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We develop a temporal and spatial partial equilibrium model to evaluate the welfare impact of new technology on the apple industry to control fire blight. We show significant benefits of GM technology relative to conventional methods and other new methods such as microencapsulation of biological agents. We also show that the cost-reduction benefits of the technology exceed the yield-increasing benefits.

Key words: apple production, fire blight, technology, welfare analysis

Introduction

Fire blight is a bacterial disease that can affect various parts of the apple tree at different growth stages, including the blossom, fruit, roots and shoots. Fire blight outbreaks cause serious damage to apple producers. In 2000, Michigan lost more than 600 acres of orchards and more than 220,000 trees aged two to five years to the disease, leading to a loss of more than $42 million to the region (Norelli, Jones, and Aldwinckle, 2003). Typical annual losses from fire blight are more than $100 million in the United States. We use a temporal and spatial partial equilibrium model to evaluate the impacts of new apple production technologies on fire blight damage in the U.S. apple industry.

Many recently introduced apple varieties, particularly 'Red Delicious' and 'Golden Delicious', are more susceptible to fire blight than the dominant traditional varieties (except 'Granny Smith', introduced in 1868) (Briggs and Yoder, 2012). These newer varieties include favorites such as 'Fuji' (introduced in 1930), 'Gala' (1974), and 'Cripps Pink' (1992). Growers of these new varieties have suffered significant production losses from fire blight, which can be as large as 5% annually (Gianessi, Silvers, and Carpenter, 2002). As consumers substitute the susceptible varieties for traditional varieties ('Red Delicious' production in 2008 was only 65% of its 2000 level, while 'Cripps Pink' production nearly tripled in that same period), there is increased concern about the sustainability of production in regions where fire blight is prevalent.

Given current concerns about bacterial resistance to commonly used antibiotics, researchers are exploring ways to chemically and genetically reduce fire blight damage. Three important advances have been achieved in the past century to help control fire blight: rootstock breeding programs, the development of genetically engineered cultivars, and advances in chemical treatments (Norelli, Jones, and Aldwinckle, 2003).

The technology that is the base for our research focuses on short-term and long-term adjustments to production. Scientists involved in the Integrated Genomics and Management Systems for Control

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of Fire Blight research project are evaluating different strategies against the bacterium that causes the disease. In the short term, research is under way to generate an environmentally safe bio-control method that is more effective against fire blight than current treatments. Kim et al. (2012) obtained promising results using a microencapsulated bio-control agent, E325, to control fire blight. In the long term, scientists are working to identify fire blight resistant genes and develop fire blight resistant cultivars of preferred varieties that are currently highly susceptible. Wang, Korban, and Zhao (2010) highlighted some of their work in isolating the genes that express resistance to fire blight. The scenarios used in our study are based on the findings of Kim et al. (2012); Wang, Korban, and Zhao (2010); and personal communication with the scientists involved in the Integrated Genomics and Management Systems for Control of Fire Blight research project. We use our model to explore technology adoption and its effects on domestic and international apple markets. In particular, we analyze the potential costs and benefits of microencapsulation of a bio-control agent and GM technology using an empirical, thirty-five-year temporal and spatial equilibrium model of orchard management. Our results fill a gap in the literature on the use and impact of these emerging apple production technologies.

Background and Literature Review

Apples are a deciduous fruit grown across the world and consumed fresh or processed as food or drink. In 2010, more than 11.7 million acres of apple orchards produced nearly 69.5 million metric tons (MT) worldwide (U.S. Department of Agriculture, Economic Research Service, 2012). China and the United States were the largest producers in 2010, supplying 48% and 6% of world production. Along with Turkey, Italy, India, and Poland, the top six producing nations accounted for 66.5% of total world production.

The United States produces about 2,500 of the approximately 7,500 apple varieties grown worldwide (University of Illinois Extension, 2011). Apples are grown in all fifty states, but nearly 90.6% of the 2010 production occurred in just six states: Washington (60.2%), New York (13.7%), Michigan (6.4%), Pennsylvania (5.1%), California (3%), and Virginia (2.2%) (U.S. Department of Agriculture, Economic Research Service, 2012). The use of apples for fresh and processed consumption was approximately 2.3 million MT, which were produced on more than 330,000 bearing acres.

Apple production can be challenging for growers because of the perennial nature of the crop. Growers make year-to-year decisions based not only on economic benefits but also on environmental and biological conditions. Apple trees vary in the length of nonbearing years after initial establishment: a standard apple tree takes six to ten years, a semi-dwarf tree takes four to six years, and the commercially common dwarf trees bear apples at two to three years of age (University of Arizona Cooperative Extension, 2011). Lengthy nonbearing periods increase the difficulty of orchard establishments, with high initial costs and no revenues from those trees. The nonbearing years occur at the beginning and at the end of the life of an orchard. Life expectancy also varies by size: standard apple trees live 35–45 years, semi-dwarf trees 20–25 years, and dwarf trees 15–20 years (University of Arizona Cooperative Extension, 2011). These timeframes for bearing years and life expectancy can also vary by variety. Tree size and variety define an orchard.

Fire blight is a potentially devastating bacterial infection, especially for pears and apples. Growers currently use chemical sprays such as streptomycin and oxytetracycline to prevent and heal the infections, but they have begun turning to recent research for alternatives, as fire blight has demonstrated a growing resistance to streptomycin, for which there are few alternatives. Streptomycin provides 90% control of the bacterial strains against which it is most effective (Norelli, Jones, and Aldwinckle, 2003), while oxytetracycline is only partially effective in most cases. The bacteria thrive in the rain and heavy dews of areas with high humidity, and a single infected tree can transmit fire blight to the entire orchard as bacteria residing in the ooze from a trunk canker are spread by insects and rain to the blossoms of other trees (Ellis, 2008). The disease continues to thrive despite recent advances in planting technology. High-density planting systems use highly susceptible dwarf rootstock (Norelli, Jones, and Aldwinckle, 2003), increasing the probability of disease and spreading infestation to areas that might not be prone to the disease otherwise. Yield and resource benefits, such as land use and maintenance work savings, make high-density planting preferred in the U.S. Northwest. Low-density planting is still common throughout the rest of the United States.

Production Technology

Technological innovations in agriculture have been extensively studied and evaluated for what they bring to the farm and to consumers. Adoption is one of the key factors that determine the success of a technology, and communication about the specific benefits of a technology is critical in technology adoption (Feder, Just, and Zilberman, 1985). Communication can help relieve uncertainty and drive diffusion of the technology. The acceptance of information and adoption of the technology impact producers in different ways, so the adoption decision is specific to each producer.

Producer decisions in the adoption process are made in the presence of risk and uncertainty about the technology and other factors of agricultural production. In their article on herbicide-resistant rice, Annou, Wailes, and Thomsen (2005) stated that "risk aversion changes the dynamics of adoption and crop planting" (p. 170) and explained producers' use of technology as a way to diversify production portfolios. Risk-averse farmers are likely to be early adopters of new technologies, adding the new technology to their decision mix as a risk-reducing strategy.

Benefits and Costs of Biotechnology

Much of the literature on the benefits and costs of biotechnology evaluates a new variety's potential impact on the market after its commercial release or during the product's testing phase. Brennan (1984) suggested that a successful evaluation of new varieties consists of the analysis of the change in farm production practices and inputs used. He also identified the significance of differences in farm and experimental yields and recognized major obstacles to the production and consumption of genetically modified (GM) commodities, including concerns of buildup of resistance against the technology and government regulations. Yet the potential benefits to society can be significant, including smaller yield loss, introduction of desirable traits, and a positive environmental footprint (Barnett and Gibson, 1999).

When considering the impact of technology use, the costs related to yield and quality losses, disease outbreaks, and production inputs must be considered. Zhao, Wahl, and Marsh (2007) evaluated the economic effects of apple maggot. They explicitly modeled the costs of quarantine, pest control, and yield loss as well as the economic costs from lost market opportunities and found that "the effects on welfare and prices of a crisis or policy are only partially evident in short-term market outcomes" (p. 500). They suggested that more substantial impacts may come in the long run because of the lag between the investment decision and revenue generation. Krissoff, Calvin, and Gray (1997) recognized the need to include tariffs and technical barriers as costs in the analysis of fire blight bio-control methods, especially in the case of new GM varieties. They found that removing tariffs and phytosanitary trade barriers for U.S. apples removes the price wedge between global and local prices and increases apple consumption in the respective countries. The inclusion of these measures presents a more complete picture of apple industry costs and—combined with the adoption evaluation criteria—permits a comprehensive analysis of the impact of new biotechnology introduced to combat fire blight.

Brookes and Barfoot (2005) evaluated the cost and impact of the first years of GM technology use. They found that GM crops such as soybeans, corn, cotton, and canola had an overall beneficial impact on farm income in the first nine years as a result of increased productivity and efficiency gains. The authors also found indirect benefits—including reduced tillage, convenience in production practices, and reduced exposure to pesticides—from increased knowledge and new techniques from the use of the GM varieties. These indirect benefits are important for a comprehensive evaluation of new technologies.

Moschini (2001) analyzed the benefits and costs associated with Roundup Ready technology in his theoretical paper. He discussed the intellectual property rights of the innovator as well as the pricing of the innovation, which is determined by market power. He showed that farmers' net benefit could be positive or negative under competitive pricing, making it important to evaluate pricing strategies in the marketing of a technology through an analysis of supply and demand.

Building on the studies of annual crops mentioned above, we model the production of a perennial crop and equilibrium in apple markets to evaluate the impact of biotechnology. Benefits of the new technology include reducing production costs to growers and increasing production of susceptible apple varieties such as 'Gala', 'Fuji', 'Jonathan', 'Pink Lady', 'Granny Smith', and 'Honeycrisp'. Our model opens the door to technology research based on realized or anticipated costs and allows for careful regionalization and specifications critical to the analysis of U.S. production. The model can be applied to other perennial products in other places.

Theoretical Framework

We develop a temporal and spatial partial equilibrium model to evaluate the impact of new technology adoption on the U.S. apple industry over a thirty-five-year horizon. Our model generates a picture of the industry once the technology is available and can be adopted by growers in all regions. We specifically consider the perennial nature of the crop, the investment planting decisions of the growers, and interactions between U.S. and world markets through international trade.

To find the market equilibrium, the model maximizes the sum of producers' and consumers' surpluses subject to apple supply-demand balances and regional resource (land) constraints determining the domestic supply of apples. This methodology was introduced by Samuelson (1952) and developed further by Takayama and Judge (1964, 1971). A theoretical elaboration and review of early empirical studies using this methodology can be found in McCarl and Spreen (1980). Most of the applications presented in the literature deal with static (annual) market equilibrium, but this method can also incorporate dynamic aspects of production and consumption. Incorporating a dynamic component is especially important when decision makers face production situations in which there is temporal uncertainty and in which actions in the current period shape productivity in future periods (McCarl and Spreen, 2007). In our particular application, the model incorporates producers' tree planting and removal decisions in a dynamic framework, consumers' demand for apples, and global apple trade for each year, all essential features of the apple industry as it is presented with new technology. The time component allows us to simulate the impact of disease or government policies on short- and long-term market outcomes. The true, long-term effects of such factors can be quite different from short-term effects (Zhao, Wahl, and Marsh, 2007).

Dynamics

When modeling the dynamics of apple production, it is important to consider the "terminal condition" and value of standing trees that have productive years remaining beyond the specified time horizon in addition to year-to-year planting decisions and aging processes. We consider a thirty-five-year horizon, so tree ages in year thirty-five span from newly-planted to thirty-five years of age (the latter is the maximum expected productive life of apple trees assumed in this study). The remaining value of each tree in a given age category is determined first *a priori* and then using an iterative procedure assuming a fixed expected price and the discounted future returns and costs throughout the remaining productive years.

Spatial Market Equilibrium

Because of the interaction between apple production and consumption in major markets, it is important to simulate the impact of one country's technology adoption on both domestic and foreign apple markets. We incorporate such linkages through the model's spatial equilibrium component, in which each exporting country's production is allocated between domestic consumption and exports, while the demand of each importing country equals domestic production plus imports. Each of the countries included in the model is a major producer or major importer in world apple market. We place special focus on important importers of U.S. apple varieties.[1] The model includes a "rest of the world" region to capture production and consumption in other countries not included explicitly in the analysis.

Empirical Model

Our model's supply, demand, and cost functions are specified for each year of the thirty-five-year planning horizon and for each major apple trading country included in the model. We also include orchard density and the new technologies in the U.S. supply and cost functions. The model's base year is 2005, for which the most recent series of state-level apple production and variety-specific orchard data were available.[2] The model variables, descriptions, and data sources are presented in table 1.

Objective Function

The model's objective function is the global social surplus (welfare) summed over all producer and consumer countries. Each country's social surplus is the sum of its producers' and consumers' surpluses, which equals the sum of the areas under the demand functions up to the equilibrium quantity minus production costs. We specify the demand functions for each country for fresh and processed apples as linear demand functions by using the estimated demand elasticities and the observed base year price and quantity levels.[3] The supply structure in the United States is characterized by a cost function rather than a supply function and is determined by the choices of acres, technology (traditional, bio, or GM), and orchard density (high or low) in each production region.[4] An aggregate supply function is specified explicitly for each of the other countries included in the analysis. The supply functions are also assumed to be linear and the parameter values are specified as for the demand functions.[5] Apple supply is not segregated into separate processed or fresh production categories, because we assume that apples are segregated after harvest depending

[1] Important U.S. apple export destinations included in the analysis are Canada, Mexico, Taiwan, and the United Kingdom. Important U.S. apple import sources included are Chile, New Zealand, and Argentina. Other major world exporters included are China and Brazil, and other major world importers included are India, Japan, Russia, France, Italy, Germany, Spain, and Poland.

[2] More recent data are available from 2010, but these data are not as detailed as the data released in 2005 and do not include all of the information needed for this study. More recent data are not available for all states included in this study.

[3] For each demand function, we assume that the demand elasticity, ε, is the point elasticity at the observed equilibrium (i.e., the base year price and quantity pair (P_0, Q_0)). The slope and intercept terms of the linear demand functions, β and α, are calculated by using the formulas $\beta = P_0/(\varepsilon Q_0)$ and $\alpha = P_0(1 - \frac{1}{\varepsilon})$.

[4] By using the cost function we are able to specify the technology costs assumed in this analysis that pertain specifically to fighting fire blight in apples and highlight the impacts of the two different technologies specific to our study.

[5] The assumption of linear demand and supply functions is not restrictive. One can use constant elasticity functions, which would replace the quadratic terms in the objective function (1) with nonlinear terms representing the areas under the respective demand and supply functions. The optimization software used in the analysis can handle both functional forms easily, but the quadratic forms are computationally more convenient.

Table 1. Description of the Model Variables, Parameters, and Data Sources

Variable	Description	Source
Planting Cost	Fixed cost by technology and density	Zhao, Wahl, and Marsh (2007)
Maintenance Cost	Fixed cost by technology and density	Zhao, Wahl, and Marsh (2007)
Yield	Average yield by age and density	Zhao, Wahl, and Marsh (2007)
Removal Cost	Average used as a fixed cost for all trees	Zhao, Wahl, and Marsh (2007)
Fresh Demand Elasticity	Own-price elasticity for fresh apples	ERS-Food Demand Dataset
Processed Demand Elasticity	Own-price elasticity for processed apples	ERS-Food Demand Dataseta
Supply Elasticity	Supply elasticity for all other countries	Devadoss and Luckstead (2010)
Base Supply	Quantity supplied quantities in base year	FAS-Production, Supply and Distribution Online Database
Base Fresh Demand	Demand quantity quantities in base year	FAS-Production, Supply and Distribution Online Database
Base Processed Demand	Processed Demand quantities in base year	FAS-Production, Supply and Distribution Online Database
Producer Price	Average producer price by country in base year	FAOSTAT.fao.org
Transportation	Cost to transport apples between countries	FAOSTAT.fao.orga
Initial Inventory	Inventory by age and density in base year	NASS state-wide surveys
Acres	Acres of apples by age, density and type	Endogenously determined
Trade	Exports and imports from country A to country B	Endogenously determined
Removed Acres	Acres removed through optimization	Endogenously determined
Qsupply	Quantity supplied by countries other than the United States	Endogenously determined
Qdemand Fresh	Fresh quantity demanded by all countries	Endogenously determined
Qdemand Processed	Processed quantity demanded by all countries	Endogenously determined
Price Lambda	Price used in remaining value calculation	Endogenously determined

on quality and current market needs.[6] Transportation costs between trading countries depend on volume transported, which is endogenously determined in the model, and distances between countries. The transportation costs create price differences between each pair of countries in the base year of the analysis. The U.S. component captures the value of trees in each age group at the end of the planning horizon through calculations in the final year of the model. We optimize the discounted welfare equation to more accurately capture the decisions of the producer for our thirty-five-year horizon. The model is specified to maximize the objective function by selecting the

[6] The general practice of apple producers is to grow apples of sufficient quality to be sold on the fresh apple market. Apples that flow into the processing market are generally residual apples, sometimes slightly damaged by weather or handling. In this sense, fresh and processed apples are joint products from a single production system. Thus, in our model we distinguish between fresh and processed apples in demand but not in supply.

optimum acres and quantities of apples. The objective function is given below:[7]

$$\sum_t \left(\left(\frac{1}{1+dr} \right)^{t-1} \left(\sum_c Q^{df}_{t,c} \times (\alpha^{df}_c + 0.5 \times \beta^{df}_c \times Q^{df}_{t,c}) \right.\right.$$

$$(1) \qquad + \sum_c Q^{dp}_{t,c} \times (\alpha^{dp}_c + 0.5 \times \beta^{dp}_c \times Q^{dp}_{t,c}) - \sum_c Q^{s}_{t,c} \times (\alpha^{s}_c + 0.5 \times \beta^{s}_c \times Q^{s}_{t,c})$$

$$\left.\left. - TPC_t - \sum_{c,c'} tc_{c,c'} \times E_{t,c,c'} \right) \right) + \sum_{a,d} RV_{a,d},$$

where

$$(2) \qquad TPC_t = \sum_d pc_d \times A_{t,a1,d} + \sum_a mc_{a,d} \times A_{t,a,d} + \sum_a rc \times RA_{t,a,d}$$

and

$$(3) \qquad RV_{a,d} = A_{t^*,a,d} \times \sum_{a'>a} \left\{ (p \times y_{a',d} - mc_{a',d} - rc) \times \left(\frac{1}{1+dr} \right)^{a'-a} \right\}.$$

In equation (1), $Q^s_{t,c}$ is country c's quantity of apples supplied in year t; $Q^{df}_{t,c}$ and $Q^{dp}_{t,c}$ are the quantities demanded in country c and year t as fresh and processed apples; $tc_{c,c'}$ is the per unit transportation cost between countries c and c', and $E_{t,c,c'}$ denotes the quantity of apples exported from country c to country c' in year t. Subscripts a and d indicate tree age and planting density (high, low); $RV_{a,d}$ denotes the remaining value of trees of age a and planting density d at the end of the horizon; TPC_t denotes total U.S. apple production cost in year t. The αs and βs are the intercept and slope parameters associated with the linear supply and demand functions for fresh and processed apples. In equation (2), planting, maintenance, and removal costs are indicated by pc, mc, and rc; $A_{t,a,d}$ is an endogenous variable representing the acres of trees of age a planted at density d that are in production during year t; and $RA_{t,a,d}$ is an endogenous variable specifying the number of acres of trees removed. In equation (3), $A_{t^*,a,d}$ denotes the number of acres in place in the terminal year, t^*, of trees of age a and density d, a' represents the future age of standing trees of an age group a in the terminal year t^* (thus $a \le a' \le 35$), t^* is the last year of the planning horizon (year 35), p is the expected apple price beyond the planning horizon, and y is the apple yield for a given age group and planting density. The discount rate is dr, and subscripts a and d, and the variables $RV_{a,d}$, $A_{t,a,d}$, and $RA_{t,a,d}$ are defined only in the U.S. component of the model.

Over the past ten years, the number of high-density plantings has increased, especially in the northwest region in the United States. Therefore, we include density choice in the U.S. component of the model. The model determines the equilibrium quantities of demand for fresh apples, demand for processed apples, and total supply of apples. We calibrate the model using the base year's (2005) prices and quantities, demand elasticity estimates when specifying the domestic demand function for each country, and supply elasticities estimated for every country other than the United States.

Each year's total cost of U.S. apple production is composed of initial planting costs, yearly maintenance costs, and eventual tree removal costs. These costs include the costs of various input, such as seed, labor, machinery, and fuel. The cost function is presented in equation (2). The various exogenous costs in the model, described below in the data section, are fixed. This assumption can be easily altered to capture varied establishment and management decisions. These costs are assumed to remain fixed as many inputs in the industry, such as labor and fuel, account for only a small fraction of the U.S. total input use. It is understood that these values can and most likely will vary over

[7] For convenience, throughout the model description we use lowercase/italic symbols for indexes and parameters and uppercase symbols for variables solved endogenously by the model.

the lifetime of the orchard, yet the assumption of fixed costs is appropriate for technology adoption analysis as the apple industry consumes a relatively small share of production inputs compared to other agricultural industries.

The transportation cost segment of the objective function represents the total cost of moving apples from exporting to importing countries, including shipping costs and trade margins. The transportation cost is the product of the per unit transportation cost and the endogenously determined trade quantity.

The remaining value of standing apple trees at the end of the specified horizon permits accounting for the future value of trees, namely the growers' return to their investment beyond the terminal year of the model horizon. The remaining value in equation (3) is calculated by using a future price specified exogenously and assumed to be constant beyond the final year of the model horizon, the yields depending on the age of each tree category, maintenance costs, and removal costs that will be incurred in the remaining years. The remaining value is discounted to obtain the present value of the total future returns from the trees remaining in year 35. Since the market price of apples beyond the planning horizon is unknown, we used an iterative procedure to specify a proxy future price. This price is set initially at the 2005 level and the model is solved once; then the price is updated based on the endogenously determined market price in year 35 (given by the shadow price associated with the U.S. market-clearing equation (4).[8] This procedure is repeated until the expected price and last year's endogenous price sufficiently converge. The proxy future price enables calculation of the final acres and the remaining value of the tree crop in the final run of the model.

Constraints and Balances

The model is maximized subject to market equilibrium constraints and production constraints for both U.S. and world apple production and consumption. These constraints are

$$Q^{df}_{t,\text{``}us\text{''}} + Q^{dp}_{t,\text{``}us\text{''}} + \sum_{c} E_{t,\text{``}us\text{''},c} = \sum_{a,d} (y_{a,d} \times A_{t,a,d}) + \sum_{c} E_{t,c,\text{``}us\text{''}} \;\; \forall \; t, \tag{4}$$

$$Q^{df}_{t,c} + Q^{dp}_{t,c} + \sum_{c'} E_{t,c,c'} = Q^{s}_{t,c} + \sum_{c'} E_{t,c',c} \;\; \forall \; t \text{ and } c, \tag{5}$$

$$A_{t,a,d} - RA_{t,a,d} = A_{t-1,a-1,d} \;\; \forall \; t > 1, \; a > 1, \; d, \tag{6}$$

$$\sum_{a,d} A_{t,a,d} \leq ta \;\; \forall \; t, \tag{7}$$

where $E_{t,c,c'}$ denotes the quantity of apples exported from country c to country c' (when referring to the United States, we use "us") in year t and ta denotes the total land allocated to apple production in the base year.

The market-clearing condition (supply-demand balance) for the U.S. component of the model is imposed by equation (4). This constraint requires that the quantities demanded for processing and fresh consumption of apples plus the total exports to all other countries must be equal to domestic supply, given by the exogenous yield multiplied by endogenously determined acreage, plus U.S. imports from other countries.

A similar market-clearing constraint, shown in equation (5), is stated for the other countries included in the model. This constraint equates the total use of apples in each country (including both

[8] This issue is important when working with dynamic modeling situations where a finite horizon is considered and market price is solved endogenously. More than one iteration may be necessary to obtain a "good" proxy for the future price. In our experience, one iteration was sufficient because the price obtained in the third iteration was very close to the price obtained in the second iteration.

the fresh and processed quantities demanded plus the country's total exports) to the total quantity supplied (the country's domestic production plus apple imports).

Equation (6) describes the constraint that characterizes the dynamic, perennial nature of apples after planting. This constraint ensures that in each year the available acres of trees in each age category equal the acres in trees one year younger, minus any acres removed from production. Acres removed are limited to those trees over age ten. This restriction mimics the decision making of a rational grower, who would not uproot productive trees before recovering their planting costs (which occurs about ten years after planting).

Constraint (7) restricts total U.S. acreage in any given year to the total amount of land allocated to apple production in the base year. Thus, no expansion of land in apples is allowed, but land allocations to the tree categories using alternative technologies may vary over time based on the yields and costs associated with each technology. The no-expansion assumption can be relaxed and maximum land availability can be specified exogenously for each year of the planning horizon based on the endogenous price trend and elasticity of land supply to apple production. This could be done in an iterative procedure and the model could endogenously determine a possible expansion in the U.S. apple industry. Since our main focus is on technology adoption and potential impacts of technology choices on apple markets, we use the simplified approach implied by constraint (7).

Technology

The technology component of our model centers on growers' planting decisions (only in the United States). Growers choose among conventional rootstock (*con*), conventional rootstock with the application of bio-controls (*bio*), and GM rootstock (*gm*). The different technologies are incorporated into the model through differences in planting, maintenance costs, and yields. The estimates are based on current research findings through personal communication with project participants (Sundin, Korban, and Zhao, personal communication, March 8, 2011). A constraint is included to allow only gradual adoption of the new technologies. The gradual adoption is meant to reflect growers' risk attitudes and their likely hesitation to adopt new technologies. The adoption constraint is

$$\text{(8)} \qquad \sum_d A_{t,a1,d,\text{“}gm\text{”}} + \sum_d A_{t,a1,d,\text{“}bio\text{”}} \leq ar \times \sum_d A_{t,a1,d,\text{“}con\text{”}} \ \forall \ t,$$

where subscript $a1$ specifies the age of newly planted trees (i.e., $a = 1$) and ar is the adoption rate for each specified technology. Note that the land allocation variables in equation (8), previously denoted by $A_{t,a,d}$, include an additional subscript representing technology choices (denoted by *gm*, *bio*, and *con*, shown in the equation in quotation marks). These subscripts for technology choices were actually used throughout the entire model, but for notational simplicity they were not shown in equations (2)–(8).

In constraint (8), we consider a time-dependent adoption rate, ar, to reflect a progressive adoption behavior. Specifically, we set $ar = 0.01 \times t$. For instance, in year 2, the technology can be adopted at a rate of 0.02, meaning that the number of acres planted to biotech varieties cannot exceed 2% of the number of acres planted to conventional varieties. In year 35, the adoption rate is $ar = 0.35$ (i.e., 35% of the total conventional acres planted in apples can employ the new technologies). Finally, as the biotechnology is not yet released, we have lagged the introduction of the bio-control methods to year 6 and GM technology to year 11 (Sundin, Korban, and Zhao, personal communication, August 2011).[9]

[9] This assumption is specific to the biotechnologies analyzed in this particular study. Sundin, Korban, and Zhao are researchers on the Integrated Genomics and Management Systems for Control of Fire Blight research project.

Figure 1. Base Year Apple Production and Age Distribution

Data

Our data consist of current apple production values in the United States and abroad and prices, costs, and current trends in consumption and production. Demand functions for other countries are calculated using the 2005 data from the Production, Supply, and Distribution online dataset (U.S. Department of Agriculture, Foreign Agricultural Service, 2010). We specifically consider the base quantities of apples supplied, processed apples demanded, and fresh apples demanded. The base producer prices for each country were obtained from the Food and Agricultural Organization (FAO) statistics website (www.faostat.fao.org).[10] The demand elasticities were found in the USDA-ERS International Food Consumption Patterns dataset (U.S. Department of Agriculture, Economic Research Service, 2010), and we used the information in Bergtold, Akobundu, and Peterson (2004) to calculate the processed apple demand elasticity parameter from the fresh demand elasticity. We assumed a constant own-price supply elasticity of 0.2 for all countries based on the perennial nature of apples and growers' limited ability to adjust production directly in response to price over the medium run.[11]

The U.S. apple production data are based on published apple age- and variety-specific production surveys conducted in 2005. In the surveys, the apple orchards in the most productive states were reported in acres, and categorized by age and variety (U.S. Department of Agriculture, National Agricultural Statistic Service, Washington Field Office, 2006; U.S. Department of Agriculture, National Agricultural Statistic Service, Virginia Field Office, 2006; U.S. Department of Agriculture, National Agricultural Statistic Service, 2007; U.S. Department of Agriculture, National Agricultural Statistic Service and New York State Department of Agriculture & Markets, 2007; U.S. Department of Agriculture, National Agricultural Statistics Service and Pennsylvania Department of Agriculture, 2010). Through evaluation of the top-producing states, the number of trees for nearly 90% of U.S. apple production was calculated and used to find the division of the total U.S. acres for 2005. The baseline distribution for the age of U.S. apple acreage in 2005 is shown in figure 1. This graph shows that the age distribution is skewed right (more acres of younger trees).[12]

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[10] These base prices are also used in the calculation of the transportation costs, which is approximated to be the difference in the base prices of each country pair.

[11] This value is based on current apple production research—such as the range of price supply responses found in Devadoss and Luckstead (2010)—and was tested for sensitivity. Findings support the use of 0.2 as a lower-end estimate of the technological impact to the U.S. apple industry.

[12] Our timeframe for analysis is thirty-five years. Consequently, no new trees are planted after year 34.

Other data on production costs come from Zhao, Wahl, and Marsh (2007) and include transportation costs from the FAO dataset and removal costs from the management budget in the Pennsylvania Tree Fruit Production Guide (Penn State Extension, 2011). The model's assumptions about technology costs are based on discussions with the scholars conducting research at the Integrated Genomics and Management Systems for Control of Fire Blight project (Korban and Zhao, personal communication, August 2011).[13] Planting costs are the same for the bio-control microencapsulation and the conventional rootstock, as the rootstock does not change in this case. However, the maintenance cost of the bio-control is 1.5% greater than that of the conventional rootstock. The maintenance cost is assumed to be 7% lower for GM than for the conventional rootstock. The GM planting cost is assumed to be 1.5 times that of the conventional rootstock and the bio-control method. These cost differences reflect the data used by Zhao, Wahl, and Marsh (2007) and are based on the production management changes associated with each method and on the costs of chemicals and labor described in the Pennsylvania Tree Fruit Production Guide (Pennsylvania State University, 2011). The 5% yield gain assigned to the GM technology is equal to the typical loss to fire blight that would be recovered when switching from the conventional technology. The yield gain under the bio-control technologies is assumed to be 3%, a portion of the potential loss to fire blight (Korban and Zhao, personal communication, August 2011). Table 1 describes all the variables, parameters, and data sources used in the model.

We used the commercial optimization software GAMS (General Algebraic Modeling System) incorporated with MINOS to solve the quadratic programming model described above.

Results

As a benchmark for the technology adoption analysis, we first analyze the industry in terms of conventional production that does not include the release of technologies. The annual prices and annual production for this base scenario are shown in figures 2 and 3 (figure 3 more closely examines the dynamic price results). We find a general increase in production and corresponding decrease in prices until year 15 or 16, after which we see production decrease and prices slowly increase. The initial increase in production is as expected, as the baseline data were skewed in favor of younger trees; as such, more production is expected as the trees bear fruit. The apple price increases at the end of the model from years 32 to 35, spiking at $299.83/MT. The annual production for this scenario is approximately 381,000 acres. We consider a thirty-five-year horizon; consequently, we observe some noise as we get closer to year 35, and no new plantings occur in year 35.

In the following sections we describe the results from the various technology scenarios. First we evaluate the release of the GM and bio-control technologies. We compare results of conventional production to the results when both technologies are introduced. As GM introduction has an overpowering effect on the production decision, we also consider the release of bio-control technology only and compare it to conventional production. We performed robustness checks to evaluate the assumptions made about GM technology in the areas of maintenance cost, yield variability, and adoption restrictions. A summary of the U.S. results for the analysis is presented in table 2, and the robustness checks are summarized in table 3.

GM and Bio-Control Introduction

When GM and bio-control technologies are introduced, growers plant 415,500 acres, comprising 373,300 conventional, 5,600 bio-control, and 36,600 GM acres. As in the baseline scenario, there

[13] The assumptions are based on personal communications with the researchers on the project and their projections of the costs and impacts of the two technologies based on the cost set by Zhao, Wahl, and Marsh (2007). The 1.5% increase in the bio-control maintenance cost is equivalent to a 20% increase in the cost of the chemical treatments due to the expense of the technology over current methods. The 7% decrease in the GM maintenance cost is equivalent to the cost reduction associated with fire blight treatments.

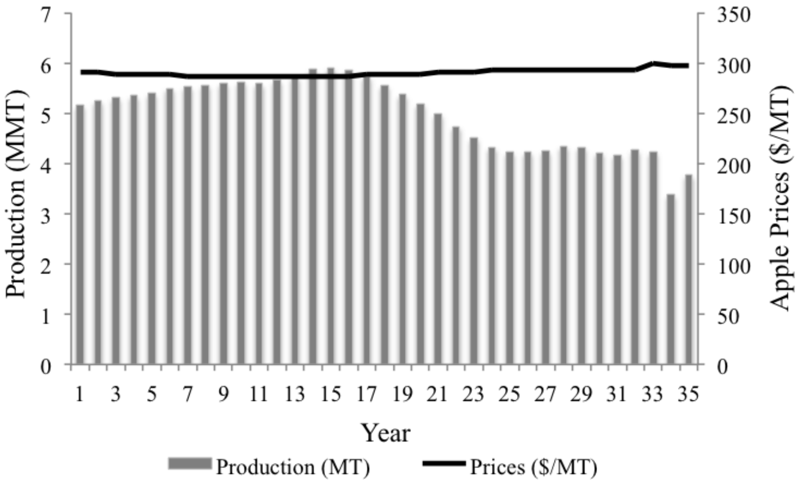

Figure 2. Annual Average Production and Prices for Conventionally Produced Apples

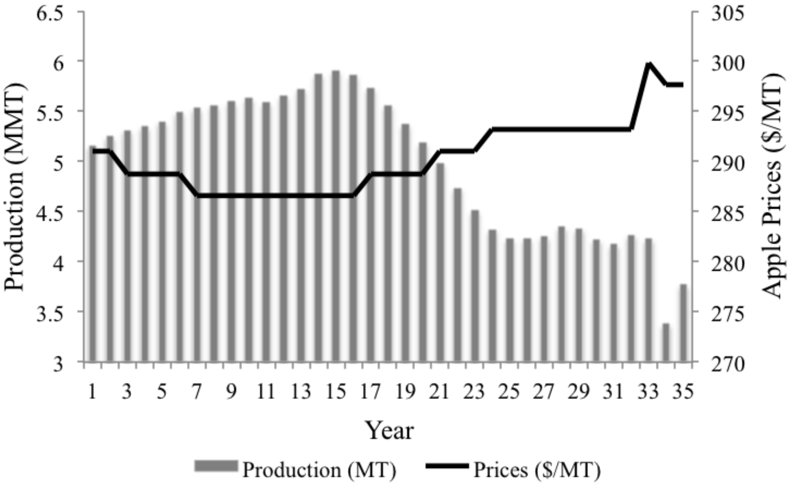

Figure 3. Annual Average Production and Prices for Conventionally Produced Apples, Zooming in on the Dynamics of the Analysis

are no high-density acres. Trees are removed at age 31 or older, but only at the end of the model in years 34 and 35. Bio-control acres are only planted in the years between the release of that technology and the release of the GM technology. The GM acres are planted from year 11 until year 28, and no conventional acres are planted in year 10. Total acreage of apples averages around 381,000 annually. These decisions lead to an average endogenous equilibrium price of $290.232/MT for fresh and processed apples.

The average U.S. grower profit is $266.35 million annually, or $698.80 per acre,, dependent on the age, density, rootstock, and variety of the trees. Maximum profit for the release of both technologies is $344.56 million in year 10, when there are no new plantings of any trees. Minimum profits are seen in year 34 and are $106.15 million, with a price of $295.42/MT. Total annual costs for the apple industry average $1,253 million. The remaining net present value (NPV) for the industry in year 35 is $596.5 million, with $57.95 million in the GM acres remaining and $529.6 million in

Table 2. Summary of the U.S. Results for Each Scenario

	Conventional Production	Bio & GM Introduction	Bio-Control Introduction Only
Avg. Price ($/lb)	0.13	0.13	0.13
Avg. Price ($/MT)	290.44	290.32	290.32
Avg. Acres (1,000)	381.16	380.94	381.16
Horizon Planted Acres (1,000)			
Conventional Low	415.48	373.3	373.30
Conventional High	0	0	0
Bio-Control Low	NA	5.6	42.1
Bio-Control High	NA	0	0
GM Low	NA	36.6	NA
GM High	NA	0	NA
Total Planted Acres (1,000)	415.48	415.46	415.46
World Horizon (million MT)			
Q demand Fresh	1,995.18	1,995.27	1,995.27
Q demand Process	595.38	595.42	595.42
Q supply	2,550.79	2,550.74	2,550.73
Trade (million MT)	236.80	206.47	258.46
U.S. Horizon (million MT)			
Q demand Fresh	85.25	85.25	85.25
Q demand Process	58.10	58.11	58.11
Q supply	183.13	183.31	183.32
Producer Profits (million $)			
U.S. Avg. Annual Profit	262.56	266.35	263.16
Total U.S. Profit Horizon	9,189.65	9,322.34	9,210.70
Max Profit	321.03	344.56	320.95
Min Profit	88.37	106.15	91.23
Average Annual Profit ($/acre)	688.86	698.80	690.44
Remaining Value (million $)			
Total	5,500.81	5,451.28	4,807.90
Total NPV	600.55	596.54	487.81

the conventional acres remaining.[14] The sharp increase in NPV in year 35 is because of reporting the discounted returns beyond the planning horizon as "observed returns" in year 35.

For the thirty-five-year horizon, the total U.S. supply, fresh apple demand, and processed apple demand are 183.3, 85.3, and 58.1 million MT. The world demand for fresh and processed apples for the thirty-five-year horizon is 2,590.7 million MT, of which 595.4 million MT is processed. The world supply is 2,550.7 million MT, of which 206.5 million MT accounts for world trade.

[14] We conducted a sensitivity analysis of the discount rate by using 2% and 10% as alternatives to the 5% rate assumed in the baseline solution. The analysis shows that the management decisions are sensitive to the discounted value in apple production. A higher value for the current dollar encourages a greater switch of acres into the GM technology.

Table 3. Summary of Robustness Checks

	No Adoption Restriction	No Decrease in Maintenance Cost	Only 3% GM Yield Increase
Avg. Price ($/lb)	0.13	0.13	0.13
Avg. Price ($/MT)	290.82	290.82	290.19
Avg. Acres (1,000)	371.35	381.16	380.94
Horizon Planted Acres (1,000)			
Conventional Low	99.1	373.3	373.3
Conventional High	0	0	0
Bio-Control Low	10.2	40.5	8.9
Bio-Control High	0	0	0
GM Low	283.3	1.6	33.3
GM High	0	0	0
Total Planted Acres (1,000)	392.6	415.46	415.46
World Horizon (million MT)			
Q demand Fresh	1,994.61	1,995.28	1,995.21
Q demand Process	595.16	595.42	595.40
Q supply	2,551.15	2,550.73	2,550.77
Trade (million MT)	226.72	242.18	247.77
U.S. Horizon (million MT)			
Q demand Fresh	85.24	85.25	85.25
Q demand Process	58.09	58.11	58.11
Q supply	181.95	183.33	183.20
Producer Profits (million $)			
U.S. Avg. Annual Profit	310.42	276.37	268.09
Total U.S. Profit Horizon	10,864.71	9,672.91	9,383.25
Max Profit	408.23	320.95	344.59
Min Profit	7.27	201.57	211.89
Average Annual Profit ($/acre)	814.42	725.08	703.37
Remaining Value (million $)			
Total	5,146.01	5,452.33	5,341.66
Total NPV	517.74	596.90	602.00

Bio-Control Introduction Only

As the selection of GM rootstock overwhelms the bio-control choice, we evaluate the introduction of bio-control methods for fire blight infections in year 6 to get a clearer perspective on its potential. In this evaluation, growers have a choice to use a microencapsulated biological agent and chemical mix or use traditional antibiotics. Over the thirty-five-year horizon, growers plant 373,300 acres for use with conventional management practices and 42,100 acres intended for use with bio-control technology. These grower decisions lead to an average endogenous equilibrium price of $290.32/MT for fresh and processed apples.

The industry average profit is $263.16 million annually, or an average of $690.44 per acre. The average profits for different tree categories vary, however, depending on the age, density, rootstock, and variety of the trees. The maximum annual profit is $320.95 million, obtained in year 12, with a price of $286.60/MT. The minimum profit for the horizon is found in year 34, with a price of

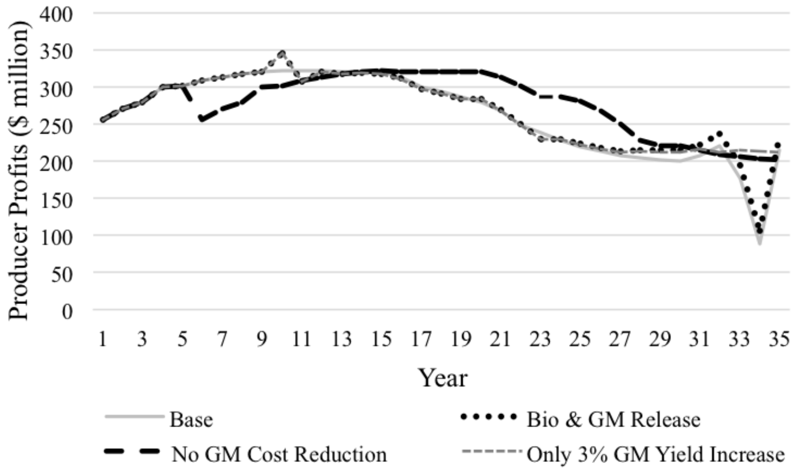

Figure 4. Annual Producer Profits under Different Scenarios

$295.42/MT. In that year, more than 57,000 acres are planted with trees of age 31 and older being removed from the orchards. The remaining value for the conventional and bio-control acres in year 35 is $420.88 and $66.93 million for years following the model's thirty-fifth year.

For the thirty-five-year horizon, the total U.S. supply, fresh apple demand, and processed demand are 183.3, 85.3, and 58.1 million MT. The total world demand for fresh and processed apples for the thirty-five-year horizon is 2,590.7 million MT, of which 595.4 million MT is processed. The total world supply during the same period encompasses 2,550.7 million MT, with 258.5 million MT (10% of the total supply) traded internationally.

Figure 4 compares the average annual profit levels for three of the technology-based scenarios to the conventional technology scenario. The figure shows the impact of the new technology on producer profits, specifically in the technology introduction window following the bio-control and GM introduction. For this time-frame, we see that the market adjusts to the new production technologies and producer profits improve following each technology introduction. In general, we see a steady increase in profits for all scenarios until around year 10. Following year 10, profits steadily decrease until around year 29, when they begin to level out. Because we see this trend in all scenarios, we can explain it as a function of the model's supply and demand specifications. An excess of supply results in a general decrease in prices during that time period. Prices do not recover until after year 20. Price changes are seen more clearly in figure 5. Profit is then able to recover after prices stabilize between years 23 and 30. The end of the horizon experiences heavy investment (drop in profits) followed by increased supply (increased profits). The model design encourages this behavior because it looks at the NPV of the plantings in the final years.[15]

Robustness Checks

We tested the results for sensitivity to the assumptions specific to the technologies evaluated in this research. We found that given no adoption restrictions (growers have no concerns about GM production), GM acres replaced conventional acres in the production mix. With no adoption restriction, the average annual industry profits increased by more than $115.6/acre while planted acres decreased by more than 22,000, or 5.5%, for the thirty-five-year horizon. This reduction in acreage is somewhat higher than expected. However, the increased production from the new technology (due to higher yields and fire blight protection) makes up for the decrease in acreage to meet the demand. When considering no maintenance cost reductions to GM production, we

[15] Note that we are holding demand constant and the model ends in year 35.

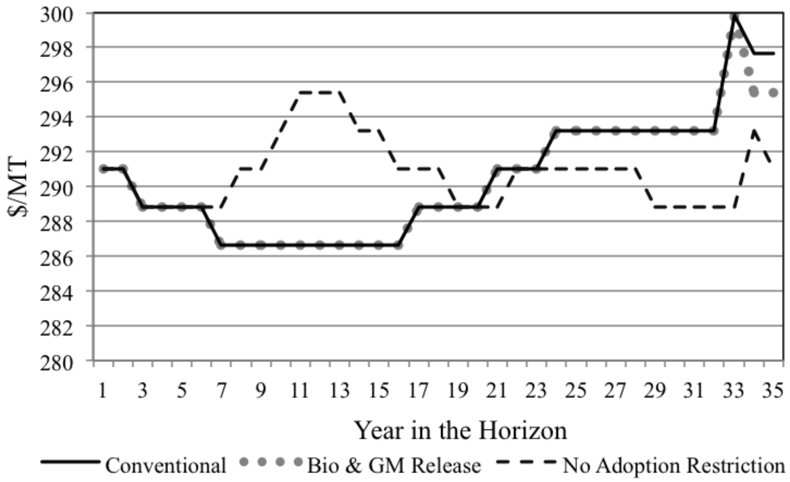

Figure 5. Annual Prices Comparison of Conventional Production to the Release of Both Technologies with and without the Adoption Restricition

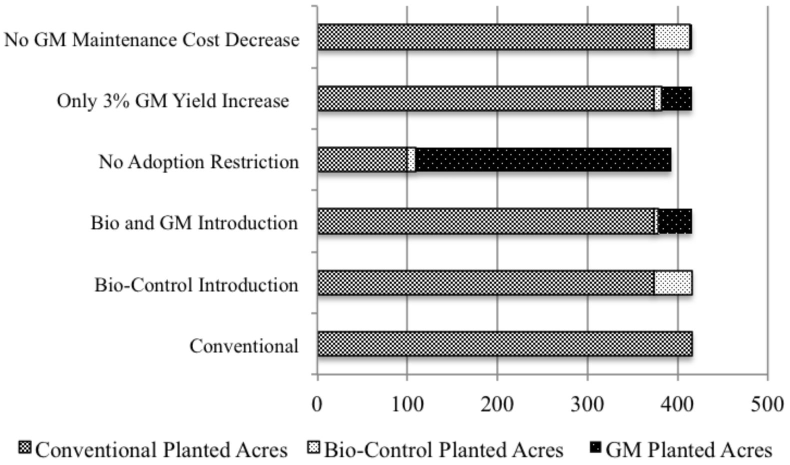

Figure 6. Planted Acreage Totals for the Model Horizon (1,000 Acres)

see a shift of the GM acres to bio-control acres. We also tested the sensitivity of our results to yield-increase estimates. Comparing acreage planted reported in the third column of table 2 to that reported in the fourth column of table 3, we see that under a 3% yield increase from GM production, the number of acres managed under each of the GM, bio-control, and conventional technologies is only negligibly different from the number of acres managed under those technologies when the GM technology provides a 5% yield increase. The summary of the robustness checks is presented in table 3.

Figure 6 breaks down the planted acres for the model horizon of each of the scenarios and robustness checks analyzed. Only when there is no adoption restriction and both technologies are released do we see a definite change in production types, leaning heavily toward the production of the GM technology. Overall, conventional acres hold the majority share of apple acres. When the maintenance cost reduction is removed we see a larger switch from GM to the bio-control technology.

Discussion and Conclusions

In the model results, acres in production were reduced when GM technology was adopted. There is a concern about where the acres are lost. One explanation is based on categorization of the U.S. apple producers into three groups: early adopters, late adopters, and producers who do not adopt (likely small growers). This categorization is realistic even though we do not incorporate specific grower size directly in the model. Early adopters typically see the greatest benefit from the technology. Benefits are usually lower for late adopters, who strain under market pressures and see an even longer delay in recouping costs because of the perennial nature of the crop. The technological change may therefore lead late adopters to decrease acreage in apples. Small growers will be challenged by the high initial costs of the technology, especially if they face capital constraints, and therefore may also reduce acreage. If these growers could find an apple demand niche in their regions, they would have the opportunity for success on a small scale while avoiding the larger market where the new technology dominates. However, these small growers will reduce acres and orchards if no niche market exists.

In reality, U.S. apple growers in some regions are currently shifting to high-density production. Our model seems conservative in that it does not predict this high-density planting, neither in its base scenario nor in any of the new technology scenarios. The assumed magnitudes of higher planting density costs relative to the endogenously determined prices are viewed as a possible reason why the model does not predict high-density planting. Additionally, aggregating all U.S. production in the model limits the selection of high-density planting choices in specific regions, even in the scenarios featuring the new technologies and their boost to production.

Overall, we find that the adoption of GM technology can generate large profits for growers, especially when there are no restrictions on GM adoption. Our results are robust to yield gains from the GM technology (3% and 5%). Producers' welfare still increases if there is no GM maintenance cost reduction, but this is due to a switch to bio-control acres and not the production of GM acres. Generally, if consumers accept the GM technology, its benefits can exceed those of the bio-control method for producers, as shown by the increased profits in figure 4. These results support the underlying motivation of technology use—to help limit production losses and reduce chemical inputs, which can lead to increased profits if the technology is adopted. The agricultural industry has experienced these benefits previously with the introduction of other GM technologies such as Bt cotton (Barnett and Gibson, 1999) and GM corn seed technologies (Brookes and Barfoot, 2005). Our results follow industry and project expectations.

Our analysis finds that, given the benefits of the technologies and the size of the U.S. apple industry, the research done by the scientists in the Integrated Genomics and Management Systems for Control of Fire Blight project has significant value to the industry. We find that the new technologies would bring more than $132 million to the U.S. apple industry over the thirty-five-year horizon. This value can be considered a willingness to invest in the development and implementation of the technologies to help stabilize and secure production. Our results provide estimates of what the technologies mean to the current apple industry when considering currently productive acres. However, there is potential beyond the acres currently in production, and further research could explore the direction that the industry could take on an even larger scale.

The results of our study are consistent with previous literature focusing on production technologies. Moschini (2001), who focused on Roundup Ready technology, and Brookes and Barfoot (2005), who looked at GM technology in crops like soybeans and canola, are only two examples of studies that describe overall positive impacts to the industries in *ex post* analyses. The benefits include lower costs of production, increased production in the orchards, and overall increased profits to the growers. We see the same benefits in our analysis.

Following the release of technologically advanced foods, consumer opinion will have an important effect on consumption. In our analysis, we consider consumer hesitation about the GM technology through the rate in which producers adopt the technology. We consider how producers perceive consumer acceptance or hesitation through producer expectations about the demand for apples. Using an adoption rate quantifies potential producer hesitance about technology adoption, modeling producer anticipation of negative feedback from apple consumers, especially in the case of direct consumer interaction. This assumption improves our estimation of the potential technological impact to the industry. However, further research is needed on this topic.

Our assumptions highlight some limitations that need to be considered for future research and policy implications. Our results are specific to the technologies explored in the Integrated Genomics and Management Systems for Control of Fire Blight project, which have yet to be completed for commercial use. Each technology will have its own important costs and benefits that would need to be carefully analyzed for a specific impact to be measured. Additionally, we assume a fixed upper bound in U.S. apple acreage. This assumption is necessary to narrow the evaluation to the current industry. There is a potential to expand acreage and convert current orchards, pastures, and fields. Future research would need to look closely at possible impacts to other crops and land from the use and acceptance of this technology. Finally, the true consumer acceptance of GM technology is uncertain. While positive strides are being made to understand the health and safety of consumption and consumer opinion, there is still a long way to go.

We have provided evidence that through technology adoption the apple industry can thrive and consumers can benefit. When GM and bio-control technologies are adopted, fewer acres are required to meet demand. We show that maintenance cost reductions and recovering the production losses to fire blight are important to both producers and consumers. The release of the bio-control technology benefits growers and consumers both when there are producer adoption restrictions stemming from consumer concerns about GM products and when GM technology is fully accepted. Consumers see the benefits directly in the form of lower prices. Figure 5 shows the annual prices under: 1) the release of both GM and bio-control technologies (with the GM adoption restriction), 2) the robustness check in the case of no adoption restriction when both technologies are released, and 3) the scenario under conventional production methods.[16] In our analysis, consumers directly benefit from the adoption of either technology because of the general price drop for around twenty years. Consumers also indirectly benefit in terms of a reduction of chemicals used on the crops, by design of the technology (Korban and Zhao, personal communication, August 2011).

The GM and bio-control technologies have the potential to make a great impact on the U.S. apple industry. The technologies' effects on producer income will depend on the demand elasticity of apples. Typically, demand for fruit and vegetables is inelastic and needs a substantial price change to significantly impact the quantity demanded (U.S. Department of Agriculture, Economic Research Service, 2010). Consumption of fresh fruits and vegetables in the United States, however, is limited for families in the lower income brackets, which may be an important determinant of demand inelasticity. Price could play a more important role in demand for apples if the demand elasticity for apples changes as consumer trends, income, or preferences change. Of course, the perennial nature of apple production stabilizes apple supply and makes it difficult for producers to respond to price changes in the short run. Even with the challenges of demand, a careful evaluation of the benefits from GM and bio-control technologies will enable the industry to successfully introduce those technologies. Perhaps the best option for the industry would be to introduce the technologies as a way to recover production while not distorting the market through more traditional government price support policies. Technology adoption can be marketed as stabilizing the industry by reducing fire blight outbreaks. Careful consideration must be made in the approach to consumers. Evaluating consumer benefits and comparing them to producer benefits will be critical to the market viability of the technology.

We find that the GM and bio-control technologies are attractive to the industry regardless of growers hesitate to adopt because of consumer concerns about GM products. Further evaluation of

[16] Figure 5 shows three distinctive pricing situations from this analysis. The robustness check with only a 3% increase in yield prices matches the no adoption rate scenario while the no maintenance cost robustness check and bio-control introduction only scenario follows the pricing of the release of both technologies in the figure.

these technologies with experimental data from the scientists' trials will be important in exploring the impact to the industry and society in more detail. The inclusion of specific experimental data about the impacts on yields and production costs will generate a more accurate impact analysis.

Consumer concerns about GM technology are inevitable, especially, for example, from parents buying food for their children. But unlike prevailing GM technologies that provide herbicide and pest resistance, which transfer genes between crop species, the fire blight technology transfers a gene between currently produced apple varieties. The FDA has already approved GM varieties of apples with characteristics preferred by consumers. Arctic Apple is one company that has recently had two varieties of non-browning GM apples approved (Nosowitz, 2015). These apples have been modified such that the enzyme in the apple that causes the browning of apples after slicing has been removed. They created a similar modification for potatoes that has also been FDA approved. Acceptance of GM soybeans, corn, and cotton is limited in much of the world, although U.S. consumers have come to accept these products. However, acceptance of directly consumable GM technologies could be a different story.

A survey of U.S. residents in 2014 by Lusk, McFadden, and Rickard (2015) provided some insight into the potential demand for genetically engineered food. They found that there is a level of acceptance for genetically engineered food for desirable characteristics such as nutrition, keeping production local, and lowering consumer prices. However, the results of the survey showed a more limited acceptance for less processed foods (Lusk, McFadden, and Rickard, 2015). Concerns are expected and research should be conducted to ensure the safety of consumers eating GM apple varieties.

Our research has implications beyond the U.S. apple industry, as it provides evidence of the true impact beyond production that government funding can have on an industry. The value of the impact and designations of beneficiaries help policy makers understand the impact that they can make. Further research in this area will define policy makers' impacts even more, and applications of these principles can be expanded to other industries and to evaluate potential impacts for future research areas.

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