Effects of trade policy on technological innovation in agricultural markets - implications for the developing economies

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Effects of Trade Policy on Technological Innovation in Agricultural Markets - Implications for the Developing Economies

Lei LEI*

Abstract

An induced technological innovation, which may be biased as a result of policy orientation, can have a complex impact on the traded commodity, particularly in a market with highly differentiated products. Furthermore, especially for developing countries, most of which are based on agriculture, it is important to understanding that impact. This paper aims to study a recent policy change at the European Union, by using an *Ex-Ante* method and a displacement model. The policy change affected global apple exports, particularly for large exporters such as China, South Africa, Chile, and the United States. Considering data availability, the project focuses on the U.S. market to study the impact of the EU's policy-induced, biased, and technological innovation in the U.S. agricultural industry. The results and policies implications are generally applicable to other major agricultural exporters, including those from developing countries.

Keywords: technological innovation, differentiated products, input and output markets

JEL classification: Q12, Q16, Q17

* Research Fellow, Global Value Chains Studies Group, Inter-disciplinary Studies Center, IDE (Lei_Lei@ide.go.jp)

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INSTITUTE OF DEVELOPING ECONOMIES (IDE), JETRO
3-2-2, WAKABA, MIHAMA-KU, CHIBA-SHI
CHIBA 261-8545, JAPAN

Introduction

The increasing global interdependency between countries has induced a new set of technological innovations as a result of food-safety issues and environmental policies in international trade (Hayami and Ruttan 1971; Cavallo and Mundlak 1982; Coeymans and Mundlak 1993; Carletto, De Janvry, and Sadoulet 1996; Macnaghten 2016). Among these technological innovations, some have specifically reformed the agricultural industry (Sunding and Zilberman 2000; Schut et al. 2016). These policy-induced technological innovations sometimes favor certain final commodities, which are most affected by the policy. This study examines the impact of policy-induced, biased, technological innovation in the agricultural industry, from the prospective of developing economies. Following a conceptual model on biased technology for differentiated products, the paper tests the impact of biased technological innovation, focusing on the apple industry. Furthermore, suggestions are provided to policy makers and agricultural producers.

Technological innovation significantly impacts agricultural development (Schultz 1964; Cochrane 1979) and several technological innovations have been induced by government policies and regulations (Sunding and Zilberman 2000). For example, tomato harvesters, which are biased toward labor input, were introduced after the Bracero Program[1] which is implemented in the 1960s. In recent years, food-safety regulations and environmental concerns have led to more intensive research and alternatives to the widespread use of chemicals in many stages of the production process. Examples in agricultural and food markets include the emergence of integrated farm management systems and various biotechnologies (Sunding and Zilberman 2000).

Internationally, food-safety regulation and environmental policies enacted by international organizations and major trade destinations also induce biased technological innovation for countries to 1) fulfill global responsibility; 2) avoid any non-tariff barriers (NTBs) or meet Sanitary and Phytosanitary (SPS) standards; and 3) enjoy favorable prices created by trade constraints. For example, because of its ozone-depleting effects, the use of methyl bromide in agricultural production was scheduled to be banned in the U.S. in 2005 under the Montreal Protocol. As a widely used fumigator in the agricultural sector, especially in the strawberry industry, the economic impact of banning methyl bromide can be significant and complex. Industry groups that invested heavily in developing alternative fumigants were induced by the policy ban and biased toward fumigant input (Carter et al. 2005; Goodhue, Fennimore and Ajwa 2005). Related research studied market responses to the policy ban and to the adoption of alternatives among U.S. trading partners (Braun and Supkoff 1994; Duniway 2002; Byrd et al. 2005).

Agricultural trade is especially important for developing countries because agricultural sectors compose a large percentage of their economies (IDE-JETRO and UNIDO 2013). In addition to various non-tariff measures faced by such countries when exporting to developed countries, technological innovation is another factor that could affect their export markets (Massa 2015; Maswana 2015). Because of strong economic support and research and development (R&D) investment, technological innovations tend to take place first in developed countries before spreading to developing countries. Although missing some exporting opportunities, developing countries take time to adopt technological innovations while observing the market's response to policy changes and induced technology innovations in developed countries. Later, when the induced technology spreads to its own markets, the markets in developing countries can be prepared and have more efficient responses. Producers then can reduce risks when adopting those new technologies.

This paper provides a general framework to study market responses to policy-induced technological innovations, focusing on how biased technology affects differentiated products in different ways. In addition, it examines a specific example of a food-safety policy that caused technological innovation to avoid SPS barriers in international trade. Further, the paper analyzes the potential economic impact of this biased technology, incorporating product differentiation in U.S. apple markets. When studying this example, we derive parallel implications for developing countries from the prospects of innovative technologies, public R&D efforts in agricultural markets, and the development of agricultural trade policies.

Policy Background

With increasing food-safety concerns, the rules governing food production and trade have become more and more stringent. This is particularly true for the chemicals used in agriculture, which may harmfully affect humans if used excessively. To regulate food-safety, Maximum Residue Limits (MRLs) are applied to both domestic and foreign products. However, the heterogeneity of MRL across countries, which frequently causes trade frictions and disputes, has become a major NTB issue (Burnquist et al. 2011; Li and Beghin 2012; Xiong and Beghin 2012).

A recent SPS standard initiated by the European Union (EU) was based on MRL. In August 2013, the EU lowered the MRL of Diphenylamine (DPA) on apples[2] to 50 times below the current standard because of food-safety concerns, allowing a phase-out period until March 2014. DPA is a chemical antioxidant widely applied to control post-harvest, physiological storage disorders in apples. It is the most widely used post-harvest storage method in the apple industry because it is effective, easily accessible, and cost-saving. However, as one of the most popular fruits, apples have been consistently listed near to the top of the annual list of the “Dirty Dozen” because of high chemical residuals (Environmental Working Group 2017). Among chemical residuals, DPA is ranked as the second most often found residual. The EU initiated discussions about such a DPA regulation in 2009, and a final decision was made in 2013 after consulting with trading partners in the World Trade Organization. As one of the world’s leading apple-consuming and importing regions, the EU’s new MRL challenged apple producers and trade operators around the world.

Because several EU member states have a relatively high consumption of apples, the new policy will significantly impact the global apple market, including not only EU member states but also third countries and global food producers. The strictness of the new MRLs not only rules out DPA-treated products but also any cross-contaminated products in the process of storage, packing, and shipping. In general, any industry that has not operated in a DPA-free environment for the last few years will find it difficult to meet the new requirements (USAEC 2013). Regarding this, concerns have been expressed by major apple-producing countries, such as Chile, China, South Africa, and the U.S. The EU’s new MRL bans DPA on apples in most cases. Since these new MRLs for DPA were implemented, the volume of apples exported to the EU has substantially decreased. Only a few shippers have designated special DPA-free facilities that meet the currently allowed MRLs and continue exporting to Europe (USDA FAS 2016).

The EU’s apple market is important for numerous developing as well as developed countries. Among the top 15 apple-exporting countries, by value (based on FAO 2016), are five developing countries: China, Chile, South Africa, Serbia, and Argentina. China, one of the top apple-producing and exporting countries, grows a variety of apples. The local wholesale prices of Fuji apples, a premium variety, have been relatively low and competitive in export markets. However, access to some major export markets, including the EU, has been hampered. In competition with that of Poland, the EU's regional trade is one reason for stricter Non-tariff measures (NTMs), including the new MRLs of DPA (Sijmonsma 2016). To access the EU's agricultural and food markets, China and other developing countries face strict food-safety regulations and standards (IDE UNIDO 2013). It is important to study as to how the EU regulates international food and agricultural trade to foster exports from developing countries.

The U.S. Apple Market

The EU has been an important market for U.S. apple exports, which have moved steadily upward since 1990 (Figure 1). The share of total exports to the EU has been around 7%, slightly increased over that of 2004. The U.K.—the largest import market in the EU—ranks among the top six U.S. apple-exporting destinations and accounts for about 69% of the total U.S. apple exports over the past three decades (USITC ITS 2010). Although Brexit (still in negotiation) could change these figures, other important EU markets, such as Finland, the Netherlands, Spain, and Sweden, exist for U.S.'s apple exports.

Before 2013, SPS barriers existed for U.S. apples entering the EU. However, this new regulation could decrease Washington state's apple exports to Europe by over 50% (Karst 2013). The East Coast of the U.S., another major apple-producing region, also faces challenges. Complaints have been raised from various stakeholders in the apple industry. However, although it is risky to export apples to Europe, most apple industry participants would be reluctant to give up the European market. If the extra supply of apples were domestically absorbed, the U.S. apple market would be depressed. Furthermore, exploring new export destinations could be extremely expensive. In addition, the EU's new MRL regulation has induced attention of other countries on the use of DPA in apples. Similar discussions about reducing DPA in apples have been taking place in other countries (Gillam 2014). Therefore, implementing new equipment, packing lines, and storage rooms may be a sound investment in the long run. If the trade rule becomes permanent, it may lead to a complete infrastructure overhaul, possibly causing the adoption of new technologies and modernization of agricultural practices (Sunding and Zilberman 2001). Although the overhaul brings benefits, it increases producers' costs. The actual effect on producers' welfare can be highly complex, changing according to location, time, and the degree of product differentiation. This paper focuses on measuring the impacts (primarily measuring welfare) of the EU's policy change in the highly differentiated U.S. apple market.

Producers' Responses to Input Bans in Agricultural Markets

Environmental and food-safety concerns have led to bans and other policy changes in the agricultural industry. Previous research has studied technological and non-technological alternatives to the system of banning substances or of becoming compliant to the new standards. Pesticide bans provide strong incentive for the development of alternatives by manufacturers and for the adoption of alternative strategies, including non-chemical treatments and biological control. Examples include the elimination of dibromochloropropane, a chemical that enhanced the adoption of drip irrigation and enabled the application of alternatives (Sunding and Zimmerman 2001). Banning methyl bromide on nursery plants induced both chemical and non-chemical innovations to replace it (Braun and Supkoff 1994; Duniway 2002; Byrd et al. 2005; Carter et al. 2005; Goodhue, Fennimore and Ajwa 2005). These studies reveal that because of policies mandating certain technologies, in the long run, producers were benefited and rewarded for adopting them. However, short-run costs initially caused a reduction in welfare. At the macro level, the impact of the policies, together with biased technology, even affected agricultural trade patterns and production levels for certain regions (Lynch, Malcolm and Zilberman 2005).

Regarding apples, no perfect chemical alternative for DPA currently exists. The only feasible way for apple producers to meet the EU's MRL is farm management, which includes expediting or postponing harvests, shortening post-harvest periods, and enhancing sorting, packaging, transport, and other elements of the post-harvest stage (McPhee 1999).

With public R&D supported by the U.S. government, a recently developed biomarker technology may prove to be a solution because of its easy accessibility, cost savings, and effectiveness in solving post-harvest apple storage problems. This metabolic and genetic biomarker could predict, diagnose, and distinguish potential post-harvest disorders, allowing marketers to release their products before the disorders evolve too far. It ensures that high-quality and disorder-free products remain available throughout the supply chain. The biomarker technology is an effective alternative of DPA in various ways. For instance, it shifts apple storage from "treatment-type" to more economically feasible, sustainable, and management-based systems. A biomarker favors high-value, more susceptible apples in particular, and enhances their yield. To better evaluate the economics of biomarkers on high- and low-value commodities, while assessing the welfare of producers and consumers, this paper simulates the possible impact of biomarkers on the prices and quantities of apples at both the retail and farm levels,.

Conceptual Model

Biased technological innovation has played a significant role in social development and economic growth. Labor and capital savings plus neutral technological progress lead to different forms of economic growth (Ruttan and Hayami 1984; Lucas 1988; Helpman 1998; Card and DiNardo 2002). Previous research on biased technology focused on relative factor prices, factor proportions in production, equilibrium analysis of technology adoption, and economic growth (Kennedy 1964; Romer 1990; Acemoglu 2007). These papers studied biased technological innovation from producers' perspectives on adopting such technology in order to minimize cost and to enhance firms' ability to maximize profit. However, most of this work focuses on how biased technology directly impacts factors rather than how it impacts the output of using the technologically innovated biased factors. In addition, this paper studies how classical, biased technological innovation favors different outputs in industries with highly differentiated products. As these commodities require different factor amounts in production, they are affected by biased technological innovation in different ways; such innovation favors certain commodities through the factors toward which it is biased.

The model is set up according to the basic set up of a producer profit maximization problem. Consider a producer who produces two products, y_1 and y_2, using two factors, x_1 and x_2. y_1 and y_2 are two different types of products of the same commodity (one is an imperfect substitution of the other). They are differentiated by certain commodity characteristics. Factor ratios are fixed but distinct in the production of y_1 and y_2. Producing both products requires two common factors x_1 and x_2. Product y_1 is relatively more intense in factor x_1 than product y_2. In other words, producing one unit of product y_1 requires more x_1 than producing the same amount of product y_2. In our case, suppose a technological innovation biased toward factor x_1 is used in the production of both y_1 and y_2. Consider the objective function of a profit-maximizing producer who operates in a competitive goods market, facing given factor and goods prices, as follows:

$$\max_{x_1,x_2} \quad \pi = \pi^1 + \pi^2 = [P^1 g(x_1^1, x_2^1) - w_1 x_1^1 - w_2 x_2^1] + [P^2 g(x_1^2, x_2^2) - w_1 x_1^2 - w_2 x_2^2]$$

The superscript indicates output and the subscript represents input. P is the output price. Products y_1 and y_2 have different prices and are not perfect substitutes for each other. g, the production function of output commodities for both the products, is a real-valued function and is twice continuously differentiable (the first derivative with respect to x_1 is monotonic and increases its evaluation at x_1). Products y_1 and y_2 are produced using the same production function, but product y_1 is x_1-intensive relative to product y_2. In addition, w_1 and w_2 are the prices of x_1 and x_2, respectively. Technological innovation enters the profit maximization problem by affecting the production function g.

A biased technology that augments x_1 favors the production of commodity y_1, which is relatively x_1-intensive in production. Adopting the technology increases the cost because the factor price of x_1 increases from w_1 to w_1^t. With the new technology, the producer who only produces product y_1 will increase his profit, π_1. This can be seen from the first-order condition. With the technology, the marginal product of factor x_1 increases while the factor price of x_1 increases to w_1^t. For the biased-technology-favored commodity y_1, $P^1 g_{x_1}(x_1^1*, x_2^1*) > w_1^t$. The producer could increase his profit π_1 by augmenting x_1. The marginal unit of x_1 contributes $P^1 g_{x_1}(x_1^1*, x_2^1*)$ to revenue but costs the producer only w_1^t. Hence, using more x_1 in production would generate more revenue than the associated cost. This is a net addition to profit. The producer will continue doing this until the first-order condition holds with equality again. This process is shown in Figure 2a. With biased technology, the initial equilibrium point for profit maximization (x_1^1*, x_2^1*) moves to (x_1^1*', x_2^1*'), which is the new tangent point of the new iso-cost and iso-quant lines. The slope of the iso-cost line changes due to the increased factor price of w_1^t. The new iso-quant line is not parallel to the original one because of the x_1-augmenting technology, indicating that the marginal product of x_1 increases faster than that of x_2. In the new equilibrium, the producer increases his use of x_1 and produces more y_1 for a higher profit.

On the other hand, with the technology biased toward factor x_1, the producer who only produces y_2 will earn less or even experience a drop in profit π_2. The reason behind this is that as the quality and productivity of product y_1 improves with the new technology, its price increases and the price of product y_2 decreases, assuming that only two products exist for the same commodity. Meanwhile, given the production function $g_{x_1}(x_1^2*, x_2^2*) < g_{x_1}(x_1^1*, x_2^1*)$, and depending on the value of w_1^t, it is possible that product y_2 has a first-order condition $P^2 g_{x_1}(x_1^2*, x_2^2*) < w_1^t$, the value of the marginal product of x_1, less its market price. The producer profit π_2 decreases because the additional revenue of one more unit of x_1 is less than the marginal cost of using one more unit of x_1. This process is shown in Figure 2b. With biased technology, the initial equilibrium point for profit maximization (x_1^2*, x_2^2*) moves to (x_1^2*', x_2^2*'), which is the new tangent point of the new iso-cost and iso-quant lines. The producer continues production in order to reach a new profit maximization, where the use of x_1 is actually reduced. If the π_2 profit does not decrease initially, it will decrease later. As product y_1 increases profits, resources will move to produce y_1 from y_2. Gradually, the producer who only produces y_2 will see lower profits.

To balance the risks of technology adoption, producers benefit from including both products. Whether the producers of both the products will benefit from biased technological innovation depends on their production shares of y_1 and y_2. On the basis of the above conceptual model, this paper proposes the following hypothesis:

H_0: Technological innovation biases favor intensive product factors. However, this could lower the manufacturing of products with less intensive biased factors.

In the following section, this paper will test this hypothesis using a simulation analysis. To avoid potential profit loss caused by the adoption of new technology, producers could diversify their product lineup to include both commodities, which would show gains and losses.

A simulation model is developed to test the hypothesis, using data from the U.S. apple industry. Apple production consists of marketing and farming, and storage is part of farming. The biomarker is biased toward marketing in apple production. As a highly differentiated commodity, apples are susceptible to post-harvest disorders. These highly susceptible apples are more valuable, with higher market prices, whereas non-susceptible apples are less valuable (House 2012). Therefore, in the apple industry, the biomarker, which favors the former type of apples, will increase the profits and welfare of apple producers. The biomarker will have a smaller impact on less-valuable apples and their producers. To avoid losing the biomarker, apple producers could produce high-value and less-valuable apples. This paper develops an equilibrium displacement model of the apple industry in order to simulate the impact of biased technology on different stakeholders in the industry, in specific producers of different apple varieties.

Modeling the Apple Industry

As biomarker technology is still in the testing stage, an ex-ante approach is adopted, following the frameworks typically used by agricultural economists to analyze new technologies. Because of highly differentiated characteristics across products in the apple market, this paper explicitly takes into account the interrelationships 1) between input usage in different output markets; 2) between different categories of apples, defined by variety and grade; and 3) between domestic demand and export demand. It also considers exogenous policy shifts in input markets, technology adoption that causes shifts in input markets, and long-run shifts in consumer demand in output markets.

To better study the impact of policy-induced technological innovations that are biased toward certain policy factors or commodities in the agricultural sector, special attention must be paid to the degree of agricultural product differentiation. “Over the years, product differentiation in agriculture has increased along with an increase in the importance of factors beyond the farm gate and within specialized agribusiness” (Sunding and Zilberman 2000). This evolution is affecting the nature and analysis of agricultural research. When a policy-induced, biased technology enters the economy, it is important to study the vertical market structure of agriculture and how farm-level innovation may contribute to changes in both downstream and upstream sectors (Alston, Sexton and Zhang 1997; Hamilton and Sunding 1998).

The model is based on previous simulation studies that evaluate the impact of the biotechnologies that are adopted in agricultural markets (Binswanger 1974; Heuth and Just 1987; Lemieux and Wohlgenant 1989) and extended to incorporate biased technological impacts in multi-input and multi-output models. Here, exogenous shocks are imposed by considering the vertical linkage of multi-input and multi-output markets. The linear elasticity model is compatible with parameter values selected through econometric or programming approaches. In addition to the agricultural industry’s major empirical contributions in policy making and technological innovation, this paper’s analysis could be generally applied to other markets with highly differentiated products.

As a widely consumed and popular commodity, about 20 major varieties of apples are planted in the U.S. Stakeholders in the commercial apple industry include apple orchards, storage carriers, packing facilitators, and wholesalers and retailers in international markets. As shown in Figure 3, this model simplifies the apple market. As this paper focuses on the EU–U.S. apple trade, subject to the EU’s SPS regulation in the output market, representative varieties of apples are selected as follows: 1) varieties exported to the EU market (Empire, Gala, Honey Crisp, and Granny Smith) and 2) varieties that suffer most from post-harvest disorders (Honey Crisp, Granny Smith, and Empire). Of the four varieties of apples exported from the U.S. to the EU, three are highly susceptible. These varieties suffer from the following disorders: Empire (browning, external CO_2 injury), Honey Crisp (soft scald), and Granny Smith (superficial scald). Gala is a non-susceptible variety. Empire, Honey Crisp, and Granny Smith apples are higher-value apples, garnering higher market prices, whereas Gala is relatively less expensive. Therefore, the former group is considered high-value (H-type) and the latter is low-value (L-type).

In addition to variety-based classification, apples are also categorized by grade. Apple grades are based on size, shape, color, and overall quality. Higher-grade (E) apples are sold as a fresh fruit while culls (C) usually are processed to make juice, jam, and apple sauce. Combining these classifications, this paper studies four types of apples: higher-value high-grade (HE), higher-value culls (HC), lower-value low-grade (LE), and lower-value culls (LC). The high- and low-value classification of apples directly captures biomarkers' biased impact of preferring storage as an input. Further grade classification explicitly studies policy and induced technology impacts. Higher-grade, exported apples are directly affected by the EU's SPS regulation, while culls (C) are not. In addition, induced, biased technological innovations (i.e., a biomarker) could "upgrade" culls to higher-grade (E) apples. The detailed classification of apples is used to capture product-level details and substitution effects in the apple market.

Our model includes two inputs: farm inputs and marketing inputs. Storage of apples is a major component of farm input, and apple varieties determine the required farm input. Farm inputs are used for both higher-value (FH) and lower-value apples (FL). Apple grades determine how much marketing input is needed. Marketing inputs are used for higher-grade apples (ME) and culls (MC). In general, higher-grade apples require less marketing input than culls (Stewart et al. 2011). Considering this fixed-factor proportion assumption, for a given grade, higher-value apples use more farm input per unit (which includes storage) than lower-value apples. In other words, FH is greater than FL. For a given variety, higher-grade apples use less marketing input than culls, and thus, ME is less than MC.

The simulation model was developed to assess the impact of exogenous policy and technological innovation shocks in the highly differentiated U.S. apple market's open economy. A set of basic equations is used to describe national demand, export demand, supply, and the corresponding factor markets. This equilibrium displacement model includes markets for four outputs and two factors. As a simplification of the U.S. apple market, it captures critical characteristics found in the industry and provides a useful framework to examine the impact of policy change and biased technological innovation. The model is as follows:

(1) $QD^i = f^i(P, A^i)$

(2) $QX^i = g^i(P, AX^i)$

(3) $QS^i = QD^i + QX^i$

(4) $P^i = MC^i(W)$

(5) $XD_l = \sum_{i=1}^{N} \frac{\partial c^i(W_l, 1)}{\partial W_l} QS^i$

(6) $XS_l = h_l(W_l, B_l)$

(7) $XD_l = XS_l$

Apple output is denoted by superscript i and input is denoted by subscript l. In the output retail/wholesale market, variable QD represents domestic apple demand, with an exogenous demand shift A in the output market. Variable QX represents apples exported abroad (international and country-specific apple demand), subject to an exogenous shift *AX*. Variable P is an apple price vector, which assumes that domestic prices equal the world price. Variable QS represents apple supply. For the two input markets, XS represents input supply and XD is a derived input demand (a constant-output, demand-input function). Factor prices of farm and marketing inputs are denoted by W. The adoption of new technology biomarkers brings an exogenous shift to the input supply, represented by B. In equations (4) and (5), MC is the marginal cost function, and $c^i(W_l,1)$ denotes the unit cost function.

Equations (1) and (2) represent domestic and export demand for output apple *i*. Equation (3) shows the clearing condition of the apple output market. Apple *i's* retail and wholesale price equals the marginal cost of producing it. Equation (4) shows the competitive equilibrium, which is the price linkage between output and input markets. Equation (5) is the derived demand function of input *l*. The summation of XD_l^i across all varieties of apples generates total input demand *l*, which indicates the input market equilibrium. Equation (6) is the supply of input *l*. The last equation (7) is the clearing condition of the input market.

For the simulation, differentiating the above model yields equation (1') to equation (7'). Equilibrium adjustments can be simulated by exogenously specifying changes in the shift parameters. In the following equations, for any variable V, notation E(V) represents $\frac{dV}{V}$, where *d* is the total differential.

$$(1') \qquad \mathrm{EQD}^i = \sum_{j=1}^{N} \eta^{ij} \mathrm{EP}^j + \alpha^i$$

$$(2') \qquad \mathrm{EQX}^i = \sum_{j=1}^{N} \eta x^{ij} \mathrm{EP}^j + \alpha x^i$$

$$(3') \qquad \mathrm{EQ}S^i = S^i \mathrm{EQD}^i + (1 - S^i)\mathrm{EQX}^i$$

$$(4') \qquad \mathrm{EP}^i = \sum_{l=1}^{M} \gamma_l^i \mathrm{EW}_l$$

$$(5') \qquad \mathrm{EXD}_l = \sum_{i=1}^{N} \lambda_l^i \sum_{k=1}^{M} (\gamma_k^i \sigma_{lk}^i \mathrm{EW}_k + \mathrm{EQS}^i)$$

$$(6') \qquad \mathrm{EXS}_l = \varepsilon_l \mathrm{EW}_l + \beta_l$$

$$(7') \qquad \mathrm{EXD}_l = \mathrm{EXS}_l$$

Notations for share and elasticity parameter values used in the simulation are reported in Table 1. A detailed definition of the model's parameters is provided in the following section.

Data and Parameters

Apple data from the Washington Grower Clearing House for 2011–2012[3] are used in the model's simulation[4]. Weighted average monthly prices at "Free On Board" shipping points are used on the basis of the price information received from Washington apple growers and marketing firms in the area, considering sales price adjustments. A calculation is made to obtain the annual price, and a similar calculation is applied for apple quantities in two seasons. All quantities are measured in "Cargo," which contains 1000 40-pound cartons. As mentioned before, three varieties, Empire, Honey Crisp, and Granny Smith, were selected as high-value (H) apples. Price and quantity data for high-value apples were calculated and weighted by the market share of each variety. For apple grade, Extra Fancy and Fancy (including U.S. #1) apples were considered of the higher-grade (E). No direct data about culls (C) are available. Therefore, an average [packout rate][5] of 85% was used to calculate cull quantity on the basis of the data regarding higher-grade apples. Table 2, which shows the data used in the model, lists the quantity and price data of the four outputs and two inputs used in each output production.

Given the apple prices and quantity data for retail and wholesale markets, input prices and quantity data are calculated on the basis of a fixed-factor proportion assumption. Isolating apple output by variety is done to distribute the total farm input, which is distinguished only by variety. Similarly, isolating apple output by grade is done to distribute marketing inputs, which vary only by grade. As per the model's setup, the key parameters in evaluating the economic impact of the biomarker are (1) the elasticities of supply, demand, and export demand; (2) cost and industry share; and (3) policy shocks on the output demand side and shocks from adopting a new technology on the factor supply side.

Parameters in (1) were first obtained from baseline values in relevant literature. Then, following the studies by Davis and Espinoza (1998, 2000), Griffiths and Zhao (2000), Zhao et al. (2000), and Rickard and Lei (2011), I applied prior distributions to these parameters for a sensitivity analysis. I set the baseline parameter as the central tendency and specified a variance of 0.04 to develop beta (3,3) distributions (Brester, Marsh and Atwood 2004). The beta distribution is ideal for generating elasticity parameters because it is continuous and symmetrical when parameters are equal and equivalent to a uniform distribution when parameters equal to 1. It is often used to model events that are constrained and take place within an interval defined by minimum and maximum values. The beta distribution selected here constrains demand elasticities to be negative and supply elasticity to be positive. Iterated 1,000 times, random values are drawn for the parameters to generate empirical distribution results.

Following previous estimates about supply elasticity from previous literature (Nerlove and Addison 1958; Gardner 1979), the baseline supply elasticity parameter for apples was set to 0.5 because the supply of fruit is relatively inelastic. Furthermore, all cross-price elasticities of supply are set to zero because apples are perennial crops (Rickard and Lei 2011).

The domestic matrices of own- and cross-price elasticities of apple demand η^{ii} and η^{ij} are calculated following the Armington specification (Armington 1969).

(8) $\eta^{ii} = \varsigma^{i}\eta - (1-\varsigma^{i})\sigma$

(9) $\eta^{ij} = \varsigma^{j}(\eta + \sigma)$

The Armington specification is typically used for calculating the elasticity of differentiated commodities. It extends the homogeneous goods model to examine the demand response for differentiated goods (Rickard and Lei 2011). In this paper, it is used to define the matrix of own- and cross-price elasticities of apple demand, differentiated by both variety and grade. In equations (8) and (9), the overall demand elasticity η and the elasticity of substitution across the four different apple types σ are set as equal to baseline values from the literature. The baseline value of the overall demand elasticity η is based on the demand elasticity of the top eight apple varieties,[6] as estimated by Richard and Patterson (2000). I averaged and weighted them by the market share of these varieties of apple, and the value was calculated to be −0.762. The baseline value of the substitution across apples, σ, is set equal to 1, following range estimates used in the literature on agricultural economics (Alston, Gray and Sumner 1994; Rickard and Lei 2011). Substitution between fruit products has not been directly estimated and is not available in previous literature. Simulation results are relatively independent of the baseline elasticity of substitution, and results are robust across a range of plausible values.

Several studies (e.g., Alston, Gray and Sumner 1994) have discussed the limitations of the Armington specification. However, based on the specific differentiation of apples in this paper and data availability, the Armington specification is an appropriate method to generate the matrices of elasticities. The same method is applied for export demand elasticity. The only difference in this specification, with regard to the Arlington specification, is the overall demand elasticity for exports, which is set to –1.5—more elastic than domestic estimation—on the basis of the estimates by the U.S. International Trade Commission (2010). On an average, between 2004 and 2008, about 8%–16% of U.S. apple production was exported. Simulation results are robust for demand elasticity's chosen value, within a range of -1.0–-2.5.

Parameters in (2) are shares calculated from the data on quantity and by applying certain assumptions. The share of consumption S derives from the apple export studies by the United States International Trade Commission (USITC) (2010), from the data in Table 2, and by following assumptions and common knowledge supplied by stakeholders in the apple industry (Washington Grower House 2012; Reed, Elitzak and Wohlgenant 2002). The cost share of input γ_l^i is calculated following the "20% and 80%" rule (Stewart et al. 2011), which states that for each dollar invested in apple production, 80 cents are used for marketing and 20 cents are used for farm production. For industry share λ_l^i, I assume that higher grades of apples usually need less marketing than the lower ones. Higher-grade apples require a smaller share for marketing (65%) but a higher one for farming (35%). The cull percentages are 85% and 15%, respectively. The Allen elasticity of substitution σ_{lk}^{i} is assumed to be 0 across different inputs on the basis of the fixed-factor proportion assumption, and 1 for the same input (Sumner, Lee and Hallstrom 1999; Rickard and Lei 2011).

Parameters in (3) represent exogenous shocks. Parameter α^{i} describes the EU's SPS regulation change and estimates a policy shock in the simulation model. Considering that new SPS regulations were implemented on March 2, 2014, no accurate data is available to estimate this parameter. About 23% U.S. apple exports go to the European market (USITC 2010). With the new SPS regulation, exports from the two major U.S. apple-growing and exporting states, Washington and New York, are expected to drop noticeably. Between 8% and 16% of U.S. apple production was exported annually between 2004 and 2008 (USITC 2010). The maximum 16% figure produces a calculated 5% drop in apple demand. As higher-value apples are susceptible to post-harvest disorders and are being exported to the EU, high-value and higher-grade apples will get the most affected by the policy shock. I assume that the same shock will affect export demand for U.S. apples.

Parameter β^{i}, which describes technological change as an exogenous variable, is used in the simulation model to introduce shocks caused by biased technological innovation. The biomarker increases marginal farm input products. On the other hand, apple producers pay to buy the biomarker and thus the difference between them will be a net shock applied to farm input. Due to limited data availability and the complexity of the impact, some assumptions and approximations are made in the calculation. A biomarker could "upgrade" low-grade apples to higher-grade apples, i.e., from culls to high-value apples. Given an 85% packout rate, 50% culls can be upgraded to higher-grade apples after applying the biomarker in the post-harvest stage.[7] As a result, the new packout will be 92.5%, with a 7.5% improvement. The biomarker has not been priced yet because price data are required to understand consumers' willingness to pay. For now, based on the information provided by the biomarker developer, production cost is quite low. I assume that adopting the biomarker will only increase farm input cost by 2.5%. Therefore, for higher-value apples, the net benefit of farm input for adopting technological innovation is 5%.

Measuring Welfare

Simulated changes are reported for prices and quantities as a result of the EU's policy change. Welfare changes accruing to consumers and producers are measured using information about initial product prices and simulated changes in product prices and quantities. To obtain a mean prediction of changes in surplus measures, 1,000 iterations are repeated in the simulation model. Each iteration draws values for elasticity parameters from empirical distributions that rely on estimates in the literature while initial prices and quantities remain the same across all iterations. As welfare is calculated on the basis of a range of elasticities with fixed prices and quantities, welfare results as well are generated as distributions. Studying welfare results provides a better understanding of the impact of technological changes.

The following equations are used to calculate welfare accruing to consumers of product *i* and to producers from factor *l*. Policy changes or technological innovations in the market are reflected by the variables EP, EQD, EW, and EXS. Therefore, the following equations capture changes in welfare:

$$\Delta CS^{i} = -P^{i}QD^{i}EP^{i}[1 + 0.5EQD^{i}] \qquad (10)$$

$$\Delta PS_l = W_l XS_l EW_l [1 + 0.5 EXS_l] \qquad (11)$$

The initial price and quantity of apple *i* and the initial price and quantity of factor *l* are shown in Table 2. Factor quantities are calculated on the basis of output quantities, following the fixed-factor assumption, and each value is weighted by market shares of different apples. Factor prices are calculated according to the "80%/20%" rule based on output prices and are weighted by market share.

Results and Discussion

Below are the results for four simulations:

1. A 5% decrease in export demand for high-value, higher-grade apples because of the EU's SPS regulation change. No other changes to apples occur.
2. A 5% increase in the farm input for high-value apples because of new, biased technology. No other changes to apples occur.
3. Simulations 1 and 2 simultaneously
4. With consumers recognizing biomarker-treated apples, a 15% increase in both domestic and export demand takes place for high-value and higher-grade apples, in conjunction with Simulation 2.

Simulation 1 captures the EU's SPS impact on the U.S. apple market. A 5% exogenous shock is applied to high-value, higher-grade apples, because this type of apples, highly susceptible to post-harvest disorders, is the most affected by the change. Using DPA is a must in its storage. Higher-grade, fresh apples are primarily exported to the European market (USITC 2010).

Simulation 2 adopts new biomarker technology.[8] The 5% net biomarker benefit is imposed on farm input, specifically on farm inputs used for higher-grade apples because benefits primarily derive from culls upgraded to higher-grade apples.

Simulation 3 compares policy and technology impacts to determine the effectiveness of biomarker technology. Can it be an effective, alternative method to avoid using DPA, so that U.S. apples can comply with the new MRL set up by the EU? Will it be able to mitigate the impact of certain policies in the U.S. apple market? If so, to what extent? Simulation 4 shows the long-run result. If the biomarker is an effective alternative for the DPA, the U.S. market will see no more policy shocks. Given the function of the biomarker, it should be well accepted by consumers because treated apples will not suffer post-harvest disorders (i.e., flesh browning, superficial scalding, and other issues). This will increase consumer demand for such good-quality apples. Although consumer demand for this type of apples may change, lower-grade apples also are expected to experience a quality upgrade with biomarkers. Therefore, the supply of different types of apples changes. Given that the share of higher-grade apples of each variety is 85%, and the market share of the three high-value varieties selected here is about 17%, a conservative estimate of the increase in consumer demand is set to 15%.

Each simulation imposes exogenous shock(s) to the system of equations and generates empirical distributions for changes in prices and quantities as well as welfare changes for the four apple outputs and the two input factors used in the four outputs. Empirical distributions are used to calculate the mean and a 95% confidence interval for price, quantity, and welfare variables across 1,000 iterations (more iterations have been calculated but the results do not differ greatly. Therefore, I report the mean value in the results table, plus a 95% confidence interval).

Focusing on the supply side, Table 3 shows the price and quantity effects of apple output and input markets. The four columns correspond to each of the simulation scenarios. The first column represents when the U.S. apple market is subject to the policy change. The EU's SPS regulation change affects apples with post-harvest disorder problems exported to the EU. With a natural decrease in apple export demand from the European market, the supply of high-value, higher-grade apple product declines by 16.73%. This drop is distributed into a 13.98% decrease in farm input and a 0.12% increase in marketing input. The decreased farm input supply also affects high-value culls by −0.58% because high-value apples have intensive farm input. Decreasing the supply of all high-value apples leads to increasing production of low-value apples in both the grades, in the form of consumer substitutes. Therefore, the policy shock decreases supply (and demand) for all high-value exported apples but has a positive effect on low-value apples. The derived demand of farm supply decreases, principally because of lower MRL in the EU. Before an effective alternative is introduced, this trend is expected to continue.

In the second scenario, adopting a biased technological innovation increases the farm factor supply of high-value apples by 2.34%. Together with marketing inputs, the retail-level supply of three types of apples (excluding high-value culls) increases. A lower supply of high-value culls proves the effectiveness of the biomarker, which "upgrades" apples by avoiding further post-harvest disorder problems. This "upgrading" partly contributes to increased high-value, higher-grade supply. Retail prices of apples change accordingly, depending on the equilibrium status of the retail market. When biomarker technology is the only shock to the apple industry, the new technology seems to be an effective alternative to banning farm input.

It is meaningful to compare the results of simulations 2 and 3 in order to emphasize the bias of technological innovation. Despite the presence of both policy changes and a biased technology, high-value apple supplies still drop (by −12.19% and −0.02%). However, these lower grades for high-value apples are smaller than the results in Simulation 1. Moreover, all the results listed in column 3 have the same sign as those in column 1, but the absolute values of all the negative changes are smaller in Simulation 3 compared to those in Simulation 1, and the values of all the positive changes are larger than those in Simulation 1. Therefore, biomarker technology effectively mitigates the effects of the EU policy ban on the U.S. apple market.

In the long run (Simulation 4), a biomarker is accepted by consumers, which stimulates the production of better-quality and higher-grade apples. With positive impacts from both the biased technology (+5%) and consumer recognition (+15%) on high-value, high-grade apples, farm supplies of high-value apples increases by 3.49% (compared to 2.34% with biomarker adoption only in Simulation 2). Low-value apple production decreases by 0.53% (compared to −0.01% with the biomarker alone in Simulation 2). Meanwhile, 0.03% less marketing input is needed to sell high-value apple products, but 0.04% more is required for low-value apple products. Apple producers have to put more effort into promoting the sale of low-value apples. This result can also be observed at the retail level. Both the grades of high-value apples increase—4.18% for higher-grade apples and 0.15% for culls, whereas decreases of 0.65% and 0.003% occur for low-value higher-grade apples and low-value culls, respectively. More high-value apples and fewer low-value apples are demanded and supplied. As a result, prices of high-value higher-grade apples increase by 1.98%, which lead to higher profits for producers.

In addition to price and quantity results, the four simulations in Table 4 present welfare changes. In the first column, the SPS regulation change causes farm input producers to lose $7.86 million from high-value apple markets and $360,000 from low-value markets. Marketing input producers gain a surplus of $11.32 million from higher-grade apples but lose $20 million from culls. Producers are worse off in general, especially those who produce high-value higher-grade apples that are affected by the EU policy ban. Consumers of high-value higher-grade apples lose $79.91 million because of the policy change, for two reasons: 1) they realize the health risks of consuming high-value higher-grade apples and 2) fewer high-value higher-grade apples are available. Thus, they might be better off consuming low-value apples.

Producers who market high-value apples, using farm inputs with biased technology, are more profitable, earning $1.13 million. While the producers of low-value apples are also better off, their profits increase by a lower $180,000. In the third scenario, which incorporates both policy and technology shocks, the impact of biased technology becomes a more dominant measurement of welfare. With a policy specifically imposed on high-value higher-grade apples, the biomarker benefits producers of high-value apples but harms the producers of low-value apples. The producer surplus for the former is $14.91 million and negative $4.56 million for the latter. Furthermore, in Simulation 4, with greater consumer demand for high-value apples, the producer surplus is $24.26 million, much more than in Simulation 2. Higher demand for high-value higher-grade apples helps these apples' producers. At the same time, producers of low-value apples suffer a loss of $5.82 million. The 1.98% retail price increase of high-value higher-grade apples costs consumers about $474.9 million.

Implication and Conclusions

This paper focuses on the relation between trade policy and biased technological innovation in agricultural markets in order to examine how market production and consumption influences stakeholders' welfare. While it focuses on the U.S. apple market, its conclusions and implications can be applied to other countries, including developing countries. The EU's altered SPS regulation on imported apples has directly affected storage of apples (farm input). A biased technological innovation is a potential solution to the policy change. This paper evaluates the impact of trade policy changes and corresponding technology adoptions to highlight the effects of agricultural trade in a market with highly differentiated products. In addition, it tests a hypothesis about biased technology to provide suggestions to exporters and stakeholders about production decisions and technology adoption.

Simulation 1 examines the impact of a European trade policy change on the U.S. apple market. Although the EU market accounts for only about 16% of U.S. apple exports, as a result of the complexity of NTBs in agricultural trade, it has a large impact on the U.S. domestic market. As long as U.S. apple producers continue exporting to the European market, they will have to rebuild storage, sorting, packaging, and transportation facilities to avoid cross-contamination and to meet the EU's new MRL. Producers who achieve this will be able to earn substantial profits. Other producers will have to completely forfeit the EU market.

The policy has a negative impact on both the U.S. apple input and output markets. It causes welfare losses for producers who adopt the policy affecting farm input and for consumers who purchase exported, high-value higher-grade apples. The U.S. government and other stakeholders in the apple industry should actively seek solutions to avoid the potential losses caused by this trade policy. In addition to looking for alternative storage methods, U.S. apple producers should explore other export destinations.

Simulations 2, 3, and 4 show the effectiveness of biased technological innovation by studying its impact on quantity, price, and the welfare of stakeholders. The biomarker effectively increases the supply of high-value apples at both farm and retail levels by enhancing the efficiency of post-harvest apple storage. Future acceptance of this new technology could accelerate consumer demand for high-value higher-grade apples. Development of such a technology should be supported by both the public and private sectors. Technological innovation is particularly important in the agricultural industry, whose production always involves numerous factors (Binswanger 1974).

Simulations 2, 3, and 4 also test Hypothesis H0. Producers of high-value apples enjoy a welfare gain in all three scenarios. Those who produce low-value apples suffer a welfare loss. (This is consistent with H_0.) In the presence of a biased technology, producers in the industry should increase the production of commodities that are favored by the technology, decreasing the production of other commodities. This would maximize their welfare and minimize the risks from exogenous shocks, such as policy and regulation changes, market failures, and natural disasters. The initial cost to shift production would not be extremely high when the market includes highly differentiated products. In addition, factors required for production would largely remain the same.

To sum up, changes in a country's trade policy will affect its trading partners. One way to maintain trade is technological innovation. Policy-induced technologies may be biased toward certain production aspects of a traded commodity to be in line with altered trade policies. In our case, to meet the new MRL of DPA (a chemical used as a farm input), the new technology is biased toward farm input. Biased technology will bring shifts in production and consumption. Particularly when markets include highly differentiated products, these shifts are complex due to substitution effects between outputs and inputs and the vertical linkage between input and output markets. However, added complexity also provides producers opportunities to avoid loss and maintain a surplus. Exporters whose production is affected mostly by trade policy change will experience losses if no effective alternative technology can be found. Alternatively, producers could shift their production more toward products that take advantage of the policy and the biased technology. In a market with highly differentiated products and an effective policy-induced technology, a trade policy shock could become a net benefit for exporters who adopt the appropriate technologies.

Developing countries, which also may face the same policy change and policy-induced technological innovation, can learn from developed countries' experience. However, some policy-induced technological innovations, while facilitating trade and fostering economic growth, may bring challenges to the economy, the country’s well-being, and the environment (UNCTAD 2004). Developing countries need to be aware of the trade-offs arising from technological innovations (Massa 2015).

End Notes

[1] The termination of the Bracero Program resulted in reduced availability of inexpensive immigrant labor for California and Florida growers.

[2] COMMISSION REGULATION (EU) No 772/2013 of 8 August 2013 amending Annexes II, III and V to Regulation (EC) No 396/2005 of the European Parliament and of the Council as regards maximum residue levels for diphenylamine in or on certain products. Pear is another product targeted in the regulation, in addition to apples.

[3] Washington Grower Clearing House, 55th Annual Apple Price Summary for the 2011-2012 Marketing Season

[4] Only non-organic apples are considered in this research because organic apples do not apply DPA for post-harvest storage.

[5] "The percentage of fruit deemed acceptable for a fresh market outlet is known as the "packout percentage." For example, if a load of navel oranges has a packout of 64%, this means that out of 100 navel oranges, 64 were deemed acceptable for the fresh market. The remaining 36 were sorted out and sent to the processing plant." (Muraro, Roka and Timpner 2007)

[6] Red Delicious, Golden Delicious, Granny Smith, Fuji, Gala, Braeburn, Jongold, and Rome.

[7] The statement that 50% culls are upgraded into a higher-grade is a general assumption based on their composition. Culls are small, abnormally shaped apples. This irregular appearance is caused by post-harvest disorders (Rules and Regulations Relating To NEW YORK STATE APPLE GRADES. Available at: http://www.agriculture.ny.gov/FS/pdfs/farmcircs/circ859.pdf)

[8] Full adoption is assumed here.

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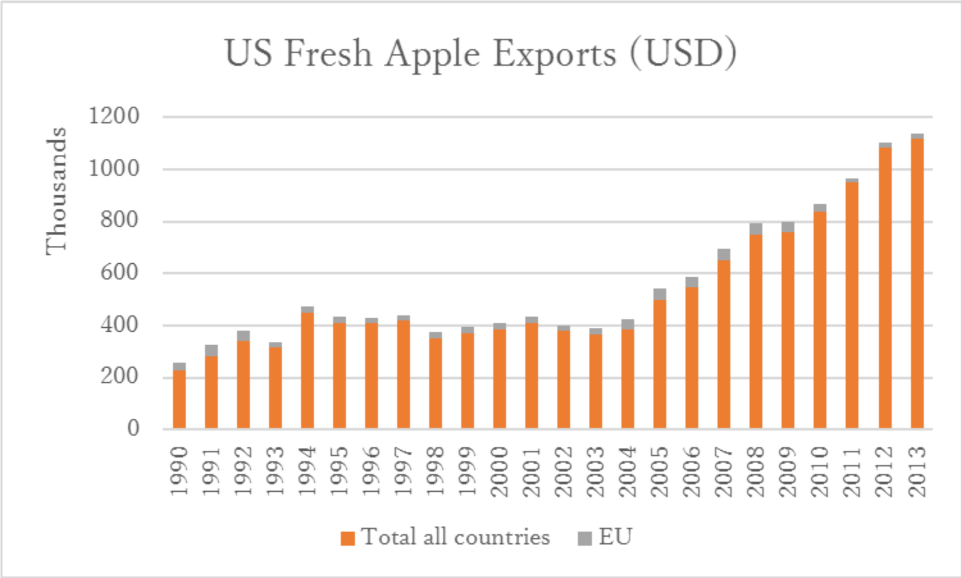
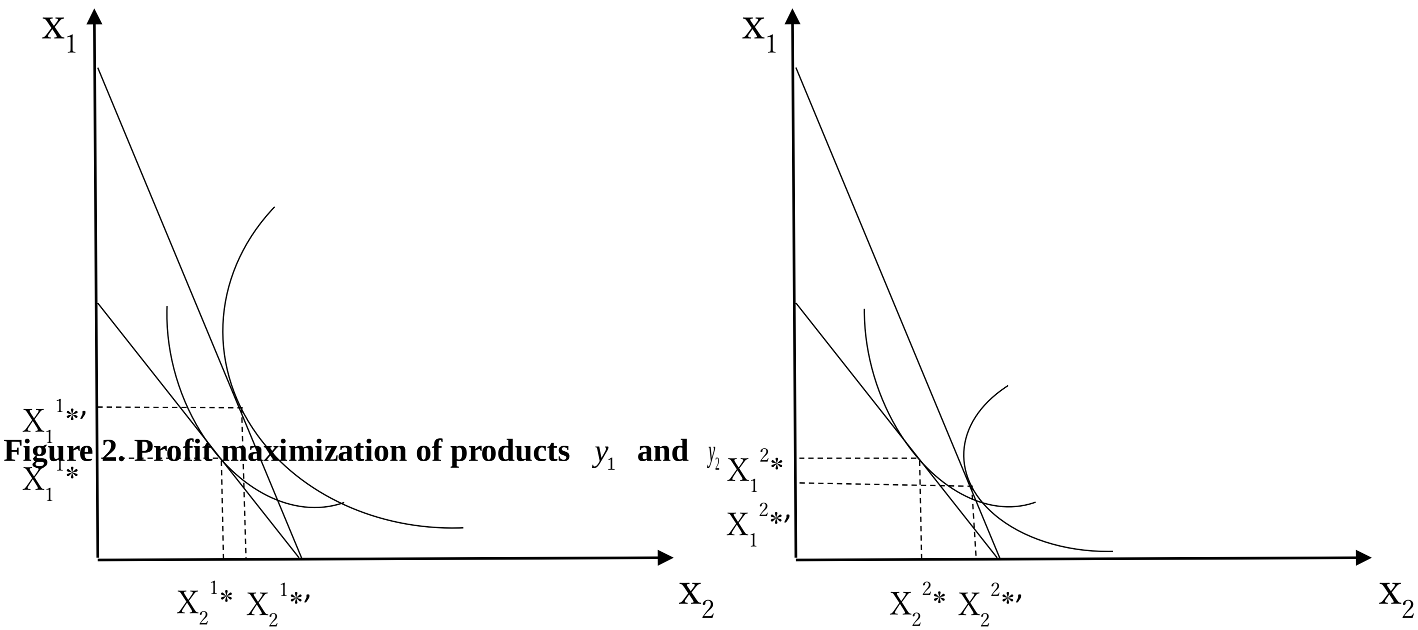


Source: FAOSTAT

Figure 1. U.S. fresh apple exports

Figure 2. Profit maximization of products y_1 and y_2



2a

2b

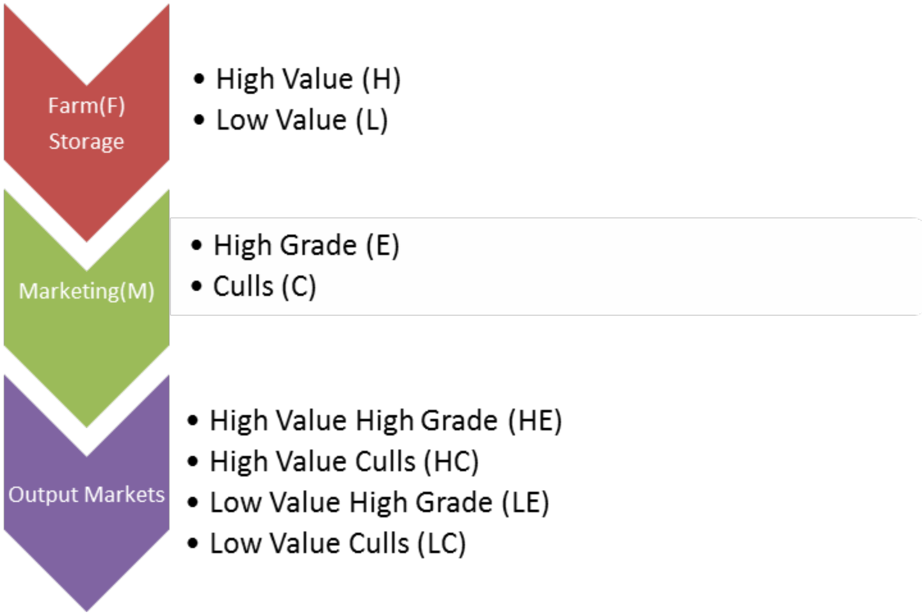


Figure 3. Apple market structure

Table 1. Parameter Specifications

Symbol	Definitions	Formula	Source
η^{ij}	Apple i domestic elasticity of demand with respect to the price of apple j	$\eta^{ij} = \frac{\partial QD^i}{\partial P^j} \cdot \frac{P^j}{QD^i}$	Armington Specification with random drawn key parameters from prior distribution
ηx^{ij}	Apple i export elasticity of demand with respect to the price of apple j	$\eta x^{ij} = \frac{\partial QX^i}{\partial P^j} \cdot \frac{P^j}{QX^i}$	Armington Specification with random drawn key parameters from prior distribution
S^i	Domestic consumption share of US apple production	-	Calculated with industry data
γ_l^i	Cost share of input l in the production of apple i	$\gamma_l^i = \frac{W_l X_l}{P^i Q^i}$	Calculated with industry data
λ_l^i	Industry share of input l used in the production of apple i	$\lambda_l^i = \frac{X_l^i}{X_l}$	Literature and industry estimation
σ_{lk}^i	Allen elasticity of substitution between input land k	$\sigma_{lk}^i = \frac{d\ln(l/k)}{d\ln MRTS_{kl}}$ [1]	Assumption
ε_l	Supply elasticity of input l	$\varepsilon_l = \frac{\partial h_l(W_l, B_l)}{\partial W_l} \cdot \frac{W_l}{X_l}$	Random draw based on prior distribution
α^i	Percentage change in consumer demand for apple i from adoption of bio-marker	$\alpha^i = \frac{\partial QD^i}{\partial A^i} \frac{A^i}{QD^i} EA^i$	Calculated based on industry information
β_l	Percentage change in costs due to adoption of bio-marker	$\beta_l = \frac{\partial h_l}{\partial B_l} \frac{B_l}{X_l} EB_l$	Calculated based on industry information

[1] $MRTS_{kl}$ is the marginal rate of technical substitution which equals the ratio between marginal product of input k and input l

Table 2. Apple and Factor Prices and Quantities

Apple	Quantity	Price
	1000 CTNS	$/CTNS
High Value High Grade (HE)	412.08	35.14
High Value Culls (HC)	61.81	0.16
Low Value High Grade (LE)	1556.75	18.07
Low Value Culls (LC)	242.78	0.16
Marketing		
High Grade (ME)	1968.83	21.28
Culls (MC)	304.60	0.128
Farm		
High Value (FH)	1799.53	3.51
Low Value (FL)	473.89	1.81

Note: 1 CNTS (box)=40lb; 1 Car=1,000 CNTS

Source: Author's calculation based on Washington Grower Clearing house

Table 3. Simulation Results of Price and Quantity Changes

		Policy	Biased Tech	Policy & Biased Tech	Demand & Biased Tech
		-5% in high value high grade apple export demand	+5% in farm supply for high value apple	-5% in high value high grade apple export demand & +5% in farm supply input for high value apple	+15% in high value high grade apple demand &+5% in farm supply for high value apple
		Percent change in quantity (Confidence interval)			
Marketing Supply	High grade	0.12	1.37	2.46	-0.03
		(0.06, 0.18)	(0.89, 2.01)	(1.09, 2.98)	(-1.86, -0.003)
	Culls	-0.17	2.17	0.18	0.04
		(-0.22, -0.07)	(1.96, 3.02)	(-0.03, 0.34)	(0.003, 0.12)
Farm Supply	High value	-13.98	2.34	-12.61	3.49
		(-15.01, -12.08)	(1.08, 2.99)	(-15.28, -9.98)	(1.64, 5.03)
	Low value	2.12	-0.01	4.29	-0.53
		(1.88, 2.42)	(-0.018, 0.12)	(2.89, 5.01)	(-2.05, -0.0068)
Retail Price	High value high grade	-5.23	-1.04	-6.27	1.98
		(-6.00, -4.46)	(-2.22, 0.34)	(-8.09, -3.02)	(0.23, 3.53)
	High value culls	0.61	0.75	1.37	-0.15
		(0.02, 1.23)	(0.33, 1.02)	(0.65, 2.05)	(-1.23, 0.08)
	Low value high grade	-2.17	-1.82	-3.99	0.54
		(-2.80, -1.68)	(-2.9, -0.06)	(-5.02, -1.98)	(0.10, 1.86)
	Low value culls	0.15	0.32	0.47	-0.04
		(0.02, 0.28)	(0.18, 0. 43)	(-0.09, 1.53)	(-2.06, 1.12)
Apple Supply	High value high grade	-16.73	1.72	-12.19	4.18
		(-18.01, -14.73)	(0.98, 2.35)	(-15.01, -8.92)	(2.64, 5.83)
	High value culls	-0.58	-0.37	-0.02	0.15
		(-0.78, -0.38)	(-1.88, 1.19)	(-0.28, -0.01)	(0.003, 0.25)
	Low value high grade	2.61	2.63	4.67	-0.65
		(1.56, 3.58)	(0.96, 3.56)	(2.30, 5.99)	(-2.39, 0.86)
	Low value culls	0.03	0.14	0.16	-0.003
		(0.002, 0.036)	(0.02, 0.30)	(-0.01, 0.92)	(-1.56, 1.63)

Note: The 95% confidence intervals are based on empirical beta distributions generated by variances on underlying elasticity parameters.

Table 4. Simulation Results Welfare Changes

		Policy	Biased Tech	Policy & Biased Tech	Demand & Biased Tech
		+5% in high value high grade apple demand	-5% in farm supply for high grade apple	-5% in high value high grade apple demand & +5% in farm supply input for high grade apple	+5% in high value high grade apple demand &+5% in farm supply for high grade apple
		Welfare change in million USD (Confidence interval)			
Producer Surplus Marketing	High grade	11.32	-1.71	-24.40	-2.89
		(9.90, 13.29)	(-1.89, -1.65)	(-27.06, -21.24)	(-3.81, -1.09)
	Culls	-20.00	0.12	-0.13	0.18
		(-22.01, -18.65)	(0.01, 0.19)	(-1.02, -0.06)	(0.06, 0.35)
Producer Surplus Farm	High value	-7.86	1.13	14.91	24.26
		(-8.21, -5.96)	(0.53, 1.82)	(13.38, 15.56)	(22.51, 26.12)
	Low value	-0.36	0.18	-4.56	-5.82
		(-1.09, -0.02)	(0.17, 0.31)	(-5.10, -3.85)	(-6.16, -3.08)
Consumer Surplus	High value high grade	-79.91	-31.12	184.1	-474.9
		(-81.25, -78.01)	(-33.29, -29.98)	(179.2, 195.3)	(-458.1, 490.6)
	High value culls	0.31	-0.73	-0.45	-1.68
		(0.19, 0.50)	(-1.23, -0.28)	(-1.02, -0.01)	(-1.88, -1.02)
	Low value high grade	46.40	19.46	-8.15	117.1
		(45.89, 46.96)	(18.53, 21.02)	(-9.66, -7.32)	(112.2, 121.6)
	Low value culls	0.35	-0.66	-0.32	-1.62
		(0.28, 0.46)	(-0.18, -0.03)	(-1.00, -0.08)	(-1.99, -0.35)

Note: The 95% confidence intervals are based on empirical beta distributions generated by variances on underlying elasticity parameters.