ABSTRACT

Title of Document: **A STRUCTURAL MODEL OF INSECT CONTROL DECISIONS: ROOTWORM RESISTANCE IN US CORN FIELDS**

Seth James Wechsler, Doctor of Philosophy, 2014

Directed By: Professor Erik Lichtenberg, Agricultural and Resource Economics Department

Recent evidence from field tests and laboratory studies suggest that rootworms are adapting to the toxins produced by genetically modified, insect resistant (Bt) seeds. Given that rootworms cause over 1 billion dollars in yield losses and treatment costs per year, finding larger scale evidence of resistance could have important policy ramifications. This dissertation analyses corn farmers' insect control decisions in an effort to determine whether rootworms have adapted to Bt seeds.

Chapter 1 provides a broad overview of the literature on genetically engineered (GE) seeds. It strives to correct many commonly held misperceptions about genetically modified seeds.

Chapter 2 provides a detailed description of the economic literature on pesticide productivity and GE seed use. It compares structural to reduced form models, and discusses how previous studies have accounted for endogeniety.

Chapter 3 develops a two stage, theoretical model of corn farmers' insect control decisions. This model is used to derive a non-linear, soil insecticide demand function.

Chapter 4 presents the dissertation's empirical approach. First, it describes the data used in the analysis. Next, it discusses how to estimate the soil insecticide demand function derived in Chapter 3. Finally, it discusses how the parameters of the structural model can be used to determine how: a) Bt adoption affects yields, b) Bt adoption affects insecticide use, and c) whether the effectiveness of Bt seeds has changed over time.

Chapter 5 provides the study's results. These results indicate that using rootworm resistant seeds would have decreased soil insecticide use by 70% in 2005 and 84% in 2010. Bt adoption would have increased yields by .6 percentage points (1.02 bushels/acre) in 2005 and .1 percentage points (.2 bushels per acre) in 2010. Alarmingly, the evidence suggests that rootworm resistant seeds were less effective in 2010 than in 2005, and less effective on farms where selective pressure was high than on farms where selective pressure was low. In other words, the results of this study support the hypothesis that rootworms are adapting to Bt seed use.

Chapter 6 concludes.

A STRUCTURAL MODEL OF US CORN FARMERS' PEST CONTROL DECISIONS: ROOTWORM RESISTANCE IN US CORN FIELDS

by

Seth James Wechsler

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2014

Advisory Committee:

Professor Erik Lichtenberg, Chair
Professor Bob Chambers
Professor Anna Alberini
Professor James Hanson
Professor Maureen Cropper

Foreword

Throughout the 1980's, large "life science" companies pursued the goal of commercializing crop biotechnologies. These efforts came to fruition in 1994 when Calgene's "flavor saving" tomato became the first genetically engineered (GE) fruit approved for sale in the United States. Despite high consumer demand for the Flavr Savr, high production and distribution costs led to its rapid withdrawal from the marketplace (Bruening and Lyons, 2000). By contrast, herbicide tolerant (HT) and insect resistant (Bt) crops have been tremendously profitable.

In 2003, Monsanto introduced genetically engineered, rootworm resistant seeds (Bt-CRW). These seeds provided farmers with a safe, effective, and relatively inexpensive method of controlling rootworm infestations. Unfortunately, frequent exposure to the toxins produced by Bt-CRW seeds may have induced rootworms to become resistant.

Unexpectedly severe yield losses were first reported on fields with rootworm resistant (Bt-CRW) corn in 2009. By 2011, resistance had been reported in Illinois, Iowa, Minnesota, Nebraska, and South Dakota. In 2012, a group of twenty-two entomologists wrote a public letter strongly suggesting that the US government "act with a sense of urgency" to further restrict the use of Bt-CRW seeds (Porter et al., 2012).

Surprisingly, despite the growing body of circumstantial evidence, only a small number of peer-reviewed studies and field tests indicate that resistance has developed (Gassmann, 2011; Gassmann, 2012; Gassmann et al., 2012; Gray, 2012; and Gray, 2014a). As of 2014, there has not been enough systematic evidence to justify further regulatory action (EPA, 2013).

Recent estimates suggest that rootworms cause over 1 billion dollars in yield losses and treatment costs per year (Gray, 2009). Though Bt-CRW adopters would be the largest group affected by the development of resistance, organic growers would lose access to one of the few effective, non-synthetic pesticides available to them.

This study searches for systematic evidence that rootworms are adapting to Bt-CRW seeds. First, a theoretical model of corn farmers' insect control decisions is used to derive a demand function for soil insecticides. Next, estimates from this demand function are used to test the hypothesis that the effectiveness of Bt-CRW seeds has changed over time. The study's unique contributions include the development of a damage abatement model that explicitly accounts for the timing of corn farmers' insect control decisions, a structural approach that isolates the impacts of rootworm resistant seeds, and an empirical test for rootworm resistance.

The format of the dissertation is as follows: Chapter 1 provides background information and context. Chapter 2 surveys the economic literature on pesticide productivity and GE seed use. Chapter 3 formulates a theoretical model of corn farmers' insect control decisions. Chapter 4 describes the data used in the analysis and presents the study's empirical approach. Chapter 5 discusses the regression results, marginal effects, and resistance tests. Chapter 6 concludes.

Acknowledgements

I would like to thank the Professors and staff of the University of Maryland's Agricultural and Resource Economics Department. I've enjoyed my time as a member of the Department and appreciate the time and energy that has been invested in me. Special thanks are due to Anna Alberini and Erik Lichtenberg, advisors who have generously provided experience and expertise. As my principal advisor, Erik's clear thinking and high standards have positively influenced every aspect of my research.

I would also like to thank the staff and economists of the USDA's Economic Research Service. During my years as a research assistant, I developed an enthusiastic interest in agricultural economics and a genuine affection for my colleagues. Richard Nehring and Jorge Fernandez-Cornejo have been exemplary coauthors. Utpal Vasavada and Jim MacDonald have been long-standing advocates, role-models, and mentors.

Needless to say, the timely completion of my degree would not have been possible without the unwavering love, confidence, and support of my parents, both of whom I love very much.

Table of Contents

List of Tables

List of Figures

Chapter 1: Background Information and Context

This chapter provides a broad overview of the literature on genetically engineered (GE) seeds. It addresses questions such as: Does genetic engineering make foods unsafe? Does GE seed use adversely impact non-target insect populations and/or ecosystems? Has the commercialization of GE crops affected the biodiversity of US seed stocks? Have high GE adoption rates led to the development of resistant pests? And, how are GE seeds regulated?

Answering these questions does not help explain the theoretical model developed in Chapter 3 or the empirical strategy described in Chapter 4. Nonetheless, GE seed use is one of the most misunderstood topics in US agriculture. The information contained in this chapter serves to correct some of the most commonly held misperceptions about genetically modified seeds.

The chapter is organized as follows: Section I describes the regulatory framework for GE seeds. Section II discusses whether GE foods are safe for human consumption. Section III analyzes the environmental impacts of GE seeds.

1. Regulations Affecting GE Seeds

1.1 A Comprehensive Federal Regulatory Framework

In 1984, under the presidency of Ronald Reagan, the United States Office of Science and Technology Policy (OSTP) convened a working group to determine if the existing regulatory framework could adequately ensure the safety of genetically modified products (OSTP, 1986). The Coordinated Framework for the Regulation of

Biotechnology (CFRB) was published two years later. Under the CFRB, three US government agencies have jurisdiction over genetically modified crops: the United States Department of Agriculture's Animal and Plant Health Inspection Service (APHIS), the Food and Drug Administration (FDA), and the Environmental Protection Agency (EPA).

APHIS employs a complicated process to ensure that genetically modified crops do not become invasive. First, seed producers develop a GE plant and test it in greenhouses. Next, the producer notifies APHIS of its intention to conduct field trials and requests a permit to do so. If the genetically modified varietal performs well in field trials, then the producer must demonstrate that the product poses no more of a plant pest risk than an equivalent non-GE organism. Once deregulated status is conferred, the new plant no longer requires APHIS review for movement or release (Fernandez-Cornejo and Caswell, 2006).

Post deregulation, the FDA has jurisdiction over a GE crop if it is a food or will be used in animal feed. The agency provides voluntary consultations to help ensure that GE crops are safe for human consumption. However, the FDA does not regulate genetically engineered products any differently than products produced using traditional techniques (OSTP, 1986).

It is the EPA's responsibility to ensure that pesticides do not pose a risk to human health or to the environment. Consequently, the agency has jurisdiction over genetically modified crops that produce plant incorporated protectants (PIPs). The EPA uses a rigorous registration process to ensure that pesticides meet regulatory standards. This process involves a human health assessment, an ecological assessment, and (when necessary) the development of resistance management plans. Most registrations are temporary, expiring after anywhere from two to fifteen years. Before a new registration is issued, the agency requires new human health and ecological assessments to be completed.

1.2 Labeling of GE Products

In 1992, the FDA published a policy statement describing its approach to regulating genetically modified foods. Because GE foods were found to be compositionally equivalent to their traditional counterparts, the FDA determined that it did not have the statutory authority to mandate labeling (FDA, 1992).[1]

In 1999, the agency solicited public opinion about its approach to regulating bioengineered foods. More than 50,000 written comments were received, the majority of which requested that foods containing GE ingredients be clearly labeled (FDA, 2001). Proponents of mandatory labeling argued that the safety of GE foods was controversial, that labelling would facilitate international trade, and that consumers had a right to know what they were purchasing. Critics claimed that consumers already had the option of purchasing GE-free (organic) products, that labeling would be costly, and that labels might signal that GE foods were unsafe for human consumption. Though the FDA did not alter its policy, it clarified that labeling would be mandated in cases where: 1) a GE food differed significantly from its traditional counterpart, 2) a GE food had significantly different nutritional properties than its traditional counterpart, or 3) a GE food included an allergen that consumers would not expect based on the name of the food (FDA, 2001).

---

[1] The Food and Drug Administration's jurisdiction to regulate the labeling of food products stems from the Federal Food, Drug and Cosmetic Act of 1938 (FDA, 2001). Section 403 of this act defines food as misbranded if its labeling fails to reveal consequences that may result from the use of that food.

In 2002, a coalition of consumer advocacy groups introduced a ballot initiative requiring the mandatory labeling of GE foods in Oregon. This initiative was soundly defeated (Senauer, 2013). Subsequently, ballot initiatives were introduced (and defeated) in both California (Proposition 37) and in Washington (I-522). Legislatures in Connecticut and Maine passed laws that mandated labeling in 2013. However, these laws do not go into effect until other states pass similar restrictions (Pfeiffer and Jolicoeur, 2014). As of 2013, 26 states were considering legislative proposals (or ballot initiatives) to require the labeling of GE foods (Kucinich, 2014).

Ballot initiatives aside, it is not clear that states have the authority to mandate the labeling of GE foods (Senauer, 2013). In 1913, the Supreme Court affirmed the right of federal food labeling laws to preempt state ones (Lasker, 2013). In 1996, a federal appeals court ruled that farmers who injected their cows with a genetically altered bovine growth hormone could not be forced to label the resulting dairy products (Senauer, 2013).

These judicial decisions may have bolstered recent congressional opposition to state level legislation. In 2013, the House Agriculture committee amended the farm bill to prevent states from passing labeling legislation (Sheets, 2013). Eight days later, the US Senate overwhelmingly rejected a bill that would have allowed states to mandate labeling (Jalonick, 2013).

In the spring of 2013, Senator Barbara Boxer and Representative Peter DeFazio introduced an amendment to the Federal Food, Drug, and Cosmetic Act (the Genetically Engineered Right-to-Know Act) that would have required GE labeling on a national level. However, as of March 2014, it was estimated that the amendment had a 1% chance of passing in the House and a 0% chance in the Senate (Govtrack, 2014a; Govtrack, 2014b).

1.3 Mandatory Insect Resistance Management Plans

Prior to the development of genetically modified, insect resistant seeds, the EPA had not mandated resistance management practices. This changed in 1995 when the EPA mandated that Bt cotton growers plant 20% of their acreage using conventional seeds (EPA, 2001). This “refuge” requirement was intended to promote the survival of cotton pests that were susceptible to Bt toxins. In 2000, the EPA mandated a 20% refuge for Bt corn in the US Corn Belt, a 50% refuge for Bt corn in southern counties, and a 20% unsprayed refuge requirement for Bt potatoes (EPA, 2001).

Though new corn and cotton PIPs were registered throughout the next decade, the EPA did not readjust refuge requirements until 2009, when it registered Monsanto’s SmartStax line of Bt seeds (EPA, 2011a). SmartStax seeds produced one PIP to control corn rootworms and three PIPs to control corn borers (EPA, 2011b). Although the EPA initially denied Monsanto’s request to reduce the size of the refuge requirement for these seeds (from 20% to 5%), the agency eventually found that “the combination of two toxins targeting lepidopteran corn pests… allowed for a reduced refuge with little risk of resistance (EPA, 2008a; EPA, 2008b).” The reduced refuge requirement has provoked concern from a number of prominent plant scientists and entomologists (Alyokhin, 2011; Porter et al., 2012).

2. Are GMO’s Safe for Human Consumption:

2.1 Allergens and Toxicity

Traditional methods of producing new varietals include hybridization, irradiation, and exposure to mutagenic agents. These techniques occasionally produce plants with undesirable properties. For instance, a hybridized potato variety (Lenape) was found to contain high levels of nerve-blocking glycoalkaloids in the early 1960’s

(Ames et al., 1990). A pest-resistant celery variety had seven times the normal concentration of carcinogens in 1984 (Berkley et al., 1986).

Similarly, genetic engineering occasionally produces unmarketable crops. For instance, Pioneer created a transgenic strain of soybeans containing allergens in the early 1990's (Nordlee et al., 1996). In 2005, an insect resistant strain of peas was found to cause allergies in mice (Prescott et al., 2005).

That said, it is extremely rare for either traditional methods or genetic engineering to increase the toxicity or allergenicity of a parent line (Herman and Price, 2013). Moreover, these changes tend to occur in crops that are known to be toxic. Some would argue that GE foods are safer than foods made from conventionally bred crops because biotechnology companies tend to conduct animal feeding studies and substantial equivalence tests (Prakash, 2001).

2.2 Substantial Equivalence Tests

One method of assessing the safety of GE foods is by comparing them to isogenic, non-genetically modified counterparts. Referred to as substantial (or compositional) equivalence tests, these comparisons are made using replicated field trials. First, the transgenic and conventional varieties are grown simultaneously, at the same location, using the same production practices. Next, statistical tests are used to determine whether the transgenic crop has the same nutritional content and concentration of toxins/allergens as its conventional counterpart.

Though many scientists and regulators have embraced compositional equivalence tests, this acceptance was not always universal. In a 1999 *Nature* publication, Millstone, Brunner and Mayer argued that compositional equivalence tests were designed to reassure consumers rather than to safeguard them. Claiming that the concept of substantial equivalence was developed during a series of international meetings that included politicians but excluded consumer representatives, Millstone et al. (1999) suggested that toxicological tests should provide the basis for safety assessments. However, many biologists, plant scientists, and regulators disputed this conclusion.

Noting that many new genes were present in traditionally bred hybrids, Trewavas and Leaver (1999) argued that conducting toxicological tests was expensive and unnecessary. Kearns and Mayers (1999) emphasized the fact that government experts from nineteen countries had spent two years determining that substantial equivalence tests were an adequate standard. Derek Burke, the chairperson of the British Advisory Committee on Novel Foods and Processes (ACNFP) from 1989 to 1997, characterized Millstone et al. (1999) as “misleading and inaccurate.” He insisted that the ACNFP was not under political or commercial pressure when drafting regulations (Burke, 1999).

Since the commercial introduction of GE seeds in 1996, the FDA has analyzed 148 transgenic events. As of 2013, every GE crop was found to be substantially equivalent to a conventional variety (Herman and Price, 2013). In light of this finding, it has recently been suggested that compositional equivalence testing be discontinued altogether.

2.3 Animal Feeding Studies

The vast majority of animal feeding studies are ninety day trials conducted on mice or rats. In a recent review of these trials, the European Food Safety Authority (EFSA) concluded that consuming GE maize, rice, and soybeans did not have adverse effects (EFSA, 2008). However, the results of 90 day trials are not definitive. The EFSA argues that these tests: a) do not detect effects on reproduction or development, and b) tend not to detect weak effects.

Longer-term feeding studies have been conducted on cows, sheep, hens, birds, goats, and fish (Snell et al., 2011). In a recent review of feeding studies lasting between 182 and 728 days, Snell et al. (2012) concluded that long-term feeding studies had not revealed deleterious effects.

A 2007 review of multi-generational studies by Flachowsky et al. (2006) failed to find evidence that consuming insect resistant or herbicide tolerant crops adversely affected successive generations of hens or quail. Similarly, neither Brake and Evenson (2004) nor Haryu et al. (2009) found evidence that GE crops induced reproductive changes in successive generations of mice.

Bohme et al. (2005) found that a transgenic potato (developed to synthesize insulin) had higher levels of glycoalkaloids and lower production potential than an isogenic, conventional plant. However, there was not any evidence that consuming the transgenic variety affected average daily growth rates (in pigs).

A number of studies did find small differences in animal growth, food intake, organ weights, liver proteins, and triacylglycerol levels in studies of GE soybeans (Malatesta et al., 2008; Sissener et al., 2009; Daleprane et al., 2009; Tudisco et al., 2010). However, these studies did not have isogenic controls.

To conclude, though a small number of authors make contradictory claims, the evidence from animal feeding experiments suggests that GE and conventional crops are equally safe for human consumption.

2.4 Transcriptomic, Proteomic, and Metabolomic Studies of GE Seeds

Genetic profiling techniques were developed at the turn of the 21st century to study the composition of organisms at a molecular level (Ricroch et al., 2011). Generally, three profiling techniques have been used to compare transgenic crops to conventional ones: transcriptomic studies (which analyze the set of RNA molecules produced by a cell), proteomic studies (which analyze the set of proteins expressed by a genome), and metablomic studies (which analyze the set of metabolites found within a biological sample).

Because "model" plants have small genomes, they are often used in profiling studies. El Ouakfaoui and Miki (2005) tested whether gene insertion induced unexpected changes in a commonly studied model plant, the *Arabidopsis thaliana*. They found that less than .5% of genes were expressed differently in the transgenic and conventional lines. Because none of these differences were reproducible, they were assumed to reflect the variability of the biological system. Kristensen et al. (2005) failed to find evidence that gene insertion had inadvertent effects on *Arabidopsis thaliana*'s metablome.[2] Ricroch et al. (2011) reported that genetic variability and environmental stress had a greater influence on gene expression in *Arabidopsis thaliana* than transgene insertion does.

Other studies have analyzed GE field crops. For instance, Cheng et al. (2008) found that there were greater differences in gene expression between hybridized soybean varieties than between HT soybeans and their isogenic counterparts. Harrigan et al. (2010) found that the allergenicity of soybeans was not affected by the insertion of genes to convey herbicide tolerance.

---

[2] In a similar study, Abdeen et al. (2010) found that inserting a gene effecting drought tolerance into an *Arabidopsis thaliana* plant did not have unexpected effects on the plant's transcriptome.

Coll et al. (2010a) analyzed the transcriptome of Bt corn. They found that nitrogen availability and varietal differences dramatically impacted gene expression, but that the insertion of genes conferring insect resistance did not. Coll et al. (2010b) found that the proteomes of Bt and conventional corn were virtually identical.

Ricroch et al. (2011) conducted a recent survey of genetic profiling studies. He concluded that the opinions expressed by food safety agencies (i.e. the general 'equivalence' of GE crops with non-GE counterparts) had been corroborated. In other words, the evidence suggests that GE foods are safe for human consumption.

3. The Environmental Impacts of GE Seeds

3.1 Direct Impacts on Biodiversity/Nontarget Organisms

Before issuing the first registrations (in 1995), the EPA conducted extensive studies to ensure that PIP's did not adversely affect non-target organisms (EPA, 2001). Though the EPA was aware that the proteins produced by Bt seeds could adversely affect many species of Leidoptera (an order of insects that contains butterflies and moths), the agency concluded that few non-target species would be exposed to high concentrations of Bt toxins (EPA, 2001).

This assessment was challenged by Losey et al. (1999). Claiming that corn pollen could be dispersed up to 60 meters from planting sites, he speculated that butterfly populations would be adversely affected. However, the evidence did not support this conclusion. Oberhauser et al. (2001) found that the toxin concentration in Bt corn pollen was not high enough to adversely affect monarchs. Sears et al. (2001) estimated that less than 1% of butterflies were likely to be affected.

A 2005 edition of *Environmental Entomology* analyzed the impacts of Bt seed use on a broad range of non-target species. The editors concluded that Bt corn and cotton had a limited impact on non-target organisms, and that these impacts were far less pronounced than those induced by conventional insecticide use (Naranjo et al., 2005).

Similarly, a meta-analysis conducted by Marvier et al. (2007) found that the abundance of non-target organisms was significantly higher in Bt corn and cotton fields than in non-GM fields treated with insecticides. They concluded that GE seed use could reduce the environmental impacts of agriculture.

Wolfenbarger et al. (2008) explored the impacts of Bt adoption by ecological function guild.[3] They found that non-target herbivores, omnivores, and detritivores were unaffected by Bt corn and cotton use. As in other studies and meta-analyses, most functional guilds were more abundant in Bt fields than in non-GM fields that had been treated with insecticides.

To conclude, the vast majority of the evidence suggests that directly ingesting GE plants does not harm non-target organisms. That said, it is possible that possible that GE adoption induces shifts in production practices which have indirect effects on non-target organisms.

3.2 Indirect Impacts on Biodiversity/Non-Target Organisms

Claiming that biodiversity is dependent on weed density, Ammann (2005) contends that HT adoption reduces biodiversity if HT based weed management systems are more effective than conventional ones. Lincoln Brower, an entomologist at Sweet Briar College makes a more hyperbolic case, stating that glyphosate is “like

---

[3] A guild is comprised of insects that exploit the same resources, in related ways. For instance, herbivores feed on living plant tissues, predators feed on other insects, detrivores consume decomposing plant and animal matter, while pollinators feed on plant pollen.

Armageddon for biodiversity (Pollack, 2011).” However, there is mixed evidence to support this claim.

In 1999, a consortium of British research institutions initiated a four year evaluation of HT crops. Officially referred to as the Farm Scale Evaluation (FSE) project, this project was one of the longest, most expensive, and most controversial studies of its time (Firbank et al., 2003). The results of the FSE’s suggested that HT adoption did not affect herbaceous insects or predator insect populations (Hawes et al., 2003). However, a consistently positive relationship was found between weed biomass and pollinator populations (Hawes et al., 2003).

Recent research suggests that HT corn and soybean adoption has reduced weed populations in the US Corn Belt (Taylor, 2008). Because one of the weeds affected (milkweed) is a habitat for monarch butterflies, some academics attribute recent reductions in monarch butterfly populations to rapid increases in HT adoption rates (Brower et al., 2011; Pleasants and Oberhauser, 2013).[4]

Several federal agencies (including the USDA’s Economic Research Service) are currently assessing the extent to which agricultural practices and environmental conditions affect pollinator health.

3.3 Resistance in Weeds and Insect Populations

Glyphosate resistant waterhemp (*Amaranthus tuberculatus*) was first observed in 1998 on HT soybean fields (Owen, 2008). Glyphosate resistant horseweed (*Conyza canadensis*) was first documented in 1999 (Van Gressel, 2001). Subsequently, field

---

[4] Pleasants and Oberhauser (2012) estimate that monarch production in the Midwest dropped by 81% from 1999-2010. Brower et al. (2011) estimate that overwintering populations dropped by 65% over the same time period.

evolved resistance has been documented in populations of pigweed (*Amaranthus palmeri)* and several other weed species (Owen, 2008).[5]

Insofar as insects are concerned, resistance to Cry1AC toxins was first documented in populations of cotton bollworms in 2002 (Luttrell and Jackson, 2012). Though Monsanto introduced a pyramided Bt cotton seed expressing Cry1Ac and Cry2Ab2 in 2003, and Dow introduced a pyramided seed expressing Cry1Ac and Cry1F in 2005, single trait seeds continued to be sold until 2009 (EPA, 2011a; Tabashnik et al., 2013).

In late 2006, after only three years of usage, Puerto Rican farmers began reporting unexpectedly high yield losses on fields planted with Bt corn expressing Cry1F (Storer et al., 2010). Though the severity of these yield losses were initially attributed to environmental conditions, laboratory tests later confirmed that armyworm populations had become resistant. Dow voluntarily withdrew the transgenic crop in 2007, but laboratory tests conducted in 2011 confirmed that armyworm populations remained resistant (Storer et al., 2012).

In 2009, corn farmers planting rootworm resistant seeds experienced unexpectedly severe yield losses throughout the US Corn Belt. Concerned that rootworms were adapting to Bt seeds, the EPA tightened the monitoring and enforcement of refuge regulations in 2010. By 2011, resistance had been reported in Illinois, Iowa, Minnesota, Nebraska, and South Dakota. Subsequent testing confirmed that rootworms had become resistant to Cry3Bb1 toxins in isolated parts of Iowa and Illinois (Gassman et al., 2011; Gassman, 2012; Gassman et al., 2012). In 2012, a group

---

[5] Owens (2008) also reports increases in populations of weeds which are naturally resistant to glyphosate, such as: Common lambsquarters (*Chenopodium album*), Giant ragweed (*Ambrosia trifida*), Velvetleaf (*Abutilon theophrasti*), Asiatic dayflower (*Commelina communis*), and Tropical spiderwort (*Commelina benghalensis*). See Heap (2014) for a comprehensive list of glyphosate resistant weeds.

of twenty-two entomologists wrote a public letter suggesting that refuge requirements be raised for pyramided seeds expressing Cry3Bb1 toxins (Porter et al., 2012). Recently, Gassman et al. (2014) found that rootworms in Iowa had developed resistance to pyramided seeds expressing Cry3Bb1 and mCry3A. Though the EPA held a scientific advisory panel meeting to discuss rootworm resistance in late 2013, as of spring 2014, the agency has not taken further remedial action (EPA, 2014).

These cases demonstrate how quickly resistance is capable of developing. Currently, biotech companies are developing transgenic crops that produce new insecticidal proteins, existing Bt toxins in higher concentrations, or RNA strands which alter gene expression in insects (Gatehouse, 2008).

3.5 Impacts of GE Seed Use on the Genetic Diversity of Seed Stocks

Many studies have explored whether the commercialization of GE seeds has reduced the diversity of seed types planted. Sneller et al. (2003) analyzed the pedigrees of 312 elite soybean genotypes sold in the United States from 1999 - 2001. Noting that the coefficient of parentage (a measure of genetic diversity) had not changed over the course of the last 25 years, Sneller et al. (2003) concluded that the introduction of Roundup Ready soybeans had not negatively impacted the overall diversity of the elite soybean population. Mikel et al. (2010) indirectly corroborated this conclusion, finding that the genetic diversity of registered soybean cultivars had actually increased slightly from 1994-2008.

Bowman et al. (2003) analyzed the genetic diversity of US cotton seeds. They calculated the coefficient of parentage for varietals occupying at least 1% of US cotton acreage. Finding that the coefficient of parentage had remained fairly constant from

1995 to 2000, they concluded that the development of transgenic cultivars had not decreased the genetic diversity of the US cotton crop.

Mikel (2008) calculated the coefficient of parentage for 846 propriety inbred corn lines registered between 1976 and 2005. These calculations indicated that the genetic diversity of corn varietals was slightly (.95 percentage points) higher from 1976-1995 than it was from 1996-2005.

To summarize, it does not appear that the development of genetically modified crops has substantively affected the biodiversity of the crops cultivated by US farmers. To some extent, this is not surprising. GE plants tend to be backcrossed with high yielding conventional cultivars to create high yielding GE varieties. Contrary to popular belief, GE crops do not replace conventional ones. Rather, GE traits are incorporated into existing seed stocks.

4. Conclusions

APHIS, FDA, and EPA regulate genetically modified seed use in the United States. These agencies ensure that GE plants do not become invasive, that foods with GE ingredients are safe for human consumption, and that the pesticides produced by (or applied to) GE plants do not harm non-target organisms/ecosystems.

Though many Americans perceive GE foods to be unhealthy, a wide variety of animal feeding, compositional equivalence, and genetic profiling tests have demonstrated that GE foods are safe for human consumption. Similarly, despite concerns that GE seed use negatively impacts non-target organisms and eco-systems, the evidence suggests that GE based production systems are less harmful than conventional ones. Insofar as the genetic diversity of seed stocks are concerned, GE adoption does not appear to have substantively affected the diversity of US corn, cotton, or soybeans.

To summarize, GE crops are well regulated, safe for consumers, and good for the environment. That said, they are not a panacea. Waterhemp, horseweed, and pigweed have developed resistance to glyphosate. There is evidence that bollworms, armyworms and rootworms have developed resistance to Bt toxins. This dissertation develops an approach that assesses the severity of pest resistance problems.

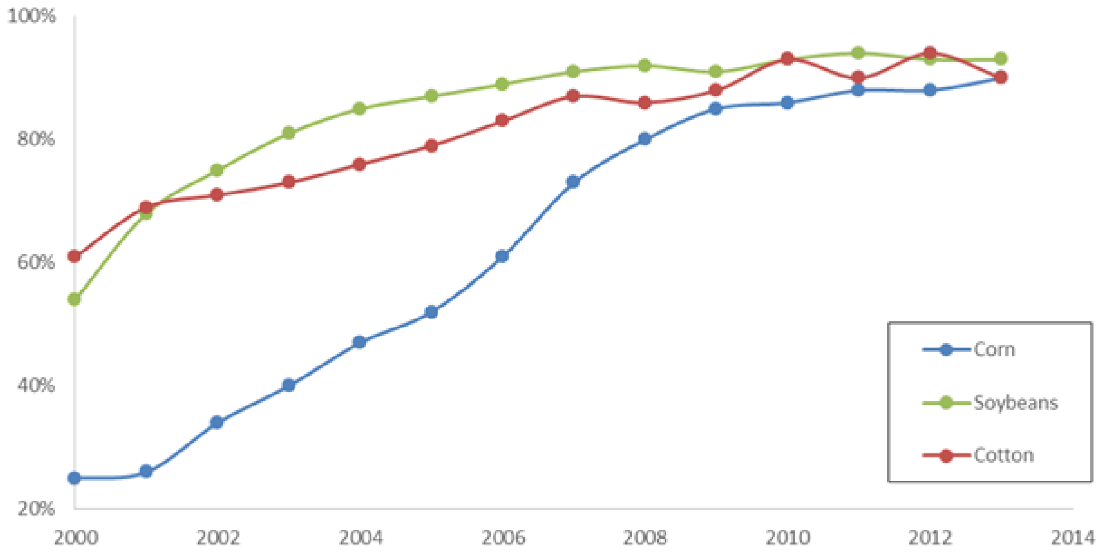

Figure 1. GE Adoption Rates in the United States, 2000-2013

Source: Fernandez-Cornejo et al. (2014a)

Chapter 2: A Survey of the Economic Literature on Pesticide Productivity and GE Seed Use

This dissertation explores how the effectiveness of Bt-CRW has changed over time. However, it is far from the first economic analysis of pesticides, resistance, or farmers' pest control decisions. While subsequent chapters discuss model formulation, estimation, and empirical results, this chapter provides methodological context. Section I provides a broad overview of the economic literature on pesticide productivity. Section II casts a critical eye on previous studies of GE adoption.

1. The Economic Literature on Pesticide Productivity

Headley (1968) was one of the first economists to analyze pesticide productivity in the US agricultural sector. Assuming that both productive and pest control inputs had a monotonically increasing impact on yields, he estimated an aggregate Cobb-Douglas production function. Surprisingly, the results of the analysis indicated that a dollar spent on pesticides generated between $3.90 to $5.66 in returns. In other words, the evidence suggested that the marginal benefits of pesticides were 4 to 6 times their cost. This finding suggested that pesticides were under-utilized (a result which contradicted the conventional wisdom of the time).

Subsequent studies corroborated Headley's results. For instance, Fischer (1970) estimated a Cobb-Douglas production function for Canadian apple orchards using data collected in 1966. He found that a dollar spent on pesticides generated between $2.34 and $12.80. Campbell (1976) estimated a Cobb-Douglas production function by analyzing a cross-section of data collected from Canadian apple, apricot, and pear farmers in 1970. His findings indicated that a dollar spent on pesticides generated approximately $12.

Lee and Langham (1973) employed a slightly different approach. Rather than estimating a linearized production function, they estimated a simultaneous system that explicitly accounted for the endogenous relationship between pest populations and agricultural production. Analyzing a panel of data collected on Florida citrus groves (during the 1955 to 1968 growing seasons), they found that the marginal value product of pesticides was only 8.2 cents per pound, well below the price of the pesticides applied.

Carlson (1977) was the first to conduct an economic study of insect resistance. He estimated Cobb-Douglas production functions for US cotton farmers using data collected in 1964, 1966, and 1972. Unlike previous analyses, this analysis controlled for the severity of pest infestations. The results suggested a substantial decrease in the marginal product of insecticides over time. However, these results were based on the assumption that pesticides increased yields monotonically.

Lichtenberg and Zilberman (1986) developed a structural model with a biological basis. Previous studies had discussed the fact that pesticides did not increase yields monotonically (Headley, 1971; Hall and Norgaard, 1973; and Talpaz and Borosh 1974), but Lichtenberg and Zilberman (1986) were the first to develop an econometric approach that accounted for the fact that pesticides were damage abating (rather than yield increasing).

The damage abatement framework proposed by Lichtenberg and Zilberman (1986) modeled production as a function of two separable processes: output generation and pest control. More specifically, the production function was specified such that $f(x, z) = H(x)G(z)$, where H represents potential yields and $G \epsilon [0,1]$ represents an abatement function (the percentage of potential output not damaged by infestations).[6] The authors proposed four functional forms for G: the Pareto Distribution ($1 - K^{\tau} z^{1-\tau}$), the Exponential Distribution ($1 - \exp(-\tau z)$), the Logistic Distribution ($\frac{1}{1+\exp(\mu - \sigma z)}$), and the Weibull Distribution ($1 - \exp(-z^{c})$).[7]

The damage abatement framework had a number of advantages over more traditional approaches. First, damage abatement models produced estimates of crop damages and abated yield losses. Second, unlike Cobb-Douglas specifications (which have constant elasticities, and thus tend to systematically overestimate the marginal product of pesticides), damage abatement specifications were flexible. Third, damage abatement models made realistic predictions about farmers' behavior.

The latter of these points is particularly salient. In traditional models, resistance is assumed to decrease a pesticide's marginal product, which reduces its usage. However, this is the opposite of how farmers tend to behave in the field. Damage abatement models predict that resistance induces a rightward shift in the marginal product curve. This shift affects the lethality of the pesticide, rather than the benefits of pest control. Farmers respond by intensifying their pesticide usage (see Figure 2).

Surprisingly, prior to this analysis, the damage abatement framework had not been used to assess the impacts of insect resistance. However, a number of modifications to the original damage abatement framework had been proposed. For instance, Babcock et al. (1992) developed a model which allowed pesticide use to affect the quality and quantity of output. Analyzing apple production on North Carolina apple

---

6 H has all of the familiar properties of production functions (e.g. concavity and monotonicity). G has the properties of a cumulative distribution.

7 K, τ, μ, σ and c are all parameters of the distributions.

orchards (using data collected from 1976 through 1978), they found that ignoring quality could induce downward bias in estimates of pesticide productivity.

Saha et al. (1997) developed a stochastic production function which had separate error terms for the potential output and abatement functions. Unlike previous models, this formulation was sufficiently flexible to accommodate the possibility that pesticide use both increased yields and reduced production risk (the variance of the production function).

Chambers and Lichtenberg (1994) analyzed the US agricultural sector using a time series of national level data (for 1949 through 1990). Unlike many previous analyses, this study accounted for the possibility that insecticide use was endogenous. The results suggested that average crop damages to US farmers had fallen from 15% during the early 1950's to 3% during the 1980's.

Fox and Weersink (1995) used a Gumbel distribution to specify the abatement function. The resulting specification was used to demonstrate that damage abatement models could accommodate increasing returns to pesticide use.

Carpentier and Weaver (1997) suggested modeling output as a function of effective input levels. In this formulation, each input is scaled by a separate abatement function.[8] Although this formulation is more general than Lichtenberg and Zilberman's "output" abatement model, it does not readily lend itself to practical application (because it is difficult to identify the many model parameters).[9]

---

[8] Specifically, the production function was specified such that: $f(x,z) = H\big(x^e(x,z)\big) = H\big(x_1^e(x_1,z), x_2^e(x_2,z) \dots x_n^e(x_n,z)\big)$, where, x^e is a vector of effective input levels, $x_h^e = x_h * \varphi_h(z)$ is an element of x^e, and $\varphi_h(z)$ is a factor-specific input "abatement" function (which can be restricted to the unit interval).

[9] The output abatement model is a special case of Carpentier and Weaver's (1997) model: one in which the production function is linearly homogenous and the input abatement functions have the same functional form/parameters.

Rather than differentiating between productive and damage abating inputs, Zhengfei et al. (2006) categorized agricultural inputs vis a vis their relationship to plant biology. “Growth” inputs, like land, weather, nutrients, or water, were directly involved in a plant’s physiological process. “Facilitating” inputs, like labor, capital or pesticides, induced conditions that were favorable for growth.

Generally, empirical tests of damage abatement models have produced favorable results. Babcock et al. (1992) found that the marginal product of fungicides was almost 10 times larger when estimated using a Cobb-Douglas specification than when estimated using a damage abating model. Saha et al. (1997) corroborated the hypothesis that incorrect model specification led to the overestimation of pesticide productivity. Chambers and Lichtenberg (1994) used J-tests to demonstrate that a damage abatement specification outperformed a traditional one.

Insofar as more recent contributions are concerned, Chambers et al. (2010) demonstrated that infestations reduced yields directly (by damaging crops) and indirectly (by decreasing productive input use). The magnitude of these effects was estimated using a panel of data collected on Greek olive farms from 1994 through 2001. The results suggested that crop damages decreased yields by 17% relative to potential profits, but that decreases in productive input use associated with these pest infestations decreased yields by an additional 8%.

Chambers and Tzouvelekas (2013) used a damage abatement model to estimate pest population dynamics. First, Tornqvist indices were calculated for farmers’ fertilizer and pesticide use. Next, an instrumental variable based approach was used to estimate a simultaneous system of cost share functions. The structural parameters of the abatement function were used to predict the severity of pest infestations. Because farmers (in the sample) gauged the severity of insect infestations using sticky traps, the authors were able to corroborate their predictions using farm level data. This highlights a major advantage of the damage abatement framework. Unlike reduced form models, which do not provide much information about variables that are not observed, damage abatement models can be used to recover information about the data generating process.

To summarize, early studies of pesticide productivity estimated aggregate Cobb-Douglas production functions. Despite anecdotal evidence to the contrary, most of these studies found that the marginal benefit of pesticides exceeded their marginal cost. Over time, the methodologies employed by economists evolved. In particular, agricultural economists strove to model biological systems more realistically. For instance, Lichtenberg and Zilberman (1986) developed an biology based model of agricultural production which explicitly differentiated between production and pest control. Subsequent to the development of the damage abatement framework, agricultural economists were able to concentrate on solving empirical problems (rather than conceptual ones).

2. The Economics of GE Seeds

Quantifying the impacts of a technology adoption decision involves accounting for the possibilities that a) adoption and input use decisions are simultaneous, and b) important variables are unobserved or have been omitted from the analyses. Both of these problems fall under the rubric of endogeneity, a problem that arises when dependent and independent variables are correlated with the model's error term.

A number of econometric techniques have been developed to account for endogeneity. Following the notation (and development) in Heckman (1978), consider the following two equation model:

$$y_{1i} = X_{1i} \propto_1 + d_i\beta_1 + y_{2i}^*\gamma_1 + U_{1i} \;\Leftrightarrow\; y_{1i} = X_{1i}\pi_{11} + X_{2i}\pi_{12} + d_i\pi_{13} + V_{1i}$$

$y_{2i}^{*} = X_{2i} \propto_2 + y_{1i}\gamma_2 + U_{2i} \iff y_{2i} = X_{1i}\pi_{21} + X_{2i}\pi_{22} + V_{2i}$

where, $d_i = 1$ if $y_{2i}^{*} > 0$ (and 0 otherwise) and $U_1, U_2 \sim N(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{matrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{matrix})$.[10]

In this example, y_{1i} is observed and y_{2i}^{*} is a latent variable. X_1 and X_2 are vectors of exogenous variables. The dummy variable d_i records the event $y_{2i}^{*} > 0$. Notice that y_{1i} is a function of y_{2i}^{*} (and vice versa). Furthermore, notice that if Equation (II. 1) was estimated using X_1 and d_i, the residual would contain y_{2i}^{*}. In other words, endogeneity would be a problem.

Heckman (1978) proposed three methods of accounting for endogeneity. One approach is to estimate y_{1i} and y_{2i}^{*} simultaneously using Maximum Likelihood. The likelihood function is: $\mathcal{L} = \prod_i \varphi(V_{1i})\Phi\left(\frac{c_i - \rho(V_{1i}/\sqrt{\omega_{11}})}{\sqrt{(1-\rho^2)}}\right)^{d_i} \Phi\left(\frac{\rho(V_{1i}/\sqrt{\omega_{11}}) - c_i}{\sqrt{(1-\rho^2)}}\right)^{1-d_i}$, where, $V_{1i} = y_{1i} - X_{1i}\pi_{11} - X_{2i}\pi_{12} - d_i\pi_{13}$, $c_i = -\left(X_{1i}\frac{\pi_{21}}{(\omega_{22})^2} + X_{2i}\frac{\pi_{22}}{(\omega_{22})^2}\right)$, and $\rho = \frac{\omega_{12}}{\sqrt{\omega_{12}\omega_{22}}}$.

A second approach involves estimating: $\mathrm{E}(y_{1i}|X_{1i}, X_{2i}, d_i) = X_{1i}\pi_{11} + X_{2i}\pi_{12} + d_i\pi_{13} + \mathrm{E}(V_{1i}|X_{1i}, X_{2i}, d_i)$ where, $\mathrm{E}(V_{1i}|X_{1i}, X_{2i}, d_i) = \frac{\omega_{12}}{\sqrt{\omega_{22}}}\left(\frac{\varphi(c_i)}{1-\Phi(c_i)}d_i - \frac{\varphi(-c_i)}{1-\Phi(-c_i)}(1-d_i)\right)$. First, a binary choice, or linear probability, model is used to estimate $\pi_{21}$and π_{22}. Next, these parameter estimates are used to estimate $\mathrm{E}(V_{1i}|X_{1i}, X_{2i}, d_i)$. Finally, an error term is appended, and $\mathrm{E}(y_{1i}|X_{1i}, X_{2i}, d_i)$ is estimated using ordinary least squares.

---

[10] Writing Equations (II.1) and (II.2) in reduced form facilitates the discussion. For future reference, $\pi_{11} = \frac{\alpha_1}{1-\gamma_1\gamma_2}$, $\pi_{21} = \frac{\alpha_1\gamma_2}{1-\gamma_1\gamma_2}$, $\pi_{12} = \frac{\alpha_2\gamma_1}{1-\gamma_1\gamma_2}$, $\pi_{22} = \frac{\alpha_2}{1-\gamma_1\gamma_2}$, $\pi_{13} = \frac{\beta_1+\gamma_1\beta_2}{1-\gamma_1\gamma_2}$, $\pi_{23} = \frac{\gamma_2\beta_1+\beta_2}{1-\gamma_1\gamma_2}$, $V_{1i} = \frac{U_{1i}+\gamma_1 U_{2i}}{1-\gamma_1\gamma_2}$, $V_{2i} = \frac{\gamma_2 U_{1i}+U_{2i}}{1-\gamma_1\gamma_2}$, $\mathrm{E}[V_{1i}] = 0, E[V_{1i}] = 0, E\left[{V_{1i}}^2\right] = \omega_{11}, E[V_{1i}, V_{2i}] = \omega_{12},\ E\left[{V_{2i}}^2\right] = \omega_{22}$.

A third approach involves estimating: $y_{1i} = X_{1i} \propto_1 + \widehat{P_i}\beta_1 + \left(\frac{\widehat{y_{2i}^*}}{\sqrt{\omega_{22}}}\right)\gamma_1^* + \varepsilon_i$, where, $\varepsilon_i = \left[U_{1i} + \left(d_i - \widehat{P_i}\right)\beta_1 + \left(\frac{y_{2i}^*}{\sqrt{\omega_{22}}} - \frac{\widehat{y_{2i}^*}}{\sqrt{\omega_{22}}}\right)\gamma_1^*\right]$, $\widehat{P_i} = \mathrm{Prob}(d_i = 1|X_{1i}, X_{2i})$, and $\frac{\widehat{y_{2i}^*}}{\sqrt{\omega_{22}}}$ is a normalized prediction of the latent variable (conditional on X_{1i} and X_{2i}). This is also a two-step method. First the results of a binary choice (or linear probability model) are used to generate estimates of $\widehat{P_i}$ and $\frac{\widehat{y_{2i}^*}}{\sqrt{\omega_{22}}}$. Next, $y_{1i} = X_{1i} \propto_1 + \widehat{P_i}\beta_1 + \left(\frac{\widehat{y_{2i}^*}}{\sqrt{\omega_{22}}}\right)\gamma_1^* + \varepsilon_i$ is estimated using ordinary least squares.

Because of its methodological simplicity, the third of these approaches is frequently employed in studies of GE seeds. However, predictions of $\frac{\widehat{y_{2i}^*}}{\sqrt{\omega_{22}}}$ are rarely included in the second stage. This implies that the residual is non-zero. Although the non-negativity of the error term is not problematic in and of itself, the results will be biased if $\widehat{P_i}$ is estimated using variables that are not exogenous. A more substantive problem, at least in the context of damage abatement models, is that substituting predictions tends to induce inconsistency in nonlinear models (Greene, 2006; Tezra et al., 2008; and Wooldridge, 2014). As will be further discussed in Chapter 4, Wooldridge (2014) recommends employing a two stage, control function based approach.[11]

With this in mind, consider Fernandez-Cornejo, Klotz-Ingram and Jans (2002), one of the first rigorous, economic analyses of GE seeds. This study analyzed the impacts of HT adoption using data collected during the USDA's 1997 Agricultural

[11] In fact, incorporating the inverse mills ratio into a model's specification is a control function based approach. Wooldridge (2014) contends that control functions can be residuals, generalized residuals, standardized residuals, or even linear functions of instrumental variables.

Resource Management Survey.[12] Recognizing that HT adoption might be endogenous, the authors employed the third of Heckman's corrections. First, a probit model was used to regress HT adoption by a number of farm (and farmer) level characteristics. Next, predicted probabilities were substituted into a seemingly unrelated system of linear profit, production, and demand functions. The results of the first stage (or Adoption model) suggested that seed expenditures, farm size, education, crop prices, and pest infestation levels increased the probability of HT adoption. The results of the second stage (or Impact model) suggested that HT adoption increased glyphosate use and decreased the use of synthetic herbicides.

Unfortunately, there were several problems with this study's implementation of the endogeneity correction. First, the authors did not justify their exclusion restrictions. Second, the authors did not discuss the probit model's goodness of fit, so it is hard to gauge whether the predicted probabilities were good instruments for HT adoption. Third, some of the variables used in the first stage of the model were clearly endogenous.[13]

To some extent, Fernandez-Cornejo et al. (2005), Fernandez and Li (2005), Gardner et al. (2009), and Fernandez-Cornejo and Wechsler (2012) also suffer from these problems. Nonetheless, these studies provided valuable insights. By analyzing how HT adoption affected off-farm income, Fernandez-Cornejo et al. (2005) found evidence that planting HT seeds simplified weed management and decreased household labor requirements. Gardner et al. (2009) corroborated this result using survey data

---

12 A preliminary version of this study can be found in Fernandez et al. (2000).

13 For instance, seed expenditures are clearly higher for HT adopters than conventional seed users. As discussed earlier in the chapter, substituting predicted probabilities only produces unbiased parameter estimates (in the model's second stage) if the instruments used in the first stage are exogenous.

collected in 2009. They found that a 10 percent increase in the probability of HT soybean adoption decreased household labor by 2.2%.

Fernandez-Cornejo and Li (2005) found that cultivating corn borer resistant plants increased US farmers' yields and decreased their insecticide use in 2001. Surprisingly, adoption did not appear to have a statistically significant impact on farmers' profits. Fernandez-Cornejo and Wechsler (2012) corroborated the finding that Bt adoption increased yields using survey data collected in 2005.

Other studies analyzed the impacts of GE adoption using damage abatement models. For instance, Huang et al. (2002) analyzed survey data collected in 2000 by estimating a damage abating production function and a reduced form insecticide demand function simultaneously. Their findings suggested that Bt cotton adoption increased Chinese farmers' yields by approximately 8% and lowered insecticide use by 58%. However, Huang et al. (2002) failed to account for the possibility that Bt adoption was exogenous.

Qaim and de Janvry (2005) analyzed the impact of Bt cotton use in India using data collected in in 2001. Their results suggested that planting Bt cotton increased yields by 30% and decreased insecticide use by 73%. However, the authors did not account for the possibility that the Bt adoption decision was endogenous.

Shankar et al. (2008) used the model developed in Saha et al. (1997) to analyze the impacts of Bt cotton adoption in South Africa. Their results suggested that both Bt cotton adoption and pesticide use increased the yields of South African farmers. Surprisingly, the results indicated that using these inputs increased the variance of the production function. Unfortunately, it is hard to know whether this result is reliable because the authors failed to account for the possibility that the adoption was endogenous.

Shankar and Thirtle (2005) used variable addition tests (the estimation and inclusion of the inverse mills ratio) to determine whether Bt adoption/insecticide use decisions were endogenous. After determining that both inputs were exogenous, the authors found that Bt cotton adoption increased the yields of South African smallholders by 19% in 2000.

Mutuc et al. (2011) also used variable addition tests to assess the endogeneity of pest control decisions. They found that insecticide use was exogenous, but that Bt adoption was not. The results of the study indicated that planting Asian corn borer resistant seeds increased the yields of Philippian farmers by 33% and 44%, in 2003 and 2007 (respectively). Unfortunately, these results may have been biased because predicted probabilities were substituted into the non-linear, damage abating production function.

Some studies avoided endogeneity problems by analyzing data from field trials. For instance, Qaim and Zilberman (2003) estimated a damage abating production function using data from field tests of Bt cotton seeds. The results of this study suggested that Bt adoption increased the yields of Indian famers by approximately 60% in 2001.

Nolan and Santos (2012) estimated a reduced form model of corn yields using data from US field trials. Their results suggested that Bt-CRB and Bt-CRW adoption increased yields by 4% and 2% (respectively). Though these results are unbiased, they do not indicate how using different types of Bt seeds affects farmers' insecticide use.

One problem with Qaim and Zilberman (2003) and Nolan and Santos (2012) is that field trials tend to inflate yields. For instance, the average mean of the crops analyzed in Nolan and Santos (2012) was approximately 30% higher than yields reported by NASS for US corn farmers. Consequently, economic analyses of field trials tend to overestimate the benefits associated with Bt seeds.

It is possible to draw several broad conclusions from this review. First, analyses of genetically modified seeds tend to do a poor job of accounting for endogeneity. Second, this problem is less pronounced in reduced form analyses than it is in (nonlinear) structural ones. Third, previous studies have failed to test the hypothesis that the effectiveness of GE based pest control systems has changed over time, or by location. In other words, there appears to be ample opportunity to contribute to this literature.

3. Conclusions

Early studies used aggregate Cobb-Douglas production functions to estimate the marginal value product of pesticides. These studies ignored issues like self-selection and simultaneity because methods of accounting for these problems had not been developed yet. Similarly, little attention was paid to plant physiology or pest population dynamics. This changed in 1978 when Heckman developed straightforward solutions to endogeneity problems, and again in 1986, when Lichtenberg and Zilberman (1986) developed a biology based model of agricultural production.

The commercial introduction of GE seeds renewed interest in studies of farmers' pest control decisions. However, few of the ensuing studies rigorously accounted for endogeneity problems. Studies employing linear, reduced form models tended to use endogenous variables as instruments for GE adoption. Studies that employed damage abatement models tended to neglect endogeneity or to employ techniques that were not appropriate in the context of non-linear models. Though studies that analyzed data from field trials were not biased by endogeneity, the results of these studies do not provide insight about farmers' behavior and tend to overestimate the impacts of adoption.

As is discussed in the subsequent chapters, this dissertation uses the damage abatement framework developed by Lichtenberg and Zilberman (1986) to formulate a realistic, biology based model of corn farmers' insect control decisions. This model is used to derive a demand function for soil insecticides, which is estimated using field level data collected in 2005 and 2010. Unlike previous damage abatement studies, this study accounts for endogeneity using an approach that is appropriate for non-linear models. The results provide insight into whether the effectiveness of Bt-CRW seeds has changed over time.

Table 1. A Summary of Selected Economic Analyses of GE Seeds

Authors	Survey Year	GE Seed Type	Country	Data Set	Model Type	End. Correction, GE Seeds	End. Correction, Pesticides	Observations	Determinants of Adoption	Impact on Profit	Impact on Yield	Impact on Pesticide Use	Other
Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans (2000)	1997	Bt/HT Cotton, HT Soybeans	USA	ARMS Survey	Sim. System (Profit: quadratic)	Two stage IV, Pred. Prob. and IMR	Simultaneous Estimation	1,444 for soybeans; 696 for cotton	Not Reported	HT Cotton: 1.8% Bt Cotton: 2.2%[1,2]	HT Cotton: 1.7% Bt Cotton: 2.1% HT Soybean: .3%[1,2]	HT Soybean: Glyphosate, 4.3%; Synthetic Herbicide Use, -1.4%[1,2]	-
Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans (2002)	1997	HT Soybeans	USA	ARMS Survey	Sim. System (Profit: quadratic)	Two stage IV, Pred. Prob.	Simultaneous Estimation	1,444	Size***, Education**, Infestation levels**, Seed Price***, Conventional Tillage*, Crop Price*	NS	0.3%**[1]	Glyphosate: 3.7%***, Synthetic Herbicide Use: -1.3%***[1]	-
Huang, J., R. Hu, S. Rozelle, F. Qiao, and C. Pray (2002)	1999	Bt Cotton	China	Huang et al. (2002)	DA Prod. Function (F: Cobb-Douglas; A: Weibull, Exponential)	No Correction[3]	Simultaneous Estimation	382	-	-	8%[2]	-58%***[4]	-
Bernard, J., J. Pesek, and C. Fan (2004)	1996-2000	HT Soybeans	USA	Bernard et al. (2004)	Linear production and cost functions	Tested: Adoption is exogenous	NA	106 for production, 88 for cost	Farm Size**, Use of a Computer*	-	10%*	-	-24%**
Thirtle, C., L. Beyers, Y. Ismael, and J. Piesse (2003)	1999, 2000[5]	Bt Cotton	S. Africa	Thirtle et al. (2003)	Stochastic Frontier Model	No Correction	No Correction	100 obs in 1999, 100 obs in 2000	Farm Size*, Nonfarm Income**, Experience**, Number of Female Laborers***	-	-	-	On average, adopters are 30 to 55% more efficient than non-adopters.[2]
Shankar, B. and C. Thirtle (2005)	2000	Bt Cotton	S. Africa	Thirtle et al. (2003)	DA Prod. Function (F: Cobb-Douglas; A: Cobb-Douglas)	Tested: Adoption is exogenous	Tested: Ins Use is exogenous	91	Not Reported	-	19%[2]	-	-
Shankar, B., R. Bennett, and S. Morse (2008)	2000	Bt Cotton	S. Africa	Thirtle et al. (2003)	DA Prod. Function (F: Cobb-Douglas; A: Logistic)	Ignorability of Treatment	No Correction	86	-	-	13%***	-	-
Fernandez-Cornejo, J., C. Hendricks, and A. Mishra (2005)	2001	HT Soybeans	USA	ARMS Survey	Linear Profit Function	Two stage IV, Pred. Prob.	NA	2,258	Seed Price***	NS	-	-	Off farm income: 8.4%[1]

Authors	Survey Year	GE Seed Type	Country	Data Set	Model Type	End. Correction, GE Seeds	End. Correction, Pesticides	Observations	Determinants of Adoption	Impact on Profit	Impact on Yield	Impact on Pesticide Use	Other
Fernandez-Cornejo, J. and J. Li (2005)	2001	Bt Corn	USA	ARMS Survey	Sim. System (Profit: quadratic)	Two stage IV, Pred. Prob.	Simultaneous Estimation	1,751	Size***, Age**, Off-farm income***, Corn revenue under contract*, Owns livestock***, Corn Price**	NS	0.4%[1,2]	-4.11%[1,2]	-
Qaim, M., E. Cap, and A. de Janvry (2003)[6]	2001	Bt Cotton	Argentina	Qaim et al. (2003)	DA Prod. Function (F: Quadratic; A: Logistic)	No Correction	Two stage IV, Ins Use Predictions	358	-	-	30%[2]	-81%[2]	-
Qaim, M. and A. de Janvry (2005)	2001	Bt Cotton	Argentina	Qaim et al. (2003)	DA Prod. Function (F: Quadratic; A: Logistic)	No Correction	Two stage IV, Ins Use Predictions	358	-	-	29.5%2	-73%2	-
Qaim, M. and D. Zilberman (2003)	2001	Bt Cotton	India	Qaim, M. and D. Zilberman (2003)	DA Prod. Function (F: Quadratic; A: Logistic)	-	No Correction	471	-	-	60%	Not reported	-
Gardner, J., R. Nehring, and C. Nelson (2009)	2001, 2002, 2003	HT Soybeans, Bt/HT Corn, Bt/HT Cotton	USA	ARMS Survey	Linear Household Demand Function (ATE Model)	Two stage IV, Pred. Prob.	No Correction	1,833 for soybeans; 1,861 for corn; 1,269 for cotton	Not Reported	-	-	-	HT Soybean adoption decreases household labor (by 2.2%)[1]
Crost, B., B. Shankar, R. Bennett, and S. Morse (2007)	2002-2003	Bt Cotton	India	Crost et al. (2007)	Cobb-Douglas Prod. Function	Farm, year fixed effects	Farm, year fixed effects	718	-	-	11%-31%2	-	-
Qaim, M., A. Subramanian, G. Naik, and D. Zilberman (2006)	2003	Bt Cotton	India	Qaim et al. (2006)	Translog Prod. Function	No Correction	No Correction	434	-	-	59%***	-	-

Authors	Survey Year	GE Seed Type	Country	Data Set	Model Type	End. Correction, GE Seeds	End. Correction, Pesticides	Observations	Determinants of Adoption	Impact on Profit	Impact on Yield	Impact on Pesticide Use	Other
Yorbe, J. and C. Quicoy (2006)	2004	Bt Corn	Philippines	ISAAA Survey	Linear Profit Function and Linearized Cobb-Douglas Production Function	Profit Function: Two stage IV, Pred. Prob. and IMR; Production Function: no correction	No Correction	470	Education**, Hired Labor**, Net Income***, Agricultural Training**, Risk Perception***	4.1%1,2	A 10% increase in acreage planted increases output by 9.2%	-	-
Gouse, M., J. Piesse, and C. Thirtle (2006)	2004	Bt Corn	South Africa	Gouse et al. (2006)	Stochastic Frontier Model	No Correction	Not included in analysis	135	-	-	-	-	On average, adopters are 4% less efficient than non-adopters.[2]
Fernandez-Cornejo, J. and S. Wechsler (2012)[7]	2005	Bt Corn	USA	ARMS Survey	Sim. System (Profit: quadratic)	Two stage IV, Pred. Prob.	Simultaneous Estimation	1,129	Farm Size***, Experience**, Crop Insurance**, Irrigation**, Perceived Yield Losses from Corn Borers***	1.65%1,2	1.71%1,2	-	Seed Demand: .97%[1,2]
Fernandez-Cornejo, J., C. Hallahan, R. Nehring, and S. Wechsler (2012)	1996-2006	HT Soybeans	USA	ARMS, CTIC, and Public Sources	Linearized Adoption/Demand Functions	Tested: Adoption is exogenous	NA	132	-	-	-	-	Conservation Tillage: 2.1%; Quality-Adjusted Herbicide Use: -3%[1,2]
Gouse, M., J. Piesse, C. Thirtle, and C. Poulton (2009)	2007	Bt/HT Corn	South Africa	Gouse et al. (2009)	Stochastic Frontier Model	No Correction	No Correction	249	-	-	-	-	On average, HT adopters are 6% less efficient, and Bt adopters are 2% less efficient than non-adopters.[2]
Mutuc, M., R. Rejesus, and J. Yorbe (2011)	2004, 2008[8]	Bt Corn	Philippines	ISAAA for 2004, IFPRI for 2008	DA Prod. Function (F: Cobb-Douglas; A: Logistic)	Two stage IV, Pred. Prob.	Tested: Adoption is exogenous	407 obs in 2004, 468 obs in 2008	-	-	33%*** in 2003, 44%*** in 2007	-	-

Authors	Survey Year	GE Seed Type	Country	Data Set	Model Type	End. Correction, GE Seeds	End. Correction, Pesticides	Observations	Determinants of Adoption	Impact on Profit	Impact on Yield	Impact on Pesticide Use	Other
Smale, M., P. Zambrano, R. Paz-Ybarnegaray, and W. Fernandez-Montano (2012)	2008	HT Soybeans	Bolivia	Smale et al. (2012)	Off-farm household income function (Tobit)	Two stage IV, control function	NA	102	Education**, Capital***, Seed Price*	-	-	-	Adoption increases off farm income by 9,000 bolivianos, a 64% increase in household income.***
Nolan, E. and P. Santos (2012)	1997-2009	Bt/HT Corn	USA	Nolan and Santos (2012)	Linearized Prod. Function	Trait Random-Effects	NA	147,790	-	-	Bt-CRB: 4%*** Bt-CRW: 2%**	-	-

1 The results are reported as elasticities. For instance, a 10% increase in the probability of adoption induces an x% increase in profits.

2 Signifigance levels are not reported.

3 T-tests are used to demonstrate that there are not differences between the explanatory variables. This is interpreted as evidence that there is no sample selection.

4 Impacts on inseciticide use were estimated using a reduced form model.

5 The authors analyzed the two years of survey data separately.

6 Qaim et al. (2003) and Qaim and de Janvry (2005) use different explanatory variables in the specification of the output generating function of the production function.

7 The insect resistance traits are not disaggregated.

8 The authors analyzed the two years of survey data separately.

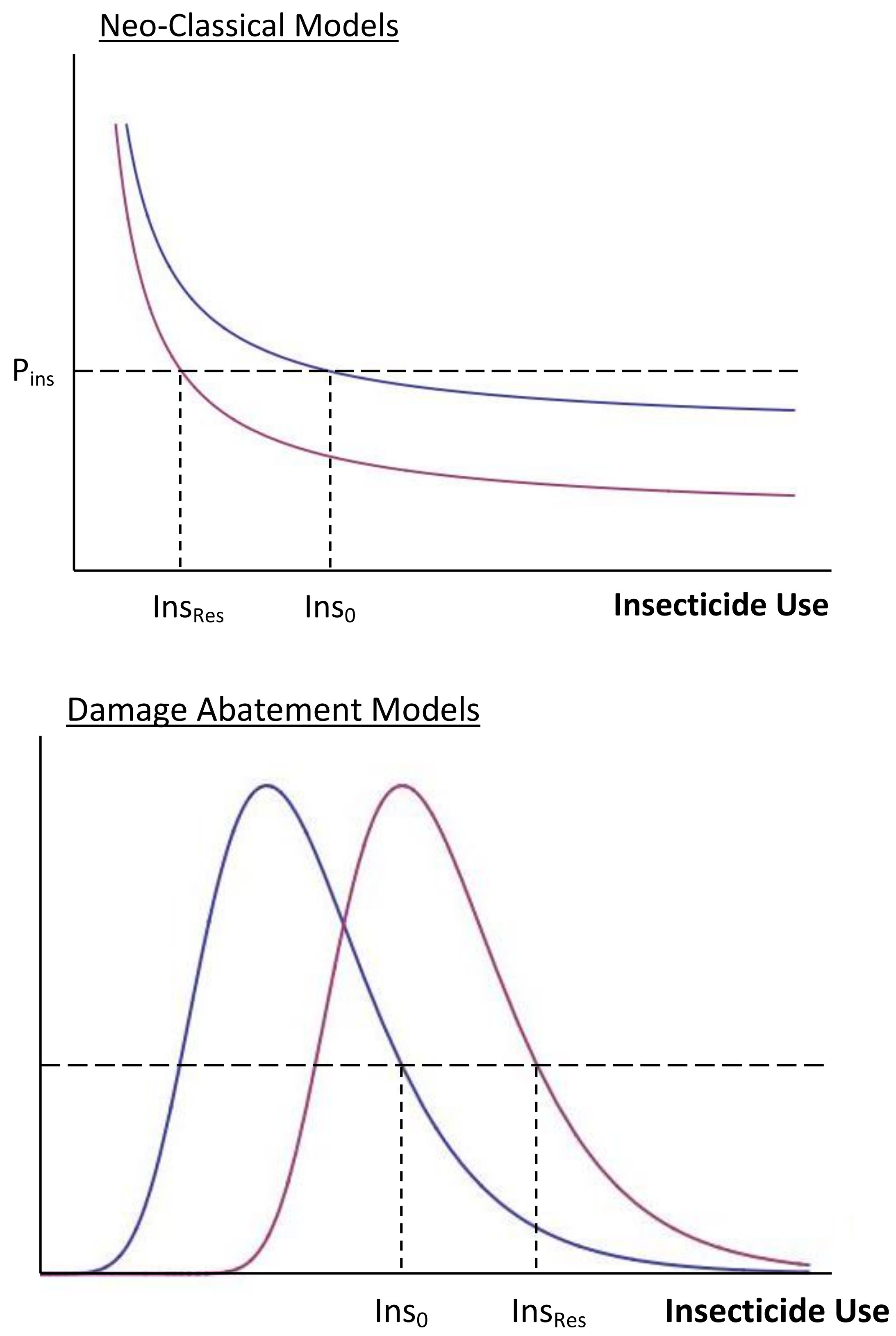

Figure 2. How Resistance Affects the Marginal Product of Insecticides

Chapter 3: A Structural Model of Corn Farmers' Insect Control Decisions

The previous two chapters surveyed the literature on genetically modified seeds. This chapter focuses on Bt corn. First, it describes major corn pests and discusses the strategies that farmers use to treat them. Next, it formulates a two stage, theoretical model and uses it to derive a soil insecticide demand function. Subsequent chapters discuss how to estimate this demand function, and how the results can be used to test the hypothesis that rootworms have developed resistance to Bt seeds.

1. Insect Physiology and the Timing of Corn Farmers' Pest Control Decisions

Rootworms and corn borers are the two most historically destructive corn pests in the United States. That distinction aside, the insects have little in common.

Rootworms lay eggs that overwinter in the soil. After hatching in late May, the larvae begin feeding on root tips and root stems. After several weeks of feeding, the larvae metamorphose into beetles and emerge from the soil (Plant & Soil Sciences eLibrary). Farmers treat rootworm infestations by applying soil insecticides at planting time or by rotating their crops regularly.

Unlike rootworms, corn borer larvae overwinter above the ground (in organic debris). After emerging from hibernation in late May, the larvae develop into moths. Sometime in mid-June, these moths lay eggs on the underside of corn leaves. One week later, the eggs hatch and the larvae begin boring into stalks and whorls (Iowa State, Department of Entomology). Topical insecticides are effective after the eggs have been laid, but before the larvae have bored into the plant. Though corn borer infestations are notoriously difficult to treat, they can be controlled using topical insecticide sprays.

To summarize, rootworm infestations are treated at planting time. Corn borer infestations are treated later in the growing season (after egg deposition, but before larvae bore into the plant).

2. A Structural Model of Corn Farmers' Pest Control Decisions

As in Lichtenberg and Zilberman (1986), this study employs a damage abatement model. Under perfect information, it is assumed that $\mathrm{Y} = HG$, where H is a traditional production function, and G is an abatement function (which maps to the unit interval). Because rootworms and corn borers are treated at different times in the growing season and with different types of insecticides, it is assumed that abatement is multiplicatively separable. The aggregate abatement function takes the form: $G = G_{CB}G_{CRW}$.

It is explicitly assumed that farmers are risk neutral. This assumption is ubiquitous in the damage abatement literature. It is especially reasonable in the context of US agriculture, where capital markets are well developed, and farms tend to be large, corporate operations.

The timing of the model is as follows: First, farmers decide whether to plant Bt seeds and/or administer soil insecticides. Next, farmers observe pest infestation levels/environmental conditions and decide whether or not to apply topical insecticides.

It is implicitly assumed that there are three sources of uncertainty: an error term affecting yield losses from corn borer infestations (ε_{CB}), an error term affecting yield losses from rootworm infestations (ε_{CRW}), and an error term affecting potential yields (ε_H). Uncertainty about yield losses are assumed to affect abatement levels multiplicatively such that $G = G_{CRW}G_{CB}\exp(\varepsilon_{CRW} + \varepsilon_{CB})$. Similarly, $\boldsymbol{H} = H\exp(\varepsilon_H)$. This implies that the production function is: $\mathrm{Y} = HG\exp(\varepsilon_{CRW} + \varepsilon_{CB} + \varepsilon_H)$. For the purposes of this analysis, the error terms will be aggregated such that $Y = HG\exp(\varepsilon)$. This formulation is appealing because of its generality and tractability.

As in Fox and Weersink (1995), abatement is specified using an extreme value distribution such that: $G_i = \exp\left(-Z_i\exp\left(-p_i{}'\beta_{pi}\right)\right)$, where Z_i represents the severity of pest infestations, p_i is a column vector of damage abating inputs, β_{pi} is a column vector of parameters, and $i \in \{CB, CRW\}$. A non-negativity constraint is imposed on Z_i by assuming that $Z_i = \exp(z_i{}'\beta_{zi})$, where z_i is a vector of field level factors and β_{zi} is a vector of parameters.

2.1 Topical Insecticide Use Decisions

The timing of the model dictates that the farmer has full information when he makes his topical insecticide use decision. Therefore, the farmer's profit maximization problem can be simplified to:

$$\underset{Ins_T}{Max}\ \pi = P\mathrm{Y} - p_T Ins_T$$

s.t. $\quad \mathrm{Y} = HG_{CRW}G_{CB}\exp(v)$

$$G_{CB} = \exp(-Z_{CB}\exp(-a - bBt_{CB} - cIns_T))$$

$$Z_{CB} = \exp\left(z_{CB}{}'\beta_{z_{CB}}\right)$$

where, Bt_{CB} is an indicator for corn borer resistant seed use, Ins_T represents topical insecticide use, v is a realization of ε, and a, b, and c are parameters. Substituting the constraints into the objective function indicates that:

$$\pi = PHG_{CRW}\exp\left(-\exp\left(-a - bBt_{CB} - cIns_T + z_{CB}{}'\beta_{z_{CB}}\right)\right)\exp(v) - p_T Ins_T$$

The first order condition of the farmers' profit maximization problem is:

$$\frac{d\pi}{dIns_T} = PHG_{CRW}G_{CB}\exp\left(-a - bBt_{CB} - cIns_T + z_{CB}{}'\beta_{z_{CB}}\right)c\exp(v) - p_T = 0$$

Therefore, the demand function for topical insecticide use is:

$$\text{(III. 1)}\ Ins_T^* = \frac{1}{c}\left[-a - bBt_{CB} + z_{CB}'\beta_{z_{CB}} + \ln\left(\frac{cPHG_{CRW}G_{CB}}{p_T}\right) + v\right]$$

This function is increasing in pest pressure, corn prices, and yields, but decreasing in topical insecticide prices.

2.2 Seed Choices and Soil Insecticide Use Choices

At planting time, the farmer faces uncertainty about the severity of pest infestations and environmental conditions. Therefore, he is forced to anticipate future soil insecticide use decisions. If It is assumed that $\mathrm{E}[\varepsilon] = 0$, then expected topical insecticide use is: $\mathrm{E}[Ins_T^*] = \frac{1}{c}\left[-a - bBt_{CB} + z_{CB}'\beta_{z_{CB}} + \ln\left(\frac{cPHG_{CRW}G_{CB}}{p_T}\right)\right]$.

Substituting $\mathrm{E}[Ins_T^*]$ into G_{CB} indicates that optimal expected abatement from corn borer infestations is:

$$G_{CB}^* = \exp\left(-\frac{p_T}{cPHG_{CRW}G_{CB}}\right)$$

This expression can be simplified to:

$${G_{CB}^*}^{G_{CB}^*} = \exp\left(-\frac{p_T}{cPHG_{CRW}}\right)$$

Appendix A demonstrates that G_{CB}^* is:

$$G_{CB}^* = \left(-\frac{p_T}{cPHG_{CRW}}\right) W\left(-\frac{p_T}{cPHG_{CRW}}\right)^{-1}$$

where, W is the product log, or Lambert function. Therefore, it is possible to substitute G_{CB}^* out of the production function:

$$\text{(III. 2)}\ \mathrm{E}[\mathrm{Y}] = HG_{CRW}G_{CB}^*\mathrm{E}[\exp(\varepsilon)] = \frac{-p_T}{cP} W\left(-\frac{p_T}{cPHG_{CRW}}\right)^{-1} \mathrm{E}[\exp(\varepsilon)]$$

This implies the farmer's maximization problem at planting time is:

$$\underset{Ins_S,\, Bt_{CRW},\, Bt_{CB}}{\mathrm{Max}}\ \mathrm{E}[\pi] = P\mathrm{E}[\mathrm{Y}] - p_S Ins_S - p_T \mathrm{E}[Ins_T^*] - p_{CRW}Bt_{CRW} - p_{CB}Bt_{CB}$$

s.t. $\mathrm{E}[Y] = \frac{-p_T}{cP} W\left(-\frac{p_T}{cPHG_{CRW}}\right)^{-1} \mathrm{E}[\exp(\varepsilon)]$

$G_{CRW} = \exp(-Z_{CRW}\exp(-d - eBt_{CRW} - fIns_S))$

$Z_{CRW} = \exp\left(z_{CRW}{'}\beta_{z_{CRW}}\right)$

$$\mathrm{E}[Ins_T^*] = \frac{1}{c}\left[-a - bBt_{CB} + z_{CB}{'}\beta_{z_{CB}} + \ln\left(\frac{cPHG_{CRW}G_{CB}^*}{p_T}\right)\right]$$

$$G_{CB}^* = \left(-\frac{p_T}{cPHG_{CRW}}\right)W\left(-\frac{p_T}{cPHG_{CRW}}\right)^{-1}$$

$Bt_{CRW}, Bt_{CB} \in \{0,1\}$

Appendix B demonstrates that the first order condition of this maximization problem is:

$$P\mathrm{E}[Y]f\exp(-d - eBt_{CRW} - fIns_S + z_{CRW}{'}\beta_{z_{CRW}}) * \varphi - p_S = 0$$

where, $\varphi = \left(\frac{cP\mathrm{E}[Y]}{p_T} - 1\right) / \left(\frac{cP\mathrm{E}[Y]}{p_T} - \mathrm{E}[\exp(\varepsilon)]\right)$.

Therefore, the demand function for soil insecticides is:

$$(\mathrm{III.3})\ Ins_S^* = \frac{1}{f}\left[-d - eBt_{CRW} + z_{CRW}{'}\beta_{z_{CRW}} + \ln\left(\frac{fP\mathrm{E}[Y]}{p_s}\right) + \ln(\varphi)\right]$$

Equation $(\mathrm{III.3})$ demonstrates soil insecticide demand is decreasing in insecticide prices, but increasing in pest pressure, corn prices, expected yields, and $\mathrm{E}[\exp(\varepsilon)]$.[14] The latter of these terms captures the impacts of uncertainty, or production risk, on soil insecticide use decisions. The larger the variance of ε, the more soil insecticides will be applied. This is not because farmers are risk averse (the model explicitly assumes risk neutrality), but because log-normal, log-gumbel, and other such distributions are increasing in the variance (or scale) parameter.

---

[14] Simple parametric assumptions help demonstrate that Ins_S^* is increasing in $\mathrm{E}[\exp(\varepsilon)]$. For instance, if $\varepsilon \sim N(0, \sigma^2)$, then $\exp(\varepsilon)$ has a log normal distribution and $\mathrm{E}[\exp(\varepsilon)] = \exp(\frac{\sigma^2}{2})$. Under perfect information, $\sigma^2 = 0$, $\exp\left(\frac{\sigma^2}{2}\right) = 1$, and $\ln(\varphi) = 0$. As the variance of ε increases, $\ln(\varphi)$ increases, which increases soil insecticide demand.

3. Conclusions

The demand functions for soil and topical insecticides (Equations III.1 and III.3) are:

$$Ins_T^* = \frac{1}{c}\left[-a - bBt_{CB} + z_{CB}{}'\beta_{z_{CB}} + \ln\left(\frac{cPHG_{CRW}G_{CB}}{p_T}\right) + v\right]$$

and,

$$Ins_S^* = \frac{1}{f}\left[-d - eBt_{CRW} + z_{CRW}{}'\beta_{z_{CRW}} + \ln\left(\frac{fP\mathrm{E}[Y]}{p_s}\right) + \ln(\varphi)\right]$$

where, $\varphi = \left(\frac{cP\mathrm{E}[Y]}{P_T} - 1\right)/\left(\frac{cP\mathrm{E}[Y]}{P_T} - \mathrm{E}[\exp(\varepsilon)]\right)$.

The similarities between the demand functions stem from the fact that G_{CRW} and G_{CB} have the same functional form and are multiplicatively separable. The differences stem from the model's timing. Notice that it is possible to estimate the soil insecticide demand function if the dataset contains information about input prices, output prices, expected yields, and pest infestation levels (or factors affecting pest infestation levels).

Chapter 4 discusses how to estimate the soil insecticide demand function, and how the results can be used to test the hypothesis that rootworms have developed resistance.

Appendix A: Isolating G^*_{CB}

As shown in Chapter Three, Section II:

$$G_{CB}^{*\;G_{CB}^*} = \exp(-\frac{p_T}{cPHG_{CRW}})$$

For ease of exposition, let $G_{CB}^* = x$ and $\exp(-\frac{p_T}{cPHG_{CRW}}) = \omega$. Then:

$$x^x = \omega$$

Next, let $x = \exp(\ln(x))$. So:

$$\exp(\ln(x))^{\exp(\ln(x))} = \omega$$

The exponent rule $\exp(a)^b = \exp(ab)$ implies that:

$$\exp(\ln(x))^{\exp(\ln(x))} = \exp(\ln(x)\exp(\ln(x))) = \omega$$

Taking the log of both sides of the equation demonstrates that:

$$\ln(x)\exp(\ln(x)) = \ln(\omega)$$

Taking the product log of both sides of the equation implies that:[15]

$$\ln(x) = W[\ln(\omega)]$$

Taking the exponent of both sides of the equation indicates that:

$$x = \exp(W[\ln(\omega)])$$

The identity $\exp(W(x)) = x/W(x)$ can be used to simplify this expression:

$$x = \ln(\omega)\, W[\ln(\omega)]^{-1}$$

[15] The product log (or Lambert) function is defined as the inverse of $f(q) = q\exp(q)$, so $q = W[q\exp(q)]$ for any complex number q.

Substituting $G_{CB}^{*} = x$ and $\exp(-\frac{p_T}{cPHG_{CRW}}) = \omega$ back into the problem demonstrates that:

$$G_{CB}^{*} = \left(-\frac{p_T}{cPHG_{CRW}}\right) W \left(-\frac{p_T}{cPHG_{CRW}}\right)^{-1}$$

Appendix B: Deriving the First Order Condition for Soil Insecticide Use

The farmer's (variable) profit maximization problem at planting time is:

$$\max_{Ins_S} \pi = P\mathrm{E}[Y] - p_S Ins_S - p_T\,\mathrm{E}[Ins_T^*]$$

Substituting Equation (III. 2), $\mathrm{E}[Y] = \frac{-p_T}{cP} W\left(-\frac{p_T}{cPHG_{CRW}}\right)^{-1} \mathrm{E}[\exp(\varepsilon)]$, into the profit function demonstrates that:

$$\pi = \frac{-p_T}{c} W\left(-\frac{p_T}{cPHG_{CRW}}\right)^{-1} \mathrm{E}[\exp(\varepsilon)] - p_S Ins_S - \frac{p_T}{c}\ln\left(-W\left(-\frac{p_T}{cPHG_{CRW}}\right)^{-1}\right) - \frac{p_T}{c}\left[-a - bBt_{CB} + z_{CB}'\beta_{z_{CB}}\right]$$

The derivative of the Lambert function is $\frac{dW(x)}{dx} = \frac{W(x)}{x(1+W(x))}$. So, the first order condition is:

$$\frac{d\pi}{dIns_S} = \left[\frac{p_T}{c} W^{-2}\right]\left[\frac{W}{\left(-\frac{p_T}{cPHG_{CRW}}\right)(1+W)}\right]\left(\frac{p_T}{cPH} G_{CRW}{}^{-2}\right) G_{CRW}(-\exp(-d - eBt_{CRW} - fIns_S + z_{CRW}'\beta_{z_{CRW}}))(-f)\mathrm{E}[\exp(\varepsilon)] - p_S$$

$$-\frac{p_T}{c}[-W]W^{-2}\left[\frac{W}{\left(-\frac{p_T}{cPHG_{CRW}}\right)(1+W)}\right]\left(\frac{p_T}{cPH}{G_{CRW}}^{-2}\right)G_{CRW}(-\exp(-d-eBt_{CRW}-fIns_S+z_{CRW}{}'\beta_{z_{CRW}}))(-f)$$

This simplifies to:

$$\frac{d\pi}{dIns_S}=\left[-\frac{p_T}{cW}\right]\frac{f\exp(-d-eBt_{CRW}-fIns_S+z_{CRW}{}'\beta_{z_{CRW}})\mathrm{E}[\exp(\varepsilon)]}{1+W}-p_S-\frac{p_T}{c}\frac{f\exp(-d-eBt_{CRW}-fIns_S+z_{CRW}{}'\beta_{z_{CRW}})}{1+W}$$

Rearranging Equation $(\mathrm{III}.2)$, demonstrates that $W=\frac{-P_T\mathrm{E}[\exp(\varepsilon)]}{cP\mathrm{E}[Y]}$ and that $1+W=\frac{1}{P\mathrm{E}[Y]}\left[P\mathrm{E}[Y]-\frac{P_T\mathrm{E}[\exp(\varepsilon)]}{c}\right]$.

Substituting these terms into $\frac{d\pi}{dIns_S}$ demonstrates that:

$$\frac{d\pi}{dIns_S}=P\mathrm{E}[Y]f\exp(-d-eBt_{CRW}-fIns_S+z_{CRW}{}'\beta_{z_{CRW}})*\frac{\left(P\mathrm{E}[Y]-\frac{p_T}{c}\right)}{\left(P\mathrm{E}[Y]-\frac{P_T\mathrm{E}[\exp(\varepsilon)]}{c}\right)}-p_S=0$$

Therefore, the demand function for soil insecticides is:

$$Ins_S^*=\frac{1}{f}\left[-d-eBt_{CRW}+z_{CRW}\beta_{z_{CRW}}+\ln\left(\frac{fP\mathrm{E}[Y]}{p_s}\right)+\ln(\varphi)\right]$$

where, $\varphi=\left(\frac{cP\mathrm{E}[Y]}{P_T}-1\right)/\left(\frac{cP\mathrm{E}[Y]}{P_T}-\mathrm{E}[\exp(\varepsilon)]\right)$.

Chapter 4: Estimation Approach and Empirical Strategy

The previous chapter derived a demand function for soil insecticides. This chapter describes how it is estimated. More specifically, it describes the study's data, estimation approach, and empirical strategy. In other words, this chapter describes the study's methodology.

Section I provides a detailed description of the datasets used in the analysis. Section II discusses empirical hurdles and model estimation. Section III describes how the regression results are used to estimate the impacts of Bt adoption. Section IV describes empirical tests of rootworm resistance.

1. The ARMS Corn Survey

The USDA's Agricultural Resource Management Survey (ARMS) is a commodity specific, cross-sectional questionnaire. It has a multi-phase, multi-frame, stratified, probability-weighted design. Phase I prescreens farmers to ensure that they are eligible survey participants. Phase II collects field-level information about production practices and expenditures. Phase III collects farm-level data about assets, income, and household characteristics.

The primary source of data used in this study is the ARMS Phase II Corn Survey. This survey has been regularly administered to farmers in Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, New York, North Carolina, North Dakota, Ohio, Pennsylvania, South Dakota, and Texas since 1996. To restrict the heterogeneity of the sample, this study focuses on farms located in or near the USDA designated Heartland region (i.e. farms located in Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin). Because rootworm resistant seeds were commercially introduced in 2003, this study analyzes data collected in 2005 and 2010, the two most recent survey years.

The Phase II Survey is an extremely detailed source of information about farmers' pesticide use. It provides the application date, the mode of application, and the quantity of every pesticide applied. This makes it possible to determine which products were used to treat rootworms and which were used to treat corn borers (see Table 2).

The Phase II survey also provides detailed information about farmers' seed choices. It indicates whether the crop being cultivated is Bt-CB, Bt-CRW, or a conventional variety. Because this information is also available for the previous rotations, it is possible to test whether planting Bt-CRW seeds in consecutive years decreases the effectiveness of the GE trait.

Ideally, the Phase II survey would contain detailed historical, field level information about pest pressure. Unfortunately, most farmers do not have this information. Though the survey solicits information about expected yield losses on untreated acres, the response rate for this question is low. Consequently, state level averages were calculated using the responses available.[16]

The structural model derived in Chapter 3 assumes that farmers make soil insecticide use decisions based on imperfect information. Fortunately, the Phase II survey collects information about farmers' yield goals. Yield goals are made at planting

16 Though it would have been possible to calculate averages at the county or crop district level, these averages would have been based on small numbers of observations (and thus, endogenous).

time based on expected input use and environmental conditions. Consequently, they are good proxies for expected yields.

In other analyses of GE seeds, farm size has been used as an instrument for adoption decisions. The ARMS Phase III survey provides information about (farm-level) acres planted and the value of fixed capital. The latter of these variables was calculated by aggregating the value of farm dwellings, structures, trucks, cars, tractors, and machinery.

NASS does not collect information about Bt-CRW seed prices. Consequently, these prices had to be estimated using ARMS data. The premium paid for Bt-CRW seeds was calculated by subtracting average state level conventional seed prices from average national level Bt-CRW seed prices. Limitations of the dataset precluded the calculation of this premium using average state level Bt-CRW prices.[17]

NASS collects state-level pesticide prices, but not for every product. Fortunately, the agency does have data for Chlorpyrifos and Terbufos (two of the most common active ingredients in soil insecticides). The average state level prices used in this study were calculated using weighted averages of the NASS prices.[18]

Average county level soil pH levels were calculated using the Natural Resources Conservation Service's (NRCS) Soil Survey Geographic Database. This information is useful because alkaline soils degrade soil insecticides (Lamboy, 1986). As will be further discussed below, the NRCS's National Commodity Crop Productivity Index, which captures the inherent productivity of soils, was also used in the analysis.

---

[17] In many cases, the average state level Bt-CRW seed prices would have been calculated using less than five observations.

[18] The weights were based on state level usage in 2005.

Data from Oregon State's Prism Climate Group was used to calculate county level deviations from average minimum winter temperatures and February precipitation levels.[19] These deviations are measured in degrees Fahrenheit and inches (respectively).

When appropriate, inflation was accounted for using the Bureau of Labor Statistic's Producer Price Index for Farm Products (series id: WPU012202). The adjustment is made at the national level.

Summary statistics for selected variables can be found in Tables 3-5. These tables provide descriptive statistics by year, state, and seed type. Notice that soil insecticide use decreased by approximately 75% over the course of the study period. This reduction was caused by a 60% drop in frequency and a 35% drop in the intensity of soil insecticide usage.

2. Estimating a Demand Function for Soil Insecticides

2.1 Accounting for Endogeneity

Full information joint maximum likelihood is one method of accounting for endogeneity in non-linear models. Though this approach is conceptually appealing, it is often difficult to derive joint likelihood functions when there are multiple sources of endogeneity (Wooldridge, 2014). A two stage, control function based approach is a feasible alternative. First, the potentially endogenous variable is regressed on a set of exogenous instruments. Next, the results of this regression are used to estimate residuals. Finally, the residuals are included in the model's second stage. The residuals are referred to as a control function because they act as a proxy, or control, for the omitted variables causing the endogeneity problem.

---

[19] The deviations were calculated using 20 year normals.

One advantage of this approach is that it serves as an endogeneity test. If the parameter estimate associated with the control function is not significant then it is possible to treat the potentially endogenous variable as exogenous.

Equation $(\mathrm{III}.3)$ contains two potentially endogenous variables: the indicator for Bt-CRW adoption and expected yields. Reduced form specifications are used to estimate control functions for each of these variables. The expected yield function was estimated using ordinary least squares. The control function was calculated by subtracting the OLS predictions from the observed values. Seed choices were analyzed using a probit model. As suggested in Wooldridge (2014), generalized residuals were used as the control function for the Bt-CRW adoption decision.

Incorporating the control functions into Equation $(\mathrm{III}.3)$ produces the following specification:

$$\widehat{Ins}_s = \frac{1}{f}[-d - eBt_{CRW} + z_{CRW}{}'\beta_{z_{CRW}} + \beta_{Bt}R_{Bt_{CRW}} + \beta_{\mathrm{E}[Y]}R_{E[Y]} + \beta_{Int}R_{Bt}R_{\mathrm{E}[Y]} + \ln\left(\frac{fP\mathrm{E}[Y]}{p_s}\right)]$$

where, $R_{Bt_{CRW}}$ represents the generalized residuals of the probit model, $R_{E[Y]}$ represents the residuals of the expected yield function, and $R_{Bt_{CRW}}R_{E[Y]}$ is an interaction term. Recall that z_{CRW} is a vector of variables that affect the initial pest population. In this analysis it is assumed that z_{CRW} is a function of consecutive corn rotations, state level yield losses from rootworms, state level indicator variables, average county level soil ph, an indicator for erodible soils, and county level deviations from average minimum temperatures and precipitation levels. For simplicities sake, it is assumed that z_{CRW} also includes farm or farmer level characteristics (like farmer education or farm size) that impact average insect mortality rates, d.

Replacing $\frac{-d}{f}$ with a constant produces the specification used in the second stage of the analysis:

$$(\text{IV}.1)\ \widehat{Ins}_s = cons + \frac{1}{f}[-eBt_{CRW} + z_{CRW}^{\prime\beta_{z_{CRW}}} + \beta_{Bt}R_{Bt_{CRW}} + \beta_{\mathrm{E}[Y]}R_{\mathrm{E}[Y]} +$$

$$\beta_{Int}R_{Bt}R_{\mathrm{E}[Y]} + \ln\left(\frac{fP\mathrm{E}[Y]}{p_s}\right)]$$

Notice that this specification does not include $\ln(\varphi)$. The control functions act as a proxy for this omitted variable.

2.2 Accounting for Censoring

Censoring occurs when the dependent variable is not fully observed. The classic case analyzes household expenditures on durable goods (Tobin, 1958). In this case, approximately 25% of the observations in the sample were concentrated at 0.

Censored regression models assume that there is a latent, continuous variable, y^*, underlying the censored variable, y. Though it is possible to model y, it is often easier to describe the behavior of y^*. Both Greene (2012) and Cameron and Trivedi (2005) recommend using the Gumbel, or extreme value, distribution to model y^* when the probability of an outcome is particularly rare. Conceptually, this is because the Gumbel distribution is asymmetric, and because a censored observation's contribution to the likelihood function tends to be larger for Gumbel than for normally distributed errors (see Figure 3).

Approximately 85% of the farmers in the sample chose not to apply soil insecticides in 2005, while 94% chose not to use soil insecticides in 2010. Therefore, it is assumed that the residuals of the soil insecticide demand function are extreme value distributed.

The extreme value distribution is characterized by the probability density function, $\phi_G = \frac{1}{B}\exp\left(-\frac{y_i - c}{B} - \exp\left(-\frac{y_i - c}{B}\right)\right)$ and the cumulative density function, $\Phi_G = \exp\left(-\exp\left(-\frac{y_i - c}{B}\right)\right)$, where c is a location parameter, and B is a scale parameter. The likelihood function for a censored regression model with extreme value distributed errors (and left censoring at 0) is: $\mathcal{L} = \prod_{i=1}^{N}\left[\frac{1}{B}\exp\left(-\frac{y_i - c}{B} - \exp\left(-\frac{y_i - c}{B}\right)\right)\right]^{I_i(y_i > 0)} \exp\left(-\exp\left(\frac{c}{B}\right)\right)^{1 - I_i(y_i > 0)}$.

The mean of a Gumbel distribution is $\mu_G = c + B\gamma$, where γ is the Euler-Mascheroni constant.[20] Therefore, substituting $c = \mu_G - B\gamma$ into $\mathcal{L}$ and assuming that $\mu_G = \widehat{Ins}_s$ implies:

$$(\text{IV}.2)\ \mathcal{L} = \prod_{i=1}^{N}[\frac{1}{B}\exp\left(\frac{\widehat{Ins}_s - Ins_s}{B} - \gamma - \exp\left(\frac{\widehat{Ins}_s - Ins_s}{B} - \gamma\right)\right)^{I_i(Ins_s)}$$

$$* \exp\left(-\exp\left(\frac{\widehat{Ins}_s}{B} - \gamma\right)\right)^{1 - I_i(Ins_s)}]$$

In order to ensure that the results were representative of the population of US farmers, each observation's contribution to the likelihood function was weighted using NASS generated probability weights. The standard errors were bootstrapped in order to account for the two-stage nature of the endogeneity correction.[21]

---

20 $\gamma \approx .58$

21 The bootstrapped covariance matrix was generated by estimating the model 500 times using observations resampled from the dataset (with replacement).

3. Model Predictions and Marginal Effects

3.1 Model Predictions

Once the parameters of the rootworm abatement function have been estimated, it is possible to generate a broad range of estimates and predictions. This study confines its interest to: the probability that a farmer uses soil insecticides, $\Pr(Ins_S > 0)$, the intensity of soil insecticide use, $\mathrm{E}[Ins_S|Ins_S > 0]$, expected soil insecticide use, $\mathrm{E}[Ins_S]$, abatement levels, G_{CRW}, adjusted potential yields, H_A, and total expected yield losses from rootworms, Yl_{CRW}. These predictions take the form:

$$(\mathrm{IV.3})\ \Pr(Ins_S > 0) = 1 - \Phi_G(0) = 1 - \exp\left(-\exp\left(\frac{\widehat{Ins_S}}{B} - \gamma\right)\right)$$

$$(\mathrm{IV.4})\ \mathrm{E}[Ins_S|Ins_S > 0] = \frac{\widehat{Ins_S} - B\mathrm{ei}\left(-\exp\left(\frac{\widehat{Ins_S}}{B} - \gamma\right)\right)}{1 - \Phi_\mathrm{G}(0)}$$

$$(\mathrm{IV.5})\ \mathrm{E}[Ins_S] = \widehat{Ins_S} - B\mathrm{ei}\left(-\exp\left(\frac{\widehat{Ins_S}}{B} - \gamma\right)\right)$$

$$(\mathrm{IV.6})\ G_{CRW} = \exp\big(-\exp\big(cons * f - eBt_{CRW} - fIns_S + z_{CRW}'\beta_{z_{CRW}}\big)\big)$$

$$(\mathrm{IV.7})\ H_A = \frac{\mathrm{E}[Y]}{G_{CRW}}$$

and,

$$(\mathrm{IV.8})\ Yl_{CRW} = \frac{\mathrm{E}[Y]}{G_{CRW}} * (1 - G_{CRW}) = \frac{\mathrm{E}[Y]}{G_{CRW}} - \mathrm{E}[Y]$$

Equations (IV. 4) and (IV. 5) are derived in Appendix C. Yl_{CRW} represents crop losses in bushels/acre. Otherwise, only H_A requires explanation.

Recall that $\mathrm{E}[Y] = HG_{CB}G_{CRW}\mathrm{E}[\exp(\varepsilon)]$. Therefore, $HG_{CB}\widehat{E[\exp}(\varepsilon)] = \frac{\mathrm{E}[Y]}{G_{CRW}}$. Notice that $H_A = H$ when pest pressure from corn borers is low and when there is not much uncertainty about environmental conditions. Therefore, H_A is a lower bound for potential yields.

3.2 Marginal Effects

In order to quantify the impacts of resistance it is necessary to determine how Bt-CRW adoption affected corn farmers' yields and soil insecticide use decisions. It is possible to accomplish this goal by estimating the impact of Bt-CRW adoption on: the probability of soil insecticide use, the intensity of soil insecticide use, average soil insecticide use, abatement levels, and expected yields. These marginal effects can be estimated using the expressions derived in the previous section:

(IV.9) $\Delta\text{Prob}(Ins_S > 0)$

$$= \text{Prob}(Ins_S > 0|Bt_{CRW} = 1) - \text{Prob}(Ins_S > 0|Bt_{CRW} = 0)$$

(IV.10) $\Delta\text{E}[Ins_S|Ins_S > 0]$

$$= \text{E}[Ins_S|Ins_S > 0, Bt_{CRW} = 1] - \text{E}[Ins_S|Ins_S > 0, Bt_{CRW} = 0]$$

(IV.11) $\Delta\text{E}[Ins_s] = \text{E}[Ins_s|Bt_{CRW} = 1] - \text{E}[Ins_s|Bt_{CRW} = 0]$

(IV.12) $\Delta G_{CRW} = (G_{CRW}|Bt_{CRW} = 1) - (G_{CRW}|Bt_{CRW} = 0)$

and,

(IV. 13) $\Delta\text{E}[Y] = (HG_{CB}G_{CRW}|Bt_{CRW} = 1) - (HG_{CB}G_{CRW}|Bt_{CRW} = 0)$

$$\approx HG_{CB}\widehat{\text{E}[\exp}(\varepsilon)] * [(G_{CRW}|Bt_{CRW} = 1) - (G_{CRW}|Bt_{CRW} = 0)]$$

$$= \frac{\text{E}[Y]}{G_{CRW}} * \Delta G_{CRW}$$

The Delta Method was used to estimate the standard errors of the marginal effects and the model predictions (see Appendix D).

4. Tests for Rootworm Resistance

Recall that $G_{CRW} = \exp\left(-\exp\left(-d - eBt_{CRW} - fIns_S + z_{CRW}'\beta_{z_{CRW}}\right)\right)$, where e represents the effectiveness of Bt-CRW seeds. If resistance developed over the course of the study period, then e should have decreased between 2005 and 2010. It is possible to test this hypothesis by incorporating an interaction term into the structural model. For instance, if $G_{CRW} = \exp\left(-\exp\left(-d - Bt_{CRW}(e + e_{10}Ind_{10}) - fIns_S + z_{CRW}'\beta_{z_{CRW}}\right)\right)$, then:

$$(\mathrm{IV}.14)\ \widehat{Ins}_s = cons + \frac{1}{f}\left[-Bt_{CRW}(e + e_{10}Ind_{10}) + \psi\right]$$

where, $\psi = z_{CRW}'\beta_{z_{CRW}} + \beta_{Bt}R_{Bt_{CRW}} + \beta_{\mathrm{E}[Y]}R_{\mathrm{E}[Y]} + \beta_{Int}R_{Bt}R_{\mathrm{E}[Y]} + \ln\left(\frac{fP\mathrm{E}[Y]}{p_s}\right)$, and Ind_{10} is a an indicator for 2010.

That said, Equation $(\mathrm{IV}.14)$ is an imperfect test for rootworm resistance. Though resistance is a plausible explanation for reductions in the effectiveness of Bt toxins, it is not the only one. A more accurate test would compare the effectiveness of Bt-CRW seeds on farms where resistance is, and is not, likely. Fortunately, this is possible.

If rootworms have adapted, then resistant populations should be concentrated near farms where selective pressure is the highest. In other words, Bt-CRW seeds should be more effective on farms that cultivated Bt-CRW seeds in 2010 than they are on farms that cultivated Bt-CRW seeds in both 2009 and 2010. This hypothesis can be tested using another interaction term. For instance, if $G_{CRW} = \exp\left(-\exp\left(-d - Bt_{CRW}\left(e + e_{10}Ind_{10} + e_{10,Btl}Bt_{CRW,lag}Ind_{10}\right) - fIns_S + z_{CRW}'\beta_{z_{CRW}}\right)\right)$, then:

$$(\mathrm{IV}.15)\ \widehat{Ins}_s = cons + \frac{1}{f}\left[-Bt_{CRW}\left(e + e_{10}Ind_{10} + e_{10,Btl}Bt_{CRW,lag}Ind_{10}\right) + \psi\right]$$

where, $Bt_{CRW,lag}$ is an indicator of lagged Bt-CRW adoption.

In Equation $(\mathrm{IV}.15)$, e_{10} captures the impacts of environmental conditions (which may or may not be related to insect resistance), while $e_{10,Btl}$ captures the impacts of selective pressure. If rootworms have developed resistance then $e_{10,Btl}$ should be negative.

The following process was used to quantify the impacts of resistance and to conduct inference: First, Equation $(\mathrm{IV}.15)$ was estimated and the marginal effects were estimated. Next, it was explicitly assumed that $e_{10,Btl} = 0$ (i.e. that there was no resistance) and the marginal effects were recalculated. Finally, the difference in the marginal effects (and the standard deviation of this difference) was calculated at the observation level. T-tests were used to determine if the average of the differences was distinct from 0.

5. Conclusions

A two stage, control function based approach can be used to consistently estimate a non-linear, censored, Gumbel distributed, insecticide demand function. The regression results can be used to determine how Bt adoption affects the probability of soil insecticide use, the intensity of soil insecticide use, and expected soil insecticide use. Because the model is structural, it is also possible to determine how Bt adoption affects yields, yield losses from corn rootworms, and potential yields.

If resistance to Bt toxins has developed amongst populations of corn rootworms, then Bt-CRW seeds should be least effective on farms where Bt-CRW seeds have been planted in consecutive rotations. In other words, it is possible to assess the extent to which rootworms have developed resistance by estimating a soil insecticide demand function.

Appendix C: Deriving the Mean of a Censored Gumbel Distribution

It is assumed that x^* is drawn from a continuous Gumbel distribution with mean μ and standard deviation, σ. The Gumbel, or extreme value, distribution is characterized by the cumulative distribution function, $\Phi_G = \exp\left(-\exp\left(-\frac{x^*-c}{B}\right)\right)$, and probability density function, $\phi_G = \frac{1}{B}\exp\left(-\frac{x^*-c}{B} - \exp\left(-\frac{x^*-c}{B}\right)\right)$, where, c is a location parameter and B is a scale parameter.

It is assumed that $x = x^*$ when $x^* > 0$, and $x = 0$ otherwise. Therefore the mean of x is:

$$(\mathrm{C.1})\ \mathrm{E}[x] = \mathrm{Prob}(x^* \leq 0) * 0 + \mathrm{Prob}(x^* > 0) * \mathrm{E}[x|x^* > 0]$$

$$= \mathrm{Prob}(x^* > 0) * \mathrm{E}[x|x^* > 0]$$

The probability that $x^* > 0$ is $1 - \Phi(0) = 1 - \exp\left(-\exp\left(\frac{c}{B}\right)\right)$. Therefore, the first step in deriving the mean of the censored normal distribution is to derive $\mathrm{E}[x|x^* > 0]$, the mean of a truncated Gumbel distribution.

Deriving the Expectation of a Truncated Gumbel Distribution

Cameron and Trivedi (2005, pg. 566) derive the mean of the truncated standard normal distribution by rescaling the truncated pdf and integrating from the point of truncation to infinity. They find that:

$$\frac{1}{1 - \Phi_{\mathrm{N}}(c)} \int_c^{\infty} z\phi_{\mathrm{N}}(z)dz = \frac{\phi_{\mathrm{N}}(c)}{1 - \Phi_{\mathrm{N}}(c)}$$

where, ϕ_N is the pdf, and Φ_N is the cdf of the standard normal distribution.

The same approach can be used to derive the mean of the truncated Gumbel distribution. Assuming that there is truncation at 0, x^* is:

$$\mathrm{E}[x^*|x^* > 0] = \frac{1}{1-\Phi(0)} \int_0^\infty x^* * \frac{1}{B} \exp\left(-\frac{x^*-c}{B} - \exp\left(-\frac{x^*-c}{B}\right)\right) dx^*$$

Using the change of variables suggested in Jawitz (2004), $y = \exp\left(-\frac{x^*-c}{B}\right)$, $x^* = c - B\ln(y)$, and $dx^* = -\frac{B}{y}dy$. Therefore,

$$\mathrm{E}[x^*|x^* > 0] = \frac{1}{1-\Phi(0)} \int_{\exp(\frac{c}{B})}^0 (c - B\ln(y))$$

$$* \frac{1}{B} \exp\left(-\frac{c - B\ln(y) - c}{B} - y\right)\left(-\frac{B}{y}\right) dy$$

This expression simplifies to:

C. 2) $\mathrm{E}[x^*|x^* > 0]$

$$= \frac{-c}{1-\Phi(0)} \int_{\exp(\frac{c}{B})}^0 \exp(-y)\, dy + \frac{B}{1-\Phi(0)} \int_{\exp(\frac{c}{B})}^0 \ln(y)\exp(-y)\, dy$$

Evaluating the integral in the first term demonstrates that:

C. 2a) $\dfrac{-c}{1-\Phi(0)} \displaystyle\int_{\exp(\frac{c}{B})}^0 \exp(-y)\, dy = c$

Evaluating the integral in the second term, $\frac{B}{1-\Phi(0)} \int_{\exp(\frac{c}{B})}^0 \ln(y)\exp(-y)\, dy$, is slightly more complicated. First, integrate by parts, setting $u(y) = \ln(y)$ and $v'(y) = \exp(-y)$. Then,

$$\int_{\exp(\frac{c}{B})}^0 \ln(y)\exp(-y)\, dy = \left(-\ln(y)\exp(-y)\ \Big|_{\exp(\frac{c}{B})}^0\right) - \int_{\exp(\frac{c}{B})}^0 \frac{\exp(-y)}{y} dy$$

$$= \left[-\ln(0) + \left(\frac{c}{B}\right)\exp\left(-\exp\left(\frac{c}{B}\right)\right)\right] - \left[\int_0^\infty \frac{\exp(-y)}{y} dy - \int_{\exp(\frac{c}{B})}^\infty \frac{\exp(-y)}{y} dy\right]$$

The exponential integral function is defined as, $\mathrm{ei}(y) = -\int_{-y}^{\infty} \frac{\exp(-t)}{t} dt$. Therefore, this expression simplifies to:

$$\left[-\ln(0) + \left(\frac{c}{B}\right)\exp\left(-\exp\left(\frac{c}{B}\right)\right)\right] - \left[-\mathrm{ei}(0) + \mathrm{ei}\left(-\exp\left(\frac{c}{B}\right)\right)\right]$$

$$= \mathrm{ei}(0) - \ln(0) + \left(\frac{c}{B}\right)\exp\left(-\exp\left(\frac{c}{B}\right)\right) - \mathrm{ei}\left(-\exp\left(\frac{c}{B}\right)\right)$$

Both $\mathrm{ei}(0)$ and $\ln(0)$ equal $-\infty$. Therefore, $\mathrm{ei}(0) - \ln(0) = -\infty + \infty$, which is indeterminate. However, $\lim_{y\to 0} \mathrm{ei}(y) - \ln(y) = \ln\left(\lim_{y\to 0} \frac{\exp(\mathrm{ei}(y))}{y}\right) = \gamma$. Therefore:

$$(\mathrm{C.2b})\ \frac{B}{1-\Phi(0)}\int_{\exp(\frac{c}{B})}^{0} \ln(y)\exp(-y)\, dy$$

$$= \frac{B}{1-\Phi(0)}\left[\gamma + \left(\frac{c}{B}\right)\exp\left(-\exp\left(\frac{c}{B}\right)\right) - \mathrm{ei}\left(-\exp\left(\frac{c}{B}\right)\right)\right]$$

Combining Equations $(\mathrm{C.1a})$ and $(\mathrm{C.1b})$ provides the mean of the truncated Gumbel Distribution:

$$(\mathrm{C.3})\ \mathrm{E}[x^*|x^* > 0] = c + c\,\frac{\Phi(0)}{1-\Phi(0)} + \frac{B}{1-\Phi(0)}\left[\gamma - \mathrm{ei}\left(-\exp\left(\frac{c}{B}\right)\right)\right]$$

$$= \frac{c}{1-\Phi(0)} + \frac{B}{1-\Phi(0)}\left[\gamma - \mathrm{ei}\left(-\exp\left(\frac{c}{B}\right)\right)\right]$$

Deriving the Expectation of a Censored Gumbel Distribution

Recall that $\mathrm{E}[x] = \mathrm{Prob}(x^* > 0) * \mathrm{E}[x|x^* > 0]$. Therefore, the mean of a left censored, Gumbel distributed variable is:

$$(\mathrm{C.4})\ \mathrm{E}[x] = \left(1 - \Phi(0)\right) * \frac{1}{1 - \Phi(0)}\left(c + B\left[\gamma - \mathrm{ei}\left(-\exp\left(\frac{c}{B}\right)\right)\right]\right)$$

$$= c + B\left[\gamma - \mathrm{ei}\left(-\exp\left(\frac{c}{B}\right)\right)\right]$$

The mean of the latent, Gumbel distributed variable is: $\mu = c + B\gamma$. Therefore, $\mathrm{E}[x]$ can be expressed as:

$$(\mathrm{C.5})\ \mathrm{E}[x] = \mu - B\mathrm{ei}\left(-\exp\left(\frac{\mu}{B} - \gamma\right)\right)$$

Appendix D: Deriving the Standard Errors of The Model Predictions and Marginal Effects

The Delta Method

Hayashi (2000) provides a clear description of the delta method. Assume that $\{X_n\}$ is a sequence of (K-dimensional) random vectors such that the plim of x_n is β and the limiting distribution of $\sqrt{n}(x_n - \beta)$ is z. Assume that $a(\beta)$ is a continuously differentiable function that maps from $\mathbb{R}^K \rightarrow \mathbb{R}^1$, and that $A(\beta)$ is a (1xK) matrix containing the partial derivatives of a (evaluated at β). Then, the limiting distribution of $\sqrt{n}[a(x_n) - a(\beta)]$ is $A(\beta)z$.

This implies that the variance of any linear or nonlinear combination of unbiased parameter estimates is $A(\beta)\,\Sigma\,A(\beta)'$, where Σ is the asymptotic variance of the parameter estimates. More formally, if the limiting distribution of $\sqrt{n}(x_n - \beta)$ is $N(0, \Sigma)$ then the limiting distribution of $\sqrt{n}[a(x_n) - a(\beta)]$ is $N(0, A(\beta)\,\Sigma\,A(\beta)')$.

Calculating the Standard Errors of Model Predictions:

Closed Form Solutions for the Standard Errors

The structural model described in Chapter III can be used to predict the probability that a farmer uses soil insecticides, $\text{Prob}(Ins_S > 0)$, the intensity of soil insecticide use, $\text{E}[Ins_S|Ins_S > 0]$, expected soil insecticide use, $\text{E}[Ins_s]$, average abatement levels, G_{CRW}, adjusted potential yields, H_A, and total expected yield losses from rootworms, Yl_{CRW}. It was assumed that:

$Z_{CRW} = \exp(z'\beta_z)$ [22]

and,

$$\widehat{Ins}_s = cons + \frac{1}{f}\left[-eBt_{CRW} + z'\beta_z + \ln\left(\frac{fPY}{p_s}\right)\right]$$ [23]

Therefore, the model predictions are:

(D.1) $\text{Prob}(Ins_S > 0) = 1 - \Phi(0) = 1 - \exp\left(-\exp\left(\frac{\widehat{Ins}_S}{B} - \gamma\right)\right)$

(D.2) $[Ins_S | Ins_S > 0] = \frac{1}{1-\Phi(0)}\left[\widehat{Ins}_s - B\text{ei}\left(-\exp\left(\frac{\widehat{Ins}_S}{B} - \gamma\right)\right)\right]$

(D.3) $\text{E}[Ins_s] = \widehat{Ins}_s - B\text{ei}\left(-\exp\left(\frac{\widehat{Ins}_S}{B} - \gamma\right)\right)$

(D.4) $G_{CRW} = \exp(-Z_{CRW}\exp(-d - eBt_{CRW} - fIns_S))$

$= \exp(-\exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z))$

(D.5) $H_A = \frac{\text{E}[Y]}{\exp(-Z_{CRW}\exp(-d - eBt_{CRW} - fIns_S))} = \frac{\text{E}[Y]}{\exp(-\exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z))}$

and,

(D.6) $Yl_{CRW} = \frac{\text{E}[Y]}{G_{CRW}} * (1 - G_{CRW}) = \frac{\text{E}[Y]}{G_{CRW}} - \text{E}[Y]$[24]

So, if:

$$A_1 = \left[\frac{d\text{Prob}(Ins_S)}{dcons}\ \frac{d\text{Prob}(Ins_S)}{df}\ \frac{d\text{Prob}(Ins_S)}{de}\ \frac{d\text{Prob}(Ins_S)}{d\beta_z}\ \frac{d\text{Prob}(Ins_S)}{dB}\right]$$

$$A_2 = \left[\frac{d\text{E}[Ins_S|Ins_S > 0]}{dcons}\ \frac{d\text{E}[Ins_S|Ins_S > 0]}{df}\ \frac{d\text{E}[Ins_S|Ins_S > 0]}{de}\ \frac{d\text{E}[Ins_S|Ins_S > 0]}{d\beta_z}\ \frac{d\text{E}[Ins_S|Ins_S > 0]}{dB}\right]$$

$$A_3 = \left[\frac{d\text{E}[Ins_S]}{dcons}\ \frac{d\text{E}[Ins_S]}{df}\ \frac{d\text{E}[Ins_S]}{de}\ \frac{d\text{E}[Ins_S]}{d\beta_z}\ \frac{d\text{E}[Ins_S]}{dB}\right]$$

$$A_4 = \left[\frac{dG_{CRW}}{dcons}\ \frac{dG_{CRW}}{df}\ \frac{dG_{CRW}}{de}\ \frac{dG_{CRW}}{d\beta_z}\ \frac{dG_{CRW}}{dB}\right]$$

---

[22] For simplicity's sake, this appendix treats the vectors z and β_z as scalars.

[23] $cons = \frac{-d}{f} \Rightarrow -d = cons * f$

[24] Notice that the derivative of (D.5) equals the derivative of (D.6). Consequently, it is not discussed in the treatment that follows.

and,

$$A_5 = \left[\frac{dH_A}{dcons}\ \frac{dH_A}{df}\ \frac{dH_A}{de}\ \frac{dH_A}{d\beta_z}\ \frac{dH_A}{dB}\right]$$

Then, the standard errors of the model predictions are:

$$\mathrm{se}_i\big(\mathrm{Prob}(Ins_S > 0)\big) = \sqrt{A_1\hat{\Sigma}{A_1}'}$$

$$\mathrm{se}_i(\mathrm{E}[Ins_S|Ins_S]) = \sqrt{A_2\hat{\Sigma}{A_2}'}$$

$$\mathrm{se}_i(\mathrm{E}[Ins_S]) = \sqrt{A_3\hat{\Sigma}{A_3}'}$$

$$\mathrm{se}_i(G_{CRW}) = \sqrt{A_4\hat{\Sigma}{A_4}'}$$

$$\mathrm{se}_i(H_A) = \sqrt{A_5\hat{\Sigma}{A_5}'}$$

where, $\hat{\Sigma}$ is the covariance matrix of the empirical model, and i is an observation level index.

In order to estimate these standard errors, it is necessary is to derive closed form solutions for the elements of A_1, A_2, A_3, A_4, and A_5, or to estimate them numerically. Though most econometrics packages make calculating numeric derivatives straightforward, closed form solutions were used to calculate the standard errors of the model predictions.

Closed form solutions for A_1: The partial derivatives of $\mathrm{Prob}(Ins_S > 0)$

$$\frac{d\mathrm{Prob}(Ins_S)}{dcons} = \phi$$

$$\frac{d\mathrm{Prob}(Ins_S)}{df} = \frac{1}{f^2}\left(1 + eBt_{CRW} - z'\beta_z - \ln\left(\frac{fPY}{p_s}\right)\right) * \phi$$

$$\frac{d\mathrm{Prob}(Ins_S)}{de} = \left(-\frac{Bt_{CRW}}{f}\right) * \phi$$

$$\frac{d\text{Prob}(Ins_S)}{d\beta_z} = \left(\frac{z}{f}\right) * \phi$$

$$\frac{d\text{Prob}(Ins_S)}{dB} = -\left(\frac{\widehat{Ins_S}}{B}\right) * \phi$$

where, $\phi = \frac{1}{B}\exp\left(\frac{\widehat{Ins_S}}{B} - \gamma - \exp\left(\frac{\widehat{Ins_S}}{B} - \gamma\right)\right)$

Closed form solutions for A_2: The partial derivatives of E[$Ins_S|Ins_S > 0$]

$$\frac{d\text{E}[Ins_S|Ins_S > 0]}{dcons} = 1 - \psi$$

$$\frac{d\text{E}[Ins_S|Ins_S > 0]}{df} = \frac{1}{f^2}\left(1 + eBt_{CRW} - z'\beta_z - \ln\left(\frac{fPY}{p_s}\right)\right) * (1 - \psi)$$

$$\frac{d\text{E}[Ins_S|Ins_S > 0]}{de} = \left(-\frac{Bt_{CRW}}{f}\right) * (1 - \psi)$$

$$\frac{d\text{E}[Ins_S|Ins_S > 0]}{d\beta_z} = \left(\frac{z}{f}\right) * (1 - \psi)$$

$$\frac{d\text{E}[Ins_S|Ins_S > 0]}{dB} = \left(\frac{\widehat{Ins_S}}{B}\right)\psi + \frac{1}{1 - \Phi(0)}\left[\left(\frac{\widehat{Ins_S}}{B}\right)\Phi(0) - \text{ei}\left(-\exp\left(\frac{\widehat{Ins_S}}{B} - \gamma\right)\right)\right]$$

where, $\psi = \frac{\phi}{[1-\Phi(0)]^2}\left[\widehat{Ins_S} - B\text{ei}\left(-\exp\left(\frac{\widehat{Ins_S}}{B} - \gamma\right)\right)\right]$

Closed form solutions for A_3: The partial derivatives of E[Ins_S]

$$\frac{d\text{E}[Ins_S]}{dcons} = 1 - \Phi(0)$$

$$\frac{d\text{E}[Ins_S]}{df} = \frac{1}{f^2}\left(1 + eBt_{CRW} - z'\beta_z - \ln\left(\frac{fPY}{p_s}\right)\right) * [1 - \Phi(0)]$$

$$\frac{d\text{E}[Ins_S]}{de} = \left(-\frac{Bt_{CRW}}{f}\right) * [1 - \Phi(0)]$$

$$\frac{d\text{E}[Ins_S]}{d\beta_z} = \left(\frac{z}{f}\right) * [1 - \Phi(0)]$$

$$\frac{d\mathrm{E}[Ins_S|Ins_S > 0]}{dB} = \left(\frac{\widehat{Ins_S}}{B}\right)\Phi(0) - \mathrm{ei}\left(-\exp\left(\frac{\widehat{Ins_S}}{B} - \gamma\right)\right)$$

Closed form solutions for A_4: The partial derivatives of G_{CRW}

$$\frac{dG_{CRW}}{dcons} = -G_{CRW} * \exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (f)$$

$$\frac{dG_{CRW}}{df} = -G_{CRW} * \exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (cons - Ins_S)$$

$$\frac{dG_{CRW}}{de} = -G_{CRW} * \exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (-Bt_{CRW})$$

$$\frac{dG_{CRW}}{d\beta_z} = -G_{CRW} * \exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (z)$$

$$\frac{dG_{CRW}}{dB} = 0$$

Closed form solutions for A_5: The partial derivatives of H_A

$$\frac{dH_A}{dcons} = \frac{\mathrm{E}[Y]}{G_{CRW}} * \exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (f)$$

$$\frac{dH_A}{df} = \frac{\mathrm{E}[Y]}{G_{CRW}} * \exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (cons - Ins_S)$$

$$\frac{dH_A}{de} = \frac{\mathrm{E}[Y]}{G_{CRW}} * \exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (-Bt_{CRW})$$

$$\frac{dH_A}{d\beta_z} = \frac{\mathrm{E}[Y]}{G_{CRW}} * \exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (z)$$

$$\frac{dH_A}{dB} = 0$$

Estimating the standard deviation of the model predictions

In order to determine how the model's performance varied by year, state, and seed type, average predictions were calculated for different subsets of the population.

The standard errors of the average predictions were calculated using a two-step process. First, $A_1\hat{\Sigma}A_1{}'$, $A_2\hat{\Sigma}A_2{}'$, $A_3\hat{\Sigma}A_3{}'$, $A_4\hat{\Sigma}A_4{}'$, and $A_5\hat{\Sigma}A_5{}'$ were calculated for each observation. Next, the variances were averaged (and square roots were taken).

Calculating the Standard Errors of the Marginal Effects

Closed Form Solutions for the Standard Errors:

The model's marginal effects indicate how Bt-CRW adoption affects the probability of soil insecticide use, $\Delta\text{Prob}(Ins_S)$, the intensity of soil insecticide use, $\Delta\text{E}[Ins_S|Ins_S > 0]$, average soil insecticide use, $\Delta\text{E}[Ins_S]$, abatement levels, ΔG, and yield impacts (in bushels per acre), $\Delta\text{E}[Y]$. These expressions take the form:

(D.6) $\Delta\text{Prob}(Ins_S) = \text{Prob}(Ins_S|Bt_{CRW} = 1) - \text{Prob}(Ins_S|Bt_{CRW} = 0)$

(D.7) $\Delta\text{E}[Ins_S|Ins_S > 0] = \text{E}[Ins_S|Ins_S > 0, Bt_{CRW} = 1]$

$-\text{E}[Ins_S|Ins_S > 0, Bt_{CRW} = 0]$

(D.8) $\Delta\text{E}[Ins_s] = \text{E}[Ins_s|Bt_{CRW} = 1] - \text{E}[Ins_s|Bt_{CRW} = 0]$

(D.9) $\Delta G_{CRW} = (G_{CRW}|Bt_{CRW} = 1) - (G_{CRW}|Bt_{CRW} = 0)$

and,

$$(D.10)\ \Delta\text{E}[Y] = (HG_{CB}G_{CRW}|Bt_{CRW} = 1) - (HG_{CB}G_{CRW}|Bt_{CRW} = 0)$$

$$\approx \widehat{HG_{CB}} * [(G_{CRW}|Bt_{CRW} = 1) - (G_{CRW}|Bt_{CRW} = 0)]$$

$$= \frac{\text{E}[Y]}{G_{CRW}} * \Delta G_{CRW}$$

So, if:

$$A_6 = \left[\frac{d\Delta\text{Prob}(Ins_S)}{dcons} \dots \frac{d\Delta Prob(Ins_S)}{dB}\right]$$

$$A_7 = \left[\frac{d\Delta\text{E}[Ins_S|Ins_S > 0]}{dcons} \dots \frac{d\Delta\text{E}[Ins_S|Ins_S > 0]}{dB}\right]$$

$$A_8 = \left[\frac{d\Delta \mathrm{E}[Ins_S]}{dcons} \dots \frac{d\Delta \mathrm{E}[Ins_S]}{dB}\right]$$

$$A_9 = \left[\frac{d\Delta G_{CRW}}{dcons} \dots \frac{d\Delta G_{CRW}}{dB}\right]$$

and,

$$A_{10} = \left[\frac{d\Delta \mathrm{E}[Y]}{dcons} \dots \frac{d\Delta \mathrm{E}[Y]}{dB}\right]$$

Then, the standard errors are:

$$\mathrm{se}_i\big(\Delta \mathrm{Prob}(Ins_S > 0)\big) = \sqrt{A_6 \hat{\Sigma} A_6{}'}$$

$$\mathrm{se}_i(\Delta \mathrm{E}[Ins_S | Ins_S]) = \sqrt{A_7 \hat{\Sigma} A_7{}'}$$

$$\mathrm{se}_i(\Delta \mathrm{E}[Ins_S]) = \sqrt{A_8 \hat{\Sigma} A_8{}'}$$

$$\mathrm{se}_i(\Delta G_{CRW}) = \sqrt{A_9 \hat{\Sigma} A_9{}'}$$

and,

$$\mathrm{se}_i(\Delta E[Y]) = \sqrt{A_{10} \hat{\Sigma} A_{10}{}'}$$

Deriving the Partial Derivatives of the Marginal Effects

Though it is possible to estimate the elements of $A_6, A_7, A_8, A_9,$ and A_{10} numerically, closed form solutions were used to calculate the standard errors of the marginal effects.

Closed form solutions for A_6, A_7, A_8, and A_9:

Notice that A_6, A_7, A_8, and A_9 are linear combinations of the elements of A_1, A_2, A_3, and A_4 (respectively). For instance, the first element of A_6 is:

$$\frac{d\Delta\text{Prob}(Ins_S)}{dcons} = \frac{d\text{Prob}(Ins_S|Bt_{CRW} = 1)}{dcons} - \frac{d\text{Prob}(Ins_S|Bt_{CRW} = 0)}{dcons}$$

where, $\frac{d\text{Prob}(Ins_S)}{dcons}$ is the first element of A_1.

Therefore,

$$\frac{d\Delta\text{Pro}b(Ins_S)}{dcons} = (\phi|Bt_{CRW} = 1) - (\phi|Bt_{CRW} = 0)$$

Because they are linear combinations of the partial derivatives derived in the previous section, expressions for the elements of A_6, A_7, A_8, and A_9 are not explicitly provided.

Closed form solutions forA_{10}: The partial derivatives of $\Delta E[Y]$

$$\frac{d\Delta\text{E}[Y]}{dcons} = \frac{\text{E}[Y]}{G_{CRW}} * \left[\exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (f) + \frac{d\Delta G_{CRW}}{dcons}\right]$$

$$\frac{d\Delta\text{E}[Y]}{df} = \frac{\text{E}[Y]}{G_{CRW}} * \left[\exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (cons - Ins_S) + \frac{d\Delta G_{CRW}}{df}\right]$$

$$\frac{d\Delta\text{E}[Y]}{de} = \frac{\text{E}[Y]}{G_{CRW}} * \left[\exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (-Bt_{CRW}) + \frac{d\Delta G_{CRW}}{de}\right]$$

$$\frac{d\Delta\text{E}[Y]}{d\beta_z} = \frac{\text{E}[Y]}{G_{CRW}} * \left[\exp(cons * f - eBt_{CRW} - fIns_S + z'\beta_z) * (z) + \frac{d\Delta G_{CRW}}{d\beta_z}\right]$$

$$\frac{dH_A}{dB} = 0$$

Estimating the standard deviation of the model marginal effects (by year, state, or seed type)

In order to determine whether the impact of Bt-CRW seeds varied by year, state, or seed type, average marginal effects were calculated for different subsets of the population. The standard error of the average marginal effects was calculated using a two-step process. First, $A_6\hat{\Sigma}A_6{}'$, $A_7\hat{\Sigma}A_7{}'$, $A_8\hat{\Sigma}A_8{}'$, $A_9\hat{\Sigma}A_9{}'$, and $A_{10}\hat{\Sigma}A_{10}{}'$ were calculated for each observation. Next, these estimates were averaged (and square roots were taken).

Table 2. Timing of Insecticide Applications (Total Pounds of AI Applied)

Active Ingredient Name	2005				2010			
	Applied Before Planting	**Applied At Planting**	**Applied After Planting**	**Total Pounds of Ai Applied**	**Applied Before Planting**	**Applied At Planting**	**Applied After Planting**	**Total Pounds of Ai Applied**
Carbofuran	0	0	2.10	2.10	0	0	0	0
Chlorethoxyfos	0	0.16	0	0.16	0	0.41	0	0.41
Chlorpyrifos	3.95	48.19	9.90	62.04	0	13.04	2.79	15.83
Methyl parathion	0	0	2.82	2.82	0	0	0	0
Tefluthrin	0.28	7.73	0.14	8.15	0	1.82	0.17	1.99
Terbufos	0	13.43	1.28	14.70	0	1.86	0.10	1.96
Other Insecticides	0.81	12.55	18.34	31.70	0.25	3.12	13.75	17.16
Total	5.04	82.06	34.58	121.68	0.25	20.24	16.81	37.35
Percent of Total Pounds Applied	4.14%	67.44%	28.42%		0.66%	54.20%	45.01%	

Table 3. Descriptive Statistics (Means) for Selected Variables

	2005	**2010**
Yields[1]	148.39	154.11
Yield Goals[1]	157.72	167.97
Corn Price[2]	2.20	5.23
Soil Insecticide Price[3]	11.35	10.81
Premium Paid for Rootworm Resistant Seeds[4]	25.21	27.19
Premium Paid for Corn Borer Resistant Seeds[4]	15.98	21.55
Premium Paid for Stacked Seeds[4]	28.75	39.45
Lbs of Soil (CRW) Insecticides Applied[5]	0.046	0.011
Lbs of Topical (CRB) Insecticides Applied[5]	0.011	0.0007
Total Lbs of Insecticide Applied[5]	0.06	0.02
Incidence of Soil Insecticide Use	16%	6%
Incidence of Topical Insecticide Use	2%	1%
Incidence of Bt-CRW use	10%	52%
Incidence of Bt-CRB use	37%	58%
Expected Yield Losses from Rootworms[6]	9.24	11.00
Soil pH	6.30	6.37
Deviation from Average Winter Temperatures[7]	1.11	-1.91
Deviation from Average February Precipitation[8]	1.03	-6.67
Number of Consecutive Corn Rotations	0.43	0.47
Farm Size[9]	574.64	433.67
Indicator for a Post-High School Education	0.24	0.21
Indicator for Erodable Soil	0.19	0.12
NCRS Soil Productivity Index	0.47	0.49
Fixed Capital[10]	641,731	632,262
Number of Observations	836	918
	0.07	0.01

[1] in bushels/acre

[2] in dollars/per bushel

[3] in dollars/per pound

[4] in dollars/bag

[5] in lbs/ai/acre

[6] in bushels/acre

[7] in degrees Fahrenheit

[8] in inches

[9] in acres

[10] in dollars

Table 4. Descriptive Statistics (Means) for Selected Variables by Seed Type

	Yield Goals[1]		Expected Yield Loss (if CRW Infestations Are Not Treated)[1]		Soil Insecticide Use[2]		Bt Adoption	
	2005	**2010**	**2005**	**2010**	**2005**	**2010**	**2005**	**2010**
Illinois	168.04	178.23	17.17	15.29	0.13	0.03	6%	74%
Iowa	174.89	187.01	14.25	15.37	0.01	0.004	13%	59%
South Dakota	136.03	152.91	12.25	12.57	0.053	0.003	16%	0.57
Wisconsin	156.27	160.86	11.67	14.90	0.04	0.01	10%	41%
Indiana	165.63	174.42	9.64	9.54	0.15	0.03	3%	51%
Michigan	149.81	147.08	8.17	6.39	0.07	0.001	8%	35%
Nebraska	167.45	165.92	7.84	13.31	0.04	0.02	27%	46%
Kentucky	147.58	159.00	7.59	4.45	0.01	0.001	5%	23%
Missouri	151.54	158.33	7.54	5.44	0.004	0	7%	33%
Minnesota	159.54	173.65	6.32	9.36	0.02	0.01	12%	65%
Kansas	134.89	137.35	4.75	5.38	0.00	0	15%	44%
Ohio	163.61	166.40	3.18	8.02	0.04	0.01	6%	48%

[1] in bushels/acre

[2] in pounds of active ingredient/ planted acre

Table 5. Descriptive Statistics (Means) by Rootworm Control Strategy

	Bt-CRW Users (only)		**Soil Insecticide Users (only)**		**Bt-CRW and Soil Insecticide Users**		**No Bt-CRW Seed or Soil Insecticide Use**	
	2005	**2010**	**2005**	**2010**	**2005**	**2010**	**2005**	**2010**
Yields[1]	162.17	162.49	157.28	164.88	178.00	167.11	144.40	143.06
Yield Goals[1]	162.96	173.87	167.83	176.25	180.71	189.39	154.73	159.67
Lbs of Soil (CRW) Insecticides Applied[2]	0.00	0.00	0.29	0.24	0.10	0.16	0	0
Lbs of Topical (CRB) Insecticides Applied[2]	0.01	0.0001	0	0	0	0.01	0.01	0.001
Total Lbs of Insecticide Applied[2]	0.02	0.005	0.30	0.24	0.10	0.16	0.02	0.005
Incidence of Soil Insecticide Use	0%	0%	100%	100%	1.00	100%	0%	0%
Incidence of Topical Insecticide Use	3%	0%	0%	0%	0%	3%	2%	2%
Expected Yield Losses from Rootworms[3]	10.60	12.56	12.93	12.49	12.08	15.84	8.27	8.91
Soil Ph	6.53	6.47	6.38	6.25	6.74	6.44	6.25	6.25
Number of Consecutive Corn Rotations	0.64	0.52	0.65	0.75	0.71	0.97	0.36	0.36
Number of Observations	80	444	127	20	7	33	622	421

[1] in bushels/acre

[2] in pounds of active ingredient/planted acre

[3] on untreated acres

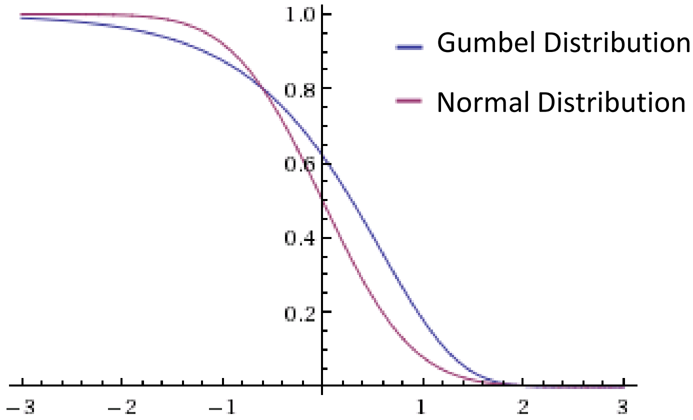

Figure 3. The Probability that X≤0

Chapter 5: Results

This chapter presents the results of the analysis. Section I discusses the results of the variable addition tests (i.e. whether it is necessary to account for endogeneity when estimating the soil insecticide demand function). Section II provides the results of the censored regression model and describes what they imply about the impacts of Bt-CRW adoption. Section III discusses the evidence that rootworms are adapting to Bt-CRW seeds.

1. Reduced Form Models and Endogeneity Tests

As previously discussed, accounting for endogeneity using control functions is a multi-step process. First, the potentially endogenous variables are regressed on a set of exogenous instruments. Next, these results are used to calculate residuals. Finally, the residuals are used as explanatory variables in the second stage of the analysis. If Wald tests demonstrate that the control functions are not significant, then it is safe to treat the potentially endogenous variables as exogenous (Woodridge, 2014).

1.1 Results of the Reduced Form Models

The results of the reduced form models conformed to a priori expectations (see Table 6). For instance, expected yields were found to be increasing in stocks of fixed capital, the productivity of soils, and soil pH levels, but decreasing in February precipitation levels and the presence of erodible soils. The probability of Bt-CRW adoption was found to be increasing in consecutive corn rotations, expected yield losses from corn rootworms on untreated acres, February precipitation levels, and soil pH.

Surprisingly, the results of the probit model indicated that the probability of Bt-CRW adoption was increasing in the premium paid for Bt-CRW seeds. This unexpected result might be due to heterogeneity in Bt-CRW seeds. For instance, though many Bt-CRW seeds produce a single toxin, others have "pyramided" traits which produce multiple PIP's.[25]

Insofar as goodness of fit is concerned, the adjusted R2 of the Probit and OLS regressions were .26 and .29 respectively. These results suggest that the instruments used in the first stage of the model explain fairly little of the variation associated with farmers' expectations.

1.2 Variable Addition Tests

Table 7 presents the results of the variable addition tests. Though $\beta_{E[Y]}$ was strongly significant in every specifications tested, neither β_{Bt} nor β_{Int} were. In other words, omitted variables associated with expected yields were correlated with soil insecticide decisions, but omitted variables associated with Bt-adoption decisions were not. Wald tests were used to confirm these results. One interpretation is that average state level yield losses are good proxies for pest pressure, but that there are not good proxies for omitted environmental factors that influence expected yields.

Notably, two stage instrumental variable based methods require exclusion restrictions. In other words, there must be at least one instrument that is correlated with the potentially endogenous variable and uncorrelated with the dependent one. Notice

---

[25] As a robustness test, the control functions were estimated with and without the Bt-CRW seed prices. The variable addition tests were not sensitive to this change in the specification.

that seed prices and continuous corn rotations strongly affected the probability of Bt-CRW seed use, but not expected yields or soil insecticide use decisions. The presence of erodible soils and stocks of fixed capital were strongly correlated with expected yields, but not soil insecticide use or seed choices. In other words, there were valid, relevant instruments for both potentially endogenous variables.

To summarize, the results of the variable addition tests imply that it is necessary to account for the endogeneity of expected yields, but that it is acceptable to treat Bt-CRW adoption decisions as exogenous.

2. Parameter Estimates, Predictions, and Marginal Effects

2.1 Goodness of fit

The parameter estimates suggest that precipitation, pest pressure, and alkaline soils increase soil insecticide use (see Tables 7). Despite controlling for changes in these factors, soil insecticide use appears lower than average in Iowa, Minnesota, and Nebraska. Though the parameter estimates suggest that Bt-CRW adoption reduces soil insecticide use, the magnitude of the impact appears small relative to other factors.

Tables 8-10 compare the model's predictions with the sample means. Notice that the predictions correspond closely to the means regardless of whether they are compared by year, across states, or for farmers using different types of seeds.

On average, the model predicts that farmers anticipated yield losses from rootworms of approximately 3.7 percentage points (or 6 bushels per acre) in 2005 and 1.2 percentage points (1.9 bushels per acre) in 2010 (see Tables 11-13). These results are lower than the 6% - 7% suggested by the sample means.[26] Future work will attempt

---

[26] Notably, results from field studies suggest that yield losses from rootworms are highly variable. Kahler et al. (1985), Sutter et al. (1990), Spike and Tollefson (1991), Riedell et al. (1996), and Cox

to provide more accurate estimates of yield losses from rootworms by incorporating better information about pest pressure, growing degree days, stress degree days, and irrigation systems.

To conclude, despite its stringent assumptions (risk neutrality, multiplicative separability of the abatement functions, etc.), the structural model makes accurate predictions about farmers' insecticide usage. The model's predictions about yield losses and the severity of rootworm infestations also appear reasonable.

2.2 Impacts on Insecticide Use

The model predicts that Bt-CRW adoption decreased the probability of soil insecticide use by approximately 10.9 percentage points (68%) in 2005 and 3.4 percentage points (56%) in 2010 (see Table 14). Adoption appears to have had a less dramatic impact on application rates, reducing the intensity of soil insecticide use by .01 pounds per acre (3.5%) in 2005, and .003 pounds per acre (1.4%) in 2010. On average, adopting rootworm resistant seeds would have decreased a farmers' expected soil insecticide use by .032 pounds per acre (70%) in 2005 and .01 pounds per acre (84%) in 2010.

Notably, the magnitudes of these impacts were larger for Bt-adopters and in states where pest pressure was high (see Tables 15-16). In Illinois, Bt-CRW adoption appears to have decreased the probability of soil insecticide usage by approximately 25.6 percentage points (57%) in 2005 and 9.6 percentage points in 2010 (44%). By

---

et al. (2008) reported that yield losses from rootworms were 6% to 9% lower than yields on treated fields. Godfrey et al. (1993), Davis (1994), Roth et al. (1995), Dun et al. (2010), and Tinsley et al. (2013) estimated that yield losses from rootworms ranged from 15% to 40%.

contrast, it decreased the intensity of usage by .033 pounds per acre in 2005 (11%) and .009 pounds per acre in 2010 (8%).

These reductions are likely to benefit US farmers. Historically, organophosates (such as Terbufos and Chlorpyrifos) have been responsible for the majority of acute occupational pesticide poisoning cases in the United States (Weisenburger, 1993). Additionally, there is evidence that long term occupational exposure to organophosphates can increase the risk of cancer, Parkinson's disease, and immune disfunction (Ragnarsdottir, 2000). Conversely, there is not any evidence that exposure to Bt toxins is detrimental to human health.

Similarly, though soil insecticides are frequently present in soil, runoff water, and runoff sediment, Bt toxins dissipate rapidly in the environment, and pose a limited risk to non-target species (Whiting et al., 2014). Therefore, replacing conventional insecticides with Bt toxins is likely to improve environmental outcomes.

To summarize, Bt-CRW adoption appears to have reduced conventional insecticide use. These reductions are likely to have had positive consequences, especially in and around agricultural communities.

2.3 Impacts of Bt-CRW Adoption on Yields:

The model predicts that Bt-CRW adoption decreased yield losses from rootworms by .6 percentage points (1.02 bushels per acre) in 2005 and .1 percentage points (.2 bushel per acre) in 2010 (see Table 7). These estimates are smaller than those reported in Nolan and Santos (2012), who found that Bt-CRW adoption increased yields by 3 bushels/acre in field trials conducted from 2004-2006. However, crops tend to perform better in field trials than they do on farms. By way of illustration, average yields in the sample analyzed by Nolan and Santos were 30% higher than those reported by NASS. This suggests that 3 bushels/per acre is an upper bound on the benefits of Bt-CRW adoption.

Insofar as the financial benefits of adoption are concerned, using rootworm resistant seeds did not appear to increase farmers' profits over the course of the study period. Rather, farmers may have chosen to purchase Bt-CRW seeds because of the non-pecuniary benefits associated with adoption.

3. Resistance Tests

Wooldridge (2014) warns against using the parameter estimates [of the structural model] to conduct inference. Rather, the delta method (or a similarly robust method) should be used to assess the statistical significance of the average marginal effects. Judging from the average marginal effects reported in Tables 18 and 19, the benefits associated with Bt-CRW adoption may have decreased rather substantively over the course of the study period.

Assuming that differences in the average annual effectiveness of Bt-CRW seeds (as reflected by the parameter estimate e_{10}) reflect an environmental impact unrelated to rootworm resistance, the model predicts that the benefits associated with adoption decreased by approximately 64% from 2005 to 2010 (see Table 18). If e_{10} reflects an impacts which is related to resistance (e.g. the migration of resistant populations), then the model predicts a 37% reduction in benefits on farms that rotate Bt-CRW seeds, and a 77% reduction on farms that use Bt-CRW seeds in consecutive rotations (see Table 19).

However, these results should be interpreted with caution. For instance, the structural model assumes that farmers are well informed. However, because resistance was first reported in 2009, accurate information about resistance might not have been well disseminated by 2010. Additionally, the model assumes that farmers are risk neutral. If farmers are risk averse then the impacts of resistance may be overstated.

4. Conclusions

This study finds that expected yields are endogenous to soil insecticide use decisions, but that seed choices are not. Estimates from the censored, structural soil insecticide demand function imply that Bt-CRW adoption increases yields and decreases insecticide use. The magnitudes of these effects suggest that adoption may improve human health and environmental outcomes. Surprisingly, there is not strong evidence that using rootworm resistant seeds increases farmers' profits.

Alarmingly, Bt-CRW seeds appear to have become less effective over the course of the study period. Because this effect is especially pronounced on farms that have planted Bt-CRW seeds in consecutive rotations, it appears likely that resistance is developing.

Table 6. Reduced Form Models of Seed Choices and Expected Yields

Reduced Form Models of Seed Choices and Expected Yields	(OLS)		(Probit)	
Variables	**Yield Goal**		**Bt-CRW Seed Use**	
Average State Level Premiums For Bt-CRW Seeds	0.87		0.07	**
State Level Premium^2	-0.006		-0.001	**
Soil Insecticide Prices	-0.34		-0.06	
Farm Size	0.001		0.0001	
ln(Fixed Capital)	4.71	***	0.045	
Consecutive Corn Rotations	0.45		0.18	***
Av. State Level Expected Yield Losses (from Rootworms)	5.51	***	0.52	***
Indicator for a Post-High School Education	1.78		0.11	
NCRS Soil Productivity Index	41.34	***	-0.30	
Indicator for Erodable Soils	-7.52	***	-0.06	
Soil Ph	14.70	***	0.72	***
Deviation from Average Winter Temperature	-0.17		0.02	
Deviation from Average February Precipitation	-0.44	***	0.002	
Indicator for Illinois	2.94		-0.18	
Indicator for Indiana	8.75	*	-0.24	
Indicator for Iowa	16.37	***	-0.12	
Indicator for Michigan	-8.50	**	-0.28	
Indicator for Minnesota	12.71	***	-0.13	
Indicator for Nebraska	15.20	**	-0.03	
Indicator for South Dakota	0.66		0.35	
Indicator for 2010	1.76		1.64	***
Constant	-37.25		-7.31	***
Pseudo R2/Adj R2	0.29		0.26	
Number of Observations	1754		1754	
Average Residual	0.02		-0.01[1]	

[1] The generalized residual is calculated for the Probit model.

Table 7. Variable Addition Tests and Parameter Estimates of the Structural Model

Variable Addition Tests and Parameter Estimates of the Structural Model		**Specification 1**		**Specification 2**		**Specification 3**	
Parameters of the Rootworm Abatement Function							
$e,$	Bt-CRW Adoption	0.58	*	0.39	*	0.19	**
e_{10}	Interaction of Bt and 2010	-0.13		-0.10		-0.07	
$e_{10,CC}$	Interaction of Bt, 2010, and Lagged Bt-CRW	-0.05		-0.09		-0.07	
$-d/f,$	Constant	-6.99	***	-6.92	***	-6.53	***
$f,$	Soil Insecticides	0.83	***	0.64	***	0.66	***
Z_{cc}	Consecutive Corn Rotations	0.04					
Z_{Yl}	Av. State Level Expected Yield Losses (from Rootworms)	0.19	**	0.16	***	0.14	***
Z_{10}	Indicator for 2010	-0.96	***	-1.02	***	-1.11	***
Z_{Ill}	Indicator for Illinois	0.12					
Z_{Ind}	Indicator for Indiana	0.15					
Z_{Ia}	Indicator for Iowa	-0.33	***	-0.32	***	-0.32	***
Z_{Mi}	Indicator for Michigan	0.07					
Z_{Mn}	Indicator for Minnesota	-0.26	**	-0.24	***	-0.26	***
Z_{Nb}	Indicator for Nebraska	-0.20	*	-0.18	***	-0.19	***
Z_{Sd}	Indicator for South Dakota	-0.06					
Z_{Ph}	Average Soil Ph	0.30	***	0.18	***	0.16	***
Z_{E}	Indicator for Erodable Soils	-0.007					
Z_{Wt}	Deviation from Average Winter Temperature	0.007					
Z_{Pr}	Deviation from Average February Precipitation	0.006	***	0.005	***	0.005	***
Z_{FC}	ln(Fixed Capital)	0.015					
Z_{Edu}	Indicator for a Post-High School Education	- 0.0009					
Z_{Fs}	Farm Size	0.0000 04					
Parameters of the Gumbel Distribution							
Standard Deviation		0.10	***	0.10	***	0.10	***
Control Functions							
β_{Bt}	Generalized Residuals, Bt Adoption	0.19		0.11			
$\beta_{E[Y]}$	Residuals of the Expected Yield Function	-0.005	***	-0.005	***	-0.005	***
β_{Int}	Interaction of the Control Functions	0.000		0.0002			
Pseudo R2		0.29		0.28		0.28	
Observations		1754		1754		1754	
P-value for the Wald Test of H_0: Zcc, ZYl, Z10, ZIll, ZInd, ZIa, ZMi, ZMn, ZNb, ZSd, ZPh, ZE, ZWt, ZPr, ZFC, ZEdu, ZFs = 0		0.93					
P-value for the Wald Test of H_0: β_{Bt}, β_{Int}= 0		0.60		0.64			

Table 8. Sample Means and Insecticide Use Predictions, by Year

	Sample Means			Model Predictions		
Year	**Ins[1]**	**Pr(Ins)**	**E[Ins|Ins>0][1]**	**Ins [1]**	**Pr(Ins)**	**E[Ins|Ins>0][1]**
2005	0.046	16.0%	0.285	0.045	16.2%	0.262
2010	0.011	6.1%	0.186	0.015	5.9%	0.253

[1]**In Pounds of Active Ingredient per Planted Acre**

Table 9. Sample Means and Insecticide Use Predictions, by Seed Type

	Sample Means			Model Predictions		
Bt Adopters	**Ins[1]**	**Pr(Ins)**	**E[Ins|Ins>0][1]**	**Ins [1]**	**Pr(Ins)**	**E[Ins|Ins>0][1]**
2005	0.008	8.0%	0.104	0.021	8.1%	0.255
2010	0.011	7.2%	0.155	0.017	6.6%	0.253
Non Adopters						
2005	0.050	17.0%	0.295	0.048	17.1%	0.263
2010	0.012	4.9%	0.237	0.014	5.2%	0.252

[1]**In Pounds of Active Ingredient per Planted Acre**

Table 10. Sample Means and Insecticide Use Predictions, by State

	Sample Means			Model Predictions		
Illinois	**Ins[1]**	**Pr(Ins)**	**E[Ins|Ins>0][1]**	**Ins [1]**	**Pr(Ins)**	**E[Ins|Ins>0][1]**
2005	0.132	44.9%	0.293	0.136	43.6%	0.294
2010	0.03	21.8%	0.117	0.05	17.4%	0.262
Indiana						
2005	0.15	40.3%	0.360	0.06	22.2%	0.265
2010	0.03	9.2%	0.280	0.029	11.1%	0.257
Iowa						
2005	0.01	10.9%	0.106	0.03	13.0%	0.258
2010	0.004	4.5%	0.098	0.012	4.7%	0.252
Other States						
2005	0.02	9.6%	0.257	0.04	12.9%	0.259
2010	0.01	2.8%	0.278	0.01	3.4%	0.251

[1]**In Pounds of Active Ingredient per Planted Acre**

Table 11. Predicted Yield Losses, by Year

Year	**G**		**Adj. Pot. Y.**		**Yield Loss, CRW**	
2005	96.3%	***	164	***	6.0	***
2010	98.8%	***	170	***	1.9	***

Table 12. Predicted Yield Losses, by Seed Type

Bt Adopters	**G**		**Adj. Pot. Y.**		**Yield Loss, CRW**	
2005	96.7%	***	170	***	5.5	***
2010	98.9%	***	177	***	1.9	***
Non Adopters						
2005	96.2%	***	163	***	6.0	***
2010	98.8%	***	162	***	1.9	***

Table 13. Predicted Yield Losses, by State

Illinois	**G**		**Adj. Pot. Y.**		**Yield Loss, CRW**	
2005	96.0%	***	175	***	7.0	***
2010	98.8%	***	180	***	2.1	***
Indiana						
2005	96.2%	***	172	***	6.4	***
2010	98.9%	***	176	***	1.9	***
Iowa						
2005	96.7%	***	181	***	6.0	***
2010	99.0%	***	189	***	1.9	***
Other States						
2005	96.3%	***	159	***	5.8	***
2010	98.8%	***	162	***	1.9	***

Table 14. Impact of Bt-CRW Adoption, by Year

	Marginal Effects					
Year	**ΔIns [1]**	**ΔPr(Ins)**	**ΔE[Ins|Ins>0][1]**	**ΔG**		**ΔE[Y]**
2005	-0.032	-10.9%	-0.010	0.6%	**	1.02
2010	-0.010	-3.4%	-0.003	0.1%		0.20

[1]**In Pounds of Active Ingredient per Planted Acre**

Table 15. Impact of Bt-CRW Adoption, by Seed Type

	Marginal Effects					
Bt Adopters	**ΔIns [1]**	**ΔPr(Ins)**	**ΔE[Ins|Ins>0][1]**	**ΔG**		**ΔE[Y]**
2005	-0.039	-13.1%	-0.012	0.7%	**	1.10
2010	-0.012	-4.3%	-0.004	0.1%		0.20
Non Adopters						
2005	-0.031	-10.6%	-0.010	0.6%	**	1.01
2010	-0.007	-2.5%	-0.002	0.1%		0.20

[1]**In Pounds of Active Ingredient per Planted Acre**

Table 16. Impact of Bt-CRW Adoption, by State

	Marginal Effects					
Illinois	**ΔIns [1]**	**ΔPr(Ins)**	**ΔE[Ins|Ins>0][1]**	**ΔG**		**ΔE[Y]**
2005	-0.09	-25.6%	-0.033	0.68%	**	1.18
2010	-0.03	-9.6%	-0.009	0.12%		0.22
Indiana						
2005	-0.04	-14.5%	-0.011	0.64%	*	1.08
2010	-0.02	-6.5%	-0.005	0.12%		0.21
Iowa						
2005	-0.03	-9.3%	-0.007	0.57%	*	1.03
2010	-0.007	-2.8%	-0.002	0.10%		0.19
Other States						
2005	-0.03	-9.1%	-0.008	0.64%	*	0.99
2010	-0.01	-2.0%	-0.001	0.13%		0.20

[1]**In Pounds of Active Ingredient per Planted Acre**

Table 17. Resistance Tests

		(1) Base		(2) 2010		(3) Lagged Bt-CRW Seed Use, 2010		(4) Lagged Bt-CRW Seed Use, All	
Parameters of the Rootworm Abatement Function									
-d/f,	Constant	-6.55	***	-6.53	***	-6.54	***	-6.53	***
e,	Bt Adoption	0.13	**	0.19	**	0.14	**	0.19	**
e_{10}	Interaction of Bt and 2010			-0.09				-0.07	
$e_{10,CC}$	Interaction of Bt, 2010, and Lagged Bt-CRW					-0.09		-0.07	
f,	Soil Insecticides	0.66	***	0.66	***	0.66	***	0.66	***
Z_{Yl}	Expected Yield Losses	0.14	***	0.14	***	0.14	***	0.14	***
Z_{10}	Indicator for 2010	-1.08	***	-1.11	***	-1.09	***	-1.11	***
Z_{Ill}	Indicator for Ia	-0.33	***	-0.32	***	-0.33	***	-0.32	***
Z_{Ind}	Indicator for Mn	-0.26	***	-0.26	***	-0.26	***	-0.26	***
Z_{Wi}	Indicator for Nb	-0.19	***	-0.19	***	-0.19	***	-0.19	***
Z_{Ph}	Average Soil Ph	0.16	***	0.16	***	0.16	***	0.16	***
Z_{Pr}	Deviation from Average February Precipitation	0.005	***	0.004	***	0.005	***	0.005	***
Parameters of the Gumbel Distribution									
Standard Deviation		0.10	***	0.10	***	0.10	***	0.10	***
Control Functions									
Residuals of the Expected Yield Function		-0.005	***	-0.005	***	-0.005	***	-0.005	***
Pseudo R2		0.276		0.277		0.277		0.278	
Observations		1702		1702		1702		1702	

Table 18. Impacts of Resistance if e10 is Environmental

	ME w/o Res	ME w/Res	ME w/Res - ME w/o Res	Standard Error of ΔME	Implied Reduction in the Benefits of Bt-CRW Adoption
ΔG	0.13%	0.05%	-0.0008	0.0003	-64% **
ΔIns	-0.015	-0.006	0.009	0.019	-58%
ΔPr(Ins)	-5.4%	-2.2%	0.032	0.05	-59%
ΔE[Ins|Ins>0]	-0.005	-0.002	0.003	0.007	-57%

Table 19. Impacts of Resistance if e10 is Due to Resistance

		ME w/o Res	ME w/Res	ME w/Res - ME w/o Res	Standard Error of ΔME	Implied Reduction in the Benefits of Bt-CRW Adoption
ΔG	1 Rotation	0.21%	0.13%	-0.0008	0.0003	-37% **
	Cons. Rot.	0.20%	0.05%	-0.0016	0.0007	-77% **
ΔIns	1 Rotation	-0.014	-0.010	0.004	0.010	-28%
	Cons. Rot.	-0.021	-0.006	0.015	0.033	-70%
ΔPr(Ins)	1 Rotation	-5.0%	-3.6%	0.014	0.03	-29%
	Cons. Rot.	-7.6%	-2.2%	0.054	0.09	-71%
ΔE[Ins|Ins>0]	1 Rotation	-0.004	-0.003	0.001	0.003	-27%
	Cons. Rot.	-0.006	-0.002	0.004	0.011	-69%

Chapter 6: Conclusions

This dissertation develops a two stage, structural model of corn farmers' insect control decisions. It estimates a demand function for soil insecticides in order to recover the parameters of the structural model. A two-stage, control function based approach is used to account for the possibility of endogeneity. A censored regression model is used to account for the infrequency of soil insecticide use.

This study's findings suggest that Bt-CRW adoption lowered farmers' insecticide use by approximately 70% in 2005 and by 84% in 2010. In other words, if Bt-CRW adopters had planted conventional seeds in 2010 their soil insecticide use would have approximately doubled. Because conventional soil insecticides are toxic (and the toxins produced by rootworm resistant seeds are not), Bt-CRW adoption is likely to have improved environmental and human health outcomes over the course of the study period.

Though Bt-CRW adoption appears to have increased yields by approximately 1 bushel per acre in 2005 and .2 bushels per acre in 2010, it does not appear to have increased corn farmers' profits. This finding is incongruous given that Bt-CRW adoption rates have risen in recent years. It is possible that the non-pecuniary benefits associated with adoption help compensate farmers for decreases in their earnings. Alternately, it is possible that farmers perceive that Bt crops are risk decreasing.

Unfortunately, this study finds that resistance may have decreased the marginal product of Bt-CRW adoption by 37% on farms that rotate Bt-CRW seeds, and 77% on farms that use Bt-CRW seeds in consecutive rotations. This finding begs an obvious question: What is the appropriate regulatory response?

First and foremost, existing refuge requirements should be tightly monitored and enforced. Second, the EPA should consider raising refuge requirements (especially for Bt-CRW seeds with pyramided traits). Third, farmers should be induced to adopt better pest management practices. Subsidies represent one (potentially) viable method of encouraging farmers to rotate Bt-CRW and conventional seeds, or shift usage from single trait to pyramided Bt-CRW seeds.

Two conclusions should be drawn from this analysis. First, the benefits of Bt-CRW seeds appear substantial. Second, the threat of rootworm resistance should be taken seriously.

Future work should develop better measures of pest pressure, incorporate risk aversion into the structural model, and explore more complicated methods of accounting for environmental interactions. Additionally, the structural model should be generalized. For instance, Bt cotton could be analyzed if the model was adapted to analyze non-sequential pest control decisions.

Bibliography

Abdeen, A., J. Schnell, and B. Miki. 2010. "Transcriptome analysis reveals absence of unintended effects in drought-tolerant transgenic plants overexpressing the transcription factor ABF3." *BioMed Central Genomics* 11(69): 1-21.

Acquaye, A. and G. Traxler. 2005. "Monopoly Power, Price Discrimination, and Access to Biotechnology Innovations." *Agbioforum* 8 (2&3): 127-133.

Alyokhin, A. 2011. "Scant evidence supports EPAs pyramided *Bt* corn refuge size of 5%." *Nature Biotechnology* 29(7): 577-578.

Amemiya, T. 1984. "Tobit Models: A Survey." *Journal of Econometrics* 24: 3-61.

Ames, B., M. Profet, and L. Gold. 1990. "Nature's chemicals and synthetic chemicals: Comparative toxicology." *Proceedings of the National Academy of Science* 87: 7782-7786.

Ammann, K. 2005. "Effects of biotechnology on biodiversity: herbicide-tolerant and insect resistant GM crops." *TRENDS in Biotechnology* 23(8): 388-394.

Animal and Plant Health Inspection Service. 2012. "Permit User's Guide With Special Guidance for ePermits." May 30, 2012. Downloadable at: http://www.aphis.usda.gov/biotechnology/downloads/permit_guidance.pdf. Accessed on March 18, 2014.

Animal and Plant Health Inspection Service. 2014. "Petitions for Determination of Nonregulated Status." Downloadable at: http://www.aphis.usda.gov/biotechnology/petitions_table_pending.shtml#not_reg. Accessed on March 24, 2014.

Babcock, B., E Lichtenberg, and D. Zilberman. 1992. "Impact of Damage Control and Quality of Output: Estimating Pest Control Effectiveness." *American Journal of Agricultural Economics* 74(1): 163-172.

Benbrook, C. 2009. "Impacts of Genetically Engineered Crops on Pesticide Use in the United States: The First Thirteen Years." *The Organic Center, Critical Issue Report*. November 2009. Downloadable at: http://www.organic-center.org/reportfiles/13Years20091126_ExSumFrontMatter.pdf. Accessed on April 9, 2014.

Benbrook, C. 2012. "Impacts of genetically engineered crops on pesticide use in the U.S. – the first sixteen years." *Environmental Sciences Europe* 24 (24): 1-13.

Berkely, S., A. Hightower, R. Beier, D. Fleming, C. Brokopp, G. Ivie, C. Broome. 1986. "Dermatitis in Grocery Workers Associated with High Natural Concentrations of Furanocoumarins in Celery." *Annals of Internal Medicine* 105: 351-355.

Bernard, J., J. Pesek, C. Fan. 2004. “Performance Results and Characteristics of Adopters of Genetically Engineered Soybeans in Delaware.” *Agricultural and Resource Economics Review* 33(2): 282-292.

Blackwell, M. and A. Pagoulatos. 1992. “The Econometrics of Damage Control, Comment.” *American Journal of Agricultural Economics* 74(4): 1040-1044.

Blake, H., P. Andrilenas, R. Jenkins, T. Eichers, and A. Fox. 1970. “Farmers’ Pesticide Expenditures in 1966.” Agricultural Economic Report No. 192, Economic Research Service, United States Department of Agriculture, Washington D.C.

Bohme, H., B. Hommel, and G. Flachowsky. 2005. “Nutritional assessment of silage from transgenic insulin synthesizing potatoes for pigs.” *Journal of Animal Feed Science* 14(Supplement 1): 333-336.

Bowman, D., O. May, and J. Creech. 2003. “Genetic Uniformity of the U.S. Upland Cotton Crop since the Introduction of Transgenic Cottons.” *Crop Science* 43: 515-518.

Brake, D. and D. Evenson. 2004. “A generational study of glyphosate-tolerant soybeans on mouse fetal, postnatal, pubertal and adult testicular development.” *Food Chemical Toxicology* 42: 29-36.

Brower, L., O. Taylor, E. Williams, D. Slayback, R. Zubieta, and M. Isabel. 2011. “Decline of monarch butterflies overwintering in Mexico: is the migratory phenomenon at risk?” *Insect Conservation and Diversity* 5: 95-100.

Bruening, G. and J. Lyons. 2000. “The case of the FLAVR SAVR tomato.” *California Agriculture* 54(4): 6-7.

Burke. 1999. “No GM conspiracy.” *Nature* 401: 640-641.

Burrows, T. 1983. “Pesticide Demand and Integrated Pest Management: A Limited Dependent Variable Analysis.” *American Journal of Agricultural Economics* 65 (1983): 806-810.

Cameron, A. and P. Trivedi. 2005. *Microeconometrics*, *Methods and Applications.* New York NY: Cambridge University Press.

Campbell, H.F. 1976. “Estimating the Marginal Productivity of Agricultural Pesticides: The Case of Tree-Fruit Farms in the Okanagan Valley.” *Canadian Journal of Agricultural Economics* 24: 23-30.

Carlson, G. 1977. “Long-Run Productivity of Insecticides.” *American Journal of Agricultural Economics* 59(3): 543-548.

Carpentier, A. and R. Weaver. 1977. “Damage Control Productivity: Why Econometrics Matters.” *American Journal of Agricultural Economics* 79(1): 47-61.

Carpenter, J. 2011. “Impact of GM crops on biodiversity.” *GM Crops* 2(1): 7-23.

Carpenter, J. and L. Gianessi. 1999. “Herbicide Tolerant Soybeans: Why Growers Are Adopting Roundup Ready Varieties.” *AgBioForum* 2(2): 65-72.

Carrasco-Tauber, C. and L.J. Moffitt. 1992. "Damage Control: Econometrics: Functional Specification and Pesticide Productivity." *American Journal of Agricultural Economics* 74(1): 158-162.

Chambers, R., G. Karagiannis, and V. Tzouvelekas. 2010. "Another Look at Pesticide Productivity and Pest Damage." *American Journal of Agricultural Economics* 92 (5): 1401-1419.

Chambers, R. and E. Lichtenberg. 1994. "Simple Econometrics of Pesticide Productivity." *American Journal of Agricultural Economics* 76 (3): 407 –417.

Champion, G., M. May, S. Bennett, D. Brooks, S. Clark, R. Daniels, L. Firbank, A. Haughton, C. Hawes, M. Heard, J. Perry, Z. Randle, M. Rossall, P Rothery, M. Skellern, R.. Scott, G. Squire, and M. Thomas. 2003. "Crop Management and Agronomic Context of the Farm Scale Evaluations of Genetically Modified Herbicide-Tolerant Crops." *Philosophical Transactions: Biological Sciences* 358 (1439): 1801-1818.

Cheng, K., J. Beaulieu, E. Iquira, F. Belzile, M. Fortin, and M. Stromvik. 2008. "Effect of transgenes on global gene expression in soybean is within the natural range of variation of conventional cultivars." *Journal of Agricultural and Food Chemistry* 56(9): 3057-3067.

Coll, A., A. Nadal, R. Collado, G. Capellades, M. Kubista, J. Messeguer, and M. Pla. 2010a. "Natural variation explains most transcriptomic changes among maize plants of MON810 and comparable non-GM varieties subjected to two N-fertilization farming practices." *Plant Molecular Biology* 73: 349-362.

Coll, A., A. Nadal, M. Rossignol, P. Puigdomenech, and M. Pla. 2010b. "Proteomic analysis of MON810 and comparable non-GM maize varieties grown in agricultural fields." *Transgenic Research* 20(4): 939-949.

Cox, W., E. Shields, and D. Cherney. 2008. "Western Corn Rootworm Damage Subtly Affects Corn Growth under Moderate Environmental Stress." *Crop Science* 48: 1164-1169.

Crost, S., B. Shankar, R. Bennett, and S. Morse. 2007. "Bias from Farmer Self-Selection in Genetically Modified Crop Productivity Estimates: Evidence from Indian Data." *Journal of Agricultural Economics* 58(1): 24-36.

Eichers, T., P. Andrilenas, H. Blake, R. Jenkins, and A. Fox. 1970. "Quantities of Pesticides Used by Farmers in 1966." Agricultural Economic Report No. 179, Economic Research Service, United States Department of Agriculture, Washington D.C.

Environmental Protection Agency. 2013. "DDT – A Brief History and Status." EPA Home, Pesticides, About Pesticides, Topical & Chemical Fact Sheets. Accessed September 2, 2013. Downloadable at: http://www.epa.gov/pesticides/factsheets/chemicals/ddt-brief-history-status.htm

D'Alessandro, A. and L. Zolla. 2011. "We Are What We Eat: Food Safety and Proteomics." *Journal of Proteome Research* 11: 26-36.

Daleprane J., J. Pacheco, G. Boaventura. 2009. "Evaluation of protein quality from genetically modified and organic soybean in two consecutives generations of Wistar rats." *Brazilian Archives of Biology and Technology* 52: 841–847.

Davis, P. 1994. "Comparison of Economic Injury Levels for Western Corn Rootworm (Coleoptera: Chrysomelidae) Infesting Silage and Grain Corn." *Journal of Economic Entomology* 87(4): 1086-1090.

Deloitte. 2010. "Food Survey Fact Sheet: Genetically Modified Foods." Deloitte Consulting LLP, Washington D.C. February 15, 2011. Downloadable at: http://www.deloitte.com/view/en_US/us/Industries/consumer-products/1912cf06d7c38210VgnVCM100000ba42f00aRCRD.htm. Accessed on March 4, 2014.

Demortain, D. 2013. "Regulatory Toxicology in Controversy." *Science, Technology & Human Values* 38(6): 727-748.

Duke, S. and S. Powles. 2009. "Glyphosate-Resistant Crops and Weeds: Now and in the Future." *AgBioForum* 12 (3&4): 346-357.

Dun, Z., P. Mitchell, and M. Agosti. 2010. "Estimating Diabrotica virgifera virgifera damage functions with field trial data: applying an unbalanced nested error component model." *Journal of Applied Entomology* 134: 409-419.

Edwards, C., D. Jordan, M. Owen, P. Dixon, B. Young, R. Wilson, S. Weller, and D. Shaw. 2014. "Benchmark study on glyphosate-resistant crop systems in the United States. Economics of herbicide resistance management practices in a 5 year field-scale study." *Pest Management Science* Early Publication: doi: 10.1002/ps.3759.

El Ouakfaoui, S. and B. Miki. 2005. "The stability of the Arabidopsis transcriptome in transgenic plants expressing the marker genes nptII and uidA." *Plant Journal* 41(6): 791-800.

Environmental Protection Agency. 2001. "Biopesticides Registration Action Document, Bacillus thuringiensis (Bt) Plant-Incorporated Protectants." October 16, 2001. Downloadable at: http://www.epa.gov/oppbppd1/biopesticides/pips/bt_brad.htm. Accessed on March 18, 2014.

Environmental Protection Agency. 2008a. "Review of the Public Interest Document in Support of the Section 3(c)7(C) Registrations of Monsanto Company's Insect-protected *Bacillus thuringiensis* Corn Products." Feburary 29, 2008. Downloadable at: http://www.epa.gov/opp00001/chem_search/cleared_reviews/csr_PC-006514_29-Feb-08_a.pdf. Accessed on March 18, 2014.

Environmental Protection Agency. 2008b. "Review of an amendment request to reduce the refuge required for MON 89034 corn in the Corn Belt." November 12, 2008. Downloadable at: http://www.epa.gov/opp00001/chem_search/cleared_reviews/csr_PC-006514_12-Nov-08_a.pdf. Accessed on March 18, 2014.

Environmental Protection Agency. 2011a. "Current & Previously Registered Section 3 PIP Registrations." November 30, 2011. Downloadable at: http://www.epa.gov/pesticides/biopesticides/pips/pip_list.htm. Accessed on March 18, 2014.

Environmental Protection Agency. 2011b. “Pesticide Fact Sheet, MON-89Ø34-3 x DAS-Ø15Ø7-1 x MON-88Ø17-3 x DAS-59122-7.” November 29, 2011. Downloadable at: http://www.epa.gov/pesticides/biopesticides/pips/smartstax-factsheet.pdf. Accessed on March 18, 2014.

Environmental Protection Agency. 2012. “EPA’s Regulation of Biotechnology for Use in Pest Management.” January 1, 2012. Downloadable at: http://www.epa.gov/oppbppd1/biopesticides/reg_of_biotech/eparegofbiotech.htm. Accessed on March 18, 2014.

Environmental Protection Agency. 2014. “A Set of Scientific Issues Being Considered by the Environmental Protection Agency Regarding Scientific Uncertainties Associated with Corn Rootworm Resistance Monitoring for Bt Corn Plant Incorporated Protectants (PIPs).” March 18, 2014. Downloadable at: http://www.epa.gov/scipoly/sap/meetings/2013/december/120413minutes.pdf. Accessed on April 6, 2014.

ETC Group. 1997. “World’s Top 10 Seed Corporations.” January 30, 1997. Downloadable at: http://www.etcgroup.org/content/worlds-top-10-seed-corporations. Accessed on April 2, 2014.

ETC Group. 2013. “Putting the Cartel before the Horse… and Farm, Seeds, Soil, Peasants, etc..” September, 2013. Downloadable at: http://www.etcgroup.org/content/new-report-putting-cartel-horse%E2%80%A6and-farm-seeds-soil-peasants. Accessed on April 2, 2014.

Falck-Zepeda, J., G. Traxler, and R. Nelson. 2000. “Surplus distribution from the introduction of biotechnology innovation.” *American Journal of Agricultural Economics* 82 (2): 360-369.

Feder, G. 1979. “Pesticides, Information, and Pest Management under Uncertainty.” *American Journal of Agricultural Economics* 61(1): 97-103.

Fernandez-Cornejo, J. 2004. “The Seed Industry in U.S. Agriculture: An Exploration of Data and Information on Crop Seed Markets, Regulation, Industry Structure, and Research and Development.” *Agricultural Information Bulletin No. 786*, Economic Research Service, United States Department of Agriculture, Washington D.C.

Fernandez-Cornejo, J. and M. Caswell. 2006. “The First Decade of Genetically Engineered Crops in the United States.” *Economic Information Bulletin Number 11*, Economic Research Service, United States Department of Agriculture, Washington D.C.

Fernandez-Cornejo, J., C. Hallahan, R. Nehring, and S. Wechsler. 2012. “Conservation Tillage, Herbicide Use, and Genetically Engineered Crops in the United States: The Case of Soybeans.” *AgBioForum* 15(3): 231-241.

Fernandez-Cornejo, J., C. Hendricks, and A. Mishra. 2005. “Technology Adoption and Off-Farm Household Income: The Case of Herbicide-Tolerant Soybeans.” *Journal of Agricultural and Applied Economics* 37(3): 549-563.

Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans. 2000. “Farm-Level Effects of Adopting Genetically Engineered Crops in the U.S.A.” in *Transitions in Agbiotech: Economics of Strategy and Policy*, ed. by W. Lesser. Amherst, University of Massachusetts Press.

Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans. 2002. “Farm-Level Effects of Adopting Herbicide-Tolerant Soybeans in the U.S.A.” *Journal of Agriculture and Applied Economics* 34(1): 149-163.

Fernandez-Cornejo, J. and J. Li. 2005. “The Impacts of Adopting Genetically Engineered Crops in the USA.” *Paper Presented at the American Agricultural Economics Association* July 24-27: 1-25.

Fernandez-Cornejo, J. and R. Just. 2007. “Researchability of Modern Agricultural Input Markets and Growing Concentration.” *American Journal of Agricultural Economics* 89 (5): 1269-1275.

Fernandez-Cornejo, J., R. Nehring, C. Osteen, S. Wechsler, A. Martin, A. Vialou, and A. Grube. 2014b. “Pesticide Use in U.S. Agriculture, 1960-2008.” Economic Information Bulletin No. 124, Economic Research Service, United States Department of Agriculture, Washington D.C. (Unpublished data product used to generate the report; contact authors for details)

Fernandez-Cornejo, J. and S. Jans. 1995. “Quality adjusted price and quantity indices for pesticides.” *American Journal of Agricultural Economics* 77(August): 645-659.

Fernandez-Cornejo, J. and S. Wechsler. 2012. “Revisiting the Impact of Bt Corn Adoption by U.S. Farmers.” *Agricultural and Resource Economics Review* 41(3): 377-390.

Fernandez-Cornejo, J., S. Wechsler, M. Livingston, and L. Mitchell. 2014a. “Genetically Engineered Crops in the United States.” *Agricultural Research Report No. 162*, Economic Research Service, United States Department of Agriculture, Washington D.C.

Fernandez-Cornejo, J. and W. McBride. 2002. “Adoption of Bioengineered Crops.” Agricutural Economic Report No. 810, Economic Research Service, United States Department of Agriculture, Washington D.C.

Firbank, L., M. Heard, I. Woiwod, C. Hawes, A. Haughton, G. Champion, R. Scott, M. Hill, A. Dewar, G. Squire, M. May, D. Brooks, D. Bohan, R. Daniels, J. Osborne, D. Roy, H. Black, P. Rothery, and J. Perry. 2003. “An introduction to the Farm-Scale Evaluations of genetically modified herbicide-tolerant crops.” *Journal of Applied Ecology* 40: 2-16.

Flachowsky, G., K. Aulrich, H. Bohme, I. Halle. 2006. “Studies on feeds from genetically modified plants (GMP) – Contributions to nutritional and safety assessment.” *Animal Feed Science and Technology* 133: 2-30.

Food and Drug Administration. 1992. “Statement of Policy: Foods Derived From New Plant Varieties” May 29, 1992. Downloadable at: http://www.fda.gov/food/guidanceregulation/guidancedocumentsregulatoryinformation/biotechnology/ucm096095.htm. Accessed on March 19, 2013.

Food and Drug Administration. 2001. “Guidance for Industry: Voluntary Labeling Indicating Whether Foods Have or Have Not Been Developed Using Bioengineering.” January 1, 2001. Downloadable at: http://www.fda.gov/Food/GuidanceRegulation/GuidanceDocumentsRegulatoryInformation/LabelingNutrition/ucm059098.htm. Accessed on March 19, 2013.

Food and Drug Administration. 2013. "Biotechnology, Genetically Engineered Plants for Food & Feed." May 31, 2013. Downloadable at: http://www.fda.gov/Food/FoodScienceResearch/Biotechnology/default.htm. Accessed on March 14, 2013.

Fox, G. and A. Weersink. 1995. "Damage Control and Increasing Returns." *American Journal of Agricultural Economics* (77)1: 33-39.

Gardner, J. and G. Nelson. 2008. "Herbicides, glyphosate resistance and acute mammalian toxicity: simulating an environmental effect of glyphosate-resistant weeds in the USA." *Pest Management Science* 64: 470-478.

Gardner, J., R. Nehring, and C. Nelson. 2009. "Genetically Modified Crops and Household Labor Savings in US Crop Production." *AgBioForum* 12(3&4): 303-312.

Gassmann, A. 2012. Field-evolved resistance to Bt maize by western corn rootworm: predictions from the laboratory and effects in the field. *J. Invertebr. Pathol* 110(3): 287-292.

Gassmann, A., J. Petzold-Maxwell, E. Clifton, M. Dunbar, A. Hoffmann, D. Ingber, and R. Keweshan. 2014. "Field-evolved resistance by Western Corn Rootworm to multiple *Bacillus thuringiensis* toxins in transgenic maize." *Proceedings of the National Academy of Sciences of the United States of America*, published ahead of print March 17, 2014, doi:10.1073/pnas.1317179111.

Gassmann, A., J. Petzold-Maxwell, R. Keweshan, and M. Dunbar. 2011. "Field-Evolved Resistance to Bt Maize by Western Corn Rootworm." *PLoS One* 6(7): 1-7.

Gassmann, A., J. Petzold-Maxwell, R. Keweshan, and M. Dunbar. 2012. "Western Corn Rootworm and Bt maize challenges of pest resistance in the field." *GM Crops and Food* 3(3):1-10.

Gatehouse, J. 2008. "Biotechnological Prospects for Engineering Insect-Resistant Plants." *Plant Physiology* 146: 881-887.

Gianessi, L. 2008. "Economic impacts of glyphosate-resistant crops." *Pest Management Science* 64: 346-352.

Gilliam, C. 2010. "Farm Groups call on U.S. to 'bust up big ag.'" *Reuters*. March 11, 2010. Downloadable at: http://www.reuters.com/article/2010/03/12/us-seeds-antitrust-idUSTRE62B0A720100312. Accessed on April 2, 2014.

Godfrey, L., L. Meinke, and R. Wright. 1993. "Vegetative and Reproductive Biomass Accumulation in Field Corn: Response to Root Injury by Western Corn Rootworm (Coleoptera: Chrysomelidae)." *Jounral of Economic Entomology* 86(5): 1557-1573.

Gouse, M., J. Piesse, and C. Thirtle. 2006. "Output and Labour Effects of GM Maize and Minimum Tillage in a Communal Area of KwaZulu-Natal." *Journal of Development Perspectives* 2(2): 71-86.

Govtrack. 2014a. "H.R. 1699: Genetically Engineered Food Right-to-Know Act." Downloadable at: https://www.govtrack.us/congress/bills/113/hr1699. Accessed on March 20, 2014.

Govtrack. 2014b. “S. 809: Genetically Engineered Food Right-to-Know Act.” Downloadable at: https://www.govtrack.us/congress/bills/113/s809. Accessed on March 20, 2014.

Gray, M. 2014a. “Field Evolved Western Corn Rootworm Resistance to Bt (Cry3Bb1) Confirmed in Three Additional Illinois Counties.” *The Bulletin*. April 3, 2014. Downloadable at: http://bulletin.ipm.illinois.edu/?p=1913. Accessed on April 6, 2014.

Gray, M. 2014b. “Western Corn Rootworm Egg Survival and the Winter of 2013-2014: What’s the Likely Outcome?” *The Bulletin.* March 18, 2014. Downloadable at: http://bulletin.ipm.illinois.edu/?p=1876. Accessed on August 22, 2014.

Green, J. 2009. “Evolution of Glyphosate-Resistant Crop Technology.” *Weed Science* 57: 108-117.

Greene, W. 2006. “A General Approach to Incorporating Selectivity in a Model.” Department of Economics, Stern School of Business, New York University, Working Paper 06-10. June, 2006. Downloadable at: http://archive.nyu.edu/bitstream/2451/26072/2/6-10.pdf. Accessed on April 27, 2014.

Greene, W. 2012. *Econometric Analysis* (7th edition). Upper Saddle River, NJ: Prentice-Hall.

Griliches, Z. 1964. “Research Expenditures, Education, and the Aggregate Agricultural Production Function.” *The American Economic Review* 54(6): 961-974.

Guan, Z., S. Kumbhakar, R. Myers, and A. Lansink. 2009. “Measuring Excess Capital Capacity in Agricultural Production.” *American Journal of Agricultural Economics* 91: 765-776.

Hall, D. and R. Norgaard. 1973. “On the Timing and Application of Pesticides.” *American Journal of Agricultural Economics* 55(2): 198-201.

Harrigan, G., D. Lundry, S. Drury, K. Berman, S. Riordan, M. Nemeth, W. Ridley, and K. Glenn. 2010. “Natural variation in crop composition and the impact of transgenesis.” *Nature Biotechnology* 28(5): 402-404.

Haryu, Y., Y. Taguchi, E. Itakura, O. Mikami, K. Miura, T. Saeki, and Y. Nakajima. 2009. “Longterm biosafety assessment of a genetically modified (GM) plant: the genetically modified (GM) insect-resistant Bt11 corn does not affect the performance of multi-generations or life span of mice.” *Open Plant Science* (3): 49-53.

Hawes, C., A. Haughton, J. Osborne, D. Roy, S. Clark, J. Perry, P. Rothery, D. Bohan, D. Brooks, G. Champion, A. Dewar, M. Heard, I. Woiwod, R. Daniels, M. Young, A. Parish, R. Scott, L. Firbank, and G. Squire. 2003. “Responses of plants and invertebrate trophic groups to contrasting herbicide regimes in the Farm Scale Evaluations of genetically modified herbicide-tolerant crops.” *Philosophical Transactions of the Royal Society of London, Series B-Biological Sciences* 358(1439): 1899-1913.

Headley, J.C. 1968. “Estimating the Productivity of Agricultural Pesticides.” *American Journal of Agricultural Economics* 50(1): 13-23.

Heard, M., C. Hawes, G. Champion, S. Clark, L. Firbank, A. Haughton, A. Parish, J. Perry, P. Rothery, R. Scott, M. Skellern, G. Squire, and M. Hill. 2003. "Weeds in fields with contrasting conventional and genetically modified herbicide-tolerant crops. I. Effects on abundance and diversity." *Philosophical Transactions of the Royal Society of London, Series B-Biological Sciences* 358(1439): 1819-1832.

Hellenas, K.E., A. Nyman, P. Slanina, L. Loof, and J. Gabrielsson. 1992. "Determination of potato glycoalkaloids and their aglycone in blood serum by high-performance liquid chromatography." *Journal of Chromatography* 573: 69-78.

Hennessy, D. 1997. "Damage Control and Increasing Returns: Further Results." *American Journal of Agricultural Economics* 79(3): 786-791.

Hensley, S. 2010. "Americans are Wary of Genetically Engineered Foods." *National Public Radio*. November 12, 2010. Downloadable at: http://www.nytimes.com/2013/07/28/science/strong-support-for-labeling-modified-foods.html?emc=eta1. Accessed on March 4, 2014.

Herman, R. and W. Price. 2013. "Unintended Compositional Changes in Genetically Modified (GM) Crops: 20 Years of Research." *Journal of Agricultural and Food Chemistry* 61: 11695-11701.

Hodgson, Erin. 2014. "Did this winter kill all the corn rootworm eggs." *It's a bug's life*. June 4, 2014. Downloadable at: http://iowabuglife.blogspot.com/2014/06/did-this-winter-kill-all-corn-rootworm.html. Accessed August 21, 2014.

Howard, P. 2009. "Visualizing Consolidation in the Global Seed Industry: 1996-2008." *Sustainability* 1: 1266-1287.

Huang, J., R. Hu, S. Rozelle, F. Qiao, and C. Pray. 2002. "Transgenic varieties and productivity of smallholder cotton farmers in China." *The Australian Journal of Agricultural and Resource Economics* 46(3): 367-387.

Hyde, J., M. Martin, P. Preckel, and C. Edwards. 1999. "The Economics of Bt Corn: Valuing Protection from the European Corn Borer." *Review of Agricultural Economics* 21(2): 442-454.

Jalonick, M. 2013. "Farm bill: Senate rejects GMO labeling amendment." *Salt Lake Tribune.* May 23, 2013. Downloadable at: http://www.sltrib.com/sltrib/money/56355087-79/amendment-senate-labeling-farm.html.csp. Accessed on March 20, 2014.

Jawitz, J. 2004. "Moments of truncated continuous univariate distributions." *Advances in Water Resources* 27: 269-281.

Kahler, A., A. Olness, G. Sutter, C. Dybing, and O. Devine. 1985. "Root Damage by Western Corn Rootworm and Nutrient Content in Maize." *Agronomy Journal* 77(5): 769-774.

Karlin, J. 2010. "July 2010 Precipitation and Temperatures in Top Corn and Bean States." *The Progressive Farmer.* August 12, 2010. Downloadable at: http://www.dtnprogressivefarmer.com/dtnag/view/ag/printablePage.do?ID=BLOG_PRINTABLE_PAGE&bypassCache=true&pageLayout=v4&blogHandle=agfundamental&blogEntryId=8a82c0bc29aa007f012a666ce6c90900&articleTitle=July+2010+Precipitation+and+Temperatures+in+Top+Corn+and+Bean+States&editionName=DTNAgFreeSiteOnline. Accessed on September 7, 2014.

Kearns, P. and P Mayers. 1999. "Substantial equivalence is a useful tool." *Nature* 401: 640.

Kleter, G., R. Bhula, K. Bodnaruk, E. Carazo, A. Felsot, C. Harris, A. Katayama, H. Kuiper, K. Racke, B. Rubin, Y. Shevah, G. Stephenson, K. Tanaka, J. Unsworth, R. Wauchope and S. Wong. 2007. *Pest Management Science* 63: 1107-1115.

Kopicki, A. 2013. "Strong Support for Labeling Modified Foods." *New York Times*. July 27, 2013. Downloadable at: http://www.nytimes.com/2013/07/28/science/strong-support-for-labeling-modified-foods.html?emc=eta1. Accessed on March 4, 2014.

Kovach, J., C. Petzoldt, J. Degni, and J. Tette. 1992. "A method to measure the environmental impact of pesticides." *New York's Food and Life Sciences Bulletin* 139: 1-8.

Krishna, V., D. Zilberman, and M. Qaim. 2009. "Transgenic Technology Adoption and On-Farm Varietal Diversity." Paper presented at the 2009 International Association of Agricultural Economists (IAAE) Conference, Beijing, China. Downloadable at: http://ageconsearch.umn.edu/bitstream/51750/2/COTTON.pdf.

Kristensen, C., M. Morant, C. Olsen, C. Ekstom, D. Galbraith, B. Moller, and S. Bak. 2005. "Metabolic engineering of dhurrin in transgenic Arabidposis plants with marginal inadvertent effects on the metabolome and transcriptome." *Proceedings of the National Academy of Science* 102: 1779-1784.

Kucinich, E. 2014. "Members of Congress, Farmers and Business Call on Obama to Fulfill Campaign Promise on GMO Labeling." *Huffington Post*. January 16, 2014. Downloadable at: http://www.huffingtonpost.com/elizabeth-kucinich/post_6676_b_4612219.html. Accessed on March 19, 2014.

Lamboy, J. 1986. "Alkaline Degradation of Pesticides." *New York State Integrated Pest Management Program.* Downloadable at: http://www.nysipm.cornell.edu/publications/alkaline_deg/. Accessed on September 7, 2014.

Lansink, A. and A. Carpentier. 2001. "Damage Control Productivity: An Input Damage Abatement Approach." *Journal of Agricultural Economics* 52(3): 11-22.

Lasker, E. 2005. Federal Preemption and State Anti-GM Food Laws. *Legal Background* 20(60): 1-4.

Lee, J. and M. Langham. 1973. "A Simultaneous Equation Model of the Economic-Ecologic System in Citrus Groves." *Southern Journal of Agricultural Economics* 5(1): 175-180.

Lehman, A., L. Woodard, D. Fitzhugh, and J. Nelson. 1949. "Procedures for the Appraisal of the Toxicity of Chemicals in Food." *Food Drugs and Cosmetics Law Journal* 4 (3): 412-434.

Lence, S. and D. Hayes. 2005. "Genetically modified crops: their market and welfare impacts." *American Journal of Agricultural Economics* 87: 931-950.

Lichtenberg, E. and D. Zilberman. 1986. "The Economics of Damage Control: Why Specification Matters." *American Journal of Agricultural Economics* 68: 261-273.

Lichtenberg, E. and D. Zilberman. 1989. "The Economics of Damage Control: Reply." *American Journal of Agricultural Economics* 71(2): 445-446.

Losey, J., L. Rayor, and M. Carter. 1999. “Transgenic pollen harms monarch larvae.” *Nature* 399: 214.

Luttrell, R. and R. Jackson. 2012. “*Helicoverpa zea* and Bt cotton in the United States.” *GM Crops and Food: Biotechnology in Agriculture and the Food Chain* 3(3): 213-227.

Malatesta, M., F. Boraldi, G. Annovi, B. Baldelli, S. Battistelli, M. Biggiogera, and D. Quaglino. 2008. “A long-term study on female mice fed on a genetically modified soybean: effects on liver ageing.” *Histochemistry and Cellular Biology* 130: 967–977.

Marvier, M., C. McCreedy, J. Regetz, and P. Kareiva. 2007. “A Meta-Analysis of Effects of Bt Cotton and Maize on Nontarget Invertebrates.” *Science* 316:1475-1477.

Mellman Group. 2006. “Review of Public Opinion Research.” Pew Research Center, Washington D.C. November 16, 2003. Downloadable at: http://www.pewtrusts.org/uploadedFiles/wwwpewtrustsorg/Public_Opinion/Food_and_Biotechnology/2006summary.pdf. Accessed on March 4, 2014.

Mikel, M. 2008. “Genetic Diversity and Improvement of Contemporary North American Dent Corn.” *Crop Science* 48: 1686-1695.

Mikel, M., B. Diers, R. Nelson, and H. Smith. 2010. “Genetic Diversity and Agronomic Improvement of North American Soybean Germplasm.” *Crop Science* 50: 1219-1229.

Millstone, E., E. Brunner, and S. Mayer. 1999. “Beyond ‘substantial equivalence’.” *Nature* 401: 525-526.

Mitchell-Olds, T. 2001. “Arabidopsis thaliana and its wild relatives: a model system for ecology and evolution.” *TRENDS in Ecology & Evolution* 16(12): 693-700.

Mutuc, M., R. Rejesus, and J. Yorobe. 2011. “Yields, Insecticide Productivity, and Bt Corn: Evidence from Damage Abatement Models in the Philippines.” *AgBioForum* 14(2): 35-46.

National Center for Food and Agricultural Policy. 2008. “Quantification of the Impacts on US agriculture of Biotechnology-Derived Crops Planted in 2006.” February 2008. Downloadable at: http://www.ncfap.org/documents/2007biotech_report/Quantification_of_the_Impacts_on_US_Agriculture_of_Biotechnology_Executive_Summary.pdf. Accessed on April 9, 2014.

Naranjo, S. 2009. “Impacts of Bt crops on non-target invertebrates and insecticide use patterns.” *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources* 4(11): 1-23.

Naranjo, S., G. Head, and G. Dively. 2005. “Field Studies Assessing Arthropod Nontarget Effects in *Bt* Transgenic Crops: Introduction.” *Environmental Entomology* 34(5): 1178-1180.

Nolan, E. and P. Santos. 2012. “The Contribution of Genetic Modification to Changes in Corn Yield in the United States.” *American Journal of Agricultural Economics* 94(5): 1171-1188.

Nordlee, J., S. Taylor, J. Townsend, L. Thomas, and R. Bush. 1996. "Identification of a Brazil-Nut Allergen in Transgenic Soybeans." *The New England Journal of Medicine* 334: 688-692.

Oberhauser, K., M. Prysby, H. Mattila, D. Stanley-Horn, M. Sears, G. Dively, E. Olson, J. Pleasants, W. Lam, and R. Hellmich. 2001. "Temporal and spatial overlap between monarch larvae and corn pollen." *PNAS* 98(21): 11913-11918.

Oehmke, J. and C. Wolf. 2004. "Why is Monsanto leaving money on the table? Monopoly pricing and technology valuation distributions with heterogeneous adopters." *Journal of Agricultural and Applied Economics* 36 (3): 705-718.

Office of Science and Technology Policy. 1986. "Coordinated Framework for Regulation of Biotechnology." June 26, 1986. Downloadable at: http://www.aphis.usda.gov/brs/fedregister/coordinated_framework.pdf. Accessed on March 18, 2014.

Owen, M. 2008. "Weed species shifts in glyphosate-resistant crops." *Pest Management Science* 64: 377-387.

Pandey, S. 1989. "The Econometrics of Damage Control: Comment." *American Journal of Agricultural Economics* 71(2): 443-444.

Perry, J., P. Rothery, S. Clark, M. Heard, and C. Hawes. 2003. "Design, analysis and statistical power of the Farm-Scale Evaluations of genetically modified herbicide-tolerant crops." *Journal of Applied Ecology* 40: 17-31.

Perry, J., L. Firbank, G. Champion, S. Clark, M. Heard, M. May, C. Hawes, G. Squire, P. Rothery, L. Wolwod, and J. Pidgeon. 2004. "Ban on triazine herbicides likely to reduce but not negate relative benefits of GMHT maize cropping." *Nature* 428: 313-316.

Pew Center for the People and the Press. 2003. "Views of a Changing World." Pew Research Center, Washington D.C. June 2003. Downloadable at: http://www.pewglobal.org/2003/06/03/views-of-a-changing-world-2003/. Accessed on March 4, 2014.

Pfeiffer, S. and L. Jolicoeur. 2014. "Massachusetts Legislature Faces Deadline to Advance GMO Labeling Bill." *WBUR, Boston's NPR News Station*. March 13, 2004. Downloaded at: http://www.wbur.org/2014/03/13/mass-gmo-bill-deadline. Accessed on March 19, 2014.

Pilcher, C., M. Rice, R. Higgins, K. Steffey, R. Hellmich, J. Witkowski, D. Calvin, K. Ostlie, and M. Gray. 2002. "Biotechnology and the European Corn Borer: Measuring Historical Farmer Perceptions and Adoption of Transgenic Bt Corn as a Pest Management Strategy." *Journal of Economic Entomology* 95 (5): 878-892.

Pleasants, J., R. Hellmich, G. Dively, M. Sears, D. Stanley-Horn, H. Mattila, J. Foster, P. Clark, and G. Jones. 2001. "Corn pollen deposition on milkweeds in and near cornfields." *PNAS* 98(21): 11919-11924.

Pleasants, J. and K. Oberhauser. 2013. "Milkweed loss in agricultural fields because of herbicide use: effect on the monarch butterfly population." *Insect Conservation and Diversity* 6(2): 135-144.

Pollack, A. 2011. "In Midwest, Flutters May Be Far Fewer." *New York Times*. July 11, 2011. Downloadable at: http://www.nytimes.com/2011/07/12/science/12butterfly.html?pagewanted=all&_r=0. Accessed on March 27, 2014.

Porter, P., E. Cullen, T. Sappington, A. Schaafsma, S. Pueppke, D. Andow, J. Bradshaw, L. Buschman, Y. Cardoza, C. DiFonzo, B. French, A. Gassmann, M. Gray, R. Hammond, B. Hibbard, C. Krupke, J. Lundgren, K. Ostlie, E. Shields, J. Spencer, J. Tooker, and R. Youngman. 2012. "Comment submitted by Patrick Porter, North Central Coordinating Committee NCCC46 (22 members)." *Regulations.gov*. March 5, 20102. Downloadable at: http://www.regulations.gov/#!documentDetail;D=EPA-HQ-OPP-2011-0922-0013. Accessed on November 22, 2013.

Prakash, C. 2001. "The Genetically Modified crop Debate in the Context of Agricultural Evolution." *Plant Physiology* 126: 8-15.

Pray, C., J. Oehmke, and A. Naseem. 2005. "Innovation and Dynamic Efficiency in Plant Biotechnology: An Introduction to the Researchable Issues." *AgBioForum* 8 (2&3): 52-63.

Prescott, V., P. Campbell, A. Moore, J. Mattes, M. Rothenberg, P. Foster, T. Higgins, and S. Hogan. 2005. "Transgenic Expression of Bean alpha-Amylase Inhibitor in Peas Results in Altered Structure and Immunogenicity." *Journal of Agriculture and Food Chemistry* 43: 9023-9030.

Price, G., W. Lin, J. Falck-Zepeda, and J. Fernandez-Cornejo. 2003. "The size and distribution of market benefits from adopting agricultural biotechnology." *Technical Bulletin No. 1906*, Economic Research Service, United States Department of Agriculture, Washington D.C.

Prince, J., D. Shaw, W. Givens, M. Newman, M. Owen, S. Weller, B. Young, R. Wilson, and D. Jordan. 2012. "Benchmark Study: III. Survey on Changing Herbicide Use Patterns in Glyphosate-Resistant Cropping Systems." *Weed Technology* 26(3): 536-542.

Qaim, M. and A. de Janvry. 2005. "Bt cotton and pesticide use in Argentina: economic and environmental effects." *Environment and Development Economics* 10: 179-200.

Qaim, M., A. Subramanian, G. Naik, and D. Zilberman. 2006. "Adoption of Bt Cotton and Impact Variability: Insights from India." *Review of Agricultural Economics* 28(1): 48-58.

Qaim, M. and D. Zilberman. 2003. "Yield Effects of Genetically Modified Crops in Developing Countries." *Science* 299(5608): 900-902.

Qaim, M., E. Cap, and A. Janvry. 2003. "Agronomics and Sustainability of Transgenic Cotton in Argentina." *Agbioforum* 6(1&2): 41-47.

Qaim, M. and G. Traxler. 2005. "Roundup Ready soybeans in Argentina: farm level and aggregate welfare effects." *Agricultural Economics* 32: 73-86.

Ragnarsdottir, K. 2000. "Environmental fate and toxicology of organophosphate pesticides." *Journal of the Geological Society, London* 157: 859-876.

Rice, M. 2004. “Transgenic Rootworm Corn: Assessing Potential Agronomic, economic, and Environmental Benefits.” *Plant Management Network*. March 2004. Downloadable at: http://www.plantmanagementnetwork.org/pub/php/review/2004/rootworm/. Accessed on April 10, 2014.

Ricroch, A., J. Bergé, and M. Kuntz. 2011. “Evaluation of Genetically Engineered Crops Using Transcriptomic, Proteomic, and Metabolomic Profiling Techniques.” *Plant Physiology* 155: 1752-1761.

Riedell, W., T. Schumacher, and P. Evenson. 1996. “Nitrogen fertilizer management to improve crop tolerance to corn rootworm larval feeding damage.” *Agronomy Journal* 88(1): 27-32.

Roldan-Tapia, L., T. Parron, and F. Sanchez-Santed. 2005. “Neuropsychological effects of long-term exposure to organophosphate pesticides.” *Neurotoxicology and Teratology* 27: 259-266.

Roth, G., D. Calvin, and S. Lueloff. 1995. “Tillage, Nitrogen Timing, and Planting Date Effects on Western Corn Rootworm Injury to Corn.” *Agronomy Journal* 87(2): 189-193.

Rowinski, P., W. Strupczewki, and V. Singh. 2001. “A note on the applicability of log-Gumbel and log-logistic probability dsitributions in hydrological analyses: I. Known pdf.” *Hydrological Sciences* 47(1): 107-122.

Saha, A., R. Shumway, and A. Havenner. 1997. “The Economics and Econometrics of Damage Control.” *American Journal of Agricultural Economics* 79(3): 773-785.

Satran, J. 2013. “Genetically Engineered Food Labeling Taken On By Congress In Right-To-Know Act.” *Huffington Post*. April 25, 2013. Downloaded at: http://www.huffingtonpost.com/2013/04/25/genetically-engineered-food_n_3149418.html. Accessed on March 19, 2014.

Schroder, D., J. Headley, and R. Finley. 1984. “The Contribution of Herbicides and Other Technologies to Corn Production in the Corn Belt Region, 1964 to 1979.” *North Central Journal of Agricultural Economics* 6(1): 95-104.

Scursoni, J., F. Forcella, J. Gunsolus, M. Owen, R. Oliver, R. Smeda, and R. Vidrine. 2006. “Weed diversity and soybean yield with glyphosate management along a north-south transect in the United States.” *Weed Science* 54: 713-719.

Sears, M., R. Hellmich, D. Stanley-Horn, K. Oberhauser, J. Pleasants, H. Mattila, B. Siegfried, and G. Dively. 2001. “Impact of *Bt* corn pollen on monarch butterfly populations: A risk assessment.” *PNAS* 98(21): 11937-11942.

Senauer, B. “Mandatory Labeling of Genetically Engineered (GE) Foods: The Showdown Begins.” *Choices* 28(3): 1-5.

Shankar, B., R. Bennett, and S. Morse. 2008. “Production risk, pesticide use and GM crop technology in South Africa.” *Applied Economics* 40: 2489-2500.

Shankar, B. and C. Thirtle. 2005. “Pesticide Productivity and Transgenic Cotton Technology: The South African Smallholder Case.” *Journal of Agricultural Economics* 56(1): 97-116.

Sheets, C. “Monsanto protection act 2.0 would ban GMO-labeling laws in states.” *International Business Times*. May 17, 2013. Downloadable at: http://www.ibtimes.com/monsanto-protection-act-20-would-ban-gmo-labeling-laws-state-level-1267629. Accessed on March 20, 2014.

Sissener, N., M. Sanden, A. Bakke, A. Krogdahl, and G. Hemre. 2009. “A long term trial with Atlantic salmon (Salmo salar L.) fed genetically modified soy; focusing general health and performance before, during and after the parr–smolt transformation.” *Aquaculture* 294: 108–117.

Smale, M., P. Zambrano, R. Paz-Ybarnegaray, and W. Fernandez-Montano. 2012. “A Case of Resistance: Herbicide-tolerant Soybeans in Bolivia.” *AgBioForum* 15(2): 191-205.

Snell, C., A. Bernheim, J. Berge, M. Kuntz, G. Pascal, A. Paris, and A. Ricroch. 2012. “Assessment of the health impact of GM plant diets in long-term and multigenerational animal feeding trials: A literature review.” *Food and Chemical Toxicology* 50: 1134-1148.

Sneller, C. 2003. “Impact of Transgenic Genotypes and Subdivision on Diversity within Elite North American Soybean Germplasm.” *Crop Science* 43: 409-414.

Spike, B. and J. Tollefson. 1991. “Yield Response of Corn Subjected to Western Corn Rootworm (Coleoptera: Chrysomelidae) Infestation and Lodging.” *Journal of Economic Entomology* 84(5): 1585-1590.

Storer, N., J. Babcock, M. Schlenz, T. Meade, G. Thompson, J. Bing, and R. Huckaba. 2010. “Discovery and Characterization of Field Resistance to Bt Maize: *Spodoptera frugiperda* (Lepidoptera: Noctuidae) in Puerto Rico.” *Journal of Economic Entomology* 103(4): 1031-1038.

Storer, N., M. Kubiszak, J. King, G. Thompson, and A. Santos. 2012. “Status of resistance to Bt maize in *Spodoptera frugiperda*: Lessons from Puerto Rico.” *Journal of Invertebrate Pathology* 110: 294-300.

Sutter, G., J. Fisher, N. Elliot, and T. Branson. 1990. “Effect of Insecticide Treatments on Root Lodging and Yields of Maize in Controlled Infestations of Western Corn Rootworms (Coleoptera: Chrysomelidae).” *Journal of Economic Entomology* 83(6): 2414-2420.

Tabashnik, B., T. Brevault, and Y. Carriere. 2013. “Insect resistance to Bt crops: lessons from the first billion acres.” *Nature Biotechnology* 31(6): 510-521.

Talpaz, H. and I. Borosh. 1974. “Strategy for Pesticide Use: Frequency and Applications.” *American Journal of Agricultural Economics* 56(4): 769-775.

Taylor, C. 2008. “Roundup-ready crops and resistant weeds.” *Monarch Watch Blog*. January 17, 2008. Downloadable at: http://monarchwatch.org/blog/2008/01/roundup-ready-crops-and-resistant-weeds/. Accessed on March 24, 2014.

Tezra, J., A. Basu, and P. Rathouz. 2008. “Two-stage residual inclusion estimation: Addressing endogeniety in health econometric modeling.” *Journal of Health Economics* 27: 531-543.

Thirtle, C., L. Beyers, Y. Ismael, and J. Piesse. 2003. "Can GM-Technologies Help the Poor? The Impact of Bt Cotton in Makhathini Flats, KwaZulu-Natal." *World Development* 31(4): 717-732.

Yorobe, J. and C. Quicoy. 2006. "Economic Impact of Bt Corn in the Philippines." *Philippine Agricultural Scientist* 89(3): 258-267.

Tinsley, N., R. Estes, and M. Gray. 2013. "Validation of a nested error component model to estimate damage caused by corn rootworm larvae." *Journal of Applied Entomology* 137: 161-169.

Tobin, J. 1958. "Estimation of Relationships for Limited Dependent Variables." *Econometrica* 26(1): 24-36.

Tudisco, R., V. Mastellone, M. Cutrignelli, P. Lombardi, F. Bovera, N. Mirabella, G. Piccolo, S. Calabro, L. Avallone, F. Infascelli. 2010. "Fate of transgenic DNA and evaluation of metabolic effects in goats fed genetically modified soybean and in their offsprings." *Animal* 4(10): 1662-1671.

Trewavas, A. and C. Leaver. 1999. "Conventional crops are the test of GM prejudice." *Nature* 401: 640.

Valdes, A., C. Simo, C. Ibanez, and V. Garcia-Canas. 2013. "Foodomics strategies for the analysis of transgenic foods." *Trends in Analytical Chemistry* 52: 2-15.

VanGessel, M. 2001. "Glyphosate-resistant horseweed from Delaware." *Weed Science* 49: 703-705.

Weisenburger, D. 1993. "Human Health Effects of Agrichemical Use." *Perspectives in Pathology* 24: 571-576.

Whiting, S., K. Strain, L. Campbell, B. Young, and M. Lydy. 2014. "A multi-year field study to evaluate the environmental fate and agronomic effects of insecticide mixtures." *Science of the Total Environment* 497-498: 534-542.

Widawsky, D., S. Rozelle, S. Jin, and J. Huang. 1998. "Pesticide productivity, host-plant resistance and productivity in China." *Agricultural Economics* 19(1): 203-217

Wolfenbarger, L., S. Naranjo, J. Lundgren, R. Bitzer, and L. Watrud. 2008. "Bt Crop Effects on Functional Guilds of Non-Target Arthropods: A Meta-Analysis." *PLoS One* 3(5): 1-11.

Wooldridge, J. 2014. "Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables." *Journal of Econometrics* 182: 226-234.

Wright, Robert. 2000. "Managing Corn Rootworm Larvae." Downloadable at http://entomology.unl.edu/pmguides/crwlarv.shtml. Accessed on August 11, 2014.

Zhengfei, G., A.O. Lansink, M. van Ittersum, and A. Wossink. 2006. "Integrating Agronomic Principles into Production Function Specification: A Dichotomy of Growth Inputs and Facilitating Inputs." *American Journal of Agricultural Economics* 88(1): 203-214.