.

Farmers specializing in corn for grain were found to have a statistically significant lower WTP (-$5.12 per acre) than farmers producing for other purposes in the nonGM case. This goes in agreement with what was hypothesized earlier, that is, that producing for grain demands less

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[16] The likelihood ratio test is a test of significance that compares a restricted versus an unrestricted model. The null hypothesis is $H_o = \beta_1 = \beta_2 = ... = \beta_k = 0$. The likelihood ratio test statistic is given by $LR = -2 \mid LLur - LLr \mid$, and is distributed chi-square with degrees of freedom equal to the number of restrictions.

[17] The Likelihood Ratio Index (also known as pseudo-R^2 or McFadden's R^2) is defined as:

$$LRI = 1 - \frac{ll(\hat{\beta})}{ll(0)} = \frac{ll(0) - ll(\hat{\beta})}{ll(0)}$$

A perfect probabilistic model would have a log-likelihood equal to zero. A pure chance (intercept) model is obtained by evaluating the model's likelihood function at $\beta = 0$. The likelihood ratio test is essentially a measure of how far we have moved from a pure chance model towards the perfect model. The likelihood ratio index takes values from 0 to 1. In our case, all parameters in θ except σ (which is set to one to avoid division by zero) are set to zero for the pure chance model.

[18] Hubbell, Marra, and Carlson (2000) and Qaim and DeJanvry (2003) report similar values.

fertilizer than other purposes which in turn traduces into a lower WTP for a FS trait. As for the GM trait, we still find a negative effect as expected, but the effect is not statistically significant. Alternatively, one could hypothesize that this negative effects follow because, as opposed to corn for silage or other purposes, grain production will most likely end in the consumer table and so farmers may be willing to pay less due to risk concerns associated with consumer preferences. However, if this were true, we would have found exactly the opposite – a significant effect for the GM trait and no effect for the nonGM.

Early adopters (*earlyad*) are in average willing to pay more than non-early adopters for both the nonGM and GM traits; $9.61 per acre and $10.94 per acre, respectively. The measure used to identify early adopters, as constructed, was also intended to measure the effect on WTP and adoption of farmer's familiarity with GM crops. If the effect would have been significant only for the GM trait we could have attributed the effect to familiarity only. That an effect is observed for both traits seems to indicate that our measure and its influence are also related to farmer's risk attitudes towards new technologies in general.

As hypothesized, higher fertilizer costs increase farmer's WTP. A positive effect is found for both types of traits. In average, farmers are willing to pay $0.06 per acre (nonGM) and $0.05 per acre (GM) more for the trait for each extra dollar they spend in fertilization costs per acre. As suggested by Qaim and DeJanvry (2003), that this effect is less than one indicates the trait is not a perfect substitute for the conventional input, in this case fertilizer. Qaim and DeJanvry (2003) explain this for Bt traits by stating that one possible reason for the imperfect substitution is that the trait is an *ex ante* input. That is, the farmer purchases the trait before the pest pressure is known; in contrast, pesticide provides more flexibility in that it may be purchased at a later stage in the production process according to need.[19] In our case, a similar reasoning may not apply so directly because fertilizer requirements and nutrients in soil are much more predictable than pest pressure. However, if fuel and therefore N-fertilizer prices fluctuate largely during the year, the *ex ante* argument may be justifiable. An alternative explanation for the imperfect substitution is that farmers may need to "see to believe". If the traits were a proven technology, the farmer might consider them as closer substitutes. A statistically significant higher WTP for both traits was also found for farmers with higher seed costs. This suggests that farmers consider the seed with the new trait to be a substitute of their current seed.

Farmers who currently plant only nonGM varieties are, in average, willing to pay $7.67 less per acre for the GM trait compared to farmers who do not specialize in nonGM varieties. This negative effect on the WTP of nonGM farmers is strongly significant and large for the GM trait but small and not significant in the nonGM trait case. This contrast may be interpreted in several different ways. One interpretation is that, if the non-separability assumption holds, farmers may have seen the hypothetical market presented in CV exercise as an opportunity to express their own personal attitudes towards GM crops. Another interpretation could be that farmers could be penalizing the GM trait because they consider it a riskier investment. [20]

The mean WTP for each trait is calculated by applying the estimated model to the mean of the sample data. The standard error for this linear function of the estimated parameters was calculated using the Delta Method. Both of the estimated mean WTP's are strongly significant

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[19] We discuss this in detail in Chapter 6.

[20] Farmers in our base sample were asked a series of attitudinal questions regarding possible barriers to Bt seed adoption. Only 8% of the 130 farmers who completed this part of the questionnaire expressed concerns about possible trouble in selling while 2% expressed concerns about getting a lower price compared to nonGM varieties. On the other hand, 16% of the farmers identified concerns about possible environmental and safety issues as an important barrier to adoption.

(at 1% level). We find that in average, farmers in the sample were willing to pay around \$19.72 per acre for the nonGM trait and \$17.25 per acre for the GM trait.

The empirical cumulative distribution for the predicted individual WTP values ($\hat{WTP}_i$) is given by $F_{nonGM}(P_i) = \Pr(\hat{WTP}_i^{nonGM} \le P_i)$ and $F_{GM}(P_i) = \Pr(\hat{WTP}_i^{GM} \le P_i)$ for the nonGM and GM traits, respectively. Another way to present these distributions is in the form of adoption potential curves. The adoption curve is simply a graphic representation of the predicted proportion of adopters in the sample at each price level (i.e., $\Pr(\hat{WTP}_i > P_i) = 1 - F(P_i)$). The adoption potential curve for both of the FS traits (GM and nonGM) is presented in Figure 4-3. Apparently, the adoption potential for the nonGM trait stochastically dominates (first order dominance) that of the GM trait (i.e., $F_{GM}(P_i) < F_{nonGM}(P_i) \;\; \forall P_i$).[21] This suggests that the nonGM trait has a better adoption potential. A non-parametric Kolmogorov-Smirnov (KS) test was used to test for differences between the two distributions. The KS test uses the maximum vertical distance D between two empirical cumulative distributions as the test statistic. The test gave a calculated D value of 0.2161 which implies strong evidence of difference between the distributions. One interesting point is that at prices above \$20 per acre the adoption potential for both traits is similar (Figure 4-3). Moreover, there is a sharp increase in the difference of adoption potentials at the \$20 per acre mark. Finally, as prices drop below this mark, the two adoption curves move in parallel fashion. The shapes of these two adoption curves may be indication that different market segments would be captured at prices below or above the \$20 per acre price.

[21] Stochastic dominance is a concept used to rank distributions. First order stochastic dominance implies that one distribution unambiguously dominates the other one because it deposits the bulk of it probability mass at higher values of the random variable. It is assumed that higher values are better than lower ones.

Drought tolerance trait

Table 4-7 shows the results for the DT traits. The choice of variables is a little different compared to the FS trait models. The main difference is the exclusion of production costs and yield and the inclusion of insurance costs and a measure of probability of severe drought. Including both insurance and production costs may result in collinearity problems. Our choice between these emphasizes the point that soil nutrients and fertilizer requirements are less variable, or at least more predictable, than rainfall and irrigation costs. An important motive for farmers adopting the DT trait could be to insure against unpredictable rainfall; thus the trait could act as a substitute for insurance costs.

The likelihood ratio test of the global null hypothesis that all coefficients are equal to zero is strongly rejected at the 1% level in both models. A Likelihood Ratio Index of 0.46 and 0.49 for the nonGM and GM versions, respectively; seems to indicate good explanatory power. The results for the *earlyadopt* and the *nonGM100p* variables are similar to what was found in the FS trait models so the following discussion focuses on the other significant effects.

Farmers seem to take the DT trait as a substitute for insurance costs. For every current extra dollar spent on insurance per acre, the average farmer in our sample is willing to pay 24 cents and 19 cents more for the nonGM and GM DT trait, respectively. Premium rates and indemnity payments of several crop insurance programs are tied to individual-specific yield (e.g. Actual Production History (APH), Crop Revenue Coverage (CRC)). The improved consistency in yields that could follow from adopting the trait should signify lower premium rates. Federal policy today recognizes this for currently marketed GM seeds.

In 2008, the Federal Crop Insurance Corporation (FCIC) started a pilot program under the name of Biotech Yield Endorsement (BYE). Under the BYE, farmers in the states of Illinois, Indiana, Iowa, and Minnesota producing non-irrigated corn for grain with at least 75 percent of their corn acres planted to a specific triple stacked biotech variety are eligible for a premium rate reduction in their “yield” or “revenue” individual insurance policies (U.S. Department of Agriculture 2008a). In August 2008 the FCIC approved an expanded Biotechnology Endorsement (BE) that replaces the BYE for the crop years 2009-2011 (U.S. Department of Agriculture 2008b). The expanded BE includes additional seed technologies and additional states. The program is based on proved increases in consistency of yields provided by qualifying GM varieties compared to conventional ones. By planting these varieties farmers reduce expected losses which in turn reduce the number of insurance claims. The key point underpinning the rate reduction, as the significance of the insurance substitution effect in both types of traits suggests, is the difference in consistency of higher yields and not whether the trait is conventional or GM. To the best of our knowledge, no public study evaluating the effects of the BE on adoption of qualifying GM seeds has been conducted yet. However, it seems reasonable to expect that it has had a positive effect on adoption. If this is the case, seed companies selling GM varieties should find it highly valuable to continue investing in good research that provides proven differences in yield consistency.

We find that a higher probability of severe drought increases the average farmer’s WTP only in the GM case. The effect is not significant for the nonGM case. This contrast seems a bit puzzling. We find that if the models are estimated for a subsample of insured farmers only, the effect results significant in both traits (Appendix B). The Drought Monitor seems to be a good proxy for farmer’s subjective probabilities in this case. One possible explanation could be that pooling both groups in a single estimation may be obscuring the effect of drought probability on WTP – making it not significant.

The mean WTP for the nonGM trait is estimated at $20.87 per acre. For the GM trait the mean WTP is estimated at $18.73 per acre. Both estimates are significant at the 1% level. The adoption potential curve for the two DT traits is presented in Figure 4-4. No first order stochastic dominance is observed in this case, thus it cannot be said which trait version unambiguously has a better adoption potential. However, the KS D-statistic was calculated at 0.2085, showing a significant difference (p-value=0.003) between the adoption potential curves. According to the shapes of the adoption curves, the GM trait holds better adoption potential at high prices compared to the nonGM trait. A final point is that, similar to what we find in the FS traits, the two curves separate from each other at the $20 per acre mark. This seems to reinforce the "different market segment" argument.

Table 4-1. Traits considered for farmer valuation

	Trait	Version
1	Fertilizer saving	nonGM
2	Fertilizer saving	GM
3	Drought tolerance	nonGM
4	Drought tolerance	GM

Table 4-2. Seed codes and variety descriptions

Seed code	Description
1	Genetically-modified (GM) herbicide resistant corn (e.g., Roundup Ready, LibertyLink)
2	Non-GM herbicide resistant seed variety (e.g., IMI-corn)
3	GM Bt variety for insect resistance to control European Corn Borer (Bt-ECB) (e.g., YieldGard, NatureGard, Knockout, Herculex)
4	GM Bt variety for insect resistance to control corn rootworm (Bt-CRW) (e.g. YieldGard Rootworm, Herculex RW)
5	Stacked gene variety with both GM Bt-ECB and Bt-CRW(e.g. YieldGard Plus, Herculex Xtra)
6	Stacked gene variety with both GM Bt-ECB and herbicide resistant (e.g. YieldGard or Herculex +Roundup Ready)
7	Stacked gene variety with both GM Bt-CRW and herbicide resistant (e.g. YieldGard Rootworm or Herculex RW + Roundup Ready)
8	Triple stacked gene variety with GM Bt-ECB and Bt-CRW plus herbicide resistant (e.g. YieldGard Plus or Herculex Xtra+ Roundup Ready)
9	None of the above

Table 4-3. CV survey versions with first and second offers

	Initial offer	Follow-up offer	
Version	P_i	P_i^L	P_i^H
A	$10	$5	$15
B	$15	$10	$20
C	$20	$15	$25
D	$25	$20	$30

Table 4-4. Description of variables selected from 2006 corn poll and 2007 corn poll

Farmer characteristics	
f_age	Age (in years)
f_educ	Education level (less than high school=1, high school diploma=2, some college=3, completed 2-year degree college=4, completed 4-year degree college=5, and some graduate school or graduate degree=6)
f_nfjob	Off-farm job (=1 if farmer has a full or part time off-farm job)
f_income	Gross income received from all farming activities in 2005 (Under $20,000 =1, from $20,000 to $39,999=2, from $40,000 to $59,999=3, from $60,000 to $79,999=4, from $80,000 to $99,999=5, from $100,000 to $119-999=6, from $120,000 to $139,999=7, from $140,000 to $159,999=8, $160,000 or more=9)
earlyadopt	Past adoption practices with respect to GM corn seeds (habit formation) (=1 if farmer adopted Bt-crw varieties in their first year in the market)
nonGM100p	Current use of GM crops (=1 if farm production is 100 percent nonGM varieties, =0 otherwise)
Farm characteristics	
farmsize	Total farm size reported in 2005 (in acres)
yield	Corn yield reported for most used seed code in 2006 (bushels per acre)
seedcost	Seed costs reported for most used seed code in 2006 ($ per acre)
herbcost	Herbicide costs reported for most used seed code in 2006 ($ per acre)
insectcost	Insecticide costs reported for most used seed code in 2006 ($ per acre)
fertcost	Fertilizer costs reported for most used seed code in 2006 ($ per acre)
insurcost	Corn insurance costs reported by farm in 2006 ($ per acre)
grain	Purpose of corn production (=1 if corn produced for grain, =0 if produced for other purposes (i.e., silage, sweet corn, other)
mD2	Probability of drought (average percentage area under severe drought in farm's county in 2006)

Table 4-5. Proportion tests and number of farmers by version of Contingent Valuation (CV) survey

Version	2007 Corn Poll (n=451)		Subsample nonGM				Subsample GM			
	n	Proportion	n	Proportion	Diff	z[i]	n	Proportion	Diff	z
		(1)[ii]		(2)	(1)-(2)			(3)	(1)-(3)	
Fertilizer Saving										
A	85	0.1885	30	0.1714	0.0171	0.51	26	0.1677	0.0208	0.59
B	121	0.2683	41	0.2349	0.0340	0.90	35	0.2258	0.0425	1.09
C	128	0.2838	52	0.2971	-0.0133	-0.33	45	0.2903	-0.0065	-0.15
D	117	0.2594	52	0.2971	-0.0377	-0.93	49	0.3161	-0.0567	-1.30
Total	451	1.0000	175	1.0000			155	1.0000		
Drought Tolerance										
A	85	0.1885	28	0.1879	0.0006	0.02	26	0.1898	-0.0013	-0.03
B	121	0.2683	36	0.2416	0.0267	0.67	31	0.2263	0.0420	1.03
C	128	0.2838	45	0.3020	-0.0182	-0.42	41	0.2993	-0.0155	-0.34
D	117	0.2594	40	0.2686	-0.0091	-0.22	39	0.2847	-0.0253	-0.57
Total	451	1.0000	149	1.0000			137	1.0000		

[i]The calculated statistic is $z = (\hat{p}_1 - \hat{p}_2) \Big/ \sqrt{(\hat{p}_1(1-\hat{p}_2)/n_1) + (\hat{p}_2(1-\hat{p}_1)/n_2)}$, where $z \sim N(0,1)$. [ii]The numbers in parenthesis (e.g., (1)) indicate the columns being compared. [iii]A value of $z > 1.65$ indicates a significance level of 0.1, a value of $z > 1.96$ indicates a significance level of 0.05.

Table 4-6a. Summary statistics and comparison of means (fertilizer saving trait)

	2006 Corn Poll n=945			2007 Corn Poll n=451			Subsample nonGM n=175				Subsample GM n=155			
	n	Mean	s.d.	n	Mean	s.d.	Mean	s.d.	Diff [i]	t [ii]	Mean	s.d.	Diff [i]	t [ii]
f_age	911	54.20	12.51				53.01	11.11	1.19	1.27	52.83	10.90	1.37	1.41
f_sex	919	1.02	0.13											
f_educ	918	2.87	1.36				3.27	1.47	-0.40**	-3.34	3.33	1.48	-0.46**	-3.62
f_nfjob	910	0.42	0.49				0.39	0.49	0.03	0.74	0.39	0.49	0.03	0.77
f_income	832	3.75	2.17				3.93	2.22	-0.18	-0.98	3.87	2.21	-0.12	-0.63
grain	833	0.76	0.42				0.79	0.41	-0.03	-0.88	0.80	0.40	-0.04	-1.13
earlyadopt	833	0.05	0.21				0.05	0.22	0.00	0.00	0.05	0.21	0.00	0.27
yield				300	149.28	46.62	143.90	43.91	5.38	1.26	143.12	44.26	6.16	1.38
seedcost				310	46.00	22.85	46.07	22.35	-0.07	-0.03	46.51	21.32	-0.51	-0.24
herbcost				310	21.72	12.62	20.08	11.97	1.64	1.42	19.86	12.11	1.86	1.54
insectcost				310	3.32	7.06	3.14	6.90	0.18	0.27	2.88	6.52	0.44	0.67
fertcost				310	52.92	35.08	50.25	33.29	2.67	0.83	51.36	32.72	1.56	0.47
farmsize	898	338.40	565.22				388.46	446.49	-50.06	-1.29	400.54	439.29	-62.14	-1.55
nonGM100p				429	0.24	0.43	0.23	0.42	0.01	0.26	0.20	0.40	0.04	1.04

[i] The column diff presents calculated differences between subsample means and their respective original sample means. [ii] The t statistics are calculated for two tailed tests assuming different variances. [iii] Degrees of freedom are sufficiently large in all mean comparisons to allow for use of critical values from the standard normal distribution (** indicates significance level of 0.05).

Table 4-6b. Summary statistics and comparison of means (drought tolerance trait)

	2006 Corn Poll n=945			2007 Corn Poll n=451			Subsample nonGM n=149				Subsample GM n=137			
	n	Mean	s.d	n	Mean	s.d	Mean	s.d	Diff [i]	t [ii]	Mean	s.d	Diff [i]	t [ii]
f_age	911	54.20	12.51				53.07	10.92	1.13	1.15	52.82	10.62	1.37	1.37
f_sex	919	1.02	0.13											
f_educ	918	2.87	1.36				3.19	1.41	-0.32**	-2.59	3.25	1.44	-0.38**	-2.92
f_nfjob	910	0.42	0.49				0.39	0.49	0.03	0.63	0.39	0.49	0.03	0.66
f_income	832	3.75	2.17				3.93	2.24	-0.18	-0.91	4.02	2.32	-0.28	-1.30
grain	833	0.76	0.42				0.79	0.41	-0.02	-0.56	0.79	0.41	-0.02	-0.62
earlyadopt	833	0.05	0.21				0.06	0.24	-0.01	-0.65	0.06	0.24	-0.01	-0.54
yield				300	149.28	42.62	142.94	43.28	6.34	1.47	143.32	43.65	5.96	1.33
seedcost				310	46.00	22.85	43.96	21.80	2.03	0.92	44.20	20.14	1.80	0.83
herbcost				310	21.72	12.62	20.07	12.02	1.65	1.35	19.88	12.09	1.84	1.46
insectcost				310	3.32	7.06	2.92	6.61	0.40	0.59	2.82	6.50	0.50	0.72
fertcost				310	52.92	35.08	48.58	28.08	4.35	1.43	49.31	26.52	3.62	1.20
farmsize	898	338.40	565.22				375.14	427.56	-36.73	-0.92	392.79	444.90	-54.39	-1.28
nonGM100p				429	0.24	0.43	0.25	0.43	-0.01	-0.14	0.23	0.42	0.02	0.39
insurcost				394	10.86	18.23	9.35	15.09	1.51	0.98	9.71	15.53	1.15	0.71

[i] The column diff presents calculated differences between subsample means and their respective original sample means. [ii] The t statistics are calculated for two tailed tests assuming different variances. [iii] Degrees of freedom are sufficiently large in all mean comparisons to allow for use of critical values from the standard normal distribution (**indicates significance level of 0.05).

Table 4-7. Definitions of drought measures

Category	Description	Possible impacts	Ranges: Palmer Drought Index	CPC Soil Moisture Model (Percentiles)	USGS Weekly Streamflow (Percentiles)	Standardized Precipitation Index (SPI)	Satellite Vegetation Health Index
D0	Abnormally Dry	Going into drought: short-term dryness slowing planting, growth of crops or pastures; fire risk above average. Coming out of drought: some lingering water deficits; pastures or crops not fully recovered.	-1.0 to -1.9	21-30	21-30	-0.5 to -0.7	36-45
D1	Moderate Drought	Some damage to crops, pastures; fire risk high; streams, reservoirs, or wells low, some water shortages developing or imminent, voluntary water use restrictions requested	-2.0 to -2.9	11-20	11-20	-0.8 to -1.2	26-35
D2	Severe Drought	Crop or pasture losses likely; fire risk very high; water shortages common; water restrictions imposed	-3.0 to -3.9	6-10	6-10	-1.3 to -1.5	16-25
D3	Extreme Drought	Major crop/pasture losses; extreme fire danger; widespread water shortages or restrictions	-4.0 to -4.9	3-5	3-5	-1.6 to -1.9	6-15
D4	Exceptional Drought	Exceptional and widespread crop/pasture losses; exceptional fire risk; shortages of water in reservoirs, streams, and wells, creating water emergencies	-5.0 or less	0-2	0-2	-2.0 or less	1-5

Source: Drought Monitor website available at http://drought.unl.edu/dm/classify.htm

Table 4-8. Estimation results for fertilizer saving trait

	Fertilizer nonGM		Fertilizer GM	
Variable	Estimate	p-value	Estimate	p-value
constant	12.035**	(0.031)	2.733	(0.684)
f_age	0.029	(0.698)	0.096	(0.260)
f_educ	0.569	(0.324)	0.740	(0.267)
f_nfjob	-0.267	(0.879)	-1.734	(0.394)
f_income	0.630*	(0.079)	0.868**	(0.030)
grain	-5.129**	(0.013)	-2.534	(0.300)
earlyadopt	9.617**	(0.017)	10.994**	(0.013)
yield	-0.016	(0.419)	0.003	(0.901)
seedcost	0.086**	(0.031)	0.075*	(0.096)
herbcost	0.074	(0.266)	0.090	(0.245)
insectcost	-0.212*	(0.078)	-0.027	(0.853)
fertcost	0.067***	(0.007)	0.051*	(0.078)
farmsize	-0.001	(0.429)	-0.002	(0.315)
nonGM100p	0.572	(0.776)	-7.678***	(0.002)
sigma	8.768***	(0.000)	9.360***	(0.000)
N	175		155	
Log-likelihood	-223.931		-193.012	
Mean WTP [i]	19.723***	(25.999)	17.248***	(19.814)
C.I. 95 L	18.236		15.542	
C.I. 95 U	21.210		18.954	
LR Index	0.62		0.55	
LR statistic	198.501***	(0.000)	131.608***	(0.000)

[i] For Mean WTP the t-statistic is reported in parenthesis. Standard error for mean WTP was calculated using the Delta Method. *** indicates significance at 0.01 level, ** indicates significance level of 0.05, and * indicates significance level of 0.1. LR statistic is for likelihood ratio test with $H_o : \beta_1 = \beta_2 = ... = 0$, sigma is left unconstrained.

Table 4-9. Estimation results for drought tolerance trait

	Drought nonGM		Drought GM	
Variable	Estimate	p-value	Estimate	p-value
constant	25.291***	(0.002)	7.543	(0.321)
f_age	-0.149	(0.201)	0.147	(0.191)
f_educ	-0.736	(0.462)	-0.937	(0.331)
f_nfjob	0.951	(0.748)	3.524	(0.222)
f_income	0.847	(0.146)	1.075**	(0.045)
earlyadopt	12.842**	(0.021)	14.967***	(0.007)
farmsize	-0.006	(0.125)	-0.003	(0.359)
nonGM100p	3.085	(0.321)	-6.638**	(0.031)
insurcost	0.243**	(0.039)	0.189*	(0.072)
mD2	0.127	(0.348)	0.210*	(0.092)
sigma	12.868***	(0.000)	11.527***	(0.000)
N	149		137	
Log-likelihood	-186.997		-163.210	
Mean WTP [i]	20.873***	(16.852)	18.738***	(16.154)
C.I. 95 L	18.445		16.465	
C.I .95 U	23.301		21.012	
LR Index	0.46		0.49	
LR statistic	107.609***	(0.000)	99.072***	(0.000)

[i] For mean WTP the t-statistic is reported in parenthesis. Standard error for mean WTP was calculated using the Delta Method. *** indicates significance at 0.01 level, ** indicates significance level of 0.05, and * indicates significance level of 0.1. LR statistic is for likelihood ratio test with $H_o : \beta_1 = \beta_2 = ... = 0$, sigma is left unconstrained.

7) Consider a new corn seed technology that comes along that maintains your same yield but reduces your nitrogen fertilizer requirements by one-third (33%).

Would you pay $10 extra per acre for this seed…	… **if it did <u>not</u> involve genetic modification?**		… **if it did <u>did</u> involve genetic modification?**	
	☐ Yes ⟹	If **yes,** would you buy it if it cost $15 extra per acre? ☐ **YES** ☐ **NO**	☐ Yes ⟹	If **yes,** would you buy it if it cost $15 extra per acre? ☐ **YES** ☐ **NO**
	(check one)		(check one)	
	☐ No ⟹	If **no,** would you buy it if it cost $5 extra per acre? ☐ **YES** ☐ **NO**	☐ No ⟹	If **no,** would you buy it if it cost $5 extra per acre? ☐ **YES** ☐ **NO**

8) Now consider a new corn seed technology that is drought tolerant so that under severe drought conditions it would still yield 75% of your normal yield.

Would you pay $10 extra per acre for this seed…	… **if it did <u>not</u> involve genetic modification?**		… **if it <u>did</u> involve genetic modification?**	
	☐ Yes ⟹	If **yes,** would you buy it if it cost $15 extra per acre? ☐ **YES** ☐ **NO**	☐ Yes ⟹	If **yes,** would you buy it if it cost $15 extra per acre? ☐ **YES** ☐ **NO**
	(check one)		(check one)	
	☐ No ⟹	If **no,** would you buy it if it cost $5 extra per acre? ☐ **YES** ☐ **NO**	☐ No ⟹	If **no,** would you buy it if it cost $5 extra per acre? ☐ **YES** ☐ **NO**

Figure 4-1. Contingent Valuation (CV) questionnaire portion of the 2007 Corn Poll.

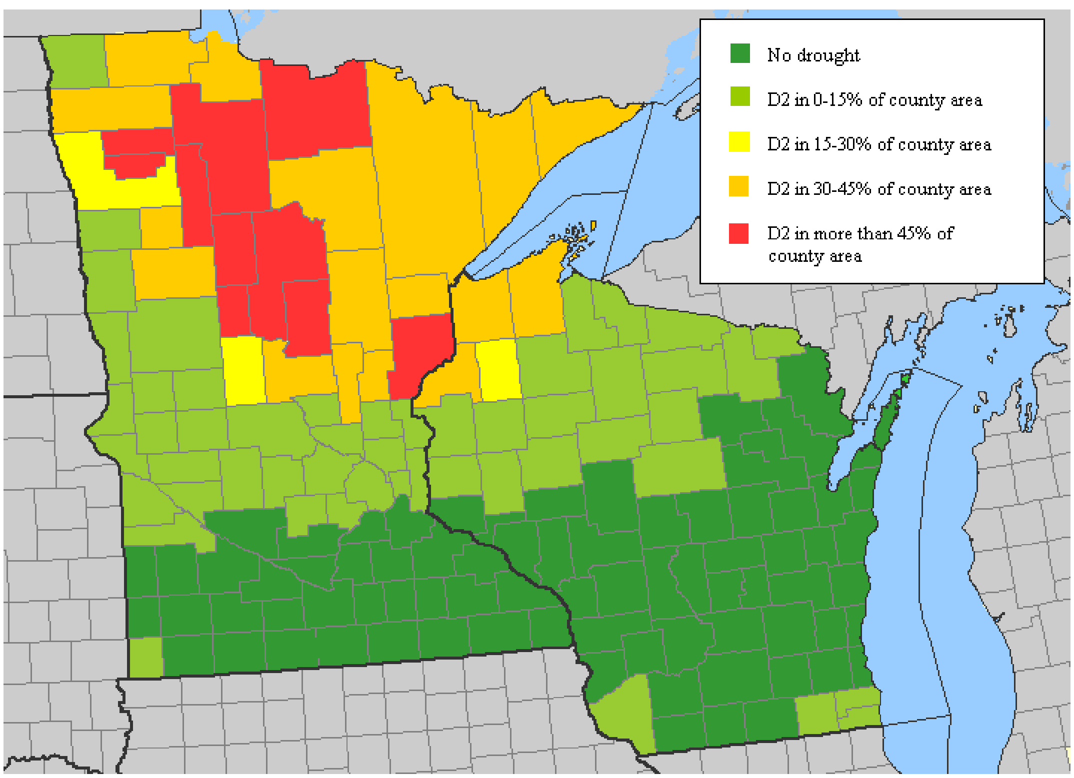

Figure 4-2. Map of average percentage area affected by severe drought (D2) for counties in Minnesota and Wisconsin, 2006. (Data Source: Drought Monitor Archives 2006).

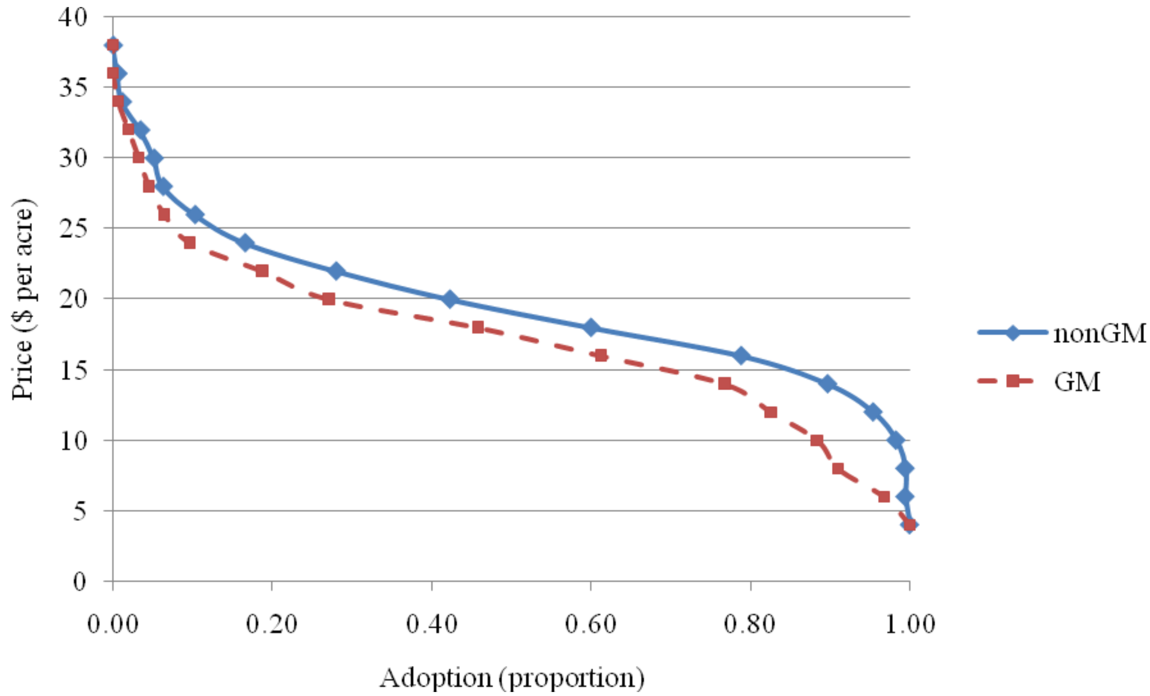

Figure 4-3. Potential adoption curve for nonGM and GM fertilizer saving trait.

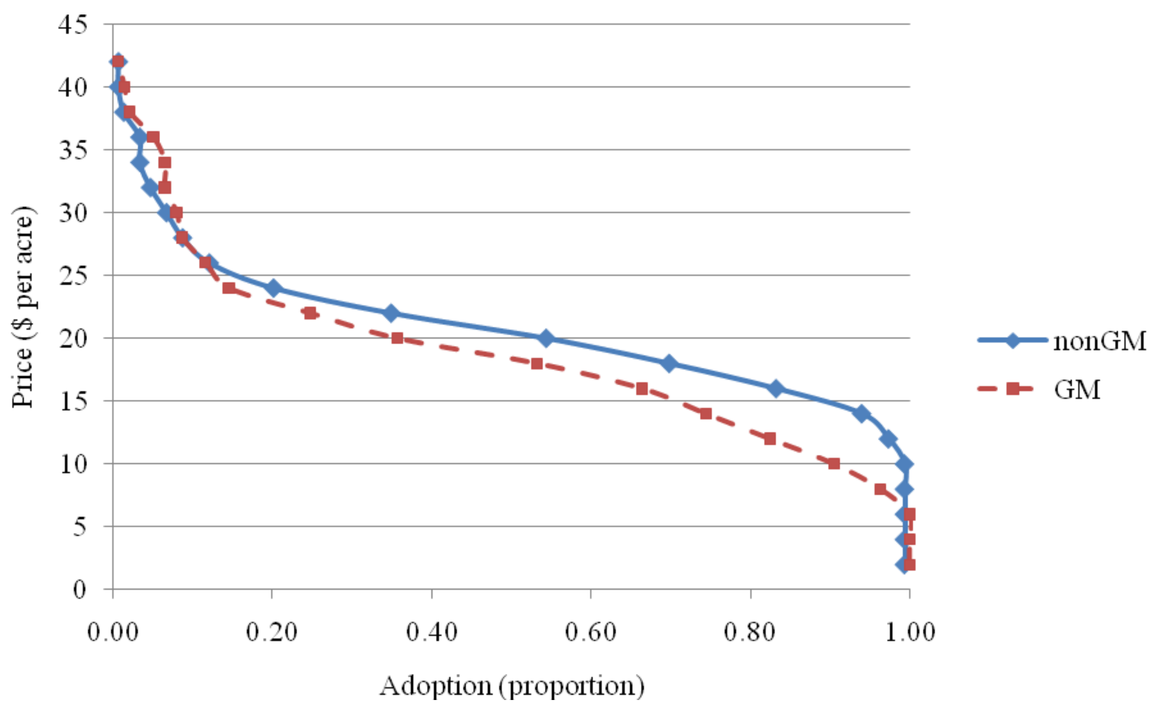

Figure 4-4. Potential adoption curve for nonGM and GM drought tolerance trait.

CHAPTER 5
TESTING FOR SAMPLE SELECTION BIAS IN OUR WTP ESTIMATES

This chapter explores the possibility that sample selection bias may be affecting the estimates of farmer's willingness-to-pay (WTP) for the genetically modified (GM) traits that we obtained in Chapter 4. The application of a sample selection model was motivated by the observation, in our sample, of a considerably larger number of non-respondents to the Contingent Valuation (CV) questions concerning the GM version of a trait compared to the number of non-respondents to CV questions concerning the nonGM version of the same trait. While high rates of non-response seem to be ubiquitous in CV research, the contrast in response rates between the GM and nonGM questions appeared unusual. This observation led us to consider the possibility that failure by the farmer to respond to GM questions could be systematically related to his WTP. If that were the case, it would imply underlying sample selection problems.

Testing for sample selection in our results from Chapter 4 is important because if detected it would suggest we have inconsistent estimates for the parameters of the population initially targeted. On the other hand, if no sample selection is detected, it would provide more reliability to our findings.

At first instance, it could appear as a simple matter to assume *de facto* that non-responses to GM questions are correlated to respondents WTP. However, as we shall see, it could be that individuals who fail to respond do so because they are not familiar enough and fail to construct their valuation. Which is culprit, unfamiliarity or sample selection, is empirically testable and empirically determined.

The possibility of sample selection bias has not been considered by previous studies of GM seed adoption similar in spirit to this one. The reported non-response rates in those studies are varied. For example, Hubbell, Marra, and Carlson (2000), using CV methods to study farmer adoption of Bt-cotton varieties, report a non-response rate of 62% which is low even for CV studies. On the other hand, Qaim and DeJanvry (2003) report only a 10% non-response rate in their study of Bt-cotton adoption among farmers in Argentina. Regardless of non-response rates, it would have not been possible for those studies to observe a contrast in behavior since they only considered GM versions of the trait in their CV questionnaire. Observing the contrast in response rate between the two versions (nonGM and GM) of each trait was possible in our study due to the specific design of the survey instrument with nonGM and GM questions being asked side by side.

Besides being unable to observe the contrast just mentioned, another possible reason for the unpaid attention to potential sample selection problems in those studies may have been the lack of an appropriate model to test for its presence. Application of Heckman's sample selection framework to the case of a double bounded (DB) dichotomous choice (DC) elicitation format has escaped the CV literature for many years. The model used in this chapter to test for sample selection was developed by Yoo and Yang (2001) and has only recently seen some applications in the CV literature (Yoo 2007; Yoo, Lim, and Kwak 2009).[1] When we discuss this model later, we will refer to it as the DB-DC Sample Selection model.

Non-Response and Sample Selection in CV

Non-response is common and often large[2] in CV surveys (Elköf and Karlsson 1999). This makes CV surveys vulnerable to serious non-response bias problems (Mitchell and Carson 1989). Non-response in CV studies can bias results in two ways (Elköf and Karlsson 1999).

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[1] To the best of our knowledge, no other sample selection model has been developed for DB-DC elicitation formats.

[2] "Response rates for the mail shot were good by CVM standards, being greater than 50% in almost all sub-samples." (Álvarez-Farizo, Hanley, and Wright 1996), "40-60% [response rate] seems average for general population CVM surveys" (Loomis 1987), "…minimizing both sample non-response and item non-response are

The first case is known as non-response bias[3]. Obtaining mean WTP estimates is usually one important objective in CV studies. The mean WTP estimate is usually calculated by estimating a model and then evaluating it at the mean values of the observable characteristics (i.e., the explanatory variables). If the population mean μ for each observable characteristic is unknown it is usually estimated using the averages calculated from the sample of respondents. If non-respondents differ significantly from respondents in observable characteristics that influence WTP, the mean WTP will be affected by non-response bias. The common way to test for this type of bias is to perform a t-test comparing the means of the characteristics of respondents versus those of non-respondents. If non-response bias is identified, a possible correction is to use the population means instead of the sample means when calculating mean WTP (i.e., when the population means are available). That this type of bias may affect our estimates was explored in Chapter 4 (See Table 4.6a and Table 4.6b). In this chapter we focus on the second type of potential bias which we explain in the following.

The second type of bias is sample selection bias. Bias may result even if non-respondents and respondents are similar in observed characteristics but differ systematically in their WTP due to unobservable characteristics (i.e., if non-response is systematically related to WTP). As we explain later in detail, this type of bias may be explained as a correlation between the error term in a selection equation determining participation in the sample and the error term in an outcome equation of interest. If the error terms are correlated, the estimates obtained using only the sample of respondents will be inconsistent estimates for the parameters of the population initially targeted.

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important. The former is unlikely to be below 20% even in very high quality surveys…" (Arrow et al. 1993). "Response rates on CV mail surveys typically range between 20% and 60%." (Whitehead, Groothuis, and Blomquist 1993).

[3] We follow Elköf and Karlsson's (1999) terminology.

Sample selection bias in CV studies may arise from two sources (Edwards and Anderson 1987). First, researchers may unintentionally create an artificial sample selection bias by culling "outliers". If the culling criterion is systematically related to the response variable (WTP) the result is sample selection bias. Second, non-respondents may naturally self-select themselves out of the sample (i.e., decide not to respond). In this case, sample selection bias will be present if non-respondents' WTP for the good in case is substantially and systematically different from that of respondents. This latter case is the focus of this chapter.[4]

The remainder of this section is organized as follows: (i) First we present Heckman's (1979) framework and sample selection model in the context of CV methods and discuss the statistical theory underlying it. (ii) Second, we define the scope of Heckman's two-stage procedure as those cases where the outcome equation is linearly specified and the dependent outcome variable is continuous; and survey the literature for extensions of Heckman's framework to the case of SB and DB elicitation formats. (iii) Finally, we outline the difficulties in gathering the necessary data to apply self-selection tests and models in CV research, and describe some of the surveying strategies found in the literature that are used to deal with these difficulties.

Heckman Selection Model and Two-Stage Procedure

It seems Randall, Hoehn, and Tolley (1981) were the first to suggest the use of Heckman's model in the CV literature. Heckman (1979) developed the basic sample selection model in the context of specification error and proposed a two stage estimator to correct for the presence of sample selection. In the following we develop the Heckman model in the context of CV methods.

[4] We focus in this type of sample selection because no culling rule was used when estimating the models in Chapter 4.

Consider a sample of size N and the two following behavioral equations:

$$WTP_i = \mathbf{x}_i'\beta + u_i \quad , \quad i = 1,...,n < N \tag{5-1}$$

$$S_i = \mathbf{z}_i'\gamma + v_i \quad , \quad i = 1,..., N \tag{5-2}$$

Equation 5-1 is usually called the output equation, however, in the CV literature it is directly referred to as the WTP equation. Equation 5-2 is called the selection equation (or selection mechanism equation) and determines which individuals give responses to the CV survey (i.e., enter the hypothetical market) and which individuals don't. Also, $\mathbf{x}_i$ is a vector of factors influencing the individual's WTP and the $\mathbf{z}_i$ is a vector of factors influencing his decision to participate in the CV questionnaire; S_i is a binary choice variable (=1) if the individual gives a response and (=0) if he "selects out" of the sample; β and γ are parameter vectors to be estimated; and u_i and v_i are zero mean stochastic error terms.

Notice that Equation 5-2 is defined over the whole sample of N individuals. On the other hand, Equation 5-1 is defined only for a subsample of $n < N$ individuals for which $S_i = 1$. The subsample of n individuals is usually referred to as the "selected sample".

One important point to consider is that sample selection can only be an issue after a population of interest is clearly specified (Wooldridge 2002). For example, if our target population were only individuals who usually accept contingent markets,[5] then the n observations satisfying $S_i = 1$ form a representative random sample from the population, and regression fit of Equation 5-1 gives consistent estimates. The sample selection problem possibility arises only when we define the population of interest as the "whole" population, including those who may usually reject contingent markets.

---

[5] And therefore answer CV surveys.

Heckman showed that sample selection bias occurs when behavioral parameter estimates (β) in the WTP equation (Equation 5-1) are confounded with parameter estimates (γ) appearing in the selection equation (Equation 5-2). Notice that Equation 5-1 is defined only for the selected sample, thus it is correctly modeled as

$$E[WTP_i \mid \mathbf{x}_i, S_i = 1] = \mathbf{x}_i'\beta + E[u_i \mid S_i = 1] \qquad (5\text{-}3)$$

Using Equation 5-2, we can re-write Equation 5-3 as:

$$E[WTP_i \mid \mathbf{x}_i, S_i = 1] = \mathbf{x}_i'\beta + E[u_i \mid v_i = 1 - \mathbf{z}_i'\gamma] \qquad (5\text{-}4)$$

From Equation 5-4 it becomes obvious that the existence of sample selection bias depends on whether u_i and v_i are independent. If this condition is not satisfied, using regression fit on Equation 5-3 will omit the final term in Equation 5-4 and the obtained parameter estimates will be inconsistent estimates for the β's of the "whole" population. Thus, the sample selection bias problem can be thought of as an omitted variable problem.

In order to obtain selection-corrected estimates of the parameters, the model presented in Equations 5-1 and 5-2 may be estimated using maximum likelihood methods by specifying a joint distribution for (u_i, υ_i) and normalizing the variance of the error in the selection equation to one (i.e., $Var(\upsilon_i) = \sigma_\upsilon^2 = 1$). [6]

Heckman (1979) devised a simple two step procedure that can be used to estimate the same model of Equations 5-1 and 5-2 but avoids the complications of using ML estimation. Under the assumption of a joint normal distribution for (u_i, υ_i), the following can be shown for the last term (omitted variable) in Equation 5-4:

---

[6] The respective log-likelihood function is presented as Equation [25] in Dubin and Rivers, (1989, pp. 370).

$$E[u_i \mid v_i = 1 - \mathbf{z}_i'\gamma] = \frac{\sigma_{12}}{\sigma_2}\lambda_i(\mathbf{z}_i'\gamma) = \delta \cdot \lambda_i(\mathbf{z}_i'\gamma) \quad (5\text{-}5)$$

where $\lambda_i(.)$ is the inverse Mills ratio and δ is a parameter to be estimated. Heckman showed a consistent estimator for λ_i is $\hat{\lambda}(\mathbf{z}_i'\hat{\gamma})$, where the estimate $\hat{\gamma}$ is available from a conventional probit estimation of Equation 5-2 alone. Heckman procedure then amounts to: (i) using probit estimation of Equation 5-2 alone to obtain $\hat{\gamma}$, then (ii) using $\hat{\gamma}$ to construct $\hat{\lambda}(\mathbf{z}_i'\hat{\gamma})$, and finally (iii) using $\hat{\lambda}(\mathbf{z}_i'\hat{\gamma})$ as an explanatory variable in regression fit of Equation 5-3 alone to obtain $\hat{\beta}$.

Modeling Sample Selection in Single Bounded and Double Bounded CV

Heckman developed his model to correct for selectivity bias when the outcome equation (i) presents a continuous dependent variable, and (ii) is modeled using a linear specification. In the CV literature obtaining a continuous dependent variable requires using an open ended (OE) elicitation format. In the context of CV methods this means that the Heckman model is correct only for the OE elicitation format. Most of the early CV studies that dealt with sample selection issues used only OE formats (e.g., Edwards and Anderson 1987; Loomis 1987). However, as mentioned in previous chapters, DC (or closed ended) formats are considered superior and recommended over OE formats.

Closed ended formats require discrete-choice statistical models that differ from the linear regression model assumed by Heckman. For example, correct modeling (without sample selection) when assuming normal errors in the single bounded (SB) case requires a probit model for the outcome equation, while assuming logistic errors implies a logit. Even though the conceptual framework used by Heckman carries over naturally to the case of probit and logit outcome equations, the convenience of the Heckman two-step procedure does not.[7] Nevertheless, some theoretical studies have succeeded in adapting Heckman's framework to deal with probit and logit outcome equations (Dubin and Rivers 1989; van de Ven and van Praag 1981; Meng and Schmidt 1985). CV authors have followed to apply these models to SB CV data. For example, Whitehead, Groothuis, and Blomquist (1993) use the bivariate probit (or biprobit) model developed by Dubin and Rivers, while Whitehead et al. (1994) and Eklöf and Karlsson (1999) use the censored probit presented in Meng and Schmidt.

Applying a sample selection framework to the case of DB CV data has proven more complicated. The bivariate probit of Dubin and Rivers, used to deal with sample selection in SB CV research, is correct for cases where the dependent variables in both the selection and the outcome equations are binary and the joint distribution is assumed normal. The dependent variable in the outcome equation for the DB case is not binary as it is in the SB case, so the correct model is not a biprobit. An appropriate model for studying sample selection in the DB case has only recently appeared, introduced by Yoo and Yang (2001). To the best of our knowledge, only two other applications of this model currently exist (Yoo 2007; Yoo, Lim, and Kwak 2009). This chapter explores the possibility of sample selection in the estimations presented in Chapter 4 using Yoo and Yang's model. The DB-DC Sample Selection of Yoo and Yang is developed in detail in a later section in this chapter. The derivation follows closely that used by Dubin and Rivers (1989) to develop their biprobit model.

[7] A two-step procedure, analog to Heckman's procedure, exists for the case of an outcome equation with binary choice dependent variable (Dubin and Rivers 1989). However, the computational advantages of the two-step estimator over ML estimation are less in this case compared to Heckman's case with a continuous dependent variable and linear outcome equation.

Issues with Data Availability and Surveying Strategies

As mentioned, issues of self-selection are frequent in CV studies and are well-known to CV researchers. However, tests and correction for self-selection bias have been scarce in the literature mainly because data on non-respondents necessary to conduct such tests is usually not available (Yoo and Yang 2001). Earlier we identified culling and self-selection as two possible causes of sample selection bias in CV.

In practice, from a logistics perspective, testing for sample selection bias in the self-selection case is considerably more difficult than doing so in the culling case (Edwards and Anderson 1987). In the culling case, the researcher initially holds N observations for the variables WTP_i, $\mathbf{x}_i$ and $\mathbf{z}_i$. He then uses S_i to censor some of these data points leaving only a subsample of n “valid” observations $\{WTP_i, \mathbf{x}_i\}; i = n < N$ to estimate Equation 5-1 and has at hand the necessary N observations $\{S_i, \mathbf{z}_i\}; i = N$ to estimate Equation 5-2.

Data availability is considerably more complicated in the case of self-selection. Suppose a random sample from a population is designed to have N observations but after data collection we observe n responses and $N-n$ non-responses. CV studies have usually collected data for $\mathbf{x}_i$ and $\mathbf{z}_i$ in a same single survey. Respondents that participate in the survey will provide data on both $\mathbf{x}_i$ and $\mathbf{z}_i$; similarly, those that self-select out will answer neither. This means the researcher always ends up with n observations on all variables (i.e., $\{WTP_i, \mathbf{x}_i, \mathbf{z}_i\}; i = n < N$). However, in order to test and correct for sample selection, the researcher needs n data points for $\{WTP_i, \mathbf{x}_i\}$ and $N > n$ data points for $\{S_i, \mathbf{z}_i\}$. In this case, the researcher must push the issue and interview the $N-n$ non-respondents for their data on $\mathbf{z}_i$.

Those studies in the CV literature that address self-selection issues have adopted different surveying strategies in attempts to obtain the necessary data on non-respondents. Edwards and Anderson (1987) experimented with switching from mail to phone interviews in order to collect information on non-respondents. However, they desisted due to concerns about the length of the survey and the complications associated with describing changes in the good (water quality) via telephone. They were, in the end, unable to test for self-selection. Recognizing that concerns about explaining changes in the good via telephone are valid, Whitehead, Groothuis, and Blomquist (1993) used a two-stage phone sampling and mail survey strategy. They first used a phone interview to collect socioeconomic data on 926 people. Phone interviewees were asked if they would complete a mail questionnaire which contained the detailed CV scenarios and questions. Out of the 926 phone calls, 641 agreed to complete the questionnaire and 487 actually returned a completed questionnaire. Yoo and Yang (2001) also used a two-stage approach but opted for an initial face-to-face interview with a follow-up phone interview.[8] Trained interviewers visited a sample of randomly selected individuals and asked them first if they would participate. If they agreed, the interviewer proceeded with the main interview. If they declined, the interviewer asked only their names and telephone. After a few days, trained enumerators called to collect socioeconomic data on those non-respondents.

We used a surveying strategy involving two separate face to face interviews. The advantages and disadvantages of our strategy are discussed later in the empirical section of this chapter.

[8] They did not use mail surveys due to the unfamiliarity and extremely low-response rates these have in Korea where the study was conducted.

Theoretical Model

In this section we present the details of the DB-DC Sample Selection model (Yoo and Yang 2001) that we use to test for the possibility of sample selection bias in the estimates obtained in Chapter 4. If sample selection is detected, the same model obtains consistent estimates of the parameters explaining individual WTP. The section is organized as follows. First, we present a brief initial setup of the two equation Sample Selection model in the context of CV research. Second, we revisit the DB-DC mechanism (without sample selection) and look at it in a less formal but more intuitive manner than we did in Chapter 3 and 4. This allows us a better understanding of the DB-DC mechanism and provides the tools to develop the DB-DC Sample Selection model that we use in the empirical application section of this chapter.

Initial Setup

We consider the two following behavioral equations. Let the equation representing the selection mechanism be:

$$y_{1i}^* = \mathbf{x}_{1i}'\beta_1 + \varepsilon_{1i} \tag{5-6}$$

and the outcome or WTP equation be:

$$y_{2i}^* = \mathbf{x}_{2i}'\beta_2 + \varepsilon_{2i} \tag{5-7}$$

We do not observe the latent variable y_{1i}^*, only whether y_{1i}^* is greater than zero or not. Therefore, we observe:

$$y_{1i} = 1(y_{1i}^* > 0) \tag{5-8}$$

where 1(.) is an indicator function equal to 1 if its argument is true (i.e., the person participates in the CV survey) and 0 otherwise (i.e., does not participate). The latent dependent variable y_{1i}^* may be understood as a threshold which triggers the individual's decision to participate in the hypothetical market presented by the CV exercise; possibly the level of interest of the respondent. Information on each individual's WTP for the technology (y_{2i}^{*}) is also limited (i.e., categorical) due to the dichotomous nature of the DB elicitation format we use.

In the following we revisit a topic already presented in a Chapter 3 – the DB-DC mechanism – and reformulate it in a manner that will facilitate the derivation of the DB-DC Sample Selection Model. To simplify exposition, we abstract for a moment from the sample selection issues and work only with the WTP equation (Equation 5-7) which represents the traditional DB-DC model. That is, for a moment we ignore any selection mechanism (Equation 5-6). We will come back to incorporate the selection equation into our model later when we discuss the DB-DC Sample Selection model.

Double Bounded Mechanism Revisited

Intuitively, the DB-DC elicitation method results in a classification of individual WTP's into four different regions (or bins) across the range of possible WTP values. These regions are presented in Figure 5-1 and are labeled from 1 to 4. From Chapter 4 we know that $\Pr(Adopt) = \Pr(WTP_i > P_i)$, that is, the respondent will agree to pay a given price P_i and adopt the technology if his WTP exceeds that price; otherwise, he will reject the technology. Observe Figure 5-1: In the case of SB elicitation, a "No" answer to a price P_i places a given individual's WTP to the left of P_i in the region $(-\infty, P_i)$. Alternatively, a "Yes" answer would place his WTP on the right of P_i, in the region (P_i, ∞). The follow-up offer in DB elicitation allows for further subdivision of the range of WTP values into four regions: $(-\infty, P_i^L), (P_i^L, P_i), (P_i, P_i^H)$ and (P_i^H, ∞). The mechanism of DB-DC elicitation may be better understood with an example. Suppose an individual responds "No" to the original offered price P_i. This response places his

WTP somewhere on the left of P_i in Figure 5-1 (i.e., region 1+region 2). If the DB-DC methodology is followed, a "No" response to the first price offer P_i would be followed by a second price offer P_i^L. If the respondent then answers "Yes" to the second price offer, his WTP falls in region 2. If his answer to the second price offer is a "No", his WTP falls in region 1. On the other hand, if his response to the first price offer would have been a "Yes", the second price offer would have been P_i^H and the response to this higher bid would place the individual's WTP in either region 3 (if no) or region 4 (if yes). This further subdivision into four distinct regions is responsible for the significant improvement in statistical efficiency observed in the DB-DC method compared to the SB-DC method (Hanemann, Loomis, and Kaninnen 1991). We can see that more information is revealed about the individual's WTP by using the DB-DC methodology as opposed to the SB-DC methodology. More information results in higher efficiency in the DB-DC method versus the SB-DC method at similar sample sizes. The possible answer sequences to the original and follow-up bids and their corresponding regions are summarized in the Table 5-1. The indicators (I^{yy}, I^{yn}, I^{ny}, and I^{nn}) identify each individual by their response sequence (i.e., $I^{yy} = 1$ (respondent answers were "Yes", "Yes")) where 1(.) is an indicator function equal to 1 if its argument is true and zero otherwise. The indicators basically tell us which region the individual's WTP falls into.

In Chapter 4 we presented a formal mathematical derivation for the likelihood of a "yes-yes" sequence π_i^{YY}; while the likelihoods for the three other possible sequences (π_i^{YN}, π_i^{NY} and π_i^{NN}) were briefly discussed. We present here a less rigorous but more intuitive derivation of these four likelihoods. From Figure 5-1 and the preceding discussion, we know that different response sequences to DB-DC questions result in classification of the individual's WTP into four different regions. The four likelihoods are simply the areas below each region of the distribution. The upper and lower bounds (A_i^U and A_i^L , respectively) of integration for each region are given by P_i, P_i^L and P_i^H ; and depend on the response sequence given by the individual (see Figure 5-1 and Table 5-1). The following derivation uses Equation 5-7 as the model for WTP and assumes a symmetric distribution for the error term ε_{i2} . You can refer to Figure 5-1 to visualize each region.

Region 1 ($A_i^L = -\infty, A_i^U = P_i^L$):

$$
\begin{aligned}
\pi_i^{NN} &= \Pr(-\infty < y_{2i}^* < P_i^L) = \Pr(-\infty < \mathbf{x}_{2i}'\beta_2 + \sigma_2\,\varepsilon_{2i} < P_i^L) \\
&= \Pr\left(-\infty < \varepsilon_{2i} < \frac{P_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right) \\
&= F\left(\frac{P_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right)
\end{aligned}
$$

Region 2 ($A_i^L = P_i^L, A_i^U = P_i$):

$$
\begin{aligned}
\pi_i^{NY} &= \Pr(P_i^L < y_{2i}^* < P_i) = \Pr(P_i^L < \mathbf{x}_{2i}'\beta_2 + \sigma_2\,\varepsilon_{2i} < P_i) \\
&= \Pr\left(\frac{\mathrm{P}_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma_2} < \varepsilon_{2i} < \frac{\mathrm{P}_i - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right) \\
&= F\left(\frac{\mathrm{P}_i - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right) - F\left(\frac{\mathrm{P}_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right)
\end{aligned}
$$

Region 3 ($A_i^L = P_i, A_i^U = P_i^H$):

$$
\begin{aligned}
\pi_i^{YN} &= \Pr(P_i < y_{2i}^* < P_i^H) = \Pr(P_i < \mathbf{x}_{2i}'\beta_2 + \sigma_2\,\varepsilon_{2i} < P_i^H) \\
&= \Pr\left(\frac{P_i - \mathbf{x}_{2i}'\beta_2}{\sigma_2} < \varepsilon_{2i} < \frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right) \\
&= F\left(\frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right) - F\left(\frac{P_i - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right)
\end{aligned}
$$

Region 4 ($A_i^L = P_i^H, A_i^U = \infty$):

$$\pi_i^{YY} = \Pr(P_i^H < y_{2i}^* < \infty) = \Pr(P_i^H < \mathbf{x}_{2i}'\beta_2 + \sigma\varepsilon_{2i} < \infty)$$
$$= \Pr\left(\frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma_2} < \varepsilon_{2i} < \infty\right)$$
$$= 1 - F\left(\frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma_2}\right)$$

where σ_2 is a scale parameter.

We can then write the log-likelihood function under the assumption of $e_{2i} \sim N(0,1)$ by using our indicator variables as:

$$\begin{aligned}\ln L(\beta,\sigma \mid y_{2i,} x_{2i}) = \sum_{i=1}^{N} \Bigg\{ & I_i^{yy} \ln\left[1 - \Phi\left(\frac{P_i^H - x_{2i}'\beta_2}{\sigma_2}\right)\right] \\ & + I_i^{yn} \ln\left[\Phi\left(\frac{P_i^H - x_{2i}'\beta_2}{\sigma_2}\right) - \Phi\left(\frac{P_i - x_{2i}'\beta_2}{\sigma_2}\right)\right] \\ & + I_i^{ny} \ln\left[\Phi\left(\frac{P_i - x_{2i}'\beta_2}{\sigma_2}\right) - \Phi\left(\frac{P_i^L - x_{2i}'\beta_2}{\sigma_2}\right)\right] \\ & + I_i^{nn} \ln\Phi\left(\frac{P_i^L - x_{2i}'\beta_2}{\sigma_2}\right)\Bigg\}\end{aligned} \tag{5-9}$$

The likelihood function presented in Equation 5-9 is identical to that presented in Equation 4-9 of Chapter 4 but we have derived it in a different manner. As we have already mentioned, Maximum Likelihood methods may be used on Equation 5-9 to obtain estimates of the population parameters: β_2 and σ_2. This completes the mathematical derivation of the likelihood for the traditional DB-DC model. We now follow to derive the likelihood for the DB-DC Sample Selection model.

Sample Selection Model

Our understanding of the DB-DC mechanism should now allow us to introduce the selection mechanism shown in Equation 5-6 into our model. The selection mechanism shows that response to the WTP questions is contingent on some latent variable y_{1i}^* being positive; that is, the respondent only participates in the sample if $y_{1i}^* > 0$, otherwise we observe a missing value for that individual. In the context of CV research the latent variable y_{1i}^* may be understood as a threshold which triggers the decision to participate in the hypothetical market presented by the valuation exercise; possibly the level of interest of the respondent.

As before, denote A_i^L and A_i^U as the lower and upper bounds for WTP, respectively. The general likelihood function for the model that takes the selection mechanism into account is:

$$L = \prod_{y_{1i}=0} \Pr(y_{1i}^* \le 0) \prod_{y_{1i}=1} \Pr(y_{1i}^* > 0, A_i^L < y_{2i}^* < A_i^U) \qquad (5\text{-}10)$$

A Maximum Likelihood approach to estimating this model necessitates full specification of the joint distribution of (y_{1i}^*, y_{2i}^*). We assume a bivariate normal distribution $BVN(x_{1i}'\beta_1, x_{2i}'\beta_2, \sigma_1^2, \sigma_2^2, \rho)$, where σ_1, σ_2 and ρ are the standard deviations of the marginal distributions of y_{1i}^* and y_{2i}^*, and the correlation coefficient between y_{1i}^* and y_{2i}^*, respectively. Let Σ represent the covariance matrix of the errors from both equations: $\Sigma = \text{cov}(\varepsilon_1, \varepsilon_2)$. The parameters in the covariance matrix Σ must be normalized for identification. Following Amemiya (1984), if there is no constraint on the parameters, we can use $\sigma_1 = 1$ and $\sigma_2 / \sigma_1 = \sigma$ for identification without any loss of generality. The covariance matrix is given by:

$$\Sigma = \text{cov}(\varepsilon_{1i}, \varepsilon_{2i}) = E[\varepsilon'\varepsilon] = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix} \qquad (5\text{-}11)$$

where $\varepsilon = [\varepsilon_1 \quad \varepsilon_2]$ represents an $n x 2$ matrix containing the disturbance vectors, and the second equality follows from $E[\varepsilon_1 \quad \varepsilon_2] = [0 \quad 0]$. The normalization is achieved by (i) dividing each element of Σ by σ_i^2, (ii) realizing $\sigma_{12} = \sigma_{21} = \rho\sigma_1\sigma_2$, and (iii) letting $\sigma_2 / \sigma_1 = \sigma$:

$$\Sigma = \begin{bmatrix} \frac{\sigma_1^2}{\sigma_1^2} & \frac{\sigma_{12}}{\sigma_1^2} \\ \frac{\sigma_{21}}{\sigma_1^2} & \frac{\sigma_2^2}{\sigma_1^2} \end{bmatrix} = \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{bmatrix}$$

so that ε is distributed,

$$\begin{bmatrix} \varepsilon_{1i} \\ \varepsilon_{2i} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{bmatrix} \right)$$

Let, $z_{1i} = \varepsilon_{1i}$ and $z_{21} = \varepsilon_{2i} / \sigma$ denote the two corresponding standard normal errors distributed jointly as $f(z_{1i}, z_{2i}) = BVN(0,0,1,1,\rho)$. Our model, as presented in Equation 5-10, divides the entire (z_{1i}, z_{2i}) support plane of $f(z_{1i}, z_{2i})$ into the following five separate regions:

Region 1 ($A_i^L = -\infty, A_i^U = P_i^L$):

$$\begin{aligned}
\Pr(y_{1i}^* > 0, -\infty < y_{2i}^* < P_i^L) &= \Pr(\mathbf{x}_{1i}'\beta_1 + z_{1i} > 0, -\infty < \mathbf{x}_{2i}'\beta_2 + \sigma \cdot z_{2i} < P_i^L) \\
&= \Pr\left(z_{1i} > -\mathbf{x}_{1i}'\beta_1, -\infty < z_{2i} < \frac{P_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma} \right) \\
&= \Pr\left(z_{1i} < \mathbf{x}_{1i}'\beta_1, -\infty < z_{2i} < \frac{P_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma} \right) \\
&= \int_{-\infty}^{\mathbf{x}_{1i}'\beta_1} \int_{-\infty}^{(P_i^L - \mathbf{x}_{2i}'\beta_2)/\sigma} f(z_{1i}, z_{2i}) dz_{1i} dz_{2i} \\
&= \Psi\left(\mathbf{x}_{1i}'\beta_1, \frac{P_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma}, -\rho \right)
\end{aligned}$$

Region 2 ($A_i^L = P_i^L, A_i^U = P_i$):

$$
\begin{aligned}
\Pr(y_{1i}^* > 0, P_i^L < y_{2i}^* < P_i) &= \Pr(\mathbf{x}_{1i}'\beta_1 + z_{1i} > 0, P_i^L < \mathbf{x}_{2i}'\beta_2 + \sigma \cdot z_{2i} < P_i) \\
&= \Pr\left(z_{1i} > -\mathbf{x}_{1i}'\beta_1, \frac{P_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma} < z_{2i} < \frac{P_i - \mathbf{x}_{2i}'\beta_2}{\sigma} \right) \\
&= \Pr\left(z_{1i} < \mathbf{x}_{1i}'\beta_1, \frac{P_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma} < z_{2i} < \frac{P_i - \mathbf{x}_{2i}'\beta_2}{\sigma} \right) \\
&= \int_{-\infty}^{\mathbf{x}_{1i}'\beta_1} \int_{(P_i^L - \mathbf{x}_{2i}'\beta_2)/\sigma}^{(P_i - \mathbf{x}_{2i}'\beta_2)/\sigma} f(z_{1i}, z_{2i}) dz_{1i} dz_{2i} \\
&= \Psi\left(\mathbf{x}_{1i}'\beta_1, \frac{P_i - \mathbf{x}_{2i}'\beta_2}{\sigma}, -\rho \right) - \Psi\left(\mathbf{x}_{1i}'\beta_1, \frac{P_i^L - \mathbf{x}_{2i}'\beta_2}{\sigma}, -\rho \right)
\end{aligned}
$$

Region 3 ($A_i^L = P_i, A_i^U = P_i^H$):

$$
\begin{aligned}
\Pr(y_{1i}^* > 0, P_i < y_{2i}^* < P_i^H) &= \Pr(\mathbf{x}_{1i}'\beta_1 + z_{1i} > 0, P_i < \mathbf{x}_{2i}'\beta_2 + \sigma \cdot z_{2i} < P_i^H) \\
&= \Pr\left(z_{1i} > -\mathbf{x}_{1i}'\beta_1, \frac{P_i - \mathbf{x}_{2i}'\beta_2}{\sigma} < z_{2i} < \frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma} \right) \\
&= \Pr\left(z_{1i} < \mathbf{x}_{1i}'\beta_1, \frac{P_i - \mathbf{x}_{2i}'\beta_2}{\sigma} < z_{2i} < \frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma} \right) \\
&= \int_{-\infty}^{\mathbf{x}_{1i}'\beta_1} \int_{(P_i - \mathbf{x}_{2i}'\beta_2)/\sigma}^{(P_i^H - \mathbf{x}_{2i}'\beta_2)/\sigma} f(z_{1i}, z_{2i}) dz_{1i} dz_{2i} \\
&= \Psi\left(\mathbf{x}_{1i}'\beta_1, \frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma}, -\rho \right) - \Psi\left(\mathbf{x}_{1i}'\beta_1, \frac{P_i - \mathbf{x}_{2i}'\beta_2}{\sigma}, -\rho \right)
\end{aligned}
$$

Region 4 ($A_i^L = P_i^H, A_i^U = \infty$):

$$
\begin{aligned}
\Pr(y_{1i}^* > 0, P_i^H < y_{2i}^* < \infty) &= \Pr(\mathbf{x}_{1i}'\beta_1 + z_{1i} > 0, P_i^H < \mathbf{x}_{2i}'\beta_2 + \sigma \cdot z_{2i} < \infty) \\
&= \Pr\left(z_{1i} > -\mathbf{x}_{1i}'\beta_1, \frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma} < z_{2i} < \infty \right) \\
&= \Pr\left(z_{1i} < \mathbf{x}_{1i}'\beta_1, \frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma} < z_{2i} < \infty \right) \\
&= \int_{-\infty}^{\mathbf{x}_{1i}'\beta_1} \int_{(P_i^H - \mathbf{x}_{2i}'\beta_2)/\sigma}^{\infty} f(z_{1i}, z_{2i}) dz_{1i} dz_{2i} \\
&= \int_{-\infty}^{\mathbf{x}_{1i}'\beta_1} \int_{-\infty}^{\infty} f(z_{1i}, z_{2i}) dz_{1i} dz_{2i} - \int_{-\infty}^{\mathbf{x}_{1i}'\beta_1} \int_{-\infty}^{(P_i^H - \mathbf{x}_{2i}'\beta_2)/\sigma} f(z_{1i}, z_{2i}) dz_{1i} dz_{2i}
\end{aligned}
$$

$$= \Phi(\mathbf{x}_{1i}'\beta) - \Psi\left(\mathbf{x}_{1i}'\beta_1, \frac{P_i^H - \mathbf{x}_{2i}'\beta_2}{\sigma}, -\rho\right)$$

Region 5:

$$\Pr(y_{1i}^* \le 0) = \Pr(\mathbf{x}_{1i}'\beta + z_{1i} \le 0) = \Pr(z_{1i} \le -\mathbf{x}_{1i}'\beta) = 1 - \Phi(\mathbf{x}_{1i}'\beta)$$

where, to simplify notation, we have used $\Psi(z_{1i}, z_{2i}, \rho)$ to summarize the double integral over the bivariate standard normal density function with integration limits from $-\infty$ up to the arguments inside $\Psi(.)$. The third equality in the derivation for each region follows from symmetry of the bivariate normal (BVN) density. The first term in the last equality in the derivation of Region 4 follows from the fact that integration of $f(z_{1i}, z_{2i})$ across all values of z_{2i} returns the marginal distribution of z_{1i}. All five regions are presented in Figure 5-2 where the support plane for the random error terms in our bivariate model is plotted with z_{1i} on the horizontal-axis and z_{2i} on the vertical-axis. For example, those farmers who did not enter the CV market and are therefore considered missing values are represented in Region 5. The contribution of such individuals to the likelihood function (Equation 5-12) is simply the integration of the marginal distribution of z_{1i} over the interval $(-\infty, -x_{1i}'\beta_1)$. Since z_{1i} is distributed standard normal, this is simply $1 - \Phi(x_{1i}'\beta_1)$. Those individuals who entered the market and gave a “yes,yes” response sequence are represented in region 4 and so forth.

Using our indices and the mathematical derivations for the likelihoods associated with each region we write the log likelihood function for the DB-DC Sample Selection model as.

$$
\begin{aligned}
\ln(L) = &\sum_{i=1}^{N}(1-y_{1i})\ln[1-\Phi(\mathbf{x}_{1i}'\beta_1)] \\
&+\sum_{i=1}^{N} y_{1i}\left\{ I_i^{YY}\ln\left[\Phi(\mathbf{x}_{1i}'\beta_1)-\Psi\left(\mathbf{x}_{1i}'\beta,\frac{P_i^H-\mathbf{x}_{2i}'\beta_2}{\sigma},-\rho\right)\right]\right. \\
&+I_i^{YN}\ln\left[\Psi\left(\mathbf{x}_{1i}'\beta,\frac{P_i^H-\mathbf{x}_{2i}'\beta_2}{\sigma},-\rho\right)-\Psi\left(\mathbf{x}_{1i}'\beta,\frac{P_i-\mathbf{x}_{2i}'\beta_2}{\sigma},-\rho\right)\right] \\
&+I_i^{NY}\ln\left[\Psi\left(\mathbf{x}_{1i}'\beta,\frac{P_i-\mathbf{x}_{2i}'\beta_2}{\sigma},-\rho\right)-\Psi\left(\mathbf{x}_{1i}'\beta,\frac{P_i^L-\mathbf{x}_{2i}'\beta_2}{\sigma},-\rho\right)\right] \\
&\left.+I_i^{YN}\ln\left[\Psi\left(\mathbf{x}_{1i}'\beta,\frac{P_i^L-\mathbf{x}_{2i}'\beta_2}{\sigma},-\rho\right)\right]\right\}
\end{aligned}
\tag{5-12}
$$

Estimation of Equation 5-12 is possible by Maximum Likelihood (ML) methods to obtain estimates of $\beta_1, \beta_2, \sigma, \rho$. If the true value of ρ is zero the two equations are independent. Estimating the model while forcing $\rho = 0$ will give the same results as estimating each equation separately. Testing for sample selection is possible within the model and is done by testing a single parameter restriction ($H_o : \rho = 0$).

Empirical Application

We use the DB-DC Sample Selection model to test for possible sample selection bias in the estimates of farmer's WTP for GM seed technologies we obtained in Chapter 4. Due to data limitations, estimation of a correct sample selection model is estimated and tests are carried out only for the GM fertilizer saving (FS) trait.

Data and Surveying Strategy: Some Highlights

Most of the details concerning the data were already presented in Chapter 4. Here we discuss only those characteristics of the surveying strategy that are relevant to this chapter.

The two main surveys – 2006 corn poll (CP06) and 2007 corn poll (CP07) – were carried out in separate face to face interviews with the farmers. Most of the socio-demographic data was collected with the CP06. The CP07 included some questions on individual characteristics but was mainly a CV questionnaire designed to elicit farmers' WTP for the GM traits.

Farmers who were randomly selected to participate in the CP06 were not necessarily also randomly selected to participate in the CP07.[9] Out of the 451 farmers randomly assigned to participate in the CP07, only a total of 345 farmers were also selected to participate in the CP06. Farmers were assigned the same identification number in both surveys so the two data sets were merged for those 345 farmers that participated in both polls. These 345 farmers formed the base sample for estimations in Chapter 4 and in this chapter.

The strategy just described presented some specific advantages and disadvantages. As we discussed earlier in our section on surveying strategies, estimating a self-selection model requires gathering data for non-respondents. In specific data on variables that are hypothesized to have an effect on the decision to participate in the hypothetical market – generally these are socio-economic variables. The main advantage of our surveying strategy was derived from using one survey instrument to gather CV data and a separate survey instrument to gather data on socio-economic variables. This strategy held the potential to provide a data structure that permits estimating the DB-DC Sample Selection model and testing for self-selection bias.

Unfortunately, the surveying strategy had the disadvantage that some of the non-respondents in the CP07 sample, which are the primary suspects for sample selection, were not selected to participate in the CP06. This accidental culling represented the main disadvantage of the surveying strategy. In addition, some of those suspect non-respondents from the CP07 that were indeed selected to participate in the CP06 did not respond all of the socio-economic questions, thus the observation had missing values and could not be considered for estimation.

[9] This was mainly because both surveys formed part of a larger project studying GM adoption and because of funding availability.

Fortunately, in the case of the FS GM trait, the data left after merging the two data sets and eliminating incomplete observations, had enough variability to allow us to estimate the DB-DC Sample Selection model.

Results

The application of a sample selection model was motivated by the observation, in our sample, of a considerably larger number of non-respondents to the CV questions concerning the GM version of a trait compared to the number of non-respondents to CV questions concerning the nonGM version of the same trait.

To observe this contrast in survey response behavior we started by identifying the different types of respondents that were allowed by the CV survey design. Table 5-2 presents the three main types of respondents that we identified: (i) respondents, (ii) non-bargainers, and (iii) non-respondents. Respondents are defined as individuals who provided answers to both the initial and follow-up questions. Non-respondents are exactly the opposite, those who answered neither initial nor follow-up. The last type are individuals who gave a response to the initial price offer, but refused to engage in the bargaining situation presented by a follow-up offer – we call these non-bargainers.

All three types of respondents are possible for each version of the trait (nonGM and GM). This is shown in Figure 5-3 where the arrows are drawn to illustrate the possibility of farmers changing their response behavior when asked about different versions of the trait. For example, an individual who answered both initial and follow up questions (i.e., respondent) when queried about the nonGM trait could decide to answer only the initial question when asked about the GM trait (i.e., non-bargainer). The most repeatedly observed change in behavior was switching from being a respondent in the nonGM case to a non-respondent in the GM case.

Table 5-3 presents a tabulation of the responses to the nonGM questions against the possible responses to the GM questions. Respondents are represented in the columns and rows labeled “No No”, “No Yes”, “Yes No” and “Yes Yes”. Non-bargainers are represented in columns and rows labeled “No Miss” and “Yes Miss”. Non-respondents are represented in the column and row labeled “Miss Miss”. Each element in any row/column represents the number of individuals in the sample who gave the response sequences presented in the labels of that row and column. For example, 77 individuals gave a “No No” response sequence in both the nonGM case and the GM case. Or for example the element in the “Miss Miss” column and the “No Yes” row indicates that 2 people gave a “No Yes” response sequence when asked about the nonGM trait, but answered neither initial nor follow-up question when asked about the GM trait.

Notice that out of a total of 54 missing values (see column “Miss Miss”) 41 are individuals who changed from being respondents in the nonGM questions to non-respondents in the GM questions (i.e., 16+5+6+14). These individuals were the suspects that motivated our exploration of potential sample selection problems.

The estimation results are presented in Table 5-4. The results shown under the column labeled “Univariate” correspond to those obtained by estimating each equation alone. In other words, the Univariate-Selection column presents the results of estimating Equation 5-6 using a univariate probit; while the Univariate-WTP column presents the results of estimating the traditional DB-DC model (i.e., Equation 5-7 alone). The results presented under the column labeled “Sample Selection” show the estimates obtained via Maximum Likelihood estimation of the DB-DC Sample Selection model.

The likelihood function in sample-selection models may behave in an irregular manner, but is usually well behaved for fixed values of ρ (Strazzera et al. 2003). Convergence of our sample selection model was achieved in three steps. In the first step, the model was allowed to iterate but the estimate of ρ was fixed at a value of zero. This first step obtained the estimates for the univariate models (Table 5-4). The second step used the univariate estimates as initial values in the sample selection model but restricted them so that only ρ could vary in each iteration. The last step allowed all parameter estimates to vary freely.[10]

The choice of variables in the selection equation was based on three criterions: (i) intuition as to which variables may possible affect interest and therefore decision to participate in the hypothetical market, (ii) preliminary univariate probit estimations testing for significance of the variables selected using the first criterion, and (iii) a close respect for parsimony.

Comparing the estimates obtained by the univariate models to those of the sample selection model shows no major differences in magnitude or in significance of the parameter estimates. This is similar to what was found by previous studies applying this model.

As explained earlier in this chapter, the existence of sample selection bias depends on whether the errors terms in the selection equation and the outcome equation are correlated. In the DB-DC Model, the error terms are jointly modeled as a bivariate standard normal distribution. Thus, sample selection is dependent on the value of the correlation parameter in the bivariate normal distribution (i.e., ρ). A value of ρ statistically significant different from zero would be evidence of sample selection bias affecting the univariate WTP model estimates.

Our estimated value for ρ is 0.307 with a p-value of 0.887 which is far from significant. Alternatively, one could test for sample selection by using the Likelihood Ratio (LR) test statistic[11]

---

[10] All of the estimations were carried out in GAUSS 7.0. using the maxlik add-in.

[11] Not the same as the one presented in Table 5-4. The LR statistic presented in Table 5-4 is a test for the global null hypothesis that all the betas are equal to 0.

$$LR = -2\,|\ln L_{Selection} + \ln L_{WTP} - \ln L_{SampleSelection}| \sim \quad \chi_1^2$$

where $\ln L_{Selection}$ and $\ln L_{WTP}$ are the log-likelihoods for the univariate models and $\ln L_{SampleSelection}$ is the log-likelihood for the sample selection model. The calculated LR statistic in our case was equal to 0.03=-2*|-54.29-193.01+247.28| which has a non-significant p-value of 0.84. Based on these two tests, it seems that no sample selection bias affected out estimates from Chapter 4.

It appears that farmers who decline participation in the hypothetical market presented by the CV exercise are making such decision independent of their WTP. Being a nonGM specialist was the only factor found to have a significant effect on the probability to participate – the effect is negative. Given no sample selection was detected, nonGM specialists who declined responding the GM CV question may have simply abstained from giving any comments regardless of their WTP for the GM trait.

One possible explanation for this is that farmers who chose not to participate in the hypothetical market may have done so simply because of the complexity associated with GM crop production. For example, the non-responding nonGM farmers may have been unaware (or improperly informed) of all the possible transaction costs and production requirements (e.g., fees, refuge practices) associated with GM crops and may have found themselves unable to construct their valuations. Another possible explanation for non-participation could be that nonGM farmers, regardless of their WTP for the GM trait, simply felt insufficiently motivated to give comments about a competing technology.

As a final note, one should be careful when interpreting the results and remember that, like any other ML estimate, the obtained estimates are validated by asymptotic theory. In our case, the fact that the model was empirically estimable is a good indication, but optimally, we would have liked a larger sample size. In our interpretation, we have assumed that sample size and variation have been sufficient, but we cannot provide definitive evidence that this is true given the complex nature of the model. In fact, an interesting research question for future studies could be determining appropriate sample sizes for the DB-DC Sample Selection model by use of Monte Carlo methods, for example.

Table 5-1. Regions, indicators, and possible answer sequences to DB-DC questions

Region	Indicator	P_i	P_i^L	P_i^H
4	I^{yy}	Yes		Yes
3	I^{yn}	Yes		No
2	I^{ny}	No	Yes	
1	I^{nn}	No	No	

Table 5-2. Types of respondents

	Initial bid	Follow-up
Respondents	√	√
Non-Bargainers	√	X
Non-Respondents	X	X

Table 5-3. Tabulation of responses to the fertilizer saving trait CV questions (nonGM and GM)

	GM question							
NonGM question	No No	No Yes	No Miss	Yes No	Yes Yes	Yes Miss	Miss Miss	Total
No No	77	4	1	3	3	0	16	104
No Yes	16	60	0	4	2	1	5	88
No Miss	1	0	7	0	1	0	2	11
Yes No	21	8	0	45	9	0	6	89
Yes Yes	13	5	1	9	100	1	14	143
Yes Miss	1	0	2	0	0	1	0	4
Miss Miss	0	1	0	2	0	0	9	12
Total	129	78	11	63	115	3	52	451

Table 5-4. Sample selection model estimation results

	Univariate				Sample Selection			
	Selection		WTP		Selection		WTP	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
constant	1.765**	(0.024)	2.733	(0.683)	1.802**	(0.027)	2.628	(0.717)
f_age	-0.008	(0.504)	0.096	(0.259)	-0.009	(0.497)	0.089	(0.355)
f_educ	0.134	(0.189)	0.740	(0.267)	0.133	(0.194)	0.824	(0.371)
f_nfjob	-0.333	(0.266)	-1.734	(0.394)	-0.340	(0.260)	-1.962	(0.458)
f_income	-0.029	(0.631)	0.868**	(0.030)	-0.025	(0.705)	0.840**	(0.063)
grain			-2.534	(0.300)			-2.477	(0.342)
earlyadopt			10.994**	(0.013)			11.008**	(0.013)
yield			0.003	(0.901)			0.003	(0.897)
seedcost			0.075**	(0.096)			0.075**	(0.097)
herbcost			0.090	(0.245)			0.090	(0.251)
insectcost			-0.027	(0.851)			-0.028	(0.845)
fertccost			0.051**	(0.078)			0.051**	(0.077)
farmsize			-0.002	(0.315)			-0.002	(0.315)
nonGM100p	-0.782**	(0.005)	-7.678**	(0.002)	-0.786**	(0.005)	-8.408	(0.120)
sigma			9.360**	(0.000)			9.465**	(0.000)
rho							0.307	(0.887)
N	174		155				174	
Log-likelihood	-54.294		-193.012				-247.288	
Mean WTP [i]			17.272**	(20.094)			16.287**	(4.011)
LR Index	0.550		0.548				0.544	
LR statistic [ii]	11.413*	(0.076)	131.608**	(0.000)			184.706**	(0.000)

[i] For Mean WTP the t-statistic is reported in parenthesis. Standard error for mean WTP was calculated using the Delta Method. [ii] LR statistic is for likelihood ratio test with $H_o : \beta_1 = \beta_2 = ... = 0$, sigma is left unconstrained. ** indicates significance level of 0.05 and * indicates significance level of 0.1.

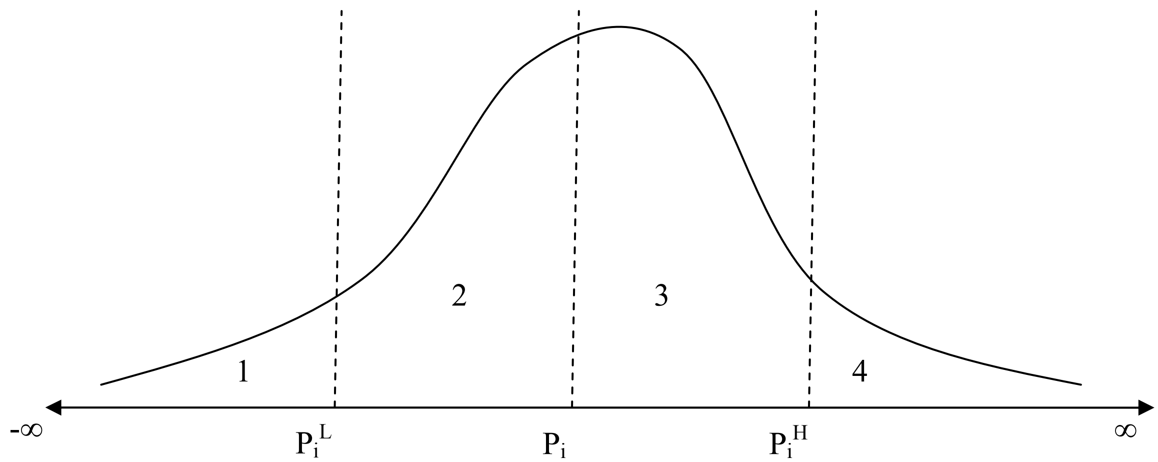

Figure 5-1. WTP regions based on the traditional double bounded (DB) model.

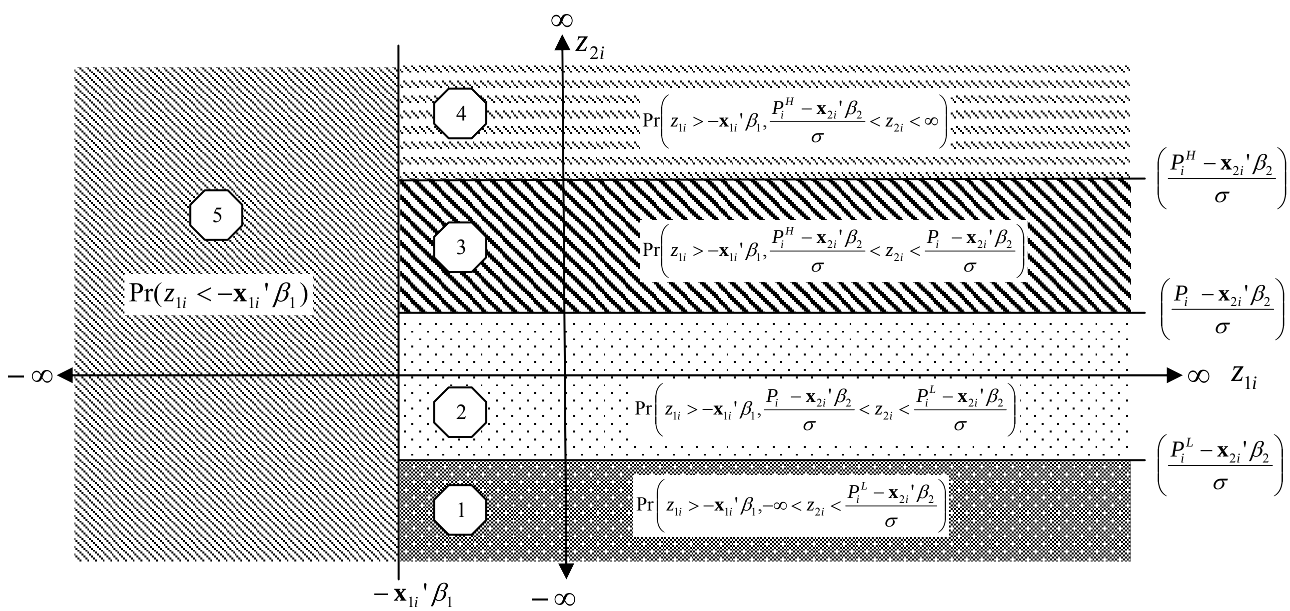

Figure 5-2. Regions over the (z_{1i}, z_{2i}) plane implied by the double bounded dichotomous choice (DB-DC) sample selection model.

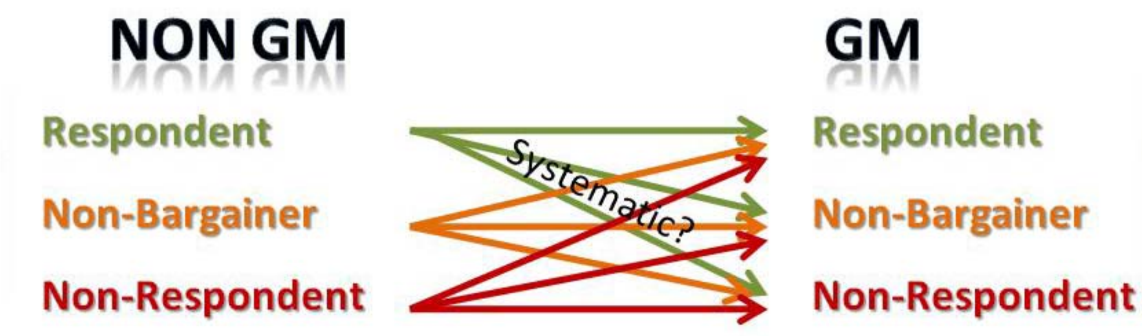

Figure 5-3. Possible changes in survey response behavior between the nonGM and GM questions.

CHAPTER 6
FURTHER RESEARCH AVENUES

In this chapter we further explore some concepts and assertions that were made in previous chapters and present some new concepts and hopefully some valuable insights. The discussion is centered upon the uncertainty in crop production. The model used in Chapter 4 considered production uncertainty by including expected profits $\bar{y}$ instead of simply profits y as the relevant variable influencing adoption decisions. Because of the framework of the model used in that chapter and because of the uncertainty inherent in agricultural production, the $\bar{y}$ approach seems more correct. A similar observation is made by Qaim and DeJanvry (2003) but ignored by Hubbell, Marra, and Carlson (2000). We provide an analysis of genetically modified (GM) seed technologies framing production uncertainty under the state contingent paradigm put forth initially by Arrow (1953, 1964) and Debreu (1952) and further developed by Chambers and Quiggin (2000).[1] As we shall see, the state contingent approach provides a more intuitive conceptualization of crop uncertainty.

Our purpose in this chapter is not that of developing and implementing a new theory, rather we hope that reframing and discussing GM crops and farming uncertainty under the more intuitive state contingent approach will help us shed some light on the GM crop farmer adoption scenario. “From an agronomic perspective, is there any inherent difference between GM seed inputs and any other agricultural input?” “Is it correct, as Qaim and DeJanvry (2003) suggest, to consider GM crops such as Bt varieties an *ex ante* imperfect substitute of more traditional inputs such as pesticide?” “Can we find any linkages between the state contingent approach presented here and the approach we followed in Chapter 4 that would reinforce our understanding of the GM seed adoption scenario?” These are some of the questions we try to answer here.

[1] See also Quiggin and Chambers (2006).

Besides the production model developed by Chambers and Quiggin (2000), the state-preference approach inaugurated by Arrow (1953,1964) and Debreu (1952) spanned another body of literature which is relevant to us. Graham (1981) formally developed the theory of option price under the state-contingent paradigm. At the end of this chapter we briefly discuss the concept of option price and again try to find the linkages between such approach and our findings in Chapter 4. Our analysis starts by discussing uncertainty in agricultural production.

Uncertainty in Agricultural Production

In the absence of knowledge, everything would be uncertain. If we had perfect knowledge about everything (including the future) uncertainty wouldn't exist. The ongoing objective of scientific human knowledge is to explain and gain control over our natural environment. As scientific knowledge evolves we develop more refined explanations of the world, we learn how our actions may affect outcomes in given states of the world, and we reduce uncertainty.[2]

This is true in all sciences and especially true in agricultural sciences since agricultural production relies heavily on the use of natural resources. The discovery and transition into agriculture by hunter gatherers (10,000 years ago) is in fact a good example of human attainment of understanding followed by appropriation and control of the natural environment to reduce uncertainty in the provision of food. It must be emphasized, however, that agriculture did not invent food production, photosynthesis already existed in nature. Agriculture simply gained us better control over the food production process that happens naturally in the plant.

Enormous advances have taken place since the first crop was grown by early proto-farmers. The set of possible actions provided by today's improved understanding of plant

[2] This is evident in the historic path followed by various physical sciences which started as primitive (sometimes metaphysical) explanations of rare observed events and evolved through time into sophisticated theories (Haavelmo 1944), and finally into practical applications used in industry and science.

biology and used to obtain desired outcomes with more predictability, may be categorized into two distinct strategies: (i) taking actions to control and modify the environment surrounding the plant, and (ii) taking actions to control and modify the metabolism and genetic material of the plant itself. The latter strategy is consistent with the action taken by farmers who adopt GM seeds. Although both strategies have different implications in terms of who is appropriating the benefits and the knowledge acquired through developing and implementing the action, we will argue that from an economic perspective which is less concerned with the distribution of these benefits but, rather, with the analysis of uncertainty, the two strategies may be analyzed using similar conceptual frameworks.

Strategy 1: Modifying the Environment Surrounding the Plant

The first strategy is to take actions in order to modify the environment immediately surrounding the plant. We now have a more or less complete knowledge of the natural factors (water, nitrogen, air, etc) that play a role in photosynthesis and that regulate crop metabolism and growth. Each crop and even each crop variety has its own characteristics. We have developed an extensive knowledge bank of optimal levels of these factors that more consistently produce high output outcomes. An army of agronomists, entomologists, plant pathologists, soil scientists, and other agriculture professionals are constantly working to expand our understanding of crop plants by performing controlled trials and presenting us with results such as optimal nutrient requirements, pest population dynamics and thresholds, water requirements, and the like.

From the perspective of a farmer whose goal is that of output maximization, nature results inefficient in providing optimal levels of production factors where and when they are necessary. Nature is unpredictable and inconsiderate to the farmer's goal of output maximization. Timely and efficient modification of the environment surrounding the plant has required the understanding and appropriation of the natural cycles of the implicated natural factors. Whereas nature provides us with uncontrollable and unpredictable factors necessary in crop production, we are persistently finding ways to appropriate those factors and develop proper (more controllable) substitutes that we use to supplement natural supplies when they are deficient. The water cycle has been appropriated to produce irrigation that supplements rainfall, the nitrogen cycle has been appropriated to produce fertilizers that supplement natural fixation by microorganisms, etc.

In microeconomics, these appropriated natural factors are called inputs. Inputs are used in agriculture to supplement uncertain natural supplies when the situation requires so[3] – for example, irrigation supplements deficient natural rainfall, fertilizer supplements low concentrations of nutrients in soil. In contrast with natural supplies, inputs are: costly and controllable. Natural supplies, on the other hand, are uncontrolled by the farmer, are free, and their provision levels are uncertain.

Strategy 2: Modifying the Genetic Material of the Plant Itself

A second strategy for reducing uncertainty is to "control" the metabolism of the crop by modifying its genetic composition. Rather than gaining control over the plant's environment, plant breeders and crop engineers are in the business of appropriating the genetic material of the crop itself. By altering the genetic material of crops, either by sexual reproduction or by recombinant DNA techniques, scientists are able to endow crops with previously identified desirable traits.

As with the case of other natural factors, here also nature is inconsiderate of the farmer's goals. There is no guarantee, nor there should be, that natural selection and mutation will provide the agronomic-desired genetic material. The use of genetic engineering and selective breeding to

[3] Which situations are considered to require supplementation depend on the requirements of the crop and the farmer's goal which is usually taken to be output maximization.

confer desired genetic material (and traits) to a crop is simply a way to supplement the uncertain genetic material provided by natural mutation and natural selection. Thus, from an agronomical perspective, appropriating the genetic material in a crop and "controlling" it is, in essence, no different than appropriating any other resource provided by nature. As such, in technical terms, conferred genes (or traits) could be seen as inputs in the production function with no fundamental difference to water, fertilizer, etc.

State Contingent Model of Production

The uncertainty inherent in GM crop adoption has traditionally been oversimplified and sometimes even neglected. Analogously, the analysis of crop production in general, models uncertainty using a stochastic production function which is simply a production function with a random error term added to it:

$$y = f(\mathbf{x}) + \varepsilon \tag{6-1}$$

This approach assumes that the decision maker cares only about the distribution of outcomes or payoffs he receives, not about the underlying events, or states of nature, that cause these outcomes. This approach is more consistent with a lottery apparatus generating these outcomes, rather than with natural factors that are localized and differ across individuals. When the random outcomes are generated by some underlying causes, a more detailed description of uncertain alternatives is possible. For example, Chambers and Quiggin (2000) propose a slightly different approach to modeling production under uncertainty based on the notion of state contingent production. Rasmussen (2003) notes that one of the major problems with the stochastic production approach is that the well-known marginal principle used to prescribe optimal production decisions (i.e., MC=MR) under certainty breaks down under uncertainty. Quiggin and Chambers (2004) argue that an even more critical weakness of the stochastic approach is that it is not amenable to diagrammatic analysis of the kind that remains the main source of intuition for economists studying production under certainty. The state-contingent approach, on the other hand, permits the application of a whole range of concepts developed for production theory under certainty, including both marginal and diagrammatic analysis and duality theory.

In the basic state-contingent model with only one output there are N different inputs and $S \in \Omega$ possible states of nature. Inputs $\mathbf{x} \in \Re_+^N$ are committed *ex ante* and fixed *ex post*. The state contingent output (or output profile) $\mathbf{z} \in \Re_+^{Sx1}$ is chosen *ex ante* but produced *ex post.* Uncertainty enters the model through the stochastic states of nature represented in the probability space $\Omega = \{1,2,..,S\}$.

The model may be understood as a two period game with nature. In period 0 (i.e., ex ante) the decision maker commits inputs $\mathbf{x} \in \Re_+^N$. The level of inputs she commits determines the vector of possible outcomes $\mathbf{z} \in \Re_+^{Sx1}$ she may observe in all possible states of nature, the exact outcome depending on which state of nature occurs. Nature "reveals" the state of nature after the decision maker has committed $\mathbf{x} \in \Re_+^N$; this results in output $z_s \in \mathbf{z}$ being produced in period 1 (i.e., ex post). [4]

The state-contingent approach seems to be a very good conceptualization of farming activities. On the field, the farmer commits inputs *ex ante* towards production but he does not immediately reap the products, he must wait for the crop to complete its cycle in order to harvest.

[4] A fundamental presumption of the state-space approach is that the decision maker can do nothing to determine which state of nature will occur. The states of nature, redundantly speaking, are provided by nature and uncontrolled by the decision maker. This does not mean, however, that the decision maker is impotent when it comes to the future. Instead of her decisions affecting which state of nature occurs, they affect the outcome realized if a given state of nature occurs. For example, a farmer may not be able to influence the chance of rain but he may be able to take actions that prepare him in the case of drought.

Basically, life and growth takes time. In the mean time, as crop growth takes place, there are numerous possible states of nature that may have different influences over output and make it uncertain. *Ex post* nature reveals the state of nature and a given output results. However, one could still think of a more careful treatment of the time component. In the following subsections we introduce some new concepts (i.e., perfect timing and perfect supplementation) that allow for a more detailed treatment of the time component; of uncertainty; and of their interactions with information technologies and characteristics inherent to the different production inputs.

Perfect Information, Perfect Timing, and Perfect Supplementation

For the sake of argument, suppose for a moment that seed is sowed on a field and then no other action is taken by the farmer (i.e., zero inputs). In this case, the uncertainty in nature's provision of natural factors will traduce directly into uncertainty in yields. For example, all other natural factors fixed, if nature provided deficient (optimal) rainfall this would traduce directly into low (high) yields. Of course, the farmer wouldn't be much of a farmer if he were to let nature alone dictate his year to year output.

To continue this argument, let us now try to picture what may be considered the other extreme. What should happen and what actions should the farmer take to completely eliminate uncertainty in yields so that he obtains the same yield every single time regardless of what nature does? In order to answer this question, let us for a moment ignore that inputs are costly. First, suppose that some new information-gathering technology provides the farmer with the ability to know exactly how much of each factor (e.g., water, nutrients) is provided by nature at any given moment in time to the plant (i.e., the farmer has perfect information). In addition, suppose some other technology allows the farmer to take action on this new information and supplement natural provision on a real-time basis (i.e., perfect timing). Given this perfect information about what enters and leaves the production system and the ability to supplement with perfect timing, in theory, a farmer should be able to perfectly increase or decrease supplementation as necessary and completely eliminate yield uncertainty. This makes sense agronomically because, for example, the plant doesn't mind where the water is coming from, whether it is from irrigation or from natural rainfall. Of course, this implicitly assumes that controlled inputs are made to quality standards that make them perfect substitutes of natural factors.

The assumptions made – perfect information and perfect timing – to achieve perfect supplementation are quite extreme. They are, however, the ultimate (possibly utopian) goals of precision agriculture. Precision agriculture uses information-gathering and input-delivery methods and technologies (e.g., soil mapping, geostatistics, geographical information systems, weather forecasting, GPS) to manage natural resource variability.[5]

In the going we have ignored costs. Notice, however, that supplementation entails costs. For example, obtaining a normal yield (z^h) in corn requires around 22 inches (2,250 m^3) of water per acre during the growing season (Wright et al. 2008).[6] Suppose rainfall during the growing season is 16 inches (1,635 m^3) per acre. This means that in order to obtain yield z^h the farmer will have to incur the costs associated with supplementing the 8-inch (615 m^3) water deficit via irrigation. If rainfall during the season were to be only 10 inches (1,022 m^3), the farmer would have to incur higher irrigation costs necessary to supplement not 8 but 12 inches of water via irrigation in order to obtain the same yield z^h. As should be obvious, perfect supplementation eliminates uncertainty in yield but traduces it to uncertain, potentially high costs.

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[5] See Precision Agriculture Journal aims and scope available at http://www.springer.com/life+sci/agriculture/journal/11119?detailsPage=aimsAndScopes.

[6] This depends on timing of supply (e.g., emergence, maturity) and on other production practices (e.g., fertilization, pest management).

Perfect Supplementation and the State Contingent Approach

In our example of perfect supplementation, we argued that given the right tools there is no reason why the farmer shouldn't be able to completely eliminate uncertainty in yields that follows from uncertainty in states of nature. We also argued that using perfect supplementation to eliminate uncertainty in yield simply traduces to uncertainty in costs. Quiggin and Chambers (2004) make this same point: "in the state-contingent model, output uncertainty is a result of producer choices. Producers, if they choose, can stabilize output completely, though they may incur (potentially very large) costs in doing so." In making this note, Quiggin and Chambers seem to make the same assumption of perfect information we used to discuss perfect supplementation.

However, the additional assumption of perfect timing that we use to define perfect supplementation implies that no two-period game takes place between farmer and nature. That is, if not only the farmer could monitor perfectly each production factor (e.g., water, nutrients) but also supplement found deficiencies on a real-time basis, then he could avoid acting before nature and eliminate uncertainty. No *ex ante* or *ex post* is necessary, everything happens on the spot.[7]

Seed Technologies

Before making quick generalizations, we should ask ourselves "Is perfect supplementation is possible for every input in agricultural production?" To answer this, let us first note that agro-ecological systems are an incredibly dynamic place. Factors constantly enter and leave the system. Nitrogen, for example, may enter the system by fixation or fertilizer application and leave the system via leaching, volatilization, or denitrification. Water may enter via rainfall or

[7] Of course, in practice this does not happen for obvious reasons (costs, time), but entertaining the example help us gain some insights.

irrigation and leave via evaporation or drainage. Pests and weeds appear and are allowed or forced to disappear. One factor, however, is a constant in the system – the seed.[8]

For the case of seeds, the farmer must necessarily engage in a two-period game with nature. Gathering more and better information or improving timing in delivery (i.e., precision agriculture) will not allow the farmer to avoid acting before nature in the case of seed inputs. The decision on quality and type of seed is made once and only once at the beginning of the growing exercise. Other factors may enter and leave the system by natural means or by actions taken by the farmer. Removing the seed from the field means the end of the farming exercise.

Thus, the case for a state contingent approach to uncertainty seems more robust when dealing with seed technologies. Going back to our definitions of strategy 1 and strategy 2, one could say that, given cost and technological limitations that proscribe perfect supplementation, the state-contingent approach makes a good conceptualization of the farming situation for both strategies; but if perfect supplementation were possible, the state-contingent approach would still be a good conceptualization for strategy 2.[9]

As for GM crops, one should consider that genetic traits are embedded in the seed. It should be clear now that in contrast to other inputs which may allow some flexibility, the decision of whether to adopt or not adopt a GM seed technology is necessarily *ex ante*. This reasoning is consistent with our findings in Chapter 4, where we argued[10] that GM seed technologies may be seen by the farmer as imperfect substitutes for other production inputs because of their *ex ante* nature.

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[8] Soil structure may also be constant.

[9] Only if the farmer had perfect information about the future could the farmer "avoid" playing a two-period game with nature.

[10] Like Qaim and DeJanvry (2003).

State-General and State-Specific Inputs

At this point, we should define some concepts developed in the state contingent literature before continuing our discussion of GM crops. Rasmussen (2003) distinguishes between two important different types of inputs: state-general and state-specific. For simplicity, following Rasmussen, in the following we will consider only two states of nature $\Omega = \{1,2\}$. A state general input (Figure 6-1) is defined as an input that influences output in one or more states of nature. Part A of Figure 6-1 shows the production function $f_1(x_1)$ for the state-general input x_1 in state 1.[11] Different levels of contingent output z_1 are obtained for different levels (a, b, and c) of x_1. In state 2 (Part B) varying x_1 also has an effect on contingent output, in this case z_2, via the production function $f_2(x_1)$. The possible pairs of contingent outputs for each level (a, b, and c) of x_1 (i.e., the transformation curve) are shown in Part C.

An example of a state-general input given by Rasmussen is fertilizer in grain production. In this case one could think of "wet weather" as state 1 and "dry weather" as state 2. State contingent output $z_1 = f_1(x_1)$ in the case of "wet weather" increases with fertilizer application. In the case of "dry weather" one can still improve output by applying fertilizer, but the effect on output for each extra unit of fertilizer is smaller as shown by a lower $f_2(x_1) < f_1(x_1)$.

A state-specific input is presented by Rasmussen as a special case of state-general inputs. A state-specific input is one that influences output in only one state of nature (Figure 6-2). If the state-specific input has an effect on output in state 1 (Part A), it will have a flat production function $f_2(x_1)$ in state 2 (Part B); its transformation function will also be flat (Part C).

[11] All other inputs are assumed fixed.

An example of a state-specific input given by Rasmussen is a pesticide that is only effective under dry weather conditions. The states of nature are the same as for our last example. If the farmer applies the pesticide and state 2 (dry) occurs, the pesticide is effective and a higher yield result. On the other hand, if state 1 occurs, marginal increases in pesticide applications have no effect on output.

Several conclusions may be derived from these definitions. First, all else fixed, state-specific inputs, since they result in larger variability between states of nature, are riskier than state-general inputs.

Second, whether an input classifies as state-general or state-specific depends on how we define the set Ω of states of nature. For example, if we considered three states "wet", "dry", and "very dry"; then the pesticide example may classify as a state general input. If instead we considered the two states "water" and "no water" then fertilizer may classify as state-specific instead of state-general. If it is the decision maker who defines the state set Ω, then a discrete set would be consistent with a view of decision makers as having bounded rationality. The decision maker uses heuristic methods to find the "optimal" action by defining a discrete number of plausible states of the world. The decision maker holds positive (>0) subjective probabilities $\pi_{\Omega}, \Omega\{1,2,...,S\}$ about each plausible state.

Finally, one could think of a third type of input – a perfectly state-general input. Such input may be defined as an input that has the same effect on yield in all possible states of nature (Figure 6-3).[12] A perfect state-general input would completely eliminate uncertainty in yields with respect to that input.

[12] As should be obvious from our "water" and "no water" example, if we consider all possible states of the world (not only those that are plausible) this type of input is impossible since it would imply that no essential factors exist in agricultural production.

Genetically Modified Traits: State Specific or State General?

In this section we see how different traits in the market (or in development) may be identified as different types of inputs based on Rasmussen's categorization.

For example, glyphosate herbicide tolerance (Ht), the most widely adopted trait, seems closer in its characteristics to a state-general input. It is generally recognized that producers of Ht crops benefit mainly from lower costs and ease of use. In most farming scenarios, chemical control results less costly than hand-weeding (e.g., Gianessi et al. 2002). The decision to adopt the Ht trait is usually depicted (in terms of gains in profitability) as depending on whether cost savings in weed control are larger than seed cost premiums.

Glyphosate is a wide-spectrum control herbicide that provides effective weed control in most cases. However, if applied on conventional crops it will also kill the crop. For conventional crops, the systemic and unselective mechanism of glyphosate requires careful application to avoid crop poisoning. The possibility of output losses due to careless application by field workers gives place to a principal-agent problem. Gains in "ease of use" from adoption of Ht varieties, as Fernandez-Cornejo and McBride (2002) put it, occur because "herbicide tolerant programs allow growers to use one product instead of several herbicides to control a wide range of both broadleaf and grass weeds without sustaining crop injury." Carpenter and Gianessi (2001) state that "the primary reason growers have adopted Roundup Ready weed control programs is the simplicity of [the] weed control program."

Because of its wide-spectrum and its systemic mechanism, glyphosate would be a good example a state-general input. Applied on conventional crops, it has an effect on output (i.e., a negative one) in more than one, possibly all states of the world. Suppose the farmer sets out (prior to planting) to use glyphosate herbicide for controlling any emerging weed competition. In doing so the farmer has narrowed the set of possible states of nature. All possible states of nature will now include the presence of glyphosate on the field. For simplicity, consider only two states of nature: "state 1, glyphosate" and "state 2, glyphosate". Let x_1 (in Figure 6-1) represent the proportion of total acres planted with Ht varieties in a given farm unit. Since the Ht trait is simply an antidote to glyphosate, given the sure presence of glyphosate on the field, changes in the level of x_1, by definition, should have an effect on output z_s in both states of nature (i.e., x_1 is state-general).

The "ease of use" so often associated with Ht adoption may be explained in part by the farmer's newly endowed ability to narrow the state set Ω (i.e., reduce uncertainty).[13] The design is simplified by an *a priori* decision for using glyphosate. The farmer avoids having to decide which herbicide to use on a case by case basis. The farmer also avoids having to monitor the careful application of the glyphosate herbicide. The *a priori* decision is possible because of: (i) the availability of a glyphosate tolerant variety, (ii) the wide spectrum of weed control and effectiveness over different states of nature of glyphosate herbicide (i.e., state-general input), and (iii) the stability and predictability of annual weed infestations.

The second most adopted trait is insect resistance (Bt). The main benefit generally associated with Bt seeds is an increase in yields as crop losses due to pest infestation are reduced. The Bt trait seems closer in its characteristics to a state-specific input. In contrast to weed infestations, annual pest infestations are less stable and less predictable (Gray and Steffey 1999). Insects are much more mobile than weeds. Such mobility allows insects to search for the best food available and concentrate in most favorable areas or niches, leaving surrounding crop areas mostly unaffected. In addition, insect populations, even when unchecked by farmers, remain checked by populations of natural enemies. All of these factors make the frequency of crop

[13] Adoption of Ht varieties may ease farming in other aspects, like for example, allowing the implementation of no-tillage systems.

damage due to pest infestation to differ across geographic regions and vary between growing seasons. It seems reasonable to consider the following two states of nature: “pest” and “no pest”. Let x_1 (in Figure 6-2) represent the proportion of total acres planted with Bt varieties in a given farm unit. Changes in the level of x_1 (i.e., rate of adoption) will only have an effect on output in the state of nature “pest”.

In the case of a Bt trait the farmer purchases the seed with the trait *ex ante* in case a pest infestation occurs. At the moment of purchase he is not sure that he will actually make use of the trait. If no infestation occurs the farmer still pays the technology fee but observes the same yield he would have observed with a similar crop variety that did not posses trait. This is, in essence, similar to what farmers do when they purchase crop insurance. With insurance, the farmer pays a risk premium and receives compensation only if certain states of nature (that are previously defined in an insurance policy) occur. This resembles closely what we argued in Chapter 4 and what seems to be part of the reasoning behind the implementation of the Biotech Yield Endorsement.

Consider now the drought tolerance (DT) and fertilizer saving (FS) traits. We can compare these two traits by analogy with the Ht and Bt traits. Like insects compared to weeds, natural water supplies are much more unpredictable and variable than natural nutrient supplies of nutrients which are more easily predicted and in general less variable. Like the Bt trait, the DT (as we argued in Chapter 4) may serve as a substitute for crop insurance. When adopting a DT trait (i.e., against severe drought), the farmer holds a relatively larger probability of not using it (i.e., no severe drought occurs) compared to the case where he adopts a FS trait.

A final point in this subsection can be made by considering our definition of a perfectly state-general input. As we defined it, such input has the same effect on yield in all possible states of nature. A perfect state-general input would completely eliminate uncertainty in yields with respect to that input. A seed technology with this characteristic, even though planted *ex ante*, would hold no uncertainty and so in some sense it would allow the farmer to avoid playing the two-period game with nature.

For example, consider a perfectly state-general version of the DT trait and a set of possible and plausible states of nature that spread across a spectrum ranging from "no drought" to "severe drought". That is, suppose multiple traits with different methods of action were inserted into the crop seed so that the same yield was obtained regardless of which of these states of nature occurred. Such a trait would eliminate uncertainty.

What is more interesting is that such trait would substantially reduce or even eliminate the need to gather information related to irrigation, rainfall, and other water supplies. Although being a bit of a stretch, this example provides a valuable insight. What it implies is that improvements in seed technologies may have the effect of deeply altering the information data sets gathered by farmers. In fact, to some extent, seed traits may reduce the need for information-intensive technologies such as precision agriculture. It is not hard to see how stacked or multiple trait varieties, as they become more state-general (e.g., Bt varieties that control a larger number of insect species or glyphosate which controls most weed species), will provide farmers with "ease of use" such as the general application of glyphosate over glyphosate-tolerant varieties as opposed to the more precise application needed for non-tolerant varieties.

Option Price

Besides the production model developed by Chambers and Quiggin (2000), the state-preference approach inaugurated by Arrow (1953, 1964) and Debreu (1952) spanned another body of literature which is relevant to us. Graham (1981) formally developed the theory of option value under the state-contingent paradigm. The related concept of "option price", presented initially by Weisbrod (1964), is defined in the CV literature as the price a current non-user would be willing-to-pay for a good in order to secure the possibility of future use of that good.

The definition of option price, as presented by Graham (1981), considers two possible states of the world. In state 1 the individual is a “user” of the good while in state 2 the individual is a “non-user”. Graham defines option price as “the sure payment [the individual] would be willing to make in both states.” The concept may be readily adapted to develop a model of GM crop/trait adoption as follows.

We prefer the terminology “states of nature” as opposed to “states of the world” to emphasize the farmer’s inability to influence which state occurs. We take state 1 to be “pest” and state 2 to be “no pest”. Let $\pi_s, S = \{1,2\}$ represent the respective subjective probabilities associated with each state of nature. Adoption of the GM trait q is represented by q^1 while non-adoption is represented by q^0. The farmer’s utility is assumed contingent on the state of nature and on whether the farmer adopted the trait:[14]

$$u_s(q^j, y_{js}) \quad ; \quad j = \{0,1\}, s = \{1,2\} \tag{6-2}$$

where y_{js} represents the profits (net of the trait’s technology fee) observed if adoption decision j is made and state s occurs. Expected utility for a non-adopter is given by

$$\overline{U} = (\pi_1)u_1(q^0, y_{01}) + (\pi_0)u_0(q^0, y_{00}) \tag{6-3}$$

The option price OP is defined as the *ex ante* payment the farmer is willing to make which satisfies

$$(\pi_1)u_1(q^1, y_{11} - OP) + (\pi_0)u_0(q^1, y_{10} - OP) = \overline{U} \tag{6-4}$$

[14] To avoid confusion between the notation used in this chapter for inputs and that used for farm and farmer attributes in Chapter 4, we suppress $\mathbf{x}$ from the derivation.

At any offered price P the farmer will adopt the technology if the expected utility under adoption equals or exceeds expected utility under no adoption. Formally this is given by

$$(\pi_1)u_1(q^1, y_{11} - P) + (\pi_0)u_0(q^1, y_{10} - P) \geq (\pi_1)u_1(q^0, y_{01}) + (\pi_0)u_0(q^0, y_{00}) \qquad \text{(6-5)}$$

In contrast to the model presented in Chapter 4 where the argument entering utility was expected profits $\bar{y}$, here profits are known to the farmer at each state of nature and adoption choice. What is uncertain is the state of nature that will occur. The expectation is taken over states of nature using subjective probabilities as weights.

As noted by Chambers and Quiggin (2006), empirical applications of the state contingent model have proven challenging. The main obstacle is that nature reveals only one of its states so that only one outcome is observable. This is the same problem we found in Chapter 4 when we pointed out that expected changes in profits are unobservable.

However, at a very general level, we could express the expected utility as $E[u(.) \mid \pi_0, \pi_1] = \overline{U}$ which highlights the dependence of expected utility on the probabilities of each state of nature. This representation goes in line with the models estimated in Chapter 4 giving us some intuition on why specific variables (i.e., *mD2*) were found to be significant.

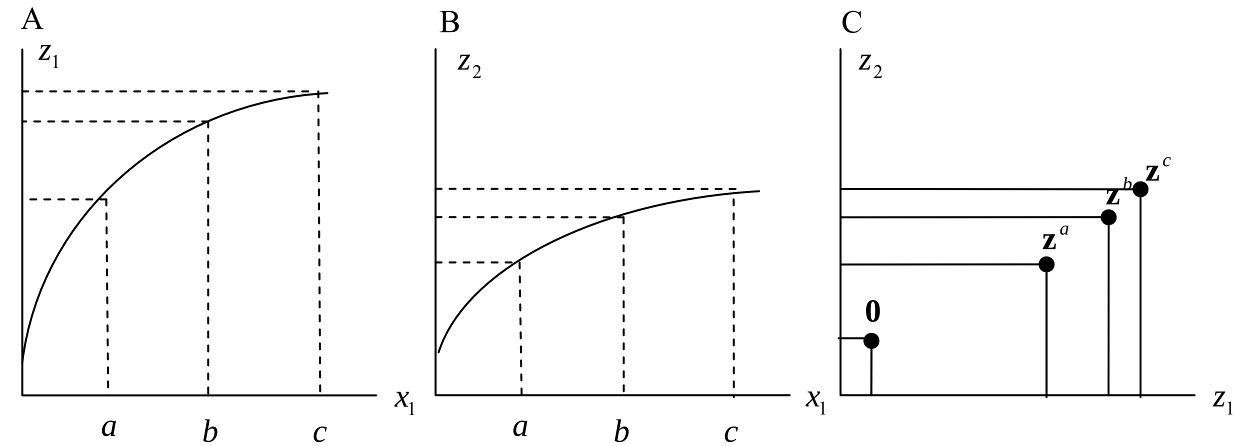

Figure 6-1. Representation of a state-general input and its transformation curve.

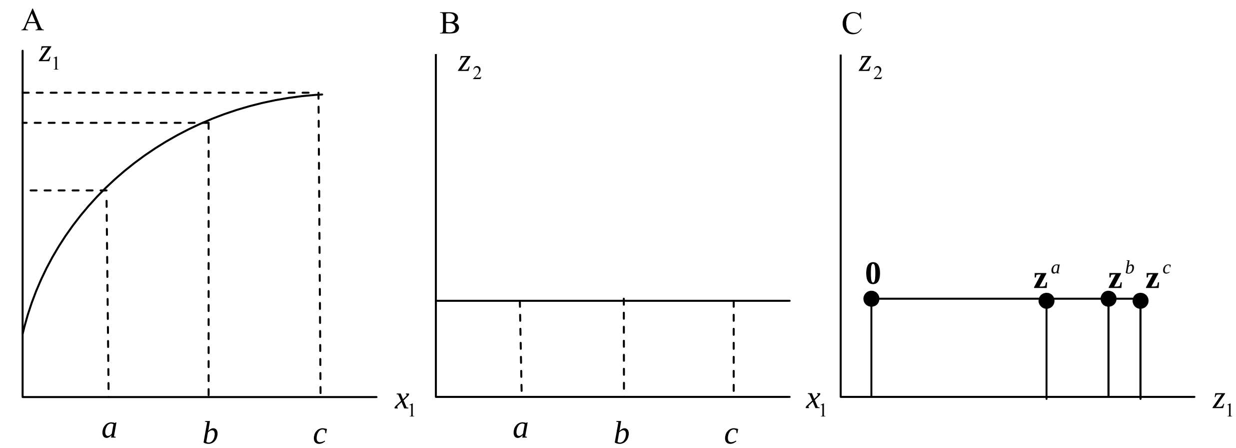

Figure 6-2. Representation of a state-specific input and its transformation curve.

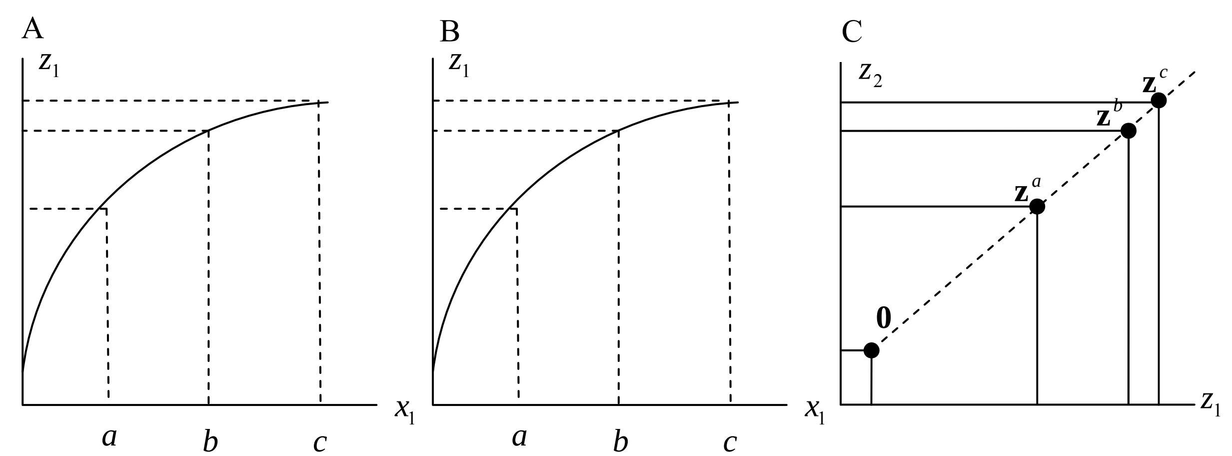

Figure 6-3. Representation of a perfectly state-general input and its transformation curve.

CHAPTER 7
CONCLUSIONS

Biotechnology has permitted the rapid production of GM seeds products (i.e., biotech crops) that are differentiated by trait (e.g., RoundupReady with herbicide tolerance, YieldGard with insect resistance). Since first commercialized in 1996, biotech crops have taken the U.S. and the global seed industries by storm. As of 2008, only 12 years into commercialization, cumulatively more than two billion acres have been planted at the global level with GM crops. In 2008 only, GM crops accounted for 125 million hectares planted in 25 different nations. Four crops (soybean, maize, cotton, and canola) and two traits (herbicide tolerance and insect resistance) have traditionally represented the bulk of the market. However, the dominance of these two traits may change in future years with the release and approval of several new traits which are currently at advanced development stages in the R&D pipelines of seed companies.

Two new specific traits are of current interest in maize: FS and DT. An important contribution of this study is the production of estimates of farmers' WTP for these two forthcoming traits. The estimates we obtained are for corn farmers in Minnesota and Wisconsin; however, our results at the local level should provide valuable insights which may guide further studies evaluating adoption of these traits on other regions. A novel design in our study was the comparison of GM and nonGM versions of the same trait. In total, four traits were presented for farmers' valuation: (i) FS-GM, (ii) FS-nonGM, (iii) DT-GM, and (iv) DT-nonGM.

Our results (Chapter 4) show that the agronomic benefits of these traits are recognized by farmers who assign them a positive value in dollars. For the FS trait, in average, farmers were willing to pay around $19.72 per acre for the nonGM version of the trait and $17.25 per acre for the GM version. For the DT trait we found a mean WTP of $20.87 per acre for the nonGM version and $18.73 per acre for the GM version.

In both FS and DT traits, in average, farmers are willing to pay more for the nonGM version compared to the GM version – \$2.47 and \$2.14, respectively. At first glance, an important farmer characteristic driving this wedge appears to be whether the farmer is specialized in nonGM production or not. Estimation results show that, whether due to personal preferences or because of associated market risks, nonGM farmers consistently penalize the trait if it is GM. On the other hand, being a nonGM specialist has no influence on the farmer's valuation of nonGM traits.

Other than the asymmetric effect of nonGM specialization, we find that the factors with statistically significant effects on valuation and adoption, and the direction and magnitude of those effects, are similar for the nonGM and GM versions of both the FS and the DT traits. Some important factors increasing farmer's WTP for these traits are: purpose of production, type of adopter and familiarity, farm income, and costs of substitute inputs. Some interesting results relating to the estimates obtained for the effects of these factors on WTP should be highlighted.

For example, those farmers identified as early adopters showed a much larger WTP for all of the new traits compared to non-early adopters. The effect was in fact the largest among the positive effects, ranging between \$9.61 and \$14.96 per acre across the traits. The effect was consistently found to be larger for the GM versions of each trait suggesting familiarity with GM technologies plays a role in farmers' valuations. These results may have interesting implications for seed companies' pricing strategies, for example, suggesting the potential to offer new products at introductory marked-up prices to capture the significantly larger rents that early adopters are willing to pay.

Another interesting result relates to the effects on WTP associated with substitute inputs. For example, farmers with higher fertilizer costs showed willing to pay more for a FS trait; while farmers that pay more in crop insurance showed willing to pay more for the DT trait. More interestingly, the substitution effects in both traits for both substitute inputs were found to be less than perfect (i.e., less than a dollar for a dollar). In Chapter 4 we argued that such imperfect substitution may be due to the fact that seed traits are *ex ante* inputs. This argument was reinforced in Chapter 6 by framing production uncertainty under the state contingent production model of Chambers and Quiggin (2000). There, a careful treatment of the time component and of the characteristics of the different inputs used in agricultural production showed that seed traits are, by their nature, necessarily *ex ante* inputs; while the "*ex anteness*" of every other input in agricultural production depends largely on the farmers ability to engage in perfect supplementation (i.e., identifying and perfectly supplementing deficiencies (water, nutrients, etc) on a real-time basis).

In Chapter 4 we were also able to plot adoption curves using the individual predicted WTP values obtained from our model and were able to say something about the adoption potential of GM seeds compared to nonGM seeds. Results from non-parametric tests suggest that nonGM versions of each of the traits studied, in general, hold better adoption potential than GM versions. For the FS trait, the adoption curve of the nonGM version stochastically dominates that of the GM version, which implies an unambiguous dominance in adoption potential of the nonGM version.

At prices above $20 per acre the adoption potential for both versions (GM and nonGM) of both traits is similar. Moreover, there is a sharp increase in the difference of adoption potentials at the $20 per acre mark (i.e., the curves separate from each other). Finally, as prices drop below this mark, the two adoption curves (GM and nonGM) move separately but in parallel fashion. These shapes of the adoption curves may be indication that different market segments are being captured at prices below or above the $20 per acre mark. Further investigation of this assertion should be an interesting topic for future studies. If it turns out to be correct seed companies could benefit by understanding how these two market segments differ in their characteristics (age, education, income, location, etc).

In Chapter 5 we investigated the possibility that sample selection bias may be affecting our estimates of farmer's WTP for the traits. Testing for sample selection in our results from Chapter 4 was important because if detected it would suggest inconsistent estimates for the parameters of the population initially targeted. The application of a sample selection model was motivated by the observation, in our sample, of a considerably larger number of non-respondents to the CV questions concerning the GM version of a trait compared to the number of non-respondents to CV questions concerning the nonGM version of the same trait. Testing for sample selection in a DB CV is not trivial, and has in fact escaped the CV literature until recently.

We estimated the DB-DC sample selection model proposed by Yoo and Yang (2001) and tested for sample selection bias in the WTP estimates for the FS GM trait. The model assumes a bivariate normal distribution for the normalized errors in the two equations forming the model. Mathematically, sample selection is present if there is correlation between these error terms (i.e., $\rho \neq 0$). Results from both a Likelihood Ratio Test and a t-test suggest no evidence of sample selection bias in our data. However, as was the case with our WTP estimates, being a nonGM specialist also played an interesting role in our analysis of sample selection. NonGM specialists were less likely to participate in the hypothetical market presented in the Contingent Valuation exercise. This finding does not necessarily contradict our assertion of no sample selection since nonGM farmers who chose not to participate in the hypothetical market may have done so simply because of their unfamiliarity regarding the complexity associated with GM crop production. For example, the non-responding nonGM farmers may have been unaware (or improperly informed) of all the possible transaction costs and production requirements (e.g., fees, refuge practices) associated with GM crops and may have found themselves unable to construct their valuations.

Two important notes should be made about the estimation and interpretation of these results. First, as pointed by Strazzerra et al. (2003), the likelihood function of sample-selection models may behave in an irregular manner, but is usually well behaved for fixed values of ρ. Convergence of our sample selection model was achieved in three steps. In the first step, the model was allowed to iterate but the estimate of ρ was fixed at a value of zero. This first step obtained the estimates for the univariate models (Table 5-4). The second step used the univariate estimates as initial values in the sample selection model but restricted them so that only ρ could vary in each iteration. The last step allowed all parameter estimates to vary freely.

Second, while the fact that our sample selection model was empirically estimable is a good indication; optimally, we would have liked a larger sample size. In our interpretation of the DB-DC sample-selection model results we have assumed that sample size and variation have been sufficient, but we cannot provide definitive evidence that this is true given the complex nature of the model. In fact, an interesting research question for future studies could be determining appropriate sample sizes for the DB-DC Sample Selection model by use of Monte Carlo methods, for example.

While the prospect of higher yields and higher profitability remains one of the most important factors determining adoption (Chapter 4), another important factor that should influence adoption is the prospect of more consistent yields and profits (i.e., reducing uncertainty) (Chapter 6). Nevertheless, the uncertainty inherent in GM crop adoption has traditionally been oversimplified and sometimes even neglected. In Chapter 6 we presented an analysis of the GM crop adoption scenario faced by the farmer while emphasizing the uncertainty in agricultural production throughout the discussion. We treated uncertainty by framing it under the state contingent production model of Chambers and Quiggin (2000). We also identified two main strategies that farmers use to obtain desired outcomes with more predictability: (i) taking actions to control and modify the environment surrounding the plant, and (ii) taking actions to control and modify the metabolism and genetic material of the plant itself. Some interesting conclusions from Chapter 6 are worth mentioning.

For example, as discussed earlier, the "*ex anteness*" of seed traits seems to be more pervasive than the "*ex anteness*" of other agricultural inputs. For other agricultural inputs, the farmer may eliminate uncertainty and the need to act *ex ante* (i.e., before nature reveals its state of nature) by perfectly monitoring and perfectly supplementing found deficiencies on a real-time basis – although he would incur in potentially large costs. The type of technologies the farmer needs to achieve this feat, are those affine to the goals of precision agriculture. On the other hand, with seed traits, the farmer necessarily acts before nature because the seed decision is made once at the beginning of the growing season. The farmer may buy a drought resistant seed but he must make this decision long before knowing if the drought will actually happen; in the meanwhile, irrigation (if available) may be adjusted "on the go" as drought severity varies during the growing season.

Another point we made was that some GM traits are better described as state-general inputs while others are best described as state-specific. Whether an input classifies as state-general or state-specific depends on which states of nature are considered and on the number of states in which the input influences output. For a good analysis, the states of nature considered should exclude those that are not plausible. State-general inputs, since they obtain similar yields under a larger number of states of nature, are less risky than state-specific inputs. As for the GM traits currently in the market, the glyphosate tolerant, for example, is state-general while a Bt trait is more of a state-specific input. Also, a stacked Bt trait would be more state-general than a single Bt trait. The DT and FS traits, as defined in our CV questionnaires, would be more correctly classified as state-specific and state-general, respectively.

We defined a perfectly-state-general input as one that obtains the same yield (all else fixed) in all plausible states of nature. While not very realistic, this type of input helped us visualize that even as an *ex ante* measure such seed trait would eliminate uncertainty in a similar way that precision agriculture aims to do. The conclusion was that making such trait available to farmers would substantially modify the types of data sets that farmers need to and actually gather. For example, a trait that completely protected the plant against all plausible levels of pest pressure in a given region would eliminate the farmers' need to monitor pest populations. As such, we argued that GM seed traits are somewhat substitutes for precision agriculture methods. It makes sense that the two strategies used to reach the same goal of reducing uncertainty (i.e., modifying the plant or modifying the surroundings of the plant) are substitutes to each other.

As a final note, while biotech crops bring with them important benefits, some argue they also bring potential risks. Most proponents of biotech crops cite enhanced crop yields, more environmentally friendly food production, and more nutritious food as the major potential benefits. Skeptics cite uncertain effects on the environment, uncertain long-term effects on human health, ethical concerns, and distribution of benefits across developed and developing nations as the major potential risks. The uncertainty regarding the long term net effects (benefits vs. risks) of the technology has implications on all levels of the seed (or crop) industry –

consumers, farmers, seed companies and policy makers. Whether advocates or skeptics, all agents across the industry are to benefit from being better informed (less uncertain) about the different aspects of emerging biotech seed products.

This study and the results obtained will likely be of high value to the U.S. agricultural sector. Understanding the factors influencing producers' WTP presents a great opportunity for improved efficiency in the market via appropriate pricing strategies and market segmentation by seed companies. Also, farmers are bound to be better serviced if better understood by the companies serving them. Finally, pre-market studies like this one provide valuable information to policy makers; WTP elicited directly from farmers provides a benchmark for future monitoring of overly monopolistic pricing and for future studies on GM crop adoption.

APPENDIX A
GM CROP REGULATION

Two contrasting types of regulatory schemes exist worldwide among governmental agencies and other stakeholders when it comes to GM foods (James and Krattiger 1996). The first scheme considers GM foods are like any other food and therefore same regulations apply. This view sees biotech engineering as a part of a natural continuum following selective breeding techniques and believes current screening and testing procedures used on conventional foods are sufficient. The second scheme views GM foods as intrinsically different from conventional foods and thus argues that separate laws and regulations are needed. Despite opposing views, there is widespread agreement on the use and need of regulation of some kind.

Existing regulations for GM crops/foods may be classified into two types (Dale 1995): (i) Under contained conditions (i.e., laboratory procedures and health safety of workers); and (ii) On field trials (i.e., assessments of risk to, or likely impact on, human health and the environment) .

Why regulate? The justification is largely based on unfamiliarity (Dale 1995; OECD 1993; James and Krattiger 1996). Plant selection, of one or another kind, has been around for some 10,000 years. We have practiced conventional selective breeding techniques for most of the 20th century and became familiarized with its products. This is not to say we understand all the possible outcomes of sexual genetic recombination that happens in conventional selective breeding. For example, the release of new potato varieties obtained via conventional breeding still requires prior analysis for high levels of toxic substances (glycoalkaloids). This toxicity as a consequence of conventional breeding may be perceived as a dangerous one, but at this point has become familiar to us giving us the ability to prevent or manage possible damages ("safety" or "risk management"). As mentioned earlier, genetic engineering techniques expand the possibilities of gene transfer by allowing for transference between unrelated species (genes outside the normal sexual gene pool) and even permit the introduction of synthetic genes. The unfamiliarity associated with GM crops comes from the increase in the number and diversity of traits that can be possibly transferred, and thus, the increased possible unfamiliar outcomes that might follow.[1] In consequence, risk assessments of potential unfamiliar outcomes must precede any release of new GM crops into the environment, or their use as food, feed, fiber, or other. Such risk assessments warrant oversight and approval from regulatory authorities.

Governments worldwide have adopted one of two types of regulatory agendas (Dale 1995): vertical or horizontal. The U.S. and Canada have adopted vertical regulation which treats new crop varieties on a case-by-case basis defining characteristics of crops that require them to be regulated; with no a priori requirement that all GM crops/foods be regulated. The European Union (EU) takes a horizontal approach requiring all transgenic foods to be regulated (James and Krattiger 1996).

In the U.S., both experimentation with GM crops/foods and their approval for commercialization are vertically regulated by government agencies. The main roles played by regulations are to – confirm performance, evaluate characteristics of food, evaluate risk to human health (allergies) and, evaluate environmental effects. Elements presented in risk assessments include (OECD 1993; Dale 1995): characterization of the function played by the gene in donor organism and effect on target organism; evidence of toxicity; persistence in natural habitats (weediness); impact on non-target organisms (unintended effects); and likelihood and consequences of undesired gene transfer to other cultivars or wild/weedy species.

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[1] Some argue that the increase in precision obtained with genetic engineering results in more thoroughly characterized and potentially more predictable organisms (OECD 1993) compared to conventional breeding where genes with unknown and possibly undesirable functions can tag along with the desired trait. For examples of undesired results from conventional breeding see Pauppke (2001). Others argue that trait expression is generally governed by a complex interaction among numerous genes and conventional breeding is more likely to pass on all the genes needed for proper expression and metabolic regulation (Palumbi 2001).

Three agencies are responsible for implementing a coordinated framework of regulations in the United States (U.S. General Accounting Office 2002; James and Krattiger 1996): (i) the USDA, (ii) the EPA, and the (iii) FDA.

Within the USDA, the Animal and Plant Health Inspection Service (APHIS) is responsible for assessing environmental safety of new GM crops, for issuing field trial permits, and for approving general environmental release.[2] If the product contains a modification involving a gene with a pesticide (i.e., resistance to insects, bacteria or viruses) the EPA is also involved in the approval. These genetically incorporated pesticides are subject to EPA's regulations on sale, distribution, and use of such substances. Finally, if the transgenic crop is intended for food or feed use, the FDA is also involved.

The FDA has primary authority over safety of most of the food supply in the U.S. The 1938 Federal Food, Drug, and Cosmetic Act (FD&C Act) establishes the FDA as the regulatory agency responsible for protecting the public from adulterated and fraudulently labeled foods other than those regulated by USDA's Food Safety and Inspection Service (FSIS).[3] Section 402 of the FD&C Act defines an adulterated food as a food which:

> "bears or contains any poisonous or deleterious substance which may render it injurious to health; but in case the substance is not an added substance such food shall not be considered adulterated under this clause if the quantity of such substance in such food does not ordinarily render it injurious to health [...]"

FDA's view and policy with respect to GM foods was established in its 1992 *Policy on Foods Derived from New Plant Varieties* policy statement published in the *Federal Register* in

[2] The familiarity concept proposed by the OECD (1993) has been adopted in the U.S. regulatory framework so that certain crops that have become sufficiently familiar and have been recognized as low risk; qualify for a simplified notification system prior to release. Under such notification system, the proposer simply notifies USDA-APHIS of an intention to release (to the environment) a new transgenic variety and can proceed to do so if no response is received from APHIS within 30 days.

[3] The FSIS is responsible for ensuring that meat, poultry, and egg products are safe, wholesome, and correctly labeled.

May of that year (Food and Drug Administration 1992). The policy statement explains how foods are regulated under the FD&C Act; it applies equally and indiscriminately to foods (including animal feeds) derived from plants modified through all methods of breeding, including genetic engineering (Food and Drug Administration 1995).

The 1992 Policy Statement recommended companies with GM food under development to consult with FDA. Even though not required, most companies voluntarily complied. In June 1996, the FDA further provided the industry with Consultation Guidelines to streamline the consultation process (Food and Drug Administration 1997). Under such guidelines, the company meets with FDA and provides a summary of scientific and regulatory assessment of the food. The FDA then evaluates and responds to the submission by letter. In January 2001, the FDA issues a proposed rule published in the *Federal Register* that would require developers to submit their scientific and regulatory assessments to the FDA 120 days before the GM food is marketed (Food and Drug Administration 2001). The proposed rule recommended consultation practices should be continued before submission of assessments.

Highlights from the 1992 *Policy on Foods Derived from New Plant Varieties* policy statement are presented below (Food and Drug Administration 1995):[4]

- **Genetic Modification** – the introduced genetic material should be sufficiently characterized so that it does not encode harmful substances. It should also show a stable insertion in the plant genome to minimize potential future undesired genetic rearrangements.

- **Toxicants** – Many existing plants are known to produce toxicants or anti-nutritional factors. Many of these factors are found in foods at levels which do not cause acute toxicity or do not affect humans. FDA's 1992 policy statement indicates new varieties

[4] FDA's review of the first GM commercialized in the U.S. (FLAVR SAVR™) was conducted consistent with the May 29, 1992 policy statement; showing how the agency interprets the Federal Food, Drug, and Cosmetic Act with respect to foods derived from new plant varieties obtain by genetic engineering methods (Food and Drug Administration 1994a).

should not contain levels of such toxicants that exceed levels found in current existing varieties.

- **Nutrients** – Genetic modifications might unintentionally (and in some cases undesirably) affect nutrient content or bioavailability of nutrients. Nutrient content of new/modified varieties should not be reduced in comparison with existing/conventional foods.

- **New Substance** – In some cases, genetic modification may encode substances that are substantially different from those originally found in food. In some of such cases, premarket approval as food additives will be required for these substances; in other cases, proper labeling will be sufficient.

- **Allergenicity** – Genetic modification may result in introduction of genetic material that produce allergic reactions in people, especially when the donor organism is known to be commonly allergic. FDA believes that proteins derived from commonly allergenic sources should be presumed to be allergens and special labeling would be required, unless scientific evidence demonstrates otherwise.

- **Antibiotic Resistance Markers** – M-genes (discussed earlier in this chapter) form part of the DNA cocktail used in the genetic engineering process. Both the (i) gene responsible for the desired trait and (ii) a marker gene which provides the modified plant cell with resistance to a given antibiotic; are jointly transferred to the target organism. Successful transference is not guaranteed, so engineers treat all resulting cells with antibiotics. Only antibiotic-resistant cells (those that were successfully modified) survive. Once this selection process is finished, the marker gene is no longer needed but remains as a DNA residue from the transformation process and keeps producing the protein responsible for inactivation of the antibiotic substance (i.e., antibiotic-resistance). The most commonly used marker traits are for resistance to antibiotics kanamycin and neomycin. The use of marker genes raises concerns about possible inactivation of oral doses of antibiotic due to human consumption of GM foods containing marker genes. Some questions have also been raised about possible transference of the antibiotic-resistance gene to pathogenic microbes in the human gastrointestinal tract. Whereas the FDA states that there are no known mechanisms by which a gene can be transferred from a plant to a microbe (Food and Drug Administration 1995), more recent evidence (Netherwood et al. 2004) shows existence of such mechanisms. The FDA also found that kanamycin and neomycin have very limited use as oral antibiotics and concentrations of antibiotic-resistant proteins in GM foods are too little to degrade a significant amount of antibiotic.

- **Animal Feeds –** Under the FD&C Act, feeds grown for animals raised as human food sources must meet same safety standards as human food. Some additional points to consider when performing risk assessment on new animal feeds are that: (i) in contrast to the human diet which consists of many plants, some animal diets may consist of a single plant; (ii) animals consume parts of the plant which are not consumed by humans; and (iii) nutritional composition of the plant is essential for efficient production and profitability.

- **Labeling –** The FD&C Act requires labeling to be truthful and not misleading. The 1992 Policy Statement makes labeling of GM foods/crops voluntary unless the composition of the GM food differs significantly from its conventional counterpart. For example, if a modified food contains a potential allergen which is not expected in that food, the consumer must be informed in the label. If the allergen has potentially serious associated effects, then the FDA evaluates if labeling is sufficient for consumer protection. One issue causing controversy (even though no food of this type has been produced yet), is whether a plant which has been conferred an animal gene must be labeled such that people with different ethical views are informed (e.g., vegetarians, specific religions).

APPENDIX B
RESULTS FOR AUXILIARY ESTIMATIONS

Table B-1. Estimation results for drought tolerance trait (insured only)

	Drought nGM		Drought GM	
	Estimate	p-value	Estimate	p-value
constant	11.359	(0.320)	4.623	(0.664)
f_age	-0.014	(0.924)	0.043	(0.763)
f_educ	-0.193	(0.885)	-0.211	(0.867)
f_nfjob	1.674	(0.598)	0.312	(0.919)
f_income	1.628**	(0.017)	2.174***	(0.001)
earlyad	10.099**	(0.046)	13.636**	(0.013)
farmsize	-0.004	(0.244)	-0.002	(0.520)
nonGM100p	8.513*	(0.059)	-3.234	(0.433)
insurcost	0.227*	(0.078)	0.265**	(0.046)
mD2	0.369**	(0.025)	0.271**	(0.039)
sigma	10.127***	(0.000)	9.669***	(0.000)
N	81		77	
Log-likelihood	-95.284		-91.192	
Mean WTP [i]	22.657***	(15.895)	20.283***	(15.139)
C.I. 95 L	19.863		17.657	
C.I. 95 U	25.451		22.909	
LR Index	0.63		0.61	
LR statistic [ii]	85.216***	(0.000)	79.781***	(0.000)

[i] For mean WTP the t-statistic is reported in parenthesis. Standard error for mean WTP was calculated using the Delta Method. [ii] LR statistic is for likelihood ratio test with $H_o : \beta_1 = \beta_2 = ... = 0$, sigma is left unconstrained. *** indicates significance at 0.01 level, ** indicates significance level of 0.05, and * indicates significance level of 0.1.

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BIOGRAPHICAL SKETCH

Paul Esteban Jaramillo Vega was born in Quito, Ecuador in 1979. His research interests are applied econometrics, pre-market and market valuation of new products, barriers to technological adoption, economic development, and behavioral and experimental economics.

He received his Associate of Science degree in agricultural production in December 2000 from the Escuela Agricola Panamericana “El Zamorano” in Tegucigalpa, Honduras, where he was awarded the Board of Trustees Scholarship for academic achievement. He graduated from the University of Florida with honors in August 2002, receiving his Bachelor of Science degree with a specialization in agribusiness, from the Food and Resource Economics Department in the College of Agriculture and Life Sciences. He continued his graduate college education at the University of Florida receiving his Master of Science degree in 2004 and was awarded an Alumni Fellowship to complete his Ph.D. degree in food and resource economics in 2009. Alumni Fellowships are the highest graduate student award available at University of Florida providing complete funding for four years to promising graduate students.

His Ph.D. research focused on corn farmers’ willingness to pay and adoption of corn seeds containing genetically modified (GM) traits that reduce fertilization requirements and increase plants tolerance to droughts. He is also involved in research in Ecuador studying the barriers to adoption of profitable and environmentally friendly technologies faced by small and low-income rice growers.