Economics of Microbial Inoculants as an Integrated Pest Management Practice in Apple Production

by

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Abstract

Demographic growth, stricter environmental concerns and regulations, and rising prices of chemical pesticides emphasize agricultural production alternatives that substitute chemical input use and increase yields. In recent years, Biological control technologies have emerged as a viable control strategy for plant disease. This thesis analyzes the impact of Microbial Inoculants (MI) technology on pesticide use and yields in apple production using 2007 farm-level data. The analysis employs a pesticide use function and different types of production functions including stochastic production frontier. The results show that pesticide use is not reduced by MI applications. However, the technology has a significant positive impact on the outputs. Adopters of the MI technology have 2.5% higher efficiency rates compared to non-adopters.

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List of Abbreviations

MI	Microbial Inoculants
BCAs	Biological Control Agents
GMOs	Genetically Modified Organisms
U.S.	United States
ERS	Economic Research Service
USDA	United States Department of Agriculture
IPM	Integrated Pest Management
ICM	Integrated Crop Management
BT	*Bacillus Thuringiensis*
ARMS	Agricultural Resource Management Survey
EPA	Environmental Protection Agency
3SLS	Three Stages Least Square
SPF	Stochastic Production Frontier

Chapter 1:

Introduction

Continually enhancing crop production is essential to supply sufficient food for the increasing human population, satisfy energy demands, and provide essential industrial inputs. However, some current production methods used in agriculture create economic, environmental and health problems. Therefore, a key challenge for agriculture in the twenty-first century is to develop and implement agricultural production systems that maintain or enhance yields while also reducing negative side-effects. Such production systems have been referred to as "environmentally friendly" or "sustainable."

Disease management in crops worldwide is heavily dependent upon the application of synthetic (chemical) pesticides for pathogen and insect control. However, their excess application can enhance the development of pest resistance thus requiring more chemicals to control possible losses. Also, stricter regulations concerning the application of agrichemicals, in the United States are based almost entirely on the direct impacts on health and environment (White 1998). Moreover, the price of chemical pesticides have been increasing because of fuel price trends, uncertainty, and also because of increasing concentration of market power in the hands of a few big transnational producers who are becoming the only suppliers (Marcoux and Urpelainen 2011; Fernandez-Cornejo and Just 2007). All of this works against farmer's profit-maximizing objectives and makes them look for alternatives that can result in higher yields.

In the last years, global demand for more environmentally friendly products and sustainable production systems has been increasing. In this context, biological control products offer an attractive alternative to synthetic pesticides. Biological control agents, by the broadest definition, are living organisms or natural products derived from them that can be used against plant damaging agents. Over the last two decades, biological control of plant pathogens has emerged as a viable pest and disease control strategy (Harman et al. 2010; Singh, Pandey, and Singh 2011).

Microbial inoculants (MI) are biological control (or often called “biocontrol”) agents that include virus, bacteria and fungi. MI represents an environmentally friendly approach to reduce losses due to pests and diseases thus representing a potential alternative to chemical pesticides (Lugtenberg, Chin-A-Woeng, and Bloemberg 2002).

Impact assessments of biological control are measured by cost-benefit analysis in an ex-ante situation but, for ex-post analysis, a production function is a standard procedure in agricultural production economics. The chosen crop for this study is apples as some MI products currently are in use and because, according to the United States-based Environmental Working Group (EWG), apples rank as the most contaminated fruit and vegetable produce (Lloyd 2011; Bagnato 2011).

The general objective of this thesis is to evaluate the impact of the adoption of the MI technology on the U.S. apple industry. The first objective is to estimate the impact of MI use on pesticide usage. The second objective is to quantify the contribution of MI and other production factors and control variables to the U.S. apple yields and estimate production efficiency.

The hypotheses of this study are as follow: First, as MI and synthetic pesticides control damaging agents, it is expected that the amount of synthetic pesticides used will be reduced only in a small portion (as they are not perfect substitutes) by the adoption of this technology. Second, the impact over apple output is positive and significant, as is the impact of some other production factors and control variables. Production efficiencies are expected to be in the 50% to 80% interval having better efficiencies in producers applying the technology.

Chapter 2:

Background

The analysis of the impact of MI technology on the U.S. apple production starts with examining the industry's production patterns. In this section, the essential components of production, like disease management components, are described. Then, the area of Biological control, including Microbial Inoculants, and its potential for future environmental regulations is explored.

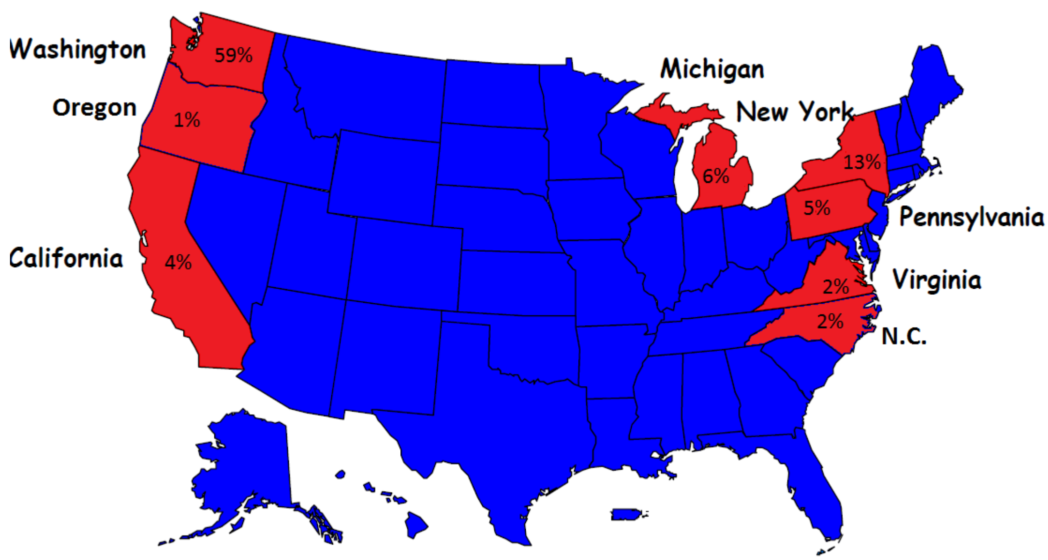
2.1 Apple Production

The apple is a pomeceous fruit of the apple tree, species *Malus domestica*. It is one of the most widely cultivated tree fruits around the world for human consumption. Apples grow on small, deciduous trees.

There are more than 7,500 known cultivars of apples, resulting in a range of desired characteristics. Different cultivars are bred for various tastes and uses, including in processed food, fresh eating food and drinks. Domestic apples are generally propagated by grafting, although wild apples grow readily from seed. Trees are prone to a number of fungal, bacterial and pest problems, which can be controlled by a number of organic and non-organic means.

In 2007, there were more than 4.8 million acres of apple trees producing nearly 69 million metric tons. China is the first apple producer in the world, representing more than 42% of world production. The United States follows with 6.5% of world production. Poland is third, followed by Iran, Turkey, Italy, India, France, Russia, Chile, Argentina, Brazil, Germany, Japan and Spain. These top 15 producing nations accounted for more than 80 percent of total world production (ERS 2012).

Apples are grown commercially in 35 states, yet nearly 92 percent of 2007 production came from only in eight states. Figure 1 shows the following rates: Washington with 59.4 percent, New York with 12.8 percent, Michigan with 6.2 percent, Pennsylvania with 4.5 percent, California with 3.8 percent, Virginia with 2.4 percent, North Carolina with 1.7 percent and Oregon with 1.3 percent (ERS 2012). According to the 2007 Census of Agriculture, there are 25,591 apple growers in the U.S. In 2007, more than 9.5 million pounds of apples were utilized for fresh and processed consumption. These apples were produced on more than 398,000 acres (2012).



Source: Compiled by author. USDA's Economic Research Service, 2012
Figure1. Percentage of 2007 apple production by state

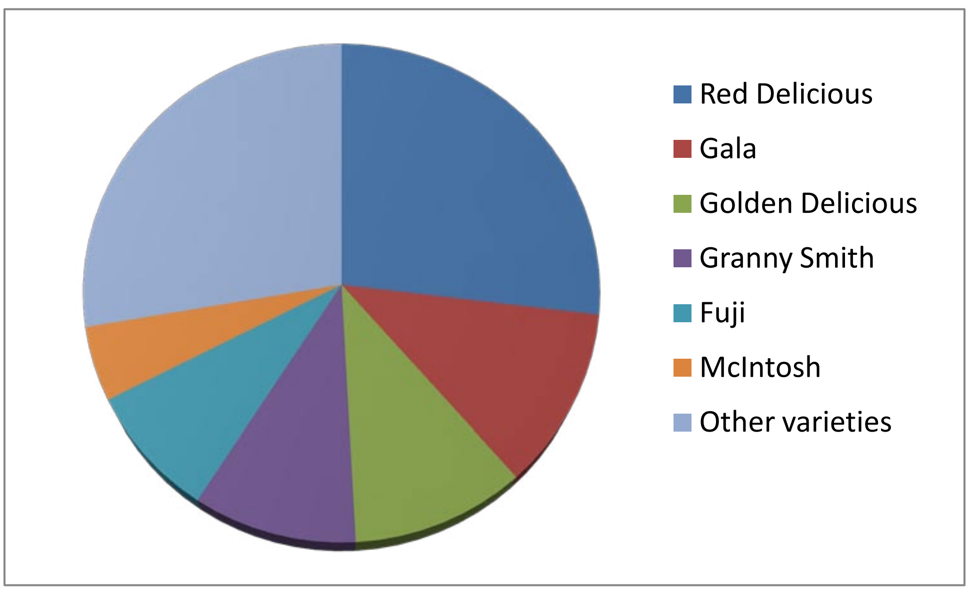
Commercial growers typically use asexual reproduction methods of budding and grafting to grow stock for their orchards. These processes enable the growth of plants identical to the parents, which allows growers to ensure the type and underlying quality of the product. Grafting is where “the upper part (scion) of one plant grows on the rootstock of another,” while budding uses the bud of one plant to grow on another (North Carolina Cooperative Extension 2012). These reproduction methods can be intensive and costly but ensure that the apple contains the exact traits that producers demand.

Apples are self-incompatible and must be cross pollinated. Only few are described as "self-fertile" and are capable of self-pollination but they tend to carry larger crops when pollinated. Apples that can pollinate one another are grouped by the time they usually flower so cross-pollinators are in bloom at the same time. Pollination management is an important component of apple culture. Before planting, it is important to arrange for pollenizers - varieties of apple or crabapple that provide plentiful, viable and compatible pollen. Orchard blocks may alternate rows of compatible varieties, or may plant crabapple trees, or graft on limbs of crabapple. Apple pollen is heavy and is not carried readily by the wind as is the pollen of some tree species, such as conifers and nuts. The pollen is transferred primarily by insects, especially honey and bumble bees (Ferree and Washington 2003). Fruit growers rent honey bees from apiculturists during the bloom period, a minimum of four or five strong colonies per hectare being recommended in mature orchards.

Apple production can be challenging for growers as it is a very perennial crop. This does not allow growers to have planting flexibility as happens with other crops. Growers make decisions based on different climate, biologic and economic conditions every year. Climatic conditions during bloom are critical for fruit set (Ferree and Washington 2003).

Apple trees vary by the number of nonbearing years after initial establishment: a standard apple tree takes six to ten years, a semi-dwarf takes four to six years and the most commercially common dwarf trees bear apples in two to three years of age (University of Arizona Extension 2012). These differences in the length of nonbearing years increase the difficulty of orchard establishments with heavy initial costs and no 5 revenues from those trees. The nonbearing years occur at the beginning and the end of the life of an orchard. The life expectancy also varies by size as the standard apple tree ranges from 35 to 45 years, the semi-dwarf tree ranges from 20 to 25 years and the dwarf tree ranges from 15 to 20 years (University of Arizona Extension 2012). These time frames for bearing years and life expectancy can also vary by variety. The decision of tree size and variety defines an orchard.

Figure 2 shows the most common varieties grown in 2007 in the United States. The most common variety was Red Delicious followed by Gala, Golden Delicious, Granny Smith, Fuji and McIntosh making up more than 72 percent of U.S. total production.



Source: Compiled by author USDA’s Economic Research Service, 2012
Figure2. 2007 U.S. apple production by variety

Cultivars differ widely by the time of ripening, the average being between 60 and 180 days after full bloom. Several methods are available to determine and/or predict optimum time of harvest such as temperature, the ethylene content of fruit and others. In Washington, which is the state with the highest production, apple harvest begins in late August and continues into October. Fruits are extracted manually and then they are transported from the field in large bins to warehouses where they are placed into standard cold storage or controlled atmosphere storage. Fruit is held for marketing in March through August of the following year. Before apples are packed, they are examined and those that have poor color or damaged by pests are removed and diverted to processing. Apples are washed, brushed and waxed prior to packing in boxes for shipment to market (Washington State University 2012).

Apple production is very labor intensive and relies on labor for many crucial tasks. As previously mentioned, labor is used in harvesting, packing and also used for maintenance activities such as pruning and thinning.

Water is very important to the function of the apple tree as water is the greatest component of the tree by mass and almost all critical processes can be limited by inappropriate water status. Insufficient water can induce excessive vegetative vigor and compromise fruit development; however, the excessive moisture of the soil can generate problems such as slow roots growth and leaching leading to nutrient deficiencies (Utah State University Cooperative Extension 2008). Irrigation is used primarily to provide supplemental water not provided by rainfall or soil water reserves. Consequently, efficient irrigation management requires knowledge of the water loss of the apple tree, the soil water reserves, and rainfall. There are several practical approaches used to estimate water status with experience being a very common and important one.

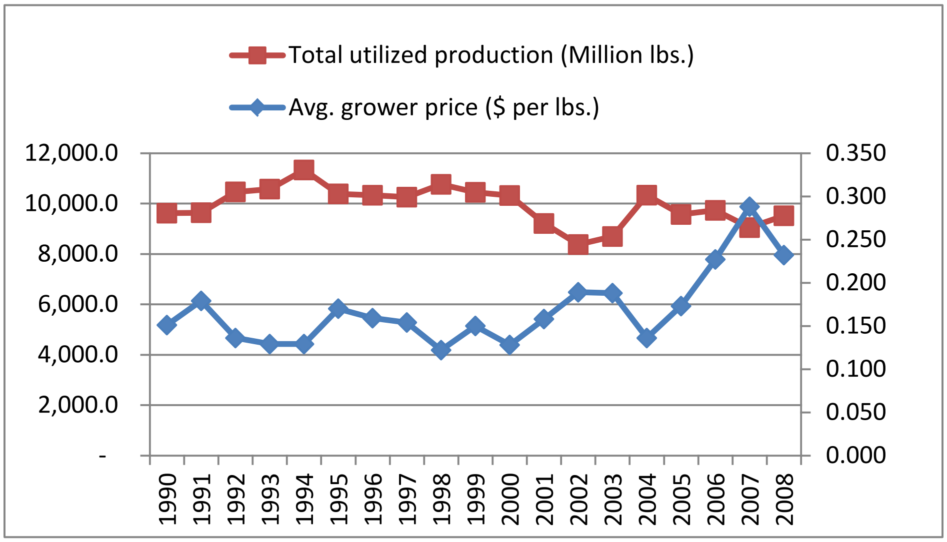
As many other plants, the mineral elements required by the plant for proper growth and fruit development include nitrogen, phosphorus, sulphur, potassium, calcium and magnesium. Other minerals such as iron, manganese, copper, zinc, boron, molybdenum and chlorine are required in lesser amounts. It is difficult to calculate the total nutrient requirements for apple trees since it is necessary to account for nutrients contained in the soil. Balance is the key for proper fertilization. For example, insufficient nitrogen results in symptoms including less vigor, light green to yellow-green leaves, less vegetative growth and low yields. However, excessive nitrogen can be equally bad causing too much vegetative growth, reduced bloom & fruit set, reduced quality of fruit, and diseases such as fire blight, brown rot and powdery mildew (Ranch 2012).

Insects and pathogens that attack apple trees or their fruit are controlled primarily through the use of pesticides. However, biological control of pests (insects and mites) and diseases is achieved in a majority of orchards where selective chemicals and reduced pesticide rates are used. The major pest in apples is codling moth. Management decisions for codling moth have a big impact on many other pests in the orchard. The type of material used to control codling moth determines which of the other pests may develop to the point where additional treatment is required. It is important to mention that in orchards where organically accepted materials are used to control codling moth, problems with secondary pests are less frequent (University of California 1999). Apples are host to over 70 infectious diseases, the vast majority of which are caused by pathogenic fungi. Scab and powdery mildew are the major diseases in apple production. However, the disease that has a major concern is fire blight, which is caused by bacteria. When this disease is epidemic, it can cause serious tree loss in nurseries and orchards even leading to orchard removal (University of California 1999).

Successful damage management usually involves integration of several methods of pest and disease control. This is called integrated pest management (IPM). The use of resistant rootstocks and scions, fungicides, bactericides, biological control agents, environmental modification and site selection are some of the means used to control apple damage factors. From now on for the easiness of the study, the word “pesticide (s)” will be referring to the control of pests and diseases, not taking into account herbicides.

This brief background of apple production has covered much of the most important components affecting apple production. All of these factors - trees management, bees pollination, fertilizers, water management and pest management - are directly included in the analysis. There are also other factors like Ph of the soil, temperature, and amount of light that influence apple productivity. These and other non-controllable factors (such as rainfall) are captured by state dummy variables.

Average annual grower prices have an obvious correlation with total utilized production. Figure 3 shows the values from 1990 to 2008. It can be seen that prices are very influenced by the amount supplied each year. Overall, national production volume has been steady for the last years; however, visual examination of the data suggests that prices are becoming more sensitive to the changes in quantity produced.



Source: Compiled by author. USDA's Economic Research Service, 2012

Figure3. Apples marketing-year average grower price and total utilized production, 1990-2008

2.2 Biological Control: Microbial Inoculants

The definition of biological control has been evolving. The definition given by the National Academy of Sciences in 1987 was: "the use of natural or modified organisms, genes, or gene products to reduce the effects of undesirable organisms (pests), and to favor desirable organisms such as crops, trees, animals, and beneficial insects and microorganisms" (Gabriel et al. 1990). Wilson's definition (1997) is broader: "The control of a plant disease with a natural biological process or the product of a natural biological process." A current definition which is particularly useful is the one proposed by Pal and Gardener (2006) which says: "Biological control refers to the purposeful utilization of introduced or resident living organisms, other than disease resistant host plants, to suppress the activities and populations of one or more plant pathogens".

Biological control agents (BCAs), or commonly called biopesticides, include predators, parasites, pathogenic microorganism, and competitors. According to the International Biocontrol Manufacturers' Association there are three categories:

- Macrobial: Insects, mites, nematodes, other non-microbial organisms.
- Microbial: virus, fungi, bacteria.
- Bio-rational: Natural products (plant extracts with insecticide or fungicide effects) and Semi-chemicals (behavior modifying agents for control of pest populations).

However, according to several pest management researchers (Chandler et al. 2008; Copping and Menn 2000), a new category exclusively including genetically modified organisms (GMOs) is recognized in some countries, such as the United States. These GMOs are basically genetically modified plants that express introduced genes that confer protection against pests or diseases.

BCAs are used in two types of agriculture. The first one is Organic farming where no chemical inputs are permitted. The second type, which is the focus of this study, is integrated crop production programs. This type of agriculture includes IPM strategies focusing on a reduction in pesticide use, resulting in improved conservation of the environment and better quality food (less pesticide residues). Biological control is considered in many ways to be the ideal pest-management tactic, because it tends to be environmentally innocuous, self-sustaining and low cost. Also, biocontrol agents can be applied together with chemicals, either in rotation to reduce the possible development of pathogen resistance or in an integrated pest management strategy with the goal of minimizing the use of synthetic pesticides.

After reaching a volume of 34 billion USD in 1995, the synthetic pesticide market is declining slowly and continuously. For 2005, the volume of synthetic pesticide sales was 26.7 billion USD (Thakore 2006). This is due to the reduction of pesticide use (IPM) and the introduction of GM crop development. Although more than 1,000 different products or technologies are available through more than 350 manufacturers in the world, the use of BCAs is still marginal: in 2005 they accounted for only around 2.5% of total of plant protection inputs market at end user prices with around 588 million USD (Guillon 2008). However, the use of biopesticides has been growing at an annual rate of 10% representing 4.25% of total pesticide market in 2010 (Ongena and Jacques 2008; Bailey, Boyetchko, and Längle 2010).

Microbial Inoculants (MI) are control agents of agricultural pests developed from microbial natural enemies in the bacteria, protozoa, fungi and viruses. Of the known potential microbial control agents, only a very small fraction has been investigated for practical use (Chandler et al. 2008). While many technical and ecological challenges remain to the exploitation of microbial control agents, they can form valuable components of Integrated Crop Management (ICM). Table 1 lists some representative species used as commercial control agents.

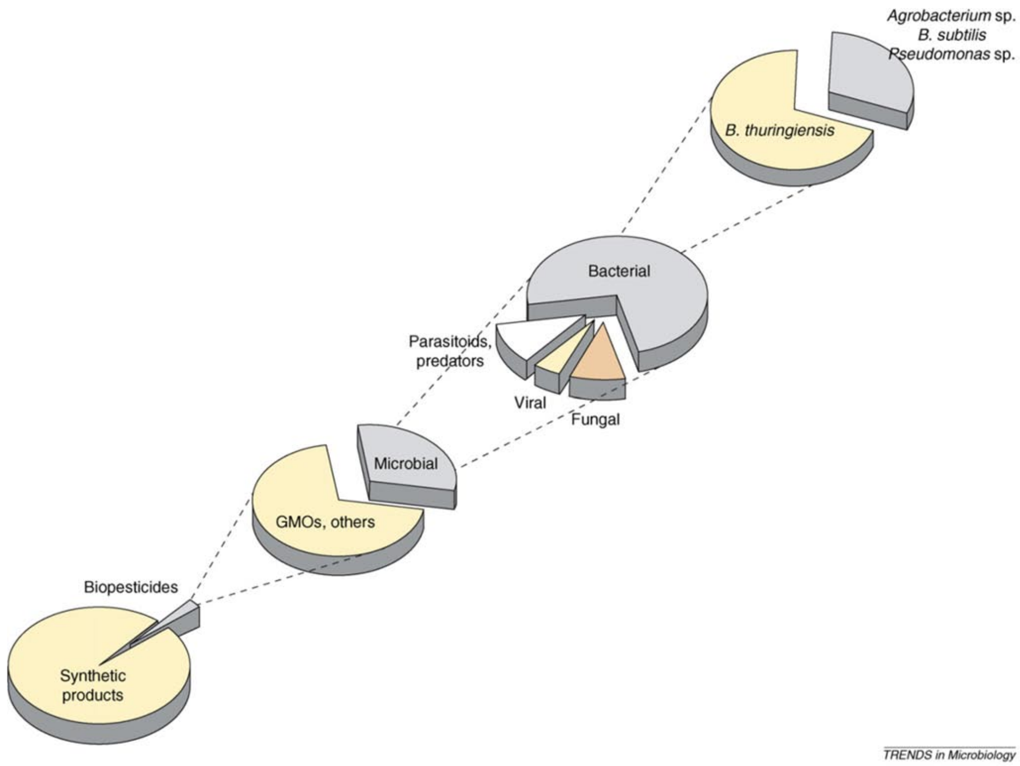
Table1. Examples of MI registered for use as control agents of agricultural pests

Organisms	Use	Pests	Target crops
Bacteria			
Agrobacterium radiobacter	Anti-bacterial agent	Crown gall (*Agrobacterium tumefasciens*)	Soft fruit, nuts, vines
Xanthomas campestris pv. poannua	Herbicide	Annual bluegrass	Turf
Bacillus subtilis	Fungicide	*Fusarium, Pythium, Rhizoctonia* spp.	Legumes, cereals, cotton
Bacillus thuringiensis	Insecticide	Various Lepidoptera, Diptera, Coleoptera	Vegetables, fruit, cotton, rice, forestry
Fungi			
Lecanicillium longisporum	Insecticide	Aphids	Glasshouse, edible & ornamental crops
Phytophthora palmivora	Herbicide	Strangler vine	Citrus
Trichoderma harzianum	Fungicide	*Pythium, Phytophthora, Rhizoctonia*	Orchards, ornamentals, vegetables, glasshouse crops
Protozoa			
Nosema locustae	Insecticide	Grasshoppers, crickets	Pasture
Viruses			
Cydia pomonella granulosis virus	Insecticide	Codling moth	Apple, pear

Source: Chandler et al, 2008

According to Bailey et al. (2010), there are approximately 225 microbial biopesticides being manufactured in the 30 members countries of the Organization for the Economic Development and Cooperation (OECD). In the U.S., there are 53 microbial biopesticides registered.

Figure 4 shows the market share for microbial inoculants. MI represented 30% of total sales of biocontrol pesticides in 2006, 75% of which was represented by bacteria. The total value of sales for MI was valued at $205 million. Most of the bacterial strains exploited as biopesticides belong to the genera Agrobacterium, Bacillus and Pseudomonas (Fravel 2005). *Bacillus thuringiensis* (Bt), specifically devoted to insect pest control, accounts for more than 70% of total biocontrol sales (Bailey, Boyetchko, and Längle 2010; Ongena and Jacques 2008; Thakore 2006).



Source: Ongena and Jacques, 2008

Figure4. Pesticide market share for biological control agents

The U.S. Environmental Protection Agency's (EPA) is the organism in charge of supervising and regulating the use of pesticides in the U.S. EPA does this under two major federal statutes. First, under the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA), EPA registers pesticides for use in the United States and prescribes labeling and other regulatory requirements to prevent unreasonable adverse effects on human health or the environment. Second, under the Federal Food, Drug, and Cosmetic Act (FFDCA), EPA establishes tolerances (maximum legally permissible levels) for pesticide residues in food. However, there were always inconsistencies in the two major pesticide statutes. (EPA 2012)

In 1996, the U.S. Congress unanimously passed a landmark pesticide food safety legislation supported by the government administration and a broad coalition of environmental, public health, agricultural and industry groups. President Bill Clinton later signed the Food Quality Protection Act (FQPA). The FQPA represented a major breakthrough, amending both major pesticide laws to establish a more consistent, protective regulatory scheme and grounded in sound science (EPA 2012). As the U.S. apple industry is a highly pesticide intensive industry, a big hit seemed to be coming (Roosen 2001).

In 2006, EPA declared that the pesticide azinphos-methyl (AZM) cannot be used in apple production after September 30, 2012. While AZM provides important pest control benefits to growers of apples and other crops, it also has potential risks to farm workers, pesticide applicators, and aquatic ecosystems (Cassey, Galinato, and Taylor 2010). This regulation will bring big economic consequences and changes in apple production practices. For example, AZM has been the pesticide most used by Washington State apple growers since the late 1960s; and in 2008, 80% of Washington apple growers used AZM primarily to control codling moth (Cassey, Galinato, and Taylor 2010). In addition, in 2011, by the National Organic Standard Board (NOSB) voted to phased out by October 2014 the antibiotics streptomycin and oxytetracycline, which are the primary tools used by conventional and organic growers to prevent fire blight (Washington State University 2012). This may be the niche opportunity that MI technology needs for a fully development in this crop.

Chapter 3:

Literature Review

This chapter is divided in two sections. The first section compiles some of the many publications about application of microbial inoculants as biopesticides in greenhouse and controlled fields for apple production. The second section reviews economic studies related to this specific topic. Until the day this thesis was written, there were no economic studies addressing the impact of this specific BCA in ex-post situations. However, several studies about the most popular type of BCAs (GMOs) are reviewed as they will become useful in developing the methodology. In these studies, authors conduct impact analysis of GMO adoption. In theory, both types of BCAs, GMOs and MI, should have similar impacts on crops (reduction in synthetic pesticides and increase in yields).

3.1 Microbial Inoculants

The main microbial insecticide registered and available for use in apple orchards is *Bacillus thuringiensis* (Bt). With multiple applications of this material, farmers have achieved some degree of control or suppression of Leafrollers, moths and fruit worms. Also important, but not as commercially available, is the granulosis or granulo virus. This virus is a highly selected targeted microbial insecticide that attacks codling moth (University of California 1999).

There are several studies about the efficacy of Bacillus for controlling many pests in apples. For example, Peighami-Ashnaei (2009) investigated fifteen strains of identified *Pseudomonas fluorescens* and *Bacillus subtilis* for biological control activity against Blue mold (*Botrytis cinerea*). *Bacillus subtilis* showed considerable results against Blue mold on apple fruits and could reduce the grey mold from 100% to less than 65% after twenty days. In addition, it was shown that bacterial strains could not only control the disease but they are a reliable replacement of a chemical pesticide called Thiabendazol. Laboratory trials were conucted by Cossentine (2003) to study how *Bacillus thuringiensis* subsp. *kurstaki* treatments on apple may be timed to maximize the survival of parasitoids of the obliquebanded leafroller (*Choristoneura rosaceana*) in the southern interior of British Columbia, Canada. The consumption of B. thuringiensis-treated leaves by host larvae significantly increased the percentage of dead host larvae in all parasitized and un-parasitized treatments.

Previously stated, the most destructive pest in the apple cultivation is the codling moth (*Cydia pomonella*)(Pemsel et al. 2010). The Granulo virus has been proven to reduce codling moth development considerably. Virus uptake was found to be independent of active feeding and larvae became infected simply by walking or browsing on sprayed leaf disc surfaces in little time (Ballard, Ellis, and Payne 2000). However, its commercial development and use has been limited because of their high costs, slow action, short persistence and specificity relative to broad spectrum pesticides. The widespread development of strains of codling moth multi-resistant to insecticides and the desire to reduce dependence on pesticides have improved the commercial prospects of Granulo virus and use is likely to increase. Development of cheaper mass production techniques and possibly *in vitro* production are expected (Cross et al. 1999).

3.2 Economics of biological control

Ex ante impacts of biological control are measured by cost-benefit analysis but, for impact analysis, a production function, lately including an integrated damage control function, is a standard procedure in agricultural production economics. In addition to this regression, a pesticide use function is often estimated to measure the substitution effect between biological control and chemical pesticides. This, if it is well specified, can also serve as an instrumental variable to avoid endogeneity in the production function using the two- or three-stage least squares regression (2, 3SLS).

One key feature in current production functions is the distinction between inputs classified as standard factors of production (e.g. labor, land, capital, etc.) and damage control agents (e.g. pesticide, biological control). This distinction is important because the second group does not enhance productivity directly as standards inputs do but contribute indirectly by reducing output losses due to pest development (Lichtenberg and Zilberman 1986).

Econometric investigations about damage control have had the tendency to rely on generic econometric models rather than to focus on knowledge about the physical and biological processes involved to specify the relevant functional form. This may generate biases of big proportions in estimates of productivity and unreliable conclusions about efficient input usage.
This phenomenon has been occurring depending on the analysis' approach. Theoretical and normative empirical models of pest management at macro levels have incorporated the available entomological knowledge in their specifications and have derived optimal management practices and policy recommendations based on this premise. In contrast, Econometric measurements of pesticide productivity have been derived from standard production theoretical models such as the Cobb-Douglas specification (Lichtenberg and Zilberman 1986).

Damage control inputs should be incorporated into production analysis in a different way than regular production inputs. Models of biological and physical processes are used to obtain specifications of production processes with damage control inputs. These specifications are appropriate for micro level analysis (farm or field level). Heterogeneity among producers and different climatic conditions mean that a proper aggregation procedure should be incorporated to derive a appropriate regional analysis.

Specification of the role of damage control agents in production functions has two important implications for theoretical and empirical work. The first one is that commonly used types of production functions specifications overestimate the productivity of damage control inputs even in larger samples. This upward bias happens because of a misspecification of the shape of the marginal factor productivity curve of damage control inputs which decrease more rapidly in the economic range than standard specifications assume. Second, damage control specifications have a different way to handle changes in damage control productivity through time. Using pesticides as an example, the spread of resistance through a pest population is an important problem. Thus treating pesticide in the same way as a regular production input will lead to predict behavior contrary to observed fact. In standard production functions, decreasing input effectiveness is reflected in decreasing marginal input productivity and thus in reduced level of input. In damage control specifications, decreasing effectiveness may increase input demand. This is exactly what is observed looking at pesticide use trends (Lichtenberg and Zilberman 1986).

Litchenberg and Zilberman (1986) established different possible specifications of damage control function such as the Pareto distribution, the exponential distribution, the logistic distribution and the Weibull distribution.

Jankowski et al. presented a paper at the conference on international agricultural research for development held on Tropentag, Germany (Jankowski et al. 2007). In the paper, they analyzed the impact of a biological control agent (insect) on the diamondback moth in cabbage production in Kenya and Tanzania. They presented a pesticide use (cost) function and a production function. It was found that pesticide expenditure was 34% lower in areas where biological control was present; however, the production function showed mixed results. The biological control coefficient was positive and significant for the exponential damage control function but negative and significant for the logistic one which generates seriously questions the correctness of these results.

Several studies on the impact and economics of GMOs will now be reviewed. Studies on using *Bacillus thuringiensis* (Bt) technology will specifically be discusses as they work very similar to MI. Bt crops produce proteins that are toxic to larvae of some insect species making it a pest-control agent that can be used, to some extent, as a substitute for chemical insecticides. Therefore, MI and Bt crops have similar properties and similar effects. All of these studies have incorporated this technology as a dummy variable, so did this thesis.

Some studies made in China are very useful for this thesis. Of the list of developing countries, China was the only one that had introduced Bt-cotton on a large scale. Recognizing the negative externalities of excessive pesticide use, China's government has made an effort to regulate pesticide production, marketing and application since the 1970s. The experience with regulation, however, has shown that when officials only promulgate rules and monitoring costs are high, reductions in the use of pesticides, the elimination of banned toxic ones, or the increase in the adoption of safe application procedures do not always follow. As a result, real reductions in the use of pesticides may have to depend on alternative approaches, such as the introduction of new technologies. An observation on the background that emerges in several studies in China is that regardless of whether farmers use Bt or non-Bt varieties, the actual level of pesticide use dramatically exceeded its economically optimal level as computed from estimated factor productivity. The authors attribute this overuse to anecdotal evidence about misguided extension advice. Since part of the income of extension workers stems from pesticide sales they have an incentive to encourage farmers to use more pesticides. They cite some studies where some other authors found that the majority of farmers in China still considered the cotton bollworm as a problem although all were using Bt-cotton. Such observations show that although the economic benefits of Bt-cotton in China were demonstrated at an early stage of adoption, the sustainability of these benefits can be questioned. They also indicate that pesticide reduction requires other (supplementary) means such as a policy changes. This observation may be of interest for this study.

A study made by Pemsl et al. (2005) used panel data of 150 farm households in the Shandong province in China for cotton production. Using the exponential damage control function, they found that there was a prevailing high level of insecticide use, despite Bt-cotton adoption. They offered the situation in the local seed markets as a possible explanation of this behavior. A vast number of different Bt varieties are available in local markets, with striking differences in price. They explained that this difference in Bt seed prices can only be explained by counterfeit varieties, thus not expressing the actual or aggregate impact of the technology. On the production function side, they found that the impact of Bt toxin on cotton yields was positive but not significant.

Another study of cotton productivity in China was made by Huang et al. (2002) showing different results. This time they surveyed 282 cotton farms using cross-sectional data but, in this case, putting more emphasis on provinces where Monsanto seed varieties were commercialized (to avoid any counterfeit issues). Their pesticide use regression analysis got a negative and highly significant coefficient on the Bt cotton meaning that Bt cotton farmers sharply reduce pesticide use when compared to non-Bt cotton farmers. *Ceteris paribus,* Bt cotton use allowed farmers to reduce pesticide use by 35.4 kilograms per hectare. For the production function, they used a regular Cobb-Douglas and also a Weibull and an exponential damage control function. All production functions obtained positive and significant coefficients for the Bt technology.

Other developing countries are using this technology as well. Studies of Argentinean cotton (Qaim and de Janvry 2005) and Indian cotton (Qaim 2003) have shown similar results. In the first one, panel data with 299 cotton farmers having 89 adopters and 210 non-adopters was used, while in the second there was a cross sectional sample of 157 farm households chosen randomly from seven different states. In both studies, the technology decreases insecticide use significantly being the net effect a saving of 1.2 kg per hectare and 0.4 kg per acre respectively. In addition, Bt technology also affected the outputs positively in both studies, whether under the Cobb-Douglas or the damage control specifications.

In the review made by Qaim (2009) about the economics of GMOs, he shows that available impact studies of insect-resistant crops show that these technologies are beneficial to farmers and consumers, producing large aggregate welfare gains as well as positive effects for the environment and human health. Bt crops can contribute significantly to global food security and poverty reduction. However, Bt does not completely eliminate the need for insecticide sprays because some crop damage still occurs when the technology is used. The reason is that Bt toxins are very specific to certain pest species, whereas other insect pests, remain unaffected. His compile of results confirm that both insecticide-reducing and yield-increasing effects can be observed internationally. Studies already reviewed are compared. As we already saw, yield effects of Bt cotton are highest in Argentina and India. For Argentina, his explanation is simple: Conventional cotton farmers underutilize synthetic insecticides, so that insect pests are not effectively controlled. In contrast, in India, insecticide use in conventional cotton is much higher. He suggests that factors other than insecticide quantity influence damage control in conventional cotton and, thus, the yield effects of Bt technology. These factors include insecticide quality, insecticide resistance, and the correct choice of products and timing of sprays.

So we have seen reviews about GMOs applications at farm level studies, especially Bt cotton, as they have a similar impact as MI on production. However, MI has a big advantage over GMOs because the second group has aroused significant opposition. According to Qaim (2009), public reservations about this technology are very strong in Europe and are gradually moving over to other countries and regions through trade regulations, public media, and outreach efforts of anti-biotech lobbying groups. The major concerns about the use of these biological control agents are related to potential environmental and health risks (Scientifics think that biological processes may be lose, and also there are no long term studies on human effect of this technology), but there are also fears about adverse social implications. Quoting Qaim (2009) "some believe that this technology could undermine traditional knowledge systems in developing countries. Given the increasing privatization of crop improvement research and proliferation of intellectual property rights (IPRs), there are also concerns about the potential monopolization of seed markets and exploitation of smallholder farmers." All of these does not happen with MI as it is a more "nature providing" technology.

Chapter 4:

Methodology and Data

This chapter describes the methods behind the model development, as well as the details of the model including the data used. A pesticide use function and several types of production functions, including a stochastic frontier, are estimated using STATA 12 and SAS 9.2.

4.1 Data

USDA's 2007 Agricultural Resource Management Survey (ARMS) data on apple production was used for this study. This survey contains information on the production practices, inputs and costs, and financial performance of America's farm households. Most of direct inputs and household characteristics come from the Phase 2 part of the survey while other variables such as yields and area harvested come from the Phase 3 part of the survey.

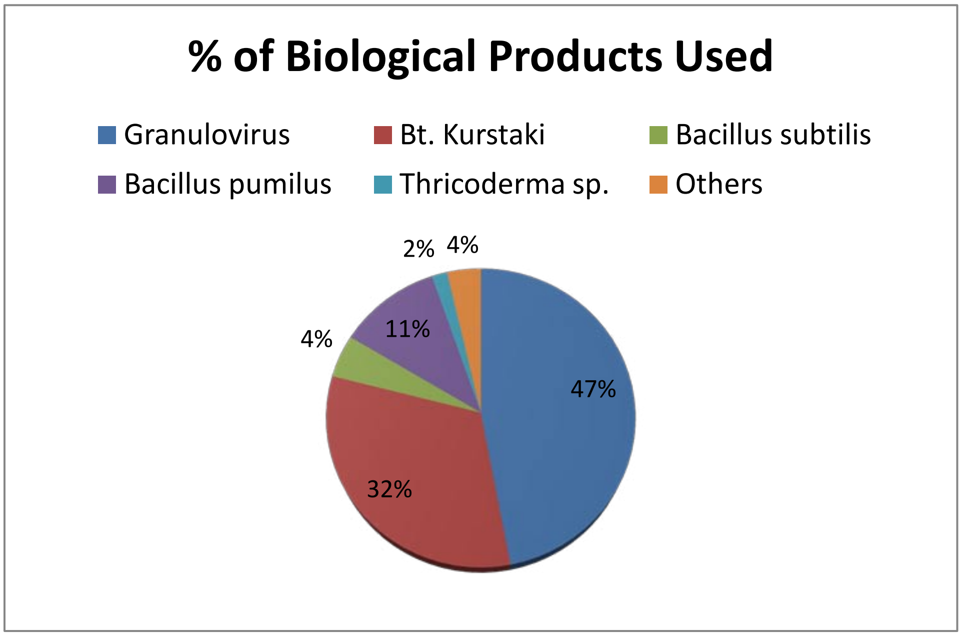
The ARMS data has 4 specific unique characteristics which make it a valuable tool for this study:

- The ARMS survey has a broad coverage, including all major States producing a particular commodity, and generally covers more than 90 percent of the acreage of targeted commodities.

- The ARMS survey uses a stratified random sample where each farm represents a known number of similar farms in the population based on its probability of being selected. Each farm is weighted by the number of farms it represents so that the ARMS sample can be expanded to reflect the targeted population.
- ARMS enterprise costs-of-production data contain sufficient detail about specific inputs to isolate the seed and pest control costs used to produce a given commodity.
- Enterprise costs of production can be estimated for each observation in the ARMS data so that a distribution of costs can be developed.

Summarizing, in this study, each farm is weighted by the number of farms it represents so the sample can be expanded to reflect the targeted population.

Only conventional (non organic) farmers were considered as the intent was to estimate the technology' impact on regular pesticide usage. Under the "pest management practices" section of the production practices and costs reports (phase 2) of the survey, an item referring to biological control was used as the variable of interest. This is a binary choice variable taking the value of "1" if the farmer was using the technology and "0" otherwise. It would have been advantageous to use a quantitative measure of the MI applications but as only a small percentage of farmers were using this technology, a dummy variable seems more appropriate. In the sample of 547 conventional farms, 197 farms were using on average 3 biological control products, from which the main ingredient included one of the following: Granulovirus, *Bacillus thuringensis*, *Bacillus subtilis*, *Bacillus pumilus* and *Thricoderma sp*. Figure 5 shows the percentage represented by each biological agent, from which, 96% fall into the MI definition.



Source: Compiled by author. 2007 apple ARMS data
Figure5. Percentage and type of biological control used.

MI provides good resistance to different varieties of insects and diseases for apples. The main microbial pesticide used is any type of bacillus, especially *Bacillus thuringensis* (Bt), due to its ability to suppress many pests at the same time. For example, the Granulovirus is used against Codling moth *(Cydia pomonella)*, but *Bacillus thuringensis* has been proven to work against Codling moth, Apple pandemis, Leafrollers, Western tussock moth, Velvetbean caterpillar and Green fruitworm (University of California 1999). *Bacillus subtilis* has been proven to work against Fire Blight, Botrytis, Sour Rot, Rust, Sclerotinia, Powdery Mildew, Bacterial Spot and White Mold (Peighamy-Ashnaei et al. 2008; Sundin et al. 2009). However, there are many other pests and diseases to which MI agents do not provide resistance. Therefore, MI does not completely eliminate the need to use chemical pesticides.

Seven states were represented in the survey: Michigan, Oregon, New York, Pennsylvania, North Carolina, California and Washington. Washington was used as the base for its continuous, successful production history, and because it is the state with more total production (ERS 2012).

4.2 Pesticide use function

As it was stated before, MI provides a good alternative to control some of the most important apple damaging agents such as the Codling moth. However, there are some major apple pests to which the technology does not provide resistance to, such as scab, powdery mildew and fire blight (provides only mid resistance). Therefore, MI does not completely eliminate the need to spray chemical pesticides in order to avoid pest damage. That is t why, it is not totally accurate to say that chemical pesticide usage may be reduced by the application of this technology as different pests are more prone to happen in different regions.

As a first step, the summary statistics of those farmers using and not using the technology are compared to have a quick look at what might have been happening. The variable pesticide includes insecticide and fungicide applications (that are the ones that can behave as pesticides substitutes) not including any biological control product. In order to confirm the findings, a more precise quantification was needed. A double-log type functional form was estimated using OLS regression to quantify the technology's impact on the pesticide use. A linear type functional form was also estimated for comparison purposes. These regressions were calculated using plot and farmer characteristic. The quantity of pesticide (pest) application is expressed in pounds per acre. The double-log model expressed in its linear form is as follows:

$$\text{Log (Pest)} = A + \beta_1 \text{ Log (price)} + \beta_2 \text{ Log (size)} + \beta_3 \text{ (MI)} + \sum \beta_i \text{ (K)} + \varepsilon \qquad (1)$$

where A is the intercept and Price is a proxy for pesticide's price. Size is used to reflect farm's characteristic and refers to the actual farm size. MI is a dummy variable which takes the value of one for MI plots and zero otherwise. K is a vector of other determining factors such as experience (characteristic), an index reflecting pest pressure, and state area variable (dummy) as proxy for the different agro-climatic conditions found in these areas. Lastly, ε is the random error term with zero mean.

Although only a single cross section of farms is used, large variations in the price of pesticides exist among the respondents, reflecting the differences in pesticide quality, pesticide prices at different times during the growing season, and the pesticide composition. Price is measured as the unit value price of pesticide purchased by the farmer. I calculate the unit value price for each farm by dividing the value of their pesticide purchases by the quantity that they purchased.

Direct production inputs were not included as exogenous assuming damage control expenditures is a separate budget category. Yields are also not included because, as it was said already, a production function is estimated in the next step. This approach was taken because endogeneity of inputs is a potential problem with production functions estimates based on farm survey data.

Pesticides in particular may be problematic if they are applied in response to high pest pressure as high levels of infestations may be correlated with lower yields (Huang et al. 2002; Qaim 2003; Qaim and de Janvry 2005). To avoid this possible econometric problem, the Instrumental Variable (IV) approach was adopted. An instrument for pesticide application in this case is a variable that is highly correlated with actual pesticide use but is not correlated to output except through its impact on pesticides. In this case, the predicted value of the pesticide use is used. As long as the variables explaining pesticide use do not have any independent explanatory power on yields, the IV approach should allow me to better examine the impacts of MI and pesticides on apple output.

Following Huang (2002) and Qaim (Qaim 2003, 2009) and Qaim and De Janvry (Qaim and de Janvry 2005), to implement the IV identification strategy, a number of control variables – such as experience and the six states dummy variables – were included in both the yield and pesticide use equations. The IV passed the Hausman-Wu exclusion restriction statistical test.

4.3 Production function and stochastic production frontier

A production function or frontier is defined as function that, given available technology, specifies of the maximum amount of output possible for a given input mix. Production functions can be estimated from sample data (in this case cross-sectional data). Different types of production functions are estimated to measure the impact of the MI technology on apple production.

Production function

The first step in any parametrical empirical application is to select an appropriate functional form for the production function. A few mathematical forms of production functions are commonly used (those that are easy to manipulate). Every analyst should first appeal to technical (biological, chemical, nutritional, etc.) theory for specification of the functional form for modeling the particular production process in question. Following Beattie et al. (Beattie, Taylor, and Watts 2009), we use the Cobb-Douglas functional form.

$$Y = Ax_1^{\beta_1} x_2^{\beta_2} \tag{2}$$

where A is a scalar referred to as a measure of total factor productivity, x_1 is one of the production factors and β_1 is the parameter to be estimated (same treatment for subscript 2). The Cobb-Douglas is easy to estimate and mathematically manipulate but is restrictive in the properties it imposes upon the production structure. For example, it has convex to origin and negative slope isoquants (input bundles for any given output) but it has unitary elasticity of substitution; it does not allow for technically independent or competitive factors. Marginal physical productivity (MPP) and Average Physical productivity are monotonically decreasing functions for all x given $0<\beta_1<1$, which is the usual case. But on the bright side, the Cobb-Douglas may be a good approximation for production processes for which factors are imperfect substitutes (as this case). Also, this functional form was chosen because it is relative easy to estimate as it can be represented in logarithmic form and it will be linear in parameters. In our case, beside of the regular production factors, we have some control variables (continuous and discrete); so, equation (2) becomes:

$$\mathrm{Y} = \mathrm{Ax_1}^{\beta_1} \mathrm{x_2}^{\beta_2}\ \mathrm{e^c} \tag{3}$$

Where c represents the control variables. Converting the model to a linear specification, we estimate the following relationship:

$$\text{Log (Y)} = a + \sum_i \beta_i \text{ Log (X)} + \beta_1 \text{ (MI)} + \sum_j \beta_j \text{ (P)} + \varepsilon \tag{4}$$

where Y is apple yields in pounds per acre, X is a vector of production inputs (including pesticides), MI is the microbial inoculants dummy variable, and P is a vector of experience and area dummy variables.

In agricultural production, inputs can be divided into 2 main categories: standard factors of production (e.g., land, labor, capital, etc.) and damage control agents (e.g., insecticides, fungicides, biological control). Damage control agents do not enhance productivity directly as standard production factors do, in fact, they may even impede productivity in some degree. For example, the application of chemical pesticides may be harmful to crop plants to a certain extent. The contribution of these damage control agents can be easier to understand conceiving actual output as a combination of two components: potential output the maximum quantity of product that can be obtained from any given combination of inputs) and losses caused by damaging agents (insects, fungi, bacteria, etc.). These looses are a function of the climatic and environmental conditions determining the destructive capacity of damaging agents and the action of damage control agents on that destructive capacity through their abatement effort. Damage and abatement are limited by two factors: potential output and destructive capacity of damaging agents. Damage can be as bad as equal to output and no smaller than zero, and abatement can be at most equal to total destructive capacity and no smaller than zero (Lichtenberg and Zilberman 1986).

Unlike the standard inputs, damage control agents enhance productivity indirectly by preventing output losses. As the damage control inputs cannot be treated in the same way as the other inputs, a separate damage control function needs to be integrated in a production function. In the analysis of pesticide productivity, the use of a standard Cobb-Douglas function is criticized for treating pesticides as a yield increasing production factor without reflecting the specific physical and biological processes of pest control agents. Lichtenberg and Zilberman (1986) explain that using a Cobb-Douglas functional form results in overestimation of productivity of damage control inputs while underestimating the productivity of the other factors and introduce the concept of a damage control function, g, which is linked to the production function in a multiplicative way:

$$Y = f(X)\, g(Z) \tag{5}$$

Where the vector X includes labor, fertilizers, other farm-specific factors that affect yields (such as the human capital characteristics of the farm household and land input) and location-specific factors (a set of state dummy variables). The term g (Z) is a damage abatement function that depends on the level of control agents Z (includes the pesticides and biological control used by farmers to control pests during outbreaks). The abatement function possesses the properties of a cumulative probability distribution. It is defined on the interval of [0, 1]. In the Lichtenberg and Zilberman's model, g (.) =1 implies full damage control (no crop yield losses due to pest related problems with certain high level of control agent) while g (.) = 0 means that the crop was completely destroyed by pest related damage. The g (Z) function is non-decreasing in Z and approaches one as damage control agent use increases.

Then, for f (.) we assume Cobb-Douglas functional form as before, whereas for g (·) different functional forms can be assumed and the specification can be crucial for parameter estimation results (Carrasco-Tauber and Moffitt 1992; Fox and Weersink 1995). Since up until now there is no consensus on which specification best suits the purpose, exponential (equation 6) and logistic (equation 7) specifications are used as they generally represent the pest abatement relationship quite well and are bounded on the [0,1] interval:

$$g(Z) = 1 - \exp(-\alpha_0 - \alpha_1 Pest - \alpha_2 MI) \tag{6}$$

$$g(Z) = [1 + \exp(\mu - \alpha 1 Pest - \alpha 2 MI)]^{-1} \tag{7}$$

$$\text{Log}(Y) = a + \sum \beta i \,\text{Log}(x) + \sum \beta i \,(P) + \text{Log}(g(Z)) + \varepsilon \tag{8}$$

The parameter α_0 is interpreted as natural control (for example the activity and pest reducing capacity of natural enemies/competitors present in the orchard) while μ is interpreted as the fixed damage (the damage without any pest/disease risk management). A standard Cobb-Douglas production function treating pesticide and biological control as conventional production factors is also estimated for comparison purposes.

A potential problem in estimating production functions is that pest control variables tend to be correlated with the production function error term ε. This is because unobserved factors like climate conditions can result in both high input levels of insecticides and low yields (Huang et al. 2002) and also because insecticides applied in response to exogenous high pest pressure can become a problem as higher pest pressure may be correlated with lower outputs (Widawsky et al. 1998). Hence, it is possible that the covariance of Z and the residuals of the yield function is non-zero, a condition that would bias parameter estimates of the impact of pesticides on output. In other words, pesticides used by farmers may be endogenous to yields and a systematic relationship among plant pests, pesticide use, and apple yields may exist. Not accounting for the endogeneity could lead to a bias in the coefficient estimates. To overcome the problem of correlation between insecticide use and the error term of the production function, an iterative three stage least square (3SLS) procedure using instrumental variables to estimate the predicted value of insecticide use can be applied. Thus, the insecticide use function and the production function (the basic Cobb-Douglas and the 2 damage control Cobb-Douglas) were estimated simultaneously. The instrumental variables (IV) should be uncorrelated with the error term (cov (IV, ε) =0) and significantly correlated with the pesticide use. For the IV, we use the predicted value of the pesticide use similarly to the specifications in previous research on the subject (Huang et al. 2002; Pemsl, Waibel, and Gutierrez 2005; Qaim 2003; Qaim and de Janvry 2005).

In principle, the endogeneity problem might also apply to other inputs, for which suitable identification variables are not available. However, since removing labor and all the different types of fertilizers from the production function has little impact on the remaining coefficients, it is inferred that there is no serious correlation with the error term.

For the computation of the parameters of the insecticide use and different production function the procedures PROC MODEL and REG of the software package SAS (release version 9.2) and STATA (release version 12) were used. The PORC MODEL procedure also contains a 3SLS command (for three stage least square estimation) and the Hausman specification test. The PROC MODEL procedure addresses the non-linearity of the functions using the Non-linear Ordinary Least Squares (NOLS).

Furthermore, two other potential problems with cross-sectional data are tested and/or corrected. The production functions are tested for multicolinearity through a Variance Inflation Factor (VIF) and corrected for heteroscedasticity using robust standard errors.

In order to see if the MI adopters and non-adopters can be pooled together, the Chow test must be performed. In this case, as we are trying to evaluate the impact of a new technology (program evaluation), the Chow test is used to determine whether the independent variables have different impacts on different subgroups of the population.

Let’s simplify and assume that we model our data as

$$\mathrm{Y} = \mathrm{a} + \mathrm{bX}_1 + \mathrm{cX}_2 + \varepsilon \qquad (9)$$

If we split our data into two groups, then we have

$$Y = a_1 + b_1X_1 + c_1X_2 + \varepsilon \tag{10}$$

$$\mathrm{Y} = \mathrm{a}_2 + \mathrm{b}_2\mathrm{X}_1 + \mathrm{c}_2\mathrm{X}_2 + \varepsilon \tag{11}$$

then, the null hypothesis of the Chow test asserts that: $\mathrm{a}_1 = \mathrm{a}_2$, $\mathrm{b}_1 = \mathrm{b}_2$ and $\mathrm{c}_1 = \mathrm{c}_2$.

Let $\mathrm{S_C}$ be the sum of squared residuals from the combined data, S_1 be the sum of squared residuals from the first group, and S_2be the sum of squared residuals from the second group. N_1 and N_2 are the number of observations in each group and K is the total number of parameters. Then the Chow test statistic is

$$\frac{(S_C - (S_1 + S_2))/(k)}{(S_1 + S_2)/(N_1 + N_2 - 2k)}. \tag{12}$$

The test statistic follows the F distribution with K and $N_1 + N_2$ – 2K degrees of freedom.

Stochastic production frontier

In addition to the Cobb-Douglas and the integrated damage control production function, a Stochastic Production Frontier (SPF) is estimated. In contrast to a regular production function, SPF allows for inefficiency as it does not assume that all farmers are producing on the production possibilities frontier.

A frontier function can be interpreted as the technological constraint for each farming system. The distance from the frontier indicates a farm's relative performance or technical efficiency. Traditional regression approaches, such as ordinary least squares (OLS), can be used to estimate production parameters, cost, and/or profit functions; however, the estimates only reflect the average farm performance.

The stochastic frontier model accommodates random shocks to the production process. Assume that cross sectional data for the quantities of N inputs used to produce a single output are available on I producers. A SPF model is written as

$$Y_i = f(X_i; \beta) \exp\{v_i\}\, TE_i \tag{13}$$

where Y_i is the scalar output of producer i, i = 1, . . . , I, X_i is a vector of N inputs used by producer i, f (X_i; β) is the deterministic production frontier, β is a vector of technology parameters to be estimated, exp $\{v_i\}$ captures the effects of statistical noise, and TE_i is the output oriented technical efficiency of producer i that varies from 0 to 1. [f (X_i; β) · exp $\{v_i\}$] is the SPF. It consists of two parts: a deterministic component f (X_i; β) common to all producers and a producer-specific component exp $\{v_i\}$ which captures the effect of random shocks on each producer.

Now, equation (13) can be rewritten as

$$TE_i = \frac{Y_i}{f(X_i;\beta).\exp\{v_i\}} \tag{14}$$

which defines technical efficiency as the ratio of observed to the maximum feasible output in an environment characterized by exp $\{v_i\}$. It follows that Y_i achieves its maximum feasible value of [f (X_i; β) · exp $\{v_i\}$] if and only if TE_i = 1. Otherwise, TE_i < 1 provides a measure of the shortfall of observed output from the maximum feasible output in an environment characterized by exp $\{v_i\}$, which is allowed to vary across producers. Rewrite equation (14) as

$$Y_i = f(X_i; \beta) \exp\{v_i\} \exp\{-u_i\} \tag{15}$$

where TE_i = exp $\{-u_i\}$ is specified for simplifying taking natural logarithms. Because we require that $TE_i \leq 1$, we have the inefficiency parameter $u_i \geq 0$. Next, assume that f (X_i; β) is of the log-linear Cobb-Douglas form. Alternative functional specifications are conceivable but this specification is computationally convenient. The SPF model (15) becomes

$$\text{Log } Y_i = \beta 0 + \sum \beta_n \text{ Log } X_{ni} + v_i - u_i \tag{16}$$

The distributional assumptions are (i) v_i ~ i.i.d. N (0, σ_v^2); (ii) u_i ~ i.i.d. N+ (0, σ_u^2), and (iii) v_i and u_i are distributed independently of each other and of the exogenous variables (Kumbhakar and Lovell 2000). However, this Normal - Half Normal model implicitly assumes that the "likelihood" of inefficient behavior monotonically decreases for increasing levels of inefficiency. In order to generalize the model, we modify assumption (ii) by allowing u to follow a truncated normal distribution: (ii)' u_i ~ i.i.d. N+ (μ , σ_u^2), where μ is the mode of the normal distribution and is truncated below at zero. The Normal‐Truncated Normal model, which has the three distributional assumptions (i), (ii)', and (iii), provides a somewhat more flexible representation of the pattern of inefficiency in the data (Kumbhakar and Lovell 2000; Coelli, Rao, and O'Donnell 2005).

The density function of v is

$$f(v) = \frac{1}{\sqrt{2\pi\sigma_v}} . \exp\{-\frac{v^2}{2\sigma_v^2}\} \tag{17}$$

The truncated normal density function for u ≥ 0 is given by

$$f(u) = \frac{1}{\sqrt{2\pi\sigma_u \phi({}^{\mu}/_{\sigma_\mu})}} . \exp\{-\frac{(u-\mu)^2}{2\sigma_u^2}\} \quad (18)$$

where Φ (·) is the standard normal cumulative distribution function. When μ = 0, the density function in equation (18) collapses to the half normal density function for the Normal‑Half Normal model. Point estimates for technical efficiency are

$$TE_i = \mathrm{E}\ [\exp\{-u_i\}\ |\varepsilon_i\ ] \quad (19)$$

where $\varepsilon_i = v_i - u_i$.

The basic stochastic frontier model analysis described here does not and cannot account for endogenous repressors. However, it is possible to estimate technical efficiency using stochastic distance functions (Kumbhakar and Lovell 2000). So, eventhough the stochastic frontier's coeficients may be biased, the tehcnical efficiency values are still valid. These are used in this study.

A comment worth making at this point is that even though the damage control production function model described in the previous sub-section is not a stochastic frontier per se, it is similar in the way actual output is modeled as a fraction of the maximum possible output (Shankar, Bennett, and Morse 2008).

Chapter 5:

Results

Through these results, I evaluate the economic impact of the MI technology over apple production. Results compare the summary statistics of adopter and non-adopters and then show the impact of MI over pesticide usage and apple yields.

First we start with the name and description of the variables used:

Table2. Variable description

Name		Description
Experience	:	Number of years since starting farm operation
Pest pressure	:	Vector of ex-ante indexes from 1 (low) to 3 (high) reflecting different pest pressures for pest and fungi.
Pesticide	:	Pounds of chemical pesticide used per acre
A.I.	:	Pounds of pesticide's active ingredient per acre (% of A.I. in each product multiplied by pounds of pesticide used)
Value of sales	:	Dollars per acres from apple sales
Yields	:	Pounds of apples per acre
Price	:	Proxy for pesticide price (expenditure over quantity)
MI	:	Microbial Inoculants (Dummy)
Farm size	:	Total farm size
Trees	:	Expenditure on trees (dollars per acre)
Labor	:	Expenditure on labor (dollars per acre)
Irrigation	:	Expenditure on irrigation (dollars per acre)
Fuel	:	Expenditure on fuel (dollars per acre)
Bees	:	Expenditure on bees (dollars per acre)
Nitrogen	:	Pounds of nitrogen used per acre
Potash	:	Pounds of potash used per acre
Phosphate	:	Pounds of phosphate used per acre
Sulfur	:	Pounds of sulfur used per acre
Acres harvested	:	Land harvested
State (e.g. Oregon)	:	Area dummy

Pesticide use function

Patterns of pesticide use with and without MI are shown in column (a) and column (b) respectively in table 3.

Table3. Summary statistics for apple production

	(a) Using MI			(b) Not using MI		(c) All farms	
Variable	mean		St. error	mean	St. error	mean	St. error
Experience	24.7		1.5	27.1	1.6	26.0	1.1
Pest pressure	14.9		0.6	14.7	0.6	14.8	0.4
Pesticide	79.9	*	11.7	63.8	3.2	70.6	5.3
A.I.	52.5	*	5.1	44.6	2.5	47.9	2.6
Value of sales	3360.7	*	377.1	2432.2	327.2	2825.8	243.5
Yield	26172.2		1445.2	25091.8	1997.8	25549.7	1302.2
# obs.	189			348		537	
Population	7104.4			9657.52		16761.9	

Note: * significantly different from mean value on non-adopter plots at 10% level.

Unexpectedly, and in contrast of what was found previously regarding biological control by the majority of the authors, the amount of pesticide used on plots with Microbial Inoculants is greater than on those who are without it. A comparison between columns (a) and (b) shows that there is a 25% increase in pesticide use associated with MI and an 18% increase in the use of active ingredients. However, this positive relationship could be explained by the higher values of sales, which is bigger by 38% in adopters plots (yields and pest pressure are 4.3% and 1.3% greater too but not significant), on the plots using MI. The differences suggest that farmers using MI have larger income which could be associated with more intensive pest management practices (biological or not); and/or being the increase of value of sales statistically different but not the increase in yields, may suggest a improved quality under this technology. At this point, there is a little bit of uncertain association between MI and pesticide but I quote a sentence by Qaim (Qaim 2009) that can help to explain the behavior we are observing with this biological control: “Insecticide reduction and yield effects are closely related: Farmers who use small amounts of insecticides in their conventional crop in spite of high pest pressure will realize a sizeable yield effect through Bt adoption, whereas the insecticide reduction effect will dominate in situations when farmers initially use higher amounts of chemical inputs. The same principles also hold for other pest-resistant GM crops.” The fact that apples is such a quality differentiated crop and also that chemical applications may improve at least the visual quality under less than strict health and environmental regulations, higher pesticide applications may persist and also explain the higher sales volumes not backed up by yield increases. It can also be seen that farmers with more experience (proxy for age) are more reluctant to accept or to try this new technology. This can fit some of the paradigms about biological control, where it has not been fully adopted because of sociological barriers (Peshin and Dhawan 2009) .

The pesticide use function is estimated by an OLS Regression. Multicollineality is not an issue as the Variance Inflation Factor (VIF) averaged 1.48 and did not exceed 2.12. Robust standard errors were used to address heteroskedasticity concerns.

Table 4 shows the results of the Cobb-Douglas type and linear type pesticide use function.

The Cobb-Douglas functional form was chosen because of a significantly better fit compared to the linear specification, possibly explained by non-linearity of the relationship. All coefficients of the Cobb-Douglas pesticide use function show the expected signs. As it was shown in the summary statistics, MI, which in theory is supposed to be a substitute for pesticide, has a positive and significant coefficient. This positive coefficient means that MI is being used more as an complement than a substitute contradicting some previous studies of other crops like

Cabbage (Jankowski et al. 2007) and cotton (Qaim and de Janvry 2005; Huang et al. 2002; Pemsl, Waibel, and Gutierrez 2005).

Table4. Pesticide use function

	Cobb-Douglas			linear		
	coefficient		t value	coefficient		t value
MI	0.22064	***	2.79	15.2919		1.6
price	-0.53831	***	-7.10	-0.0003182	***	-5.63
Pest. pressure	0.02820	***	2.90	0.6626709		0.92
farm size	0.51135	***	8.19	0.001925		0.52
experience	-0.00869	***	-3.35	-0.4752		-1.39
Michigan	-0.29136	*	-1.79	-20.6981		-1.49
Oregon	-0.18341		-1.17	-21.21234	*	-1.76
New York	-0.40624	**	-2.12	-29.72891	*	-1.84
Pennsylvania	-0.37066	***	-3.61	-25.7303	*	-1.75
North Carolina	-0.65578	***	-4.96	-14.05652		-1.14
California	-0.77040	***	-3.43	-35.67551	**	-2.07
constant	21.94957	***	4.23	1012.67		1.5
# obs.	598			608		
population	17287.78			17352.275		
R2 adjusted	0.5365			0.0812		

Note: Robust standard errors, *** p<0.01, ** p<0.05, * p<0.1

Nevertheless, this unexpected result can fit some established paradigms of biocontrol like, for example, “the more a grower is willing to gamble the better prospect he has of accepting the idea of biological control (BC). Those growers who cannot afford to lose much income usually do not want to risk using BC. They rather pay the price of "prevention" insecticide treatments than take a chance on BC not coming through for them. The prevention treatments are basically an insurance policy” (Peshin and Dhawan 2009). Prevention can be referring either to insecticides or BC. Farmers with bigger incomes tend to apply more damage control agents either in different types of BCAs, quantities or both.

Going back to the results, with an additional year from which farmers started operation (called in this study experience or proxy for age) the amount of pesticide use is reduced by

0.87%, indicating that older farmers may still have cultural paradigms like using extra pesticide is always better. The price elasticity of pesticide use is -0.54, which corroborates the “insurance” nature of the pesticide use because it is not very elastic. The elasticity of pesticide use with respect to farm size was found to be around 0.51%.

Pest pressure, which is a vector of indexes describing the degree of pest pressure before spraying decisions, is positive and significant as expected but small in magnitude. Regarding the state dummy variables, compared to Washington (the base), all states use less pesticide (Oregon has a negative coefficient but not significant).

Production functions and frontier

As shown in Table 3, MI is positively associated with pesticide use and value of sales and yields. The net yield effect can be estimated through a production function. The first column in Table 5 shows the results for the production function estimation without using the integrated damage control function. Heteroskedasticity was corrected using robust standard errors and there were no Multicolinearity problems as the mean of the Variance Inflation Factor averaged 1.56 and did not exceed 1.98. The Chow test was performed in order to see if the two groups of farmers (adopters and non-adopters) could be pooled together. The results showed that both groups can be pooled together because we have a F statistics of $F(19, 487) = 1.42$ and the critical value at 5% level of confidence is 1.61. This means that we fail to reject the null hypothesis of both groups having the same coefficients.

Overall, all of the results indicate that microbial inoculants have a positive impact on output. MI impact differs on each specification having different coefficients and different statistical power. Now, I review the different results on all the different functional forms.

Table5. Production functions and stochastic production frontier

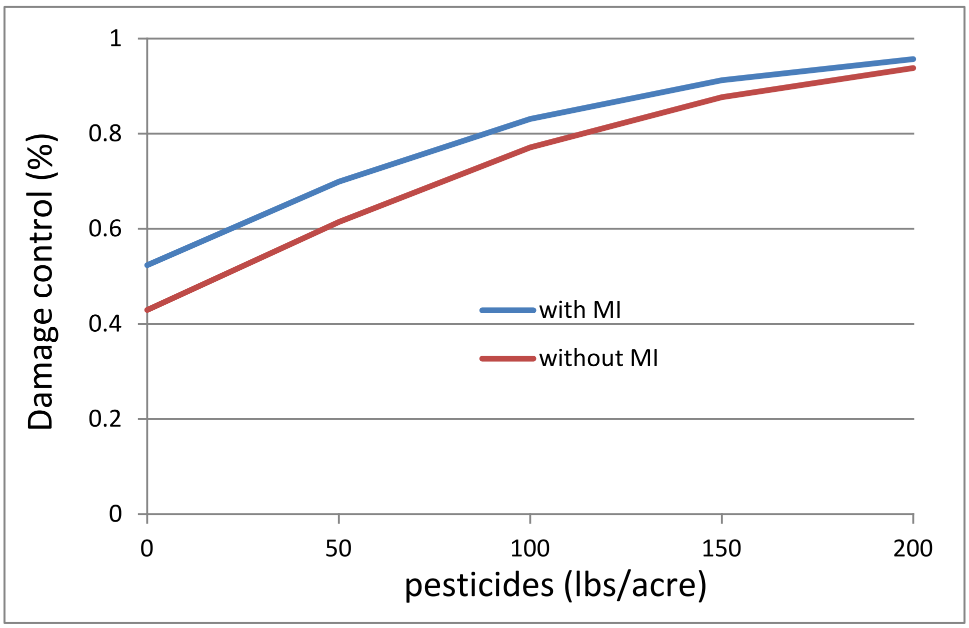
	Cobb-Douglas basic			With exponential damage			With logistic damage			Cobb-Douglas frontier		
	coefficient		t value	coefficient		t value	coefficient		t value	coefficient		t value
pesticide	0.1255	*	1.77							0.1105		1.56
experience	-0.0013		-0.56	-0.0003		-0.13	-0.0003		-0.12	-0.0009		-0.41
trees	-0.0051		-0.88	-0.0116	**	-2.18	-0.0121	**	-2.27	-0.0040		-0.75
labor	0.0886	***	4.99	0.0774	***	6.55	0.0786	***	6.73	0.0836	***	4.97
irrigation	-0.0058		-0.96	-0.0096		-1.33	-0.0093		-1.29	-0.0047		-0.81
fuel	-0.0032		-0.64	-0.0038		-0.70	-0.0039		0.70	-0.0015		-0.31
bees	0.0066		1.03	-0.0008		-0.13	-0.0009		-0.13	0.0051		0.81
nitrogen	0.0183		0.79	0.0263	*	1.79	0.0265	*	1.80	0.0177		0.81
potash	0.0410	*	1.89	0.0293		1.60	0.0285	*	1.65	0.0290		1.44
phosphate	-0.0741	**	-2.28	-0.0755	**	-2.58	-0.0747	**	-2.55	-0.0565	*	-1.89
sulfur	-0.0217		-0.45	-0.0173		-0.30	0.0143		-0.42	-0.0152		-0.35
MI (dummy)	0.1208	*	1.71							0.0908		1.36
Acres harvested	0.0762	***	2.64	0.1626	***	6.88	0.1649	***	7.01	0.0695	**	2.51
Michigan	-0.0077		-0.07	-0.0091		-0.07	0.0111		0.09	0.0234		0.22
Oregon	-0.4016		-1.58	-0.4059	***	-2.62	-0.4072	***	-2.63	-0.2493		-1.19
New York	0.1924		1.61	0.1868		1.43	0.2058		1.58	0.2183	*	1.91
Pennsylvania	0.3973	***	3.53	0.3693	***	2.64	0.3904	***	2.82	0.3916	***	3.62
North Carolina	-0.8564	***	-3.86	-0.8090	***	-3.10	-0.7913	***	-3.04	-0.7484	***	-3.45
California	-0.1268		-0.47	-0.4398	***	-3.00	-0.4279	***	-2.92	-0.0789		-0.27
constant	10.9300	**	2.39	9.6541	**	2.29	9.6114	**	2.28	10.7380	**	2.51
damage control												
Constant (α_0, μ)				0.5346	***	4.02	0.2845	*	1.65			
pesticide				0.0108	*	1.91	0.0154	**	2.56			
MI (dummy)				0.2106		1.46	0.3787	*	1.93			
number of obs.	510			525			525			510		
R2 adjusted	0.3654			0.3739			0.3751					
population	15497			15953			15953			15497		

Note: *** p<0.01, ** p<0.05, * p<0.1

In the regular Cobb-Douglas production function, all else held constant (*ceteris paribus*), the use of MI technology increases apple yields by 12.08% per hectare at the variables' mean values, which agrees with what was indicated by the summary statistics. This also corroborates the findings by Qaim and De Janvry (2005), Qaim (2003), and Huang et al. (2002) where they found that the use of Bt cotton increases yields by 507 kg./ha in Argentina, by 75% per hectare in India, and by 15% per hectare in China respectively. Chemical pesticides also contribute to higher yields. For a 1% increase in the amount of pesticides used, the yield increased by 0.1255%. The elasticity with respect to labor is 0.089%. The impact of potash fertilizers is positive but for phosphate is negative suggesting possible overuse. The production elasticity of land is 0.076%. The only state that is more productive relative to the base (Washington) is Pennsylvania; meanwhile, the only state less productive than Washington is North Carolina (86% less productive).

The coefficients of the production functions with integrated damage control are similar to those in the standard Cobb-Douglas production model. The two alternative specifications of the damage control functions, the one that uses the exponential and the one that uses the logistic damage control function, show somehow similar results for the effect of MI application (table 5, columns 2–3). The logistic damage control function is preferred over the exponential for fitting better the model (37.51% compared to 37.39%). If this specification reflect the true underlying technology, our results suggest that MI technology is effective in helping pesticides reduce the damage from pest infestations and keeping yields higher than they would have been without MI adoption. In other words, MI technology increases the productivity of apple production. Pesticides also increase productivity. Again, the coefficients in this sub function demonstrate that both pesticide and MI contribute to crop protection.

Without any pest control inputs and using the logistic damage control function approach, crop damage would have been around 57% of the mean yield. The Marginal Physical Productivity (MPP) of pesticide was obtained taking the partial derivative with respect to pesticide. Using the estimated parameters and mean values of the inputs, it was found that MI reduces the marginal productivity of pesticides. The MPP was found to be 0.1377 for non-adopters and 0.1187 for adopters. Non-adopters having greater values agree with findings on previous studies (Huang et al. 2002; Pemsl, Waibel, and Gutierrez 2005; Qaim 2003; Qaim and de Janvry 2005). Figure 6 helps to establish the linkage between pesticide, MI and yield levels.



Source: Compiled by author.
Figure6. MI, pesticides, and damage control relationship.

Now, the effect of fertilizers is more compliant with the theory, nitrogen and potash both being significant, albeit marginally. Also, the impact of land increases from 0.07% to 0.16%. These results confirm Lichtenberg and Zilberman's (1986) finding that direct inputs are underestimated in traditional Cobb-Douglas production functions. However, this does not happen for all inputs in this study as the impact of labor slightly decreases in the models with damage function specifications. Labor is impacting the yields positively, having an elasticity of 0.08%.

There are some notable similarities between our results and those obtained by the other authors in their studies. They found of a fixed effect of 56% in Argentina (Qaim and de Janvry 2005), and a 73% fixed effect in India (Qaim 2003). The biological control component was significant for all theses 2 studies and also in the one made by Huang et al. (2002) in China. In contrast, Pemsl (2005) and Jankowski et al. (2007) found biological control impacts to be not significant or negative and significant respectively suggesting that some of these products are facing a different paradigm or are still in the process of development.

Lastly, the results of the frontier analysis are similar to the regular production function but with some minor changes. Our variable of interest, the use of microbial inoculants, loses statistical power and magnitude, having decreased from 12% to 9%, with the pesticide impact on production also decreased and losing statistical power too. It is important to remember that these coefficients may be biased and inconsistent because of endogeneity issues, so not much time on interpretation is expended.

However, one reliable and important result in this study obtained from the stochastic frontier is that adopters of MI technology have 2.52 % higher efficiency rates compared to non-adopters. The results are shown in Table 6. The average technical efficiency score for all farms was found to be 0.6085, implying that the same level of production per acre can be obtained under existing technology even if the inputs used for apple production are decreased by 39%. Adopters can reduce their inputs by 37% and still have the same output meanwhile; non-adopters would be able to reduce 40% on their inputs. Apple production is more efficient in the states of Washington, Pennsylvania, Michigan and California by at least 3% compared to New York and

North Carolina. An interesting and intuitively compelling finding is that, in those states where efficiency rates are lower than the average, non-adopters have relatively higher efficiency rates. This may be due to relatively suboptimal agricultural, sociological, and economic practices.

Table6**.** Average efficiency by adoption and state

	all farms	adopters	non adopters	efficiency gains
all farms	0.6085	0.6254	0.6002	**0.0252**
California	0.6170	0.6616	0.5986	0.0630
Michigan	0.6186	0.6287	0.6140	0.0147
New York	0.5826	0.5725	0.5862	-0.0137
North Carolina	0.5829	0.5018	0.5909	-0.0891
Oregon	0.6104	0.6843	0.5661	0.1182
Pennsylvania	0.6174	0.6204	0.6162	0.0042
Washington	0.6198	0.6236	0.6157	0.0079

Because the data is insufficient for specifying a profit model (prices of inputs including MI, output prices, etc.), a simplistic financial approach was used to calculate the average impact of the MI technology use on farmers' income. The steps followed to estimate this value were the following:

- Average yield of the non-adopters was used as a starting point and the gain in the adopters yield was calculated using the production frontier MI estimate. The yield gain was calculated around 2000 pounds per acre
- Using season-average grower apple prices (according to ERS the 2007 average grower price for fresh apples was 38.30 cents per pound), the extra income was calculated at $766.
- Then to calculate the individual farmer cost for the use of MI products, I used the average adopter's usage (3 biological products) and assumed that they used different products. This is because there are 197 adopters and the numbers of different MI products used

have a similar trend by targeted pest. MI usage was as follows: 274 Granulo virus products (used for codling moth), 193 Bt products (used for different insects), and 95 were *Bacillus pumillus* and *Bacillus subtillis* (used for fire blight and powdery mildew). Then using prices per acre (as an example, the price of the most used product for codling moth, CYD-X, for a 32 ounces container is $349 and application quantities per acre recommended by the manufacturer are 3-4 ounces of CYD-X applied 9 times during a season), the total cost was calculated at $558

So, assuming that other inputs remain unchanged (for example there is no extra labor for applying MI), the net revenue was found to be around $208 per acre per growing season.

Chapter 6:

Conclusion

This thesis has empirically analyzed the effects of using a specific type of biological control agent (BCAs) called Microbial Inoculants (MI) on productivity and pesticide use in conventional (non-organic) apple production in the United States.

Analysis of the ARMS survey data statistics suggests that farmers using the technology tend to have greater rates of pesticide application. However, because the MI use is also correlated with higher value of sales, a pesticide use model is estimated. The results show that the use of the MI technology positively affects the amount of chemical pesticides used which disagrees with our first hypothesis and some studies made in other BCAs but agrees with some paradigms about them pointed out in others. Some of these paradigms are that BCAs are often seen as “insurance” components, only afforded by wealthier farmers; and the fact that the adopting producers may have been using minimal amounts of insecticides before adoption.

MI technology is an integrated pest management (IPM) approach that has not been fully adopted by apple producers due to several factors not studied in this thesis. According to this study, only 36% of the US apple producers used it in 2007. However, it is expected that, in the near future, due to the increasing concerns about pesticide residues and more strict regulations, adoption of the MI as an IPM tool will increase and some of these paradigms will disappear (Fravel 2005).

Moreover, using different types of production functions, it was shown that MI adopters benefit significantly from higher yields compared to those not using it. Efficiency rates for apple producers are around 60% and are 3% higher among the MI technology adopters. The states with the highest rates of efficiency were Washington, Pennsylvania, and California. All of These results agree with our second hypothesis.

The MI technology is an environmentally friendly alternative that does not carry the biological nor social potential problems that GMOs do; however, they can produce similar positive results. According to this study, MI can complement, rather than substitute, agricultural chemical use easing compliance with regulations and positively impacting yields. The overall impact on farmer's income depends on the tradeoff between the costs of biological control products and the resulting increase in yields. Our estimates using calibration data suggest a gain of $208 per acre per season.

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