The Welfare Impacts of New Demand-Enhancing Agricultural Products: The Case of Honeycrisp Apples*

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Abstract

Agricultural research and development programs on new demand-enhancing products have become increasingly important over the past decade. Large numbers of new agricultural products have been developed and introduced in the United States to serve consumers' heterogeneous tastes and increasing expectations of food quality. However, little is known about their economic benefits. With a focus on the apple market, this paper examines the welfare impacts of the introduction of Honeycrisp apples. We estimate structural models of consumer demand and retailer competition using store scanner data covering 61 cities across the United States in the period from March 2009 to February 2015. On average, we find the introduction of Honeycrisp apples increases consumer welfare by 3.14 cents per pound, of which 2.98 cents is explained by the increased number of total apple varieties and 0.16 cents by the decline in prices of competing apple varieties. The extent of the decline is positively associated with the market share of Honeycrisp apples. We also find that the introduction of Honeycrisp apples has increased overall market size and total apple sales. Compared to the counterfactual results, the estimates show that Honeycrisp has increased the total sales quantity by 8.03 percent and the total sales revenue by 21.25 percent over the study period. To be able to extrapolate our results to the entire U.S. apple market, we perform a back-of-the-envelope analysis and find that the introduction of Honeycrisp apples has increased total consumer welfare by about 940 million dollars during the study period. This corresponds to approximately 20 percent of the annual average domestic expenditures on public food and agricultural R&D.

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1. Introduction

Over the past decade, food and agricultural markets have become more consumer-oriented (Unnevehr et al. 2010). Large numbers of new products are developed to serve consumers' heterogeneous tastes and increasing expectations of food quality. According to Mintel's Global New Product Database, the agriculture sector in the United States (U.S.) has introduced to markets more than 3,500 new varieties of fruit and vegetables since 2011 (USDA 2017). This large-scale introduction of new varieties is primarily fueled by investments in agricultural research and development (R&D).

Public organizations and the U.S. government have a long history of funding agricultural R&D programs through the university systems (Foltz, Barham, and Kim 2000). However, the growth rate of public investment in agricultural R&D began to decrease in the early 1950s. By 1974, more than half of the total investments were provided by the private sector, and this ratio increased to 58% in 2009 (Pardey et al. 2015). The development of patent protection laws mitigates the adverse effects of the decline of public support and encourages more private investments in agricultural R&D (Pray and Fuglie 2015). The Bayh-Dole Act of 1980 and the subsequent legislation gave universities the permission to attain the ownership of inventions made with federal funding and, thereby, enabled them to finance agriculture research by transferring a part of their patent rights to the private sector.[1]

It is important to understand the economic implications for agricultural research with near-term commercial consequences. In this study, we examine the welfare impacts of new demand-enhancing products in the U.S. apple market. The U.S. apple market has several desirable features serving the interests of our paper. First, apples are the second most valuable fruit in the United States (USDA 2016b). Second, apples are marketed by variety names or trademarked brand names associated with a variety and the growth of the apple industry is rooted in the success of the breeding

[1] The provisions of the Bayh-Dole Act were further supported by the Federal Technology Transfer Act of 1986 and the National Technology Transfer and Advancement Act of 1996.

programs at land-grant universities such as Cornell University, Washington State University, and the University of Minnesota. Lastly, the apple market is dynamic and there are a large number of newly patented varieties under development (Rickard et al. 2013).

Consumers are affected by the introduction of a new apple variety in two ways. First, some consumers are better off with a growing number of apple varieties because the new apple varieties with different attributes might better serve their preferences.[2] This is interpreted as an impact mainly capturing the "consumer preference for diversity." Second, consumers will directly receive an economic benefit if the new variety increases market competition and leads to lower prices of other varieties. These lower prices would then attract more consumers and hence increase the aggregate demand for apples. Additionally, the supply side of the apple industry also garners the profits from the increased demand.

In particular, this paper evaluates the welfare changes in the apple market due to the introduction of Honeycrisp apples using structural models of consumer demand and retailer competition. On the demand side, we estimate a random utility model of demand that explicitly accounts for consumers' heterogeneous tastes and preferences. On the supply side, we model the retailer competition in a Bertrand-Nash fashion and derive the pricing rules for apples. Using the estimated demand parameters together with the pricing rules, we consequently simulate equilibrium outcomes in a counterfactual scenario wherein Honeycrisp apples are removed from the market. Then we quantify the changes in consumer welfare, market size, and sales revenue. We obtain data from multiple sources. The primary data are the point-of-sale scanner data which include apple prices and sales revenues at the Universal Product Code (UPC) level from 61 cities across the United States in the period from March 2009 to February 2015. The rest of our data comprise the population statistics of demographics, such as age and household income, and the cost data for retailers, such as apple prices in the wholesale market and wage rates in the retailing industry.

[2] The terms "attributes" and "characteristics" will be used interchangeably through this paper.

The results show that the introduction of Honeycrisp apples drives the prices of competing apple varieties downward, especially for the best-selling varieties such as Gala and Red Delicious. The extent of decline in prices is positively correlated with the market share of Honeycrisp apples. On average, the prices of Gala and Red Delicious apples decrease by 0.72 percent and 0.61 percent respectively, when the market share of Honeycrisp apples is greater than or equal to 1 percent. If the share rises up to 5 percent, the prices of Gala and Red Delicious apples decrease by 2.23 percent and 1.67 percent respectively. Compared to the results in the counterfactual scenario wherein Honeycrisp apples are removed from the markets, the estimates show that Honeycrisp has increased the total sales quantity by 8.03 percent and the total sales revenue by 21.25 percent over the study period. In addition, the results show that the consumer welfare increases from 3.03 million dollars in 2009 to 15.20 million dollars in 2014. The total changes in consumer welfare can be decomposed into the changes due to the increased number of total apple varieties and the changes due to the decline in prices of competing apple varieties. The simulated results imply that 91.60 percent of total consumer welfare changes are attributable to the increase in apple varieties. To be able to extrapolate our results to the entire U.S. apple market, we perform a back of the envelope analysis to extrapolate the estimates of welfare to the entire U.S. market and find that the introduction of Honeycrisp has increased total consumer welfare by about 940 million dollars during the study period. This corresponds to approximately 20 percent of the annual average domestic expenditures on public food and agricultural R&D.

The rest of this paper is organized as follows. Section 2 gives a brief review of the literature. Section 3 describes the background of the U.S. apple market, followed by the data introduction in Section 4. We then present the analytical model and its underlying assumptions in Section 5. Section 6 discusses the identification strategy, as well as the estimation procedure. At last, we explain results in Section 7 and conclude in Section 8.

2. Literature Review

Our study contributes to the agricultural R&D literature by examining welfare impacts from a new demand-enhancing agricultural product. A review by Alston et al. (2009) indicates that a large number of studies have measured social returns to investments in agricultural R&D by identifying the lagged effect of research (the temporal attribution problem) and the spillover effect of new knowledge in certain areas (the spatial attribution problem). They find that returns to agricultural R&D primarily rely on the size of research-induced supply shifts and the scale of the affected industry. Therefore, prior studies typically estimate a supply function that enables them to measure the extent to which the supply curve shifts due to the agricultural R&D. Then, under certain assumptions, the welfare change from a downward shift of the supply curve against a stationary demand can be evaluated. A critique of these studies is that the estimates hinge on the assumption of competitive pricing. This assumption is suspicious because the contemporary food and agricultural markets are generally oligopolistic and have a broad array of differentiated products (Moschini and Lapan 1997).

Food and agricultural markets have become more consumer-oriented and consumer expectations of food quality are increasingly higher (McCluskey et al. 2007; Unnevehr et al. 2010). Higher awareness of healthy diets and changing consumer tastes, in turn, provides incentives for producers to improve the quality of their food and agricultural products. For example, Yue et al. (2013) surveyed grower preferences for fruit traits and find that growers prioritize quality traits, such as flavor, over horticultural traits, such as disease resistance. However, despite the increasing importance of demand-enhancing agricultural products, we do not have enough knowledge about their economic benefits. Unnevehr (1986) quantifies the changes in consumer welfare from improvements in the quality of rice and concludes that economic returns to agricultural research on grain quality are substantial. In another study, Brester et al. (1993) evaluate industry profits from the introduction of low-fat ground beef and find that the new product results in a small increase of less than 1 percent in equilibrium retail price and quantity of aggregate ground beef, as well as social welfare.

Our work is closely related to the literature on measuring the economic impacts from the introduction of a new product. Estimation of demand systems is central in this literature.[3] Using the estimates from a demand model, some studies construct cost-of-living indices to summarize the total welfare changes resulting from a number new products. For example, Hausman (1999) investigates the bias of the Consumer Price Index (calculated by the Bureau of Labor Statistics) due to the omission of new products (i.e., cellular telephones). The author estimates the welfare changes due to the adoption of cellular telephones using a derived expenditure function from an estimated Hicksian demand. Similarly, Nevo (2003) develops a price index to account for the introduction of new products and quality changes in existing products based on the estimation of a brand-level demand system.

Another line of research measures the welfare changes due to a new product introduction by simulating market outcomes in certain counterfactual scenarios with estimated demand models. For example, Hausman and Leonard (2002) estimate structural models of demand and supply to simulate the equilibrium prices in the absence of a new bath tissue product and then measure the difference in consumer welfare between the observed scenario and the counterfactual scenario. Similar approaches have been adopted to analyze the introduction of new products in a number of markets. For example, Petrin (2002) evaluates welfare changes due to the introduction of minivans in the automobile market, Kim (2004) performs a similar analysis for the processed cheese market, and Pofahl and Richards (2009) quantify the consumer valuation of new products in the market for juice drinks. A notable distinction between these studies and our work is that we focus on a fresh produce item rather than a processed or highly industrial product. Although the private sector leads

[3] The literature on the demand estimation is large (e.g., Deaton and Muellbauer 1980; Hausman, Leonard, and Zona 1994; Berry 1994; Berry, Levinsohn, and Pakes 1995; Nevo 2000a, 2001). A review of these studies is beyond the scope of this paper. Nevo (2011) and Bonnet and Richards (2016) briefly survey the development of demand estimation.

the breeding programs in many vegetable crops as well as some fruit crops, the development of new produce varieties is heavily influenced by leading research and germplasm innovation at the land-grant universities.[4] Therefore, our results inform policymakers and research institutions about insights into future public and private initiatives on agricultural investments.

Our paper is also related to the literature on consumer valuation of different apple varieties. Yue and Tong (2011) conduct a choice experiment in real markets with a follow-up survey to investigate the willingness to pay for new apple varieties versus existing ones. The authors find that there is a strong preference for new varieties and that new varieties with more desired characteristics (e.g., firmness, crispness, and tartness) would receive higher premiums. Similarly, Rickard et al. (2013) develop an experiment to examine the impacts of names on a new apple variety. The results show that there is a price premium for using a sensory name for a new variety; however changing the name of an existing variety has little influence. Other studies attempt to identify the internal quality characteristics that affect the consumer valuation of apples using individual surveys with contingent valuation questions. McCluskey et al. (2007) find consumers are willing to pay more for an apple with attributes closer to their subjective perceptions for texture, flavor, firmness, and tartness. In another study, McCluskey et al. (2013) measure the consumer valuation of internal quality characteristics across varieties and find that the willingness to pay for the same attribute is different by variety and associated with consumer demographics. A limitation of these studies is that findings are based on a small sample and the sample representativeness is questionable. Carew, Florkowski, and Smith (2012) evaluate the impacts of product characteristics on apple prices using a hedonic pricing model with Canadian sales data. The authors find that there is a price premium for a new apple variety and price premiums are positively correlated to the size and the grade of apples. Using market level data, our paper contributes to this line of research not only by providing

[4] In addition to apples, there are a large number of successful breeding programs in the land-grant universities, for example, strawberries at the University of California, Davis and the University of Florida, blueberries at the University of Florida, Michigan State University, and North Carolina State University, tomatoes at the University of Florida, and wheat at Kansas State University.

new evidence on consumer valuation of apple characteristics and substitution patterns between the most popular varieties, but also by evaluating the impacts of the introduction of a new apple variety on market shares and prices.

3. The Apple Market in the United States

Apples are one of the most popular fruits worldwide and apple varieties have been improved by cultivation and selection over thousands of years. Originally from Central Asia and widely grown in Asia and Europe, apples were brought to North America by early colonists, dating back to the 1630s. There are 7,500 varieties of apples grown around the world and 2,500 in the United States, of which more than 100 have been commercially sold at retail stores. According to Rickard (2013), an abundance of newly patented apples are under development and will be ready for introduction into the market. The records of the United States Patent and Trademark Office show that 156 patents of new apple varieties were approved during the period of 2000 to 2014.

As the second most valuable fruit on the market, the sales revenue of apples has exceeded two billion dollars since 2007 (USDA 2016b).[5] Apples are grown in all contiguous states but commercially produced in 32 states, led by Washington, New York, Michigan, Pennsylvania, California, and Virginia.[6] Most apples are sold fresh in retail stores. The sales quantity of fresh apples ranged from 6,300 to 7,900 million pounds between 2009 and 2014, about 70 percent of total production (USDA 2016b). After the adjustment for loss, the annual average consumption of fresh apples was 16.6 pounds per capita in 2014, up from 14.3 pounds in 2009 (USDA 2016a).

In contrast to processed food products sold by brand, apples are one of the few produce items marketed by variety. The sustainable growth of the apple industry is attributable to the development and commercialization of new varieties (Gallardo et al. 2012). In 2014, the top ten

[5] By the Fruit and Tree Nut Yearbook (USDA 2016b), the four most-valuable fruits in the United States, are grapes, apples, oranges, and strawberries. The corresponding market sales in 2015 are, respectively, 5.56, 3.39, 2.22, and 1.96 billion dollars, which are summed up to 65 percent of total sales of fruits.
[6] Source: Apple Industry Statistics. United States Apple Association.

most purchased varieties accounted for 80 percent of total production.[7] Table 1 sketches the volume (pounds sold) market shares by variety in fall, the marketing/harvesting season of apples, from 2009 to 2014.[8] Gala is the most popular variety and accounts for one-third of total sales, while Honeycrisp is the fastest growing variety among the top five varieties. Table 2 shows that the annual average price of Honeycrisp has ranged between $1.85 and $2.30 per pound, which is about three times higher than the annual average price of Gala.

The Honeycrisp apple is a winter hardy variety developed by the apple breeding program at the University of Minnesota. After the 30-year breeding effort, it was introduced to the market in 1991 and rapidly became one of the most popular apples in the United States. In 2006, Honeycrisp was named the Minnesota State fruit. The patent protection of Honeycrisp in the United States expired in November 2008 and the University of Minnesota no longer earns royalties from the sales of Honeycrisp. But the sales in other countries where plant breeders' rights (similar to patent) and trademarks associated with Honeycrisp remain in force still generate a cash inflow to support future agricultural R&D programs at the university.

Honeycrisp apples are usually harvested in the early fall and sold until the early spring; they are not available in all seasons.[9] Figure 1 shows the annual sales quantity of Honeycrisp by season in the United States. The annual sales quantity increased fourfold from 36.02 million pounds in 2009 to 127.62 million pounds in 2014. Meanwhile, the marketing season of Honeycrisp apples has been extended. The sales in spring began to rapidly increase in 2011, and the sales in summer had a jump between 2012 and 2013 although it was relatively small.

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[7] The most-purchased apple varieties in 2014 were Gala, Red Delicious, Fuji, Granny Smith, Honeycrisp, Golden Delicious, McIntosh, Cripp's Pink/Pink Lady, Braeburn, and Jazz. Source: Retail Dietitian Toolkit. United States Apple Association.

[8] Due to seasonality in production, apple sales are significantly different by season.

[9] The sales season of Honeycrisp apples is usually from September to April. There is large variation in the sales of Honeycrisp across seasons, especially between summer and fall.

4. Data

The data used in this paper come from several sources. The main data, including market prices and sales quantities, are from the retail point-of-sale scanner data collected by Information Resources, Inc. (IRI), known as IRI InfoScan Data. In particular, we use the primary IRI InfoScan Data, purchased by the United States Department of Agriculture (USDA). The primary IRI InfoScan Data contains the weekly sales information of the representative retailers from 61 IRI cities across the United States in the period of 24 seasons from March 2009 to February 2015, where each IRI city is a collection of counties defined by the United States Census Bureau. Because of the seasonality in the apple market, this paper defines the market as the combination of city and season. These IRI cities are denoted in Figure 2 by shadowed areas with associated labels. The details of the data construction are given in section A of the Appendix.

Given the information of product attributes based on the ingredient and nutrition labels, it is straightforward to define a characteristics space for most processed food products. However, it is not applicable for fresh apples, because the product quality and nutrient contents might vary with production factors, such as chemical usage, land quality, and weather condition. In fact, existing studies have shown that consumer valuations of apple varieties are dependent on texture and flavors, such as sweetness and tartness (e.g., McCluskey et al. 2007; Yue et al. 2013; McCluskey et al. 2013). Therefore, we project apple varieties onto a space characterized by attributes relevant to flavor and texture. The data including such attributes can be obtained from the variety information provided by the Washington Apple Commission. The attribute data are only available for eight out of the top ten most-purchased apple varieties in the United States, including a continuous measure of sweetness and a set of expert rankings for multiple uses of apples (e.g., pie stuffing, applesauce, baking, and freezing), which are used as proxy variables for texture.[10] Section B of the Appendix provides further details on apple characteristics.

[10] The attribute data are available on the web page, http://bestapples.com/varieties-information/varieties/.

A maintained assumption in the subsequent analysis is that apples are differentiated by variety and by retailer. In other words, the Gala apple sold by retailer A is considered as a different product from the Gala apple sold by retailer B. This assumption is plausible as it allows us to account for consumer heterogeneous preferences for retailer types. It, however, results in a large number of differentiated apples in consumers' choice set. To reduce the dimension of the differentiated apples, we first group the retailers by channel: convenience store, defense commissary store, dollar store, drug store, grocery store, and mass merchandise store. However, our data show that more than 85 percent of total apple sales are contributed by grocery stores. The data further show that grocery retailers significantly vary by size defined as the number of IRI cities in which a retailer owns a store. Therefore, we examine the distribution of the size of retailers and divide the retailers into four groups: local retailers, small regional retailers, regional retailers, and nationwide retailers. The details are discussed in section C of the Appendix.[11]

To account for market expansion, the market share of an apple is defined by the division of its sales quantity over the total potential quantity in the market. Following previous literature (e.g., Nevo 2001; Kim 2004; Villas-Boas 2007), we assume the size of total potential quantity is proportional to the population in the IRI city with a cup of fruit per capita per day. [12, 13] Table 3 presents the summary statistics for apple sales by retailer and by variety. Panel A of the table displays sample statistics for prices and market shares of apples. All nominal values are deflated by regional price indices from the Bureau of Labor Statistics (BLS) with the base period in 1982-

[11] Due to the privacy requirements of the data agreement with the Economic Research Service, USDA, we are unable to disclose the names of retailers in each category.

[12] Two cups of apple is equivalent to a large apple, which is about 0.5 pound. The relevant population is defined as the population covered by the data used in this paper. Over the study period, the total quantities of apples sold by stores in our sample is about 13 percent of the total quantity sold by all retailers in the United States (the total apple sales is obtained from the USDA Economic Research Service). As a result, the proportionality factor for the population in the IRI city is 13 percent.

[13] Nevo (2001) assumes the market size is the total potential number of servings in a market where the potential is one serving of Ready-To-Eat breakfast cereal per capita per day. Kim (2004) calculates the market size of processed cheese as a proportion to the size of the population with the proportional factor equal to one serving per capita per day. Villas-Boas (2007) defines the potential market of yogurt as half of the resident population in the market areas under the assumption that every individual consumes one half of a serving per week.

84. Panel B shows that consumers are more likely to buy fresh apples from local and small regional retailers than from regional and nationwide retailers. The market share of local retailers ranks first with an average of 13.29%, followed by small regional retailers with 11.59%, regional retailers with 4.44%, and nationwide retailers with 2.51%. Panel C provides the sample statistics of market shares by variety and shows that on average, Gala is the most popular variety and Honeycrisp is one of the top-five.

We obtain data on consumer demographics such as age and household income from the American Community Survey from 2009 to 2014 provided by the United States Census Bureau. To investigate if the younger generation is more likely to purchase new products than the older generation, we define a variable of young adult as a binary indicator for consumers aged between 25 and 44. In addition, we use retailer cost data as instruments for the estimation of demand. The cost information consists of apple prices by variety at the terminal markets and wage rates in the retailing industry. The price data from terminal markets are provided by the USDA Agricultural Marketing Service (AMS), including monthly average prices of different apple varieties paid by retailers in selected markets across the United States. There are 15 selected terminal markets across the United States and these markets are circled in Figure 2. Retailers in a city without a terminal market are assumed to pay the prices at the closest terminal market. The details of the construction of terminal market prices for every city are discussed in section D of the Appendix. It is worth noting that Honeycrisp apples have the highest minimum price and widest price range in terminal markets. Table 4 presents summary statistics of cost-related variables. Wage rates for retailers in different cities are obtained from the BLS Occupational Employment Statistics Survey from 2009 to 2014. The survey reports wage rates at the state level for cashiers, truck drivers, tractor operators, stock movers, and packagers. Wage rates at the city level are averaged over states weighted by the associated population.[14]

5. Analytical Framework

5.1. Consumer Utility and Demand

In this section, we specify a discrete choice model of demand for apples (e.g., Berry 1994; Berry, Levinsohn, and Pakes 1995; Nevo 2001; Petrin 2002; Kim 2004). Let $j = 0, \dots, J$ denote differentiated apples, defined as a variety-retailer combination, with $j = 0$ indexing the outside option, $t = 1, \dots, T$ denote markets, defined as a city-season combination. The utility of consumer i from buying apple j in market t is

$$u_{ijt} = \boldsymbol{x}_{jt}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \boldsymbol{d}_t + \epsilon_{ijt}, \tag{1}$$

where p_{jt} is the price, $\boldsymbol{x}_{jt}$ is a $K \times 1$ vector of observed characteristics of apple j in market t, ξ_{jt} is the baseline utility of unobserved characteristics (i.e., unobserved valuation for econometricians but not consumers), $\boldsymbol{d}_t$ is a vector of dummies representing the seasonality in market t, and ϵ_{ijt} is an error term that is assumed to be independently and identically distributed (i.i.d.) across apples and be drawn from the Type I extreme value distribution. The conformable parameters (α_i, β_i) are the random coefficients to be estimated. These parameters represent consumer heterogeneous tastes for observed apple characteristics and prices, such that

$$\begin{pmatrix}\alpha_i \\ \beta_i\end{pmatrix} = \begin{pmatrix}\alpha \\ \beta\end{pmatrix} + \Pi D_i + \Sigma v_i,$$

where the parameters (α, β) represent the homogenous tastes and the component $\Pi D_i + \Sigma v_i$ capture the individual discrepancies. For consumer i, the individual tastes are jointly determined by a $L \times 1$ vector D_i of demographic background variables (i.e., age and household income) and a

[14] For example, the IRI city, Minneapolis-St. Paul (MSP), consists of counties in both Minnesota and Wisconsin. The wage rate of cashiers in MSP is hence averaged over the wage rates of cashiers in the two states by the associated population from MSP counties in Minnesota and Wisconsin.

$(1+K)\times 1$ vector v_i of the idiosyncratic tastes, where Π and Σ are the corresponding parameter matrices with the dimension of $(1+K)\times L$ and $(1+K)\times(1+K)$, respectively. To complete the demand model, the utility of consumer i from the outside option is specified as

$$u_{i0t} = \boldsymbol{d}_t + \epsilon_{i0t}.$$

The outside option includes other apples and fresh fruits sold in the stores included in this study, and any apple and fresh fruits sold in other stores. Following Nevo (2001), we denote θ_1 as a vector of the linear parameters (α,β) and θ_2 as a vector of nonlinear parameters $\big(vec(\Pi), vec(\Sigma)\big)$. The utility of consumer i can thus be written as

(2) $$u_{ijt} = \delta_{jt}\big(\boldsymbol{x}_{jt}, p_{jt}, \xi_{jt}, \boldsymbol{d}_t; \theta_1\big) + \mu_{ijt}\big(\boldsymbol{x}_{jt}, p_{jt}, D_i, v_i; \theta_2\big) + \epsilon_{ijt},$$

where δ_{jt} is the mean utility shared by all consumers, i.e., $\delta_{jt} = \boldsymbol{x}_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \boldsymbol{d}_t$, and μ_{ijt} is the consumer specific utility determined by the individual tastes, given as:

$$\begin{aligned} \mu_{ijt} \; &= \; [-p_{jt}, \boldsymbol{x}_{jt}](\Pi D_i + \Sigma v_i) \\ &= -p_{jt}\big(\pi_{p1} D_{i1} + \cdots + \pi_{pL} D_{iL} + \sigma_p v_{ip}\big) \\ &\quad + \sum_k x_{jt}^k (\pi_{k1} D_{i1} + \cdots + \pi_{kL} D_{iL} + \sigma_k v_{ik}). \end{aligned}$$

The heterogeneity is captured by the consumer specific utility, μ_{ijt}, as well as the idiosyncratic taste parameter, ϵ_{ijt}.

Let consumer i be characterized by a tuple $(D_i, v_i, \epsilon_{i\cdot t})$. The collection of consumers buying product j in market t is defined as a set C_{jt} such that

$$C_{jt} = \big\{ (D_{it}, v_{it}, \epsilon_{it}) \mid u_{ijt} \geq u_{ilt} \; \forall l = 0,1,\ldots,J \big\}.$$

Under the assumption that the distributions of demographics, idiosyncratic tastes, and error terms are independent, the market share of product j in market t is obtained as

(3) $$s_{jt} = \int_{C_{jt}} dP(\epsilon) dP(v) dP(D),$$

where $P(\cdot)$ is the population distribution function. Note that if consumers are homogeneous in market t, i.e., $(D_{it}, v_{it}) = (\bar{D}_t, \bar{v}_t)$ and error terms are drawn from the Type I extreme value distribution, then (3) reduces to a classic (multinomial) logit model of demand.

5.2. Supply Side Model

To evaluate welfare changes due to the introduction of Honeycrisp apples, we must obtain equilibrium prices of other apples in a counterfactual scenario in which Honeycrisp apples would be absent in the market. To this end, we model the competition among retailers to derive equilibrium pricing rules. For estimation to be tractable we divide retailers into four groups based on their sizes.

Let J_r be a partition of apple varieties sold by a retailer group r. Given a vector $\boldsymbol{p}_{-r}$ of prices from rival groups, the retailer group r maximizes the group profit by jointly choosing a vector $\boldsymbol{p}_r$ of prices, that is,

$$\max_{\boldsymbol{p}_r} M \times \sum_{j \in J_r} \left(p_j - mc_j\right) s_j(\boldsymbol{p}_r, \boldsymbol{p}_{-r}),$$

where mc_j is the marginal cost of product j and M is the size of market. Suppose there exists a pure-strategy Bertrand-Nash equilibrium in prices. The optimal prices then satisfy the first order condition for apple $j \in \{1, \dots, J_r\}$,

$$s_j(\boldsymbol{p}_r) + \sum_{k \in J_r} (p_k - mc_k) \frac{\partial s_j(\boldsymbol{p}_r)}{\partial p_k} = 0,$$

which implies that the substitution patterns across apple varieties (i.e., own- and cross-price effects) are involved in the optimal pricing conditions. Let $\Delta^*(\boldsymbol{p})$ be defined as a matrix of substitution patterns such that $\Delta^*(\boldsymbol{p})_{jk} = -\partial s_j(\boldsymbol{p}) / \partial p_k$, and Ω be defined as a matrix of ownership such that $\Omega_{jk} = 1$ if $j, k \in J_r$ and 0 otherwise. The first order conditions can be written in matrix notation,

$$\boldsymbol{s}(\boldsymbol{p}) - \Delta(\boldsymbol{p})(\boldsymbol{p} - \boldsymbol{mc}) = \boldsymbol{0}, \tag{4}$$

where $\boldsymbol{p}$ is a vector of prices, $\boldsymbol{mc}$ is a vector of marginal costs, $\boldsymbol{s}(\boldsymbol{p})$ is a vector of market shares, and $\Delta(\boldsymbol{p})$ is an element-wise product of ownership and the substitution matrix, i.e., $\Delta(\boldsymbol{p}) = \Omega * \Delta^{*}(\boldsymbol{p})$. Implied by (4), the vector of marginal costs is,

$$\boldsymbol{mc} = \boldsymbol{p} - \Delta(\boldsymbol{p})^{-1}\boldsymbol{s}(\boldsymbol{p}). \tag{5}$$

where the component $\Delta(\boldsymbol{p})^{-1}\boldsymbol{s}(\boldsymbol{p})$ captures the markup terms for the differentiated apples. Given the estimated demand model and observed prices, the marginal costs can be recovered by (5). Suppose that the marginal costs of apples are independent from the introduction of Honeycrisp. Then, the counterfactual prices can be obtained by using the first order conditions in (4) with the recovered marginal costs.[15]

Some non-trivial assumptions are made in the counterfactual analysis. First, the introduction of Honeycrisp apples would not affect the competition between retailer groups in the apple market. In other words, retailer groups are assumed to compete in Bertrand-Nash fashion regardless of the presence of Honeycrisp apples. Second, the demand model would not change in the counterfactual scenario. That is, we conduct the counterfactual analysis with the same demand estimates. It, however, does not imply that the substitution patterns are invariant. In fact, the substitution matrix $\Delta(\boldsymbol{p})$ is a function of market prices and hence vary with the equilibrium. Third, the value of the outside good is constant. It implies that the relative utility of an inside apple to the outside good would be the same if the attributes of the inside apple are fixed.

[15] Retailers are allowed to adjust marginal costs systematically and proportionally to achieve economies of scale. That is, $\boldsymbol{mc}_1 = c \times \boldsymbol{mc}_0$ where $\boldsymbol{mc}_0$ and $\boldsymbol{mc}_1$ represent the marginal costs of other apples when the Honeycrisp was present and absent in the market respectively and c is a constant ratio implying the marginal costs of other apples would decrease due to the introduction of the Honeycrisp. In this paper, we do not consider the economies of scale and set $c = 1$.

5.3. Evaluation of Consumer Welfare

Let $w > 0$ be a fixed expenditure on fresh fruits, $\boldsymbol{p}^{\text{with}}$ be a vector of prices when Honeycrisp apples are available in the market, and $\boldsymbol{p}^{\text{without}}$ be a vector of prices when absent. A consumer is strictly better off with the introduction of Honeycrisp apples if and only if

$$u(\boldsymbol{p}^{\text{with}}, w) - u(\boldsymbol{p}^{\text{without}}, w) > 0.$$

To measure the welfare changes in dollars, money metric indirect utility functions are employed. These functions are constructed using the means of consumer expenditures with fixed utility levels. A monetary measure of welfare changes for consumer i is

$$e\left(\overline{\boldsymbol{p}}, u_i(\boldsymbol{p}^{\text{with}}, w_i)\right) - e\left(\overline{\boldsymbol{p}}, u_i(\boldsymbol{p}^{\text{without}}, w_i)\right),$$

where $\overline{\boldsymbol{p}} \gg 0$ is an arbitrary price vector. Two natural choices for $\overline{\boldsymbol{p}}$ are price vectors $\boldsymbol{p}^{\text{with}}$ and $\boldsymbol{p}^{\text{without}}$. These two choices are equivalent under the assumption of no income effect. Following the literature (e.g., Nevo 2000b; Kim 2004), compensating variation (CV) is used to measure the welfare changes for consumer i,

$$CV_i = e\left(\boldsymbol{p}^{\text{with}}, u_i(\boldsymbol{p}^{\text{with}}, w_i)\right) - e\left(\boldsymbol{p}^{\text{with}}, u_i(\boldsymbol{p}^{\text{without}}, w_i)\right),$$

that is, $e\left(\boldsymbol{p}^{\text{with}}, u_i(\boldsymbol{p}^{\text{without}}, w_i)\right) = e\left(\boldsymbol{p}^{\text{with}}, u_i(\boldsymbol{p}^{\text{with}}, w_i)\right) - CV_i$, which implies

$$u_i(\boldsymbol{p}^{\text{without}}, w_i) = u_i(\boldsymbol{p}^{\text{with}}, w_i - CV_i).$$

Due to the linear specification of the indirect utility function in section 5.1, the compensating variation for consumer i can be written

$$CV_i = \frac{u_i(\boldsymbol{p}^{\text{with}}, w_i) - u_i(\boldsymbol{p}^{\text{without}}, w_i)}{\alpha_i},$$

where α_i is the constant marginal utility of income. Hence, the compensating variation for an average consumer can be calculated by

$$E[CV_i] = \int \frac{u_i^{\text{with}} - u_i^{\text{without}}}{\alpha_i} dP(\epsilon)dP(D)dP(v), \tag{6}$$

where u_i^{with} and u_i^{without} are the indirect utility functions with and without Honeycrisp apples and $u_i = \max_j u_{ij}$. With the assumption of the extreme value distribution for ϵ, McFadden (1981) provides the analytical solution to this integral,

$$E[CV_i] = \int \frac{\ln\left(\sum_{j=0}^{J^{\text{with}}} \exp\left(u_{ij}(\boldsymbol{p}^{\text{with}})\right)\right) - \ln\left(\sum_{j=0}^{J^{\text{without}}} \exp\left(u_{ij}(\boldsymbol{p}^{\text{without}})\right)\right)}{\alpha_i} dP(D)dP(v), \tag{7}$$

where $u_{ij}(p_j) = \boldsymbol{x}_j\beta_i - \alpha_i p_j + \xi_j$ is the utility level of consumer i from apple j evaluated at the price p_j.

The introduction of Honeycrisp apples affects the consumer welfare by increasing the number of apple varieties and changing prices for competing apples. To be able to measure these two impacts separately, the compensating variation can be decomposed as:

$$\begin{aligned} E[CV_i] = \int \Bigg[& \frac{\ln\left(\sum_{j=0}^{J^{\text{with}}} \exp\left(u_{ij}(\boldsymbol{p}^{\text{with}})\right)\right) - \ln\left(\sum_{j=0}^{J^{\text{without}}} \exp\left(u_{ij}(\boldsymbol{p}^{\text{with}})\right)\right)}{\alpha_i} + \\ & \frac{\ln\left(\sum_{j=0}^{J^{\text{without}}} \exp\left(u_{ij}(\boldsymbol{p}^{\text{with}})\right)\right) - \ln\left(\sum_{j=0}^{J^{\text{without}}} \exp\left(u_{ij}(\boldsymbol{p}^{\text{without}})\right)\right)}{\alpha_i} \Bigg] dP(D)dP(v), \end{aligned} \tag{8}$$

where the first term of the integrand represents the impact of the increase in apple varieties and the second term captures the impact of the change in prices of competing apples.

There is a caveat for the welfare analysis using the discrete choice model of demand with market level data. The welfare estimates might heavily rely on the idiosyncratic logit error due to the limited information of data (Petrin 2002). This problem arises from the assumption of the additive i.i.d. error in the random utility framework. It is clear in (8) that the direct impact of the introduction of Honeycrisp apples is always positive, since $J^{\text{with}} > J^{\text{without}}$ and $\exp(x) > 0$ for any x. In other words, consumers are always better off when Honeycrisp is in the apple market even if it is identical to a competing apple variety. As a result, the welfare impacts of the introduction of Honeycrisp apples could be overestimated. The random-coefficients model alleviates this problem, to a large extent, by separating consumers' heterogeneous tastes into two parts, ϵ_{ij} and μ_{ij}, where

ϵ_{ij} is an individual error term and μ_{ij} is determined by the interactions between apple characteristics and consumer demographics. The compensating variation can be hence decomposed into the changes related to the error term ϵ_{ij} and the changes related to observed characteristics, $\delta_j + \mu_{ij}$.

6. Estimation

6.1. Endogenous Prices and Identification

A product price represents the implicit value of its characteristics, but not all characteristics are included in the demand estimation. As a consequence, the product prices are correlated with the estimation error through the consumer valuation of unobserved characteristics (also see Figure 3). This correlation raises the problem of price endogeneity, which is well-documented in prior studies (e.g., Berry 1994; Berry, Levinsohn, and Pakes 1995; Nevo 2000a, 2001). In this study, some taste characteristics of apples, such as crispness and juiciness, and appearance characteristics, such as size and color, are not included in the demand estimation, due to the limited variety information on apples. To see the impacts of unobserved variables on the demand estimation, consider a scenario wherein a consumer prefers only crispy apples. In other words, both apple prices and market demands are positively related to the crispness of apples. If crispiness is not controlled in the demand estimation, then it will be included in the error term. In turn, the positive correlation between the apple price and the error term biases downwards the estimate of price parameter α.

A regular remedy for the problem of endogenous prices is to use product-level instruments that are highly correlated with product prices but not correlated with unobserved characteristics. In order to find valid instruments, we need to understand the structure of product prices. Product prices are a function of marginal costs and a markup term, where the markup term represents the consumer valuation of all product characteristics. The variation in product prices can, thus, be divided into the exogenous variation in marginal costs and the endogenous variation in consumer valuation.

Therefore, valid instruments are required to identify price variation through the changes in marginal costs.

There are three sets of cost-related variables employed in the estimation. First, by exploiting the panel structure of the data, Hausman (1994) and Nevo (2000a, 2001) calculate the average product prices in all other cities to capture the changes in marginal costs. These average product prices are viable instruments under the assumption that cross-city demand shocks (i.e., the change in unobserved valuation) are independent across cities. This assumption, however, is tenuous if there are cross-city advertising and promotion activities. To accommodate the potential problem of related marketing strategies across cities within a Census-defined division, we replace the average product prices over all other cities with the average product prices over cities in all other divisions.[16] Although these instruments by construction are not affected by cross-city unobservables, their exogeneity would still be questionable if there exist systematic demand shocks. For example, a sudden awareness of some nutrients in apples would increase the unobserved valuation of apples and hence the market demand across the United States. However, these demand shocks are not much of a concern in our case because all the apple varieties included in our analysis are well-established.[17] In addition, we use period dummies in the demand model that capture any time-variant national shocks (Hausman and Leonard 2002).

Second, we use terminal market prices of different apple varieties to represent the retailer costs for apples. Following Villas-Boas (2007), we interact these prices with retailer group dummies and hence obtain product-level instruments. These instruments capture the differences in costs of apples and account for the variation in prices due to the changes in marginal costs by the combination of variety and retailer.

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[16] The United States Census Bureau defines four statistical regions with nine divisions for data collection and analysis. Perez et al. (2001) find that the patterns of apple consumptions are different across Census-defined regions.

[17] To the best of our knowledge, there has not been nationwide news on apple nutrients reported over the study period.

Third, we use wage rates in the retailing industry as another set of instruments. Retailers are assumed to be price takers in the labor market. These pre-determined costs of variable inputs would influence retailers' marketing strategies (including pricing conditions) but not consumer valuation for unobserved characteristics of apples. Thus, cross-city wage rates of labor, such as cashier, truck drivers, tractor operators, stock movers, truck loaders, and packagers, are viable instruments to disentangle the cross-city variation in marginal costs from the variation in the consumer valuation.

6.2. Demand Estimation

The demand model is estimated using the generalized method of moments (GMM) and the estimates of parameters are determined to minimize the differences between the observed and the predicted market shares of apples. Calculating the integral in (3) raises a challenge for applying instruments to the endogenous apple prices, which are correlated with the consumer valuation of unobserved characteristics ξ_{jt}. The key to this challenge is to recover the mean utility δ_{jt} and construct the moments (i.e., orthogonal conditions) for ξ_{jt}. Berry (1994) provides an inversion method to obtain δ_{jt} in the (multinomial) logit model by matching the observed market share s_{jt}^{obs} with the predicted market share $s_{jt} = \delta_{jt} / \left(1 + \sum_{k=1}^{J} \delta_{kt}\right)$. The solution to δ_{jt} is of an analytical form such that $\delta_{jt} = \log\left(s_{jt}^{\mathrm{obs}}\right) - \log\left(s_{0t}^{\mathrm{obs}}\right)$. However, this analytical inversion method is impeded by the integral in the random-coefficients logit model. As a result, a numerical inversion method developed by Berry et al. (1995) is employed and the value of δ_{jt} depends on the non-linear parameters, θ_2. Suppose X_{jt} is a matrix of variables contained in the mean utility. Then the linear parameters, θ_1 can be expressed as $\theta_1 = \left(X_{jt}' X_{jt}\right)^{-1} X_{jt}' \delta_{jt}(\theta_2)$, which suggests that θ_1 is a function of θ_2. Let Z be a $n \times L$ matrix of instruments and $\xi(\theta_2)$ be a $n \times 1$ vector of the consumer valuation of unobserved characteristics. The estimation is, therefore, to find optimal θ_2^* such that

$$\theta_2^* = \arg\min_{\theta_2}\{G'W^{-1}G\}$$

where G is a sample moment $G(\theta_2) = (1/n)Z'\xi(\theta_2)$ and W is a consistent estimate of the asymptotic variance of $\sqrt{n}G(\theta_2)$. The estimation follows Nevo's (2000a, 2001) procedure using a simulated GMM objective function with analytical gradients.

7. Results

7.1. Parameter Estimates and Elasticities

We first estimate a logit model of demand for apples to explore viable specifications for the full model (i.e., random-coefficients logit model) and illustrate the problem of endogenous prices and the need for instruments. The estimates of the logit model are presented in Table 5, where the dependent variable is given by $\log(s_{jt}) - \log(s_{0t})$. The OLS results in columns 1 and 2 show that there is a small difference between estimates of price coefficients. This suggests the city-specific variables of average consumer demographics are significant but provide little information on the cross-product variation in mean utilities.[18] Columns 3 to 8 show that the orthogonality conditions for product prices might be violated and the specifications with instruments are preferable to the simple regression. Compared to the OLS results, the IV estimates of the price parameter are substantially larger in absolute value. This implies that product prices are negatively associated with mean utility but positively (negatively) with the consumer valuation of favorable (unfavorable) unobserved characteristics. The inclusion of endogenous prices without instruments leads to a relatively inelastic demand for apples. Compared to the estimates in column 3 (or 6), the estimates of the price parameter in columns 4 and 5 (or 7 and 8) are smaller in absolute value when the average product prices outside the division are used as instruments. The retailer costs, measured by terminal market prices and wage rates in the retailing industry, are included to account for the cross-variety variation in prices and the cross-city variation in prices. We also find that estimates of the

[18] The term "product" hereafter refers to the differentiated apple.

price parameter are robust to adding city-average consumer demographics. In addition, the adjusted R-squared and the F-statistic for the exclusion of instruments in the first stage regression suggest the weak instruments are less of a concern.

Table 6 displays estimates from the full model (i.e., the random-coefficients logit model of demand) based on (2) with different specifications. Consumer heterogeneity is characterized by consumer demographics and idiosyncratic shocks.[19] The inclusion of demographic variables creates a scaling problem because of differences in units. To address this issue, we apply the logarithm transformation to age and household income and express all demographic variables as the deviations from the mean (e.g., Nevo 2000a; Kim 2004; Villas-Boas 2007). The full model is estimated with all sets of instruments, including average product prices outside the division, terminal market prices, and wage rates in the retailing industry.

The linear parameters, θ_1, are the mean of random coefficients estimated by the minimum-distance procedure (e.g., Nevo 2000a, 2001), wherein the product-fixed effects are regressed on apple characteristics. The estimates of linear parameters are statistically significant with expected signs and are robust to alternative demand specifications. These negative price coefficients are greater in absolute value than those estimates from the logit model with the same set of instruments, implying more elastic demand for apples. The coefficients of observed apple characteristics suggest that consumers give credit to the varieties well-suited for making applesauce and baking but no credit to the varieties well-suited for freezing and having a high degree of sweetness. In addition, the coefficients of retailer group reveal that consumers are more likely to buy apples from a small regional retailer than a nationwide retailer.

[19] In every market (i.e., the combination of city and season), we simulate 1,000 consumers characterized by age, household income, and idiosyncratic tastes. The demographic variables of age and household income are sampled from the associated empirical distributions in the American Community Surveys. In line with Petrin (2002), we draw consumers' idiosyncratic tastes from the normal distribution truncated at 95 percent based on two reasons: these tastes are bounded above and below, and the distributions of consumers' preferences on apple characteristics are balanced.

The nonlinear parameters, θ_2, capture the heterogeneity in consumer preferences and tastes. The deviations from the homogenous tastes for apple characteristics are allowed to vary with demographic variables and idiosyncratic shocks. The coefficients of idiosyncratic shocks, age, and young adult, however, are not statistically significant. This implies that the heterogeneity in consumer preferences and tastes might not arise from the idiosyncratic shocks and the apple consumption patterns are not remarkably different by age and generation.[20] On the contrary, the coefficients of the interaction terms between apple characteristics and household income are statistically significant. This suggests that the variation in consumer preferences for apple characteristics is primarily determined by the variation in household income. In particular, the positive coefficient of the interaction term between household income and the small regional retailer group implies that the marginal utility of shopping from a small regional retailer increases with household income. The suitability for freezing is not a favorable apple characteristic for consumers with above average household income. Besides, there is a quadratic impact of household income on consumer disutility of apple prices. The coefficient signs of the interaction terms between price and household income and household income-squared are opposite. This implies that consumer insensitivity for apple prices is increasing in household income at a diminishing rate.

Next, we discuss elasticity estimates and substitution patterns between apple varieties. The own- and cross-price elasticities are associated with the empirical distribution of consumer demographics, product fixed effects, and seasonality. Because of the large dimension, we only present the summary statistics of the estimates of elasticities by variety and by retailer group in Table 7. The results show that the estimated demand curves for apple varieties are highly elastic with respect to own price. On average, the most-purchased variety, Gala apples, has the least elastic demand, which is about half of the own-price elasticity of Honeycrisp apples. Specifically, one percent decrease in the own price will increase the sales quantity of Gala apples by 2.80 percent

[20] Additional specifications that are not presented in this paper also show that the coefficient of age-related variables are not statistically significant in the demand model.

and Honeycrisp apples by 5.58 percent. Moreover, the own-price elasticities vary across retailer groups. On average, the group of nationwide retailers has lower own-price elasticities than other groups.

Table 7 also shows that cross-price elasticities of apples from the same retailer group are generally greater than those from a different group. In line with Kim (2004) and Villas-Boas (2007), we find that cross-price elasticities are relatively smaller than own-price elasticities. For example, the sales quantity of Golden Delicious will increase by 0.09 percent if the average price over other apples from the same retailer group increase by one percent, while it will increase by 0.06 percent if the average price over other apples from different retailer groups increases by one percent. It implies that consumers are more likely to substitute one variety for another in the same retailer group than in a different one. The only exceptions are consumers who buy apples from nationwide retailers. In addition, the large standard deviations of cross-price elasticities imply that cross-price elasticities would change within a wide range and the specification of the logit model is too restrictive (Villas-Boas 2007).

7.2. Counterfactual Analysis

Using the retailers' pricing rules and the estimated demand elasticities, we simulate the market outcomes in a counterfactual scenario in which Honeycrisp apples are removed from the market. The analysis focuses on markets where market shares of Honeycrisp apples are greater than or equal to 1 percent. The price changes of competing apple varieties due to the introduction of Honeycrisp are presented in Table 8, where these prices are averaged across retailer groups, weighted by sales quantity. The upper half of Table 8 displays the average price changes by variety in 481 markets. The prices of apples in most markets decline in response to the introduction of Honeycrisp. For example, the average price of Gala decreases by 0.72 percent, or a drop of 0.27 cents per pound. In contrast to Gala, Golden Delicious exhibits the least responsiveness to the introduction of Honeycrisp. The last column shows the number of markets where the introduction of Honeycrisp increases the competition and reduces the prices of competing apple varieties. Moreover, the impact of the introduction of Honeycrisp on the decline in prices of competing apple varieties is positively correlated with the market share of Honeycrisp. The lower panel of Table 8 presents the equilibrium prices of competing apple varieties in 96 markets where market shares of Honeycrisp are greater than or equal to 5 percent. In this situation, the average price of Gala decreases by 2.23 percent, or a drop of 0.71 cents per pound.

Next, we calculate changes in the market shares of competing apple varieties, the overall market size, and the total sales revenue. The estimates in Table 9 are based on the sample of 481 markets. The results show that Honeycrisp has increased both the total sales quantity and the total sales revenue. In the study period, the number of markets with market shares of Honeycrisp greater than or equal to 1 percent increased from 42 in 2009 to 111 in 2014, and the total sales quantity of Honeycrisp increased from 13.35 million pounds in 2009 to 47.66 in 2014. Compared to the counterfactual results, the introduction of Honeycrisp leads to a decrease in the total sales of other apples but an overall increase in the total sales of all apples. Table 9 shows that the total sales of other apples was 57.40 million pounds less than the total sales of other apples when Honeycrisp is removed from the markets (i.e., Counterfactual Total Quantity minus Other Apples' Quantity), and that the introduction of Honeycrisp increased the total sales of all apples by 8.03 percent from 1,574.90 to 1,701.45 million pounds. These results suggest that Honeycrisp attracted more consumers who would otherwise chose the outside option. Besides, the gain in sales revenue due to the introduction of Honeycrisp outweighed the loss in sales revenue due to the decline in prices of others. As the total sales quantity rose in the study period, the total sales revenue increased by 21.25 percent from 621.65 to 753.76 million dollars.

We evaluate the changes in consumer welfare using the measure of CV. The CV suggests the pecuniary change for consumers so that they are indifferent between the observed scenario (i.e., the data) and the counterfactual scenario. In other words, the CV measures the amount of money a Honeycrisp consumer needs to be compensated in the counterfactual scenario to maintain the same utility as before (i.e., the utility achieved when Honeycrisp apples are in the market). Before delving into the CV measure for consumer welfare, we examine the extent to which the assumption of additive i.i.d. error in the random utility framework affects the estimates of welfare change. Table 10 shows the decomposition of welfare changes for an average consumer into a component from observed characteristics, $\delta_j + \mu_{ij}$, and a component from the logit error, ϵ_{ij}. For the markets with market shares of Honeycrisp greater than or equal to 1 percent, the total average changes in consumer welfare due to the introduction of Honeycrisp are 3.14 cents per pound, of which 59.55 percent (i.e., 1.87 cents per pound) are related to the changes from observed characteristics and 40.45 percent (i.e., 1.27 cents per pound) to the changes from the logit error. In addition, the results show that the percentage change in consumer welfare stemming from the observed characteristics is positively associated with the market share of Honeycrisp. For the markets with Honeycrisp share greater than or equal to 5 percent, 70.82 percent of the total average changes in consumer welfare can be explained by the changes from observed characteristics. Thereby, the problem due to the assumption of additive i.i.d. error is less of a concern in this study.[21] The total welfare change due to the introduction of Honeycrisp is calculated by

$$\text{Total Change in Consumer Welfare} = \sum_t E[CV_{it}] \times Q_t$$

where Q_t is the total sales quantity of apples in market t. Table 11 shows that the total benefits in consumer welfare increased from 3.03 million dollars in 2009 to 15.20 in 2014. The decomposition of total changes in consumer welfare suggests that the growth of consumer welfare is primarily attributable to the increase in apple varieties rather than price competition. The total consumer welfare gains from Honeycrisp increased from 2.76 million dollars in 2009 to 13.91 million dollars in 2014, corroborating the recent growth of the Honeycrisp demand and popularity in the United States.

[21] Petrin (2002) finds the welfare analysis can be improved by augmenting the full model with additional micro-level data of households.

8. Conclusion

Agricultural research and development programs on new demand-enhancing products have become increasingly important over the past decade. Large numbers of new agricultural products have been developed and introduced in the United States to serve consumers' heterogeneous tastes and increasing expectations of food quality. However, little is known about their economic benefits. To fill this void, this paper examines the U.S. apple market and analyzes the welfare impacts of the introduction of Honeycrisp apples using structural models of consumer demand and retailer supply.

To extend the research on the economic impacts of agricultural R&D, we use a flexible demand model and relax the perfect competition assumption on the supply side. In particular, we estimate consumer demand in a discrete choice approach with random coefficients, and model the retailer competition in the Bertrand-Nash setting. With both demand estimates and retailers' pricing rules, we predict counterfactual prices of competing apple varieties in the absence of Honeycrisp and evaluate the changes in consumer welfare and total sales quantity and revenue. Aligned with prior studies on welfare evaluation of new products, we also demonstrate the problem of endogenous product prices and the importance of using instrumental variables in the estimation.

Our main results show that consumers are better off in a market with more options of apple varieties. For the sample markets, we find that the introduction of Honeycrisp has increased consumer welfare by 3.14 cents per pound on average, corresponding to a total of 49.03 million dollars overall the study period. More than 90 percent of welfare gain is explained by the increased number of total apple varieties, while the remaining part is explained by the decline in prices of competing apple varieties. The extent of the decline is positively associated with the market share of Honeycrisp. We also find that the introduction of Honeycrisp has increased the total sales of all apples by 126.48 million pounds and the total sales revenue by 132.12 million dollars, which are equivalent to 8.03 percent and 21.25 percent of their corresponding counterfactual estimates, respectively.

It is important to put the magnitude of the estimated welfare change into context. Suppose the estimated welfare change from our sample can be extrapolated to the entire U.S. apple market. In that case, a back of the envelope analysis suggests the introduction of Honeycrisp has increased total consumer welfare in the United States by about 940 million dollars between 2009 and 2014.[22] This gain corresponds to 21 percent of the annual average domestic expenditures on public food and agricultural R&D between 2000 and 2011 in the United States (Pardey et al. 2016).[23] Aligned with previous literature, our estimates also imply that there are substantially large returns to agricultural R&D.[24]

Due to the lack of disaggregated data on apple production, we do not investigate the vertical relationship between retailers and growers on the supply side. As a result, our study only accounts for the welfare changes in the total sales revenue of retailers rather than growers. The price premium paid for Honeycrisp strongly motivates growers to produce more Honeycrisp apples. Our estimated increase in apple sales revenue is consistent with recent growers' planting reports. In addition, news articles in New York Times and on National Public Radio claim that many growers in Washington state have been looking to switch from Gala and Red Delicious to Cosmic Crisp, a new variety derived from Honeycrisp (Karp 2015; Charles 2017). This is in line with our finding that Gala and Red Delicious are the two varieties that suffer the largest decreases in prices from the introduction of Honeycrisp. Nevertheless, the incentives might quickly vanish as the growth of the Honeycrisp production will eventually reduce its price premium.

[22] The estimated change in total consumer welfare is a product of total apple sales quantity and the change in average consumer welfare of buying apples (i.e., $E[CV_i]$). According to the USDA Food Availability (Per Capita) Data System, the number of total sales quantity in the U.S. apple market between 2009 and 2014 was 29,933.09 million pounds. Given that $E[CV_i]$ is 3.14 cents per pound, the estimated increase in total consumer welfare was 939.90 million dollars.
[23] Pardey et al. (2016) report that the average annual domestic expenditures on public food and agricultural R&D is about 4.47 billion dollars in United States between 2000 and 2011.
[24] As Bresnahan points out relating to Hausman's (1996) study on the valuation of new goods, the large consumer surplus results from a steep demand for the new variety (i.e., Honeycrisp) and its small substitutability between other varieties.

Appendix

A. Data

The data described in Section 4 are used for the estimation of demand. The main data are from the primary IRI InfoScan data, including weekly sales revenue and quantity from the "census" retailers at the Universal Product Codes (UPC) level. The "census" retailers are referred to those that have agreed to contribute their sales data to the IRI database. The data purchased by the USDA include only the sales data from these "census" retailers, which are an unprojected subset of the full IRI InfoScan data (Muth et al. 2016). According to agreements between the IRI and the data providing retailers, some of the InfoScan data are collected at the store level, while others are collected at the retailer market area (RMA) level. The geographic areas of the RMAs, covering several states, are self-defined and different by retailers. Therefore, the sales revenue and quantity of RMA retailers cannot be separated by (IRI) city. For a clear definition of the market, only non-RMA retailers are included in this paper. To provide insights into the degree to which these two types of retailers have systematic differences in the context of our study, we compare the distribution of apple sales quantity from RMA and non-RMA retailers over the study period in Table A1. The table shows that Honeycrisp is sold in both types of retailers and display similar increasing trends in market share. In 2014, Honeycrisp became the 5th most popular apple in both types of retailers with average market shares of 7.3 percent and 4.6 percent in non-RMA and RMA retailers, respectively.

B. Apple Characteristics and Consumer Demographics

Table A2 presents apple characteristics by variety. These data are obtained from the apple variety information provided by the Washington Apple Commission. The information include a collection of expert assessments for usage (e.g., pie stuffing, applesauce, baking, and freezing) and a measure of sweetness. In practice, we express expert assessments in binary variables, where 1 refers to "Excellent" and 0 otherwise. The variables of consumer demographics, such as age and household income, are sampled from the American Community Survey. The American Community Survey contains annual population statistics for age and household income by age at the county level. In line with the sales information, we aggregate these statistics at (IRI) city level to obtain empirical distributions of age and household income. Accordingly, we sample 1000 consumers for every market from their corresponding distributions. Table A3 describes the sample statistics for age and household income.

C. Retailer Groups

Apples are assumed to be differentiated by variety and by retailer. The retailers in our sample are divided into four groups based on their size: local retailers, small regional retailers, regional retailers, and nationwide retailers. Table A4 shows the distribution of retailers by size. Table A5 presents average prices and market shares of apples by variety and by retailer. The descriptive statistics show that retail prices are notably different across groups. In particular, compared to other retailers, the nationwide retailers sell all varieties but Golden Delicious at the lowest prices, while the regional retailers sell all varieties at the highest prices. Table A5 also shows that the local and small regional retailers account for the majority of Honeycrisp sales.

D. Terminal Market Prices

The USDA Agricultural Marketing Service (AMS) provides data on monthly average prices for apples by variety from 15 selected terminal markets across the United States. We construct the terminal market prices for 61 cities in our sample as follows. If an IRI city has a terminal market, then retailers in that city pay the prices reported in that terminal market. If an IRI city does not have a terminal market, then retailers in that city are assumed to pay the average of prices reported in terminal markets that are in the same division.[1] For example, terminal market prices in New York

[1] The United States Census Bureau defines four statistical regions with nine divisions for data collection and analysis.

are assigned as prices for retailers in Buffalo, Syracuse, and Albany. If an IRI city does not have a terminal market within its division, then retailers in that division are assumed to pay the average of prices reported in terminal markets in the adjacent division. For example, retailers in Phoenix are assumed to pay an average of prices reported in Los Angeles and San Francisco. Table A6 presents the full list of IRI cities and their corresponding terminal prices.

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Table 1. Apple Market Shares by Variety (Percent of Total Volume)

Variety	2009-Fall	2010-Fall	2011-Fall	2012-Fall	2013-Fall	2014-Fall
Gala	27.58	30.50	32.89	30.58	30.30	31.46
Red Delicious	21.66	21.66	18.18	19.11	15.73	13.25
Fuji	9.57	8.02	8.82	9.98	10.26	11.51
Granny Smith	10.70	10.48	10.82	10.69	9.50	10.75
Honeycrisp	3.81	5.83	6.63	6.34	6.79	8.56
Golden Delicious	5.74	4.84	4.32	3.78	3.58	3.48
Mcintosh	6.03	5.52	5.25	4.38	4.81	4.82
Pink Lady/Cripps Pink	0.51	0.56	0.45	1.03	1.51	1.05
Braeburn	1.19	1.22	0.61	0.80	0.71	0.67
Jazz/Scifresh	0.35	0.61	0.36	0.88	0.98	1.10
Top 5	73.31	76.50	77.33	76.70	72.59	75.53
Top 10	87.14	89.24	88.31	87.58	84.17	86.65

Source: IRI Infoscan Data.

Table 2. Apple Market Prices by Variety (Dollars per Pound)

Variety	2009	2010	2011	2012	2013	2014
Gala	0.63	0.60	0.63	0.70	0.70	0.65
Red Delicious	0.50	0.52	0.56	0.58	0.61	0.64
Fuji	0.68	0.76	0.76	0.82	0.76	0.83
Granny Smith	0.77	0.80	0.80	0.89	0.89	0.85
Honeycrisp	2.11	1.85	1.97	2.30	2.24	2.07
Golden Delicious	0.89	0.91	0.98	1.06	1.00	0.90
Mcintosh	0.63	0.63	0.68	0.79	0.67	0.62
Pink Lady/Cripps Pink	1.26	1.28	1.20	1.25	1.18	1.17
Braeburn	1.16	1.23	1.29	1.46	1.51	1.55
Jazz/Scifresh	1.75	1.46	1.17	1.10	1.24	1.21

Source: IRI Infoscan Data.

Table 3. Summary Statistics of Apple Sales by Retailer Group and Variety

	Mean	Median	SD	Min	Max
Panel A. Price (Dollars per Pound) and Market Share (Percent)					
Price	0.54	0.47	0.30	0.05	2.04
Market Share [a]	1.07	0.31	2.24	0.00	48.23
Panel B. Market Shares by Retailer (Percent)					
Local	13.29	9.18	13.59	0.00	86.48
Small Regional	11.59	3.77	13.72	0.00	50.92
Regional	4.44	2.82	5.65	0.00	35.07
Nationwide	2.51	1.78	3.22	0.00	29.44
Panel C. Market Shares by Variety (Percent)					
Gala	5.45	2.92	6.37	0.00	48.48
Red Delicious	4.56	2.92	4.60	0.00	44.35
Fuji	2.21	1.30	2.94	0.00	20.40
Granny Smith	3.06	1.88	3.03	0.00	15.35
Honeycrisp	1.45	0.46	2.73	0.00	24.10
Golden Delicious	1.39	0.77	1.72	0.00	14.62
Pink Lady/Cripps Pink	0.79	0.46	1.05	0.00	8.63
Braeburn	0.69	0.28	1.52	0.00	20.37

Note: Prices are deflated by regional price indices from the Bureau of Labor Statistics (BLS) with the base period at 1982-84.
[a] Market share is defined as the ratio of the apple sales quantity to the potential market size. The potential market size is defined in footnote 12.

Table 4. Summary Statistics for Cost Information

	Mean	Median	SD	Min	Max
Apple Prices in the Terminal Markets (Dollars per Pound)					
Minimum Prices					
Braeburn	0.28	0.27	0.06	0.10	0.53
Fuji	0.23	0.23	0.05	0.10	0.41
Gala	0.25	0.24	0.05	0.12	0.40
Golden Delicious	0.21	0.21	0.05	0.11	0.36
Granny Smith	0.25	0.25	0.05	0.11	0.40
Honeycrisp	0.43	0.39	0.19	0.12	1.60
Pink Lady/Cripps Pink	0.32	0.31	0.08	0.11	0.58
Red Delicious	0.21	0.20	0.05	0.08	0.34
Range of Prices					
Braeburn	0.15	0.12	0.11	0.00	0.63
Fuji	0.23	0.20	0.12	0.01	0.72
Gala	0.22	0.20	0.11	0.00	0.74
Golden Delicious	0.18	0.17	0.07	0.04	0.44
Granny Smith	0.20	0.17	0.12	0.03	0.78
Honeycrisp	0.25	0.21	0.24	0.00	1.23
Pink Lady/Cripps Pink	0.18	0.16	0.13	0.00	0.70
Red Delicious	0.16	0.14	0.08	0.04	0.62
Relevant Labor Costs in the Retailing Industry (Dollars per Hour)					
Minimum Wage Rates					
Cashiers	3.48	3.49	0.20	3.07	4.07
Heavy Truck Drivers	5.48	5.45	0.44	4.29	7.22
Light Truck Drivers	3.85	3.84	0.22	3.36	4.48
Tractor Operators	4.45	4.45	0.29	3.62	5.38
Stock Movers	3.68	3.68	0.17	3.30	4.13
Packagers	3.53	3.53	0.18	3.17	4.07
Range of Wage Rates					
Cashiers	2.20	1.91	0.73	1.39	4.67
Heavy Truck Drivers	7.07	7.06	0.73	4.57	9.30
Light Truck Drivers	8.32	8.37	0.89	5.40	10.33
Tractor Operators	5.41	5.21	0.96	3.64	8.80
Stock Movers	4.71	4.68	0.54	3.35	6.45
Packagers	3.46	3.54	0.56	2.01	4.94

Note: Prices and wage rates are deflated by regional price indices from the Bureau of Labor Statistics (BLS) with the base period at 1982-84. Apple prices by variety in the terminal markets are provided by the USDA Agricultural Marketing Service. Minimum prices are defined as the 5th percentile price and the ranges are defined as the associated differences between the 5th and the 95th percentile price. Relevant labor costs in the retailing industry are obtained from the BLS Occupational Employment Statistics Survey. Minimum wage rates are defined as the 10th percentile wage rate and the ranges are defined as the associated differences between the 10th and the 90th percentile wage rate.

Table 5. Results from the Logit Model

	OLS		IV					
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
p_{jt}	–2.075***	–2.127***	–12.882***	–7.320***	–7.324***	–11.831***	–7.358***	–7.305***
	(0.105)	(0.104)	(1.185)	(0.255)	(0.246)	(1.055)	(0.252)	(0.241)
Mean of Young Adult Ratio		–4.987***				–3.322*	–3.488*	–3.595**
		(1.922)				(1.987)	(1.952)	(1.770)
Mean of log(Age)		–4.434**				–9.316***	–4.964***	–6.819***
		(1.826)				(2.040)	(1.867)	(1.737)
Mean of log(Income)		50.326***				48.853***	55.185***	54.397***
		(10.069)				(11.306)	(10.534)	(10.167)
Mean of $\log(\text{Income})^2$		–2.160***				–2.094***	–2.365***	–2.336***
		(0.459)				(0.515)	(0.479)	(0.463)
Fit/Exogeneity Test for p_{jt}	0.250	0.274	89.777	271.325	216.306	98.636	270.079	225.499
Frist Stage Regression								
Adjusted R^2			0.596	0.643	0.648	0.599	0.645	0.651
F-statistic for Instruments			14.782	94.057	63.003	15.722	94.572	63.608
Average Prices Outside Division			No	Yes	Yes	No	Yes	Yes
Terminal Market Prices			Yes	No	Yes	Yes	No	Yes
Wage Rates			Yes	No	Yes	Yes	No	Yes

Note: The sample size is 26,089. The dependent variable is given by $\log(s_{jt}) - \log(s_{0t})$. All specifications include the product fixed effects and the period dummies. The null hypothesis of exogeneity test is that p_{jt} is exogenous. Standard errors are presented in parentheses with asterisks indicating the level of significance, where *** represents the 1 percent level of significance, ** 5 percent, and * 10 percent.

Table 6. Results from the Full Model

	Variable	(1)	(2)	(3)	(4)
Mean	Price	–11.048(1.800)***	–11.309(2.169)***	–11.052(2.782)***	–11.045(3.112)***
	Constant	–3.123(0.176)***	–2.480(0.275)***	–2.410(0.288)***	–2.011(0.281)***
	Sauce	0.525(0.065)***	0.228(0.041)***	0.477(0.105)***	0.432(0.107)***
	Baking	2.446(0.173)***	1.493(0.099)***	3.296(0.434)***	4.287(0.446)***
	Freezing	–5.982(0.704)***	–4.324(0.720)***	–6.070(1.047)***	–7.441(1.045)***
	Sweetness	–2.499(0.399)***	–2.393(0.366)***	–2.930(0.526)***	–4.642(0.525)***
	Local	3.204(0.099)***	3.102(0.121)***	3.011(0.164)***	3.177(0.165)***
	Small Regional	4.298(0.348)***	3.961(0.335)***	3.942(0.550)***	6.732(0.638)***
	Regional	2.319(0.095)***	0.781(0.848)	2.863(0.711)***	3.733(0.714)***
Interaction w.	Price		0.072(9.045)	0.076(11.534)	0.075(13.081)
Shocks	Constant		–0.086(6.940)	–0.091(5.962)	–0.091(6.232)
	Sauce			–0.032(6.183)	–0.031(7.205)
	Baking			–0.064(13.146)	–0.065(15.965)
	Freezing		–0.087(8.462)	–0.048(9.956)	–0.048(13.090)
	Sweetness		–0.067(12.414)	–0.041(7.732)	–0.042(9.291)
	Local		–0.020(20.600)	0.018(10.345)	0.019(12.567)
	Small Regional		–0.010(20.828)	0.041(41.967)	0.041(53.321)
	Regional		0.138(17.905)	0.118(13.765)	0.119(14.518)
Interaction w.	Price	0.055(17.856)	0.071(23.635)	0.051(26.435)	–0.091(44.344)
Young Adult	Constant				0.123(30.790)
Interaction w.	Price	0.001(15.654)	0.007(19.832)	–0.0004(26.361)	–0.209(54.739)
Age	Constant				0.178(35.595)
Interaction w.	Price	151.714(26.564)***	148.008(40.987)***	152.080(46.764)***	152.128(37.146)***
Income	Constant	4.067(5.478)	3.913(5.133)	4.071(8.582)	4.085(9.722)
	Sauce	1.287(4.534)		1.269(5.843)	1.263(6.314)
	Baking	4.729(4.636)		4.765(5.202)	4.783(5.930)
	Freezing	–20.761(7.100)***	–14.928(6.699)**	–20.843(10.353)**	–20.879(11.841)*
	Sweetness	–12.587(6.819)*	–9.316(7.001)	–12.616(10.178)	–12.658(11.037)
	Local	2.306(2.991)	0.836(3.031)	2.327(4.439)	2.336(4.929)
	Small Regional	10.929(3.801)***	10.258(4.593)**	10.985(5.210)**	10.994(5.399)**
	Regional	2.085(3.478)	1.994(5.596)	2.143(6.595)	2.161(6.914)
Inter. w. Inc^2	Price	–7.333(1.296)***	–7.139(2.004)***	–7.350(2.245)***	–7.352(1.797)***
GMM Objective		941.826	979.350	939.538	939.265
R^2 Min. Distance		0.898	0.821	0.806	0.818
Price Coef. > 0		0%	0%	0%	0%

Note: The sample size is 26,089. All specifications include the period dummies and use the same set of instruments (i.e., the average prices outside the division overall seasons, the terminal market prices, and the relevant wage rates in the retailing industry). The parameters of apple characteristics are estimated by the minimum-distance procedure. Standard errors are presented in parentheses with asterisks indicating the level of significance, where *** represents the 1 percent level of significance, ** 5 percent, and * 10 percent.

Table 7. Estimates of Own- and Cross-Price Elasticities

	Own-Price		Cross-Price					
			Same Retailer Group (Yes)		Same Retailer Group (No)		Average	
Variety	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Braeburn	–3.958	2.191	0.040	0.107	0.026	0.060	0.031	0.081
Fuji	–3.855	1.138	0.052	0.104	0.053	0.162	0.053	0.144
Gala	–2.802	1.004	0.050	0.112	0.043	0.135	0.045	0.128
Golden Delicious	–6.466	2.943	0.093	0.272	0.061	0.173	0.072	0.214
Granny Smith	–3.737	1.608	0.063	0.155	0.053	0.163	0.056	0.160
Honeycrisp	–5.584	2.712	0.030	0.086	0.021	0.052	0.024	0.067
Pink Lady/Cripps Pink	–5.639	2.972	0.050	0.192	0.027	0.081	0.035	0.133
Red Delicious	–2.961	2.011	0.033	0.135	0.022	0.060	0.026	0.094
Retailer Group								
Local	–4.243	1.998	0.072	0.193	0.026	0.079	0.043	0.136
Small regional	–5.925	3.213	0.076	0.215	0.023	0.076	0.041	0.140
Regional	–4.560	2.134	0.036	0.102	0.030	0.086	0.032	0.092
Nationwide	–3.377	2.077	0.026	0.070	0.064	0.180	0.050	0.149

Note: Means and standard deviation of estimated own- and cross-price elasticities are presented here. The third and the fourth column show the statistics for estimated elasticities only from the same retailer group by variety and by the type of retailer group. The fifth and the sixth column show the similar information but from different retailer groups. The last two columns show the overall average across retailer groups.

Table 8. Equilibrium Prices (Cent per Pound) with and without Honeycrisp

	Price	C. Price	Price Change	Number of Markets where Price ≤ C. Price (Percent in Total)
Market Shares of the Honeycrisp ≥ 1 percent (481 Markets)				
Braeburn	67.86	67.98	0.12 (0.18%)	351 (73%)
Fuji	54.05	54.17	0.13 (0.22%)	389 (81%)
Gala	37.28	37.55	0.27 (0.72%)	473 (98%)
Golden Delicious	54.16	54.18	0.02 (0.04%)	291 (61%)
Granny Smith	41.90	41.96	0.06 (0.14%)	317 (66%)
Pink Lady/Cripps Pink	63.84	64.01	0.17 (0.27%)	370 (77%)
Red Delicious	34.58	34.79	0.21 (0.61%)	449 (93%)
Market Shares of the Honeycrisp ≥ 5 percent (96 Markets)				
Braeburn	67.08	67.48	0.39 (0.60%)	73 (76%)
Fuji	53.40	53.74	0.34 (0.64%)	81 (84%)
Gala	31.37	32.07	0.71 (2.23%)	95 (99%)
Golden Delicious	52.67	52.77	0.10 (0.19%)	70 (73%)
Granny Smith	41.92	42.15	0.24 (0.55%)	69 (72%)
Pink Lady/Cripps Pink	62.50	62.93	0.43 (0.69%)	74 (77%)
Red Delicious	33.44	34.00	0.56 (1.67%)	95 (99%)

Note: Price and C. Price represent the observed and the counterfactual price respectively. Both are averaged across retailer groups by sales quantity and deflated by regional price indices from the Bureau of Labor Statistics (BLS) with the base period at 1982-84. The price change is the difference between these two prices and the percentage change in prices is presented in the associated parenthesis.

Table 9. Sales Quantity (Million Pounds) and Sales Revenue (Million Dollars)

	Num. of	Num. of	Sales Quantity					Sales Revenue				
Year	Markets	IRI Cities	Honeycrisp	Other Apples	Total	C. Total	Changes	Honeycrisp	Other Apples	Total	C. Total	Changes
2009	42	29	13.35	127.10	140.45	131.00	9.41	12.58	48.62	61.20	50.43	10.77
2010	61	38	21.06	194.80	215.86	201.20	14.63	17.77	78.09	95.86	81.03	14.84
2011	78	39	29.99	227.50	257.49	235.90	21.54	22.71	89.26	111.97	93.11	18.86
2012	82	38	29.67	267.10	296.77	277.10	19.73	28.17	112.19	140.36	117.53	22.83
2013	107	43	42.22	353.50	395.72	367.60	28.11	36.13	137.41	173.54	144.13	29.41
2014	111	43	47.66	347.50	395.16	362.10	33.06	42.46	128.37	170.83	135.42	35.41
	Total		183.95	1517.50	1701.45	1574.90	126.48	159.82	593.94	753.76	621.65	132.12

Note: These results are based on the 481 markets where the market share of the Honeycrisp is greater than or equal to 1 percent. Other apples include all competing apple varieties. C. Total in sales quantity and sales revenue respectively represent the counterfactual quantity and revenue when the Honeycrisp is removed from the markets. The values of sales revenue are deflated by regional price indices from the Bureau of Labor Statistics (BLS) with the base period at 1982-84.

Table 10. Decomposition of Welfare Changes for An Average Consumer (Cent per Pound)

Total Changes at Average in Consumer Welfare ($E[CV_i]$)	Changes from Observed Characteristics ($\delta_j + \mu_{ij}$)	Changes from Logit Error (ϵ_{ij})
Market Shares of the Honeycrisp ≥ 1 percent (481 Markets)		
3.14 (100.00%)	1.87 (59.55%)	1.27 (40.45%)
Market Shares of the Honeycrisp ≥ 5 percent (96 Markets)		
4.49 (100.00%)	3.18 (70.82%)	1.32 (29.18%)

Note: Average consumer welfare is estimated by the simulation form of $E[CV_i] = \int (u_i^{\text{with}} - u_i^{\text{without}})/\alpha_i \, dP(\epsilon)dP(D)dP(v)$ where $u_i = \max_j u_{ij}$ and ϵ is draw from the general extreme value distribution with shape parameter $\kappa = 0$, scale parameter $\sigma = 1$, and location parameter $\mu = 0$. The component ratios are presented in parentheses.

Table 11. Total Changes in Consumer Welfare (Million Dollars)

Year	Num. of Markets	Num. of IRI Cities	Change due to Increased Varieties	Change due to Decline in Prices of Competing Apples	Total Change in Consumer Welfare
2009	42	29	2.76 (91.09%)	0.27 (8.91%)	3.03 (100%)
2010	61	38	4.42 (92.28%)	0.38 (7.72%)	4.79 (100%)
2011	78	39	6.73 (92.45%)	0.54 (7.55%)	7.28 (100%)
2012	82	38	7.05 (91.56%)	0.66 (8.44%)	7.70 (100%)
2013	107	43	10.04 (91.11%)	0.98 (8.89%)	11.02 (100%)
2014	111	43	13.91 (91.51%)	1.29 (8.49%)	15.20 (100%)
	Total		44.91 (91.60%)	4.12 (8.40%)	49.03 (100%)

Note: These results are based on the 481 markets where the market share of the Honeycrisp is greater than or equal to 1 percent. The values of consumer welfare are deflated by regional price indices from the Bureau of Labor Statistics (BLS) with the base period at 1982-84. The component ratios are presented in parentheses.

Table A1. Comparison of Sales Quantity from non-RMA and RMA Retailers (Percent)

	2009		2010		2011		2012		2013		2014	
Sales Quantity	Non-RMA	RMA	Non-RMA	RMA	Non-RMA	RMA	Non-RMA	RMA	Non-RMA	RMA	Non-RMA	RMA
Gala	17.70	25.88	19.24	27.48	22.01	29.30	22.72	28.83	25.45	27.79	23.84	30.03
Red Delicious	20.11	27.77	18.65	27.56	17.32	23.99	18.17	23.50	16.67	20.85	17.24	16.90
Fuji	11.99	12.80	9.69	12.23	8.50	13.66	9.13	14.62	9.66	17.33	8.25	14.38
Granny Smith	12.12	10.67	11.30	10.48	12.25	10.83	12.84	9.49	12.12	9.46	12.14	9.99
Honeycrisp	2.48	1.39	3.64	2.24	5.27	2.44	5.33	2.84	6.82	3.37	7.34	4.58
Golden Delicious	6.06	5.65	5.67	5.11	4.98	4.78	4.37	4.41	4.08	4.19	3.98	4.25
Pink Lady/Cripps Pink	1.72	0.86	1.99	1.32	2.62	1.56	3.16	1.65	3.64	1.93	3.27	2.28
Braeburn	2.97	1.84	3.02	1.58	2.41	1.32	2.06	0.96	1.97	0.84	1.54	0.65

Table A2. Apple Characteristics by Variety

Variety	Pie	Sauce	Baking	Freezing	Sweetness
Gala	Very Good	Excellent	Very Good	Not Suggested	0.83
Red Delicious	Not Suggested	Not Suggested	Not Suggested	Not Suggested	0.33
Fuji	Very Good	Very Good	Very Good	Very Good	0.93
Granny Smith	Excellent	Excellent	Excellent	Excellent	0.08
Honeycrisp	Excellent	Excellent	Excellent	Good	0.67
Golden Delicious	Excellent	Excellent	Excellent	Excellent	0.56
Pink Lady/Cripps Pink	Excellent	Excellent	Very Good	Very Good	0.17
Braeburn	Very Good	Very Good	Very Good	Very Good	0.39

Note: The variety information is given by the Washington Apple Commission. The measure of sweetness is monotonically normalized from 0 to 1. As a result, a sweeter apple variety will have a larger measure.

Table A3. Sample Statistics for Consumer Demographics

	Mean	SD	Min	Max
Age (Years)	49.62	17.04	18	85
Household Income ($1000)	67.49	51.30	10	200
Young Adult (25-44 Years Old)	0.36	0.48	0	1

Note: Consumer demographic variables are sampled from the American Community Survey provided by the United States Census Bureau. Young adult is defined as a binary indicator for a consumer aged between 25 and 44.

Table A4. Distribution of Retailers by Size

	Local							Small Regional					Regional		Nationwide	
Numb. of covered IRI cities	1	2	3	4	5	6	7	10	13	15	18	19	22	28	60	61
Numb. of non-RMA retailer(s)	14	11	6	2	4	2	1	1	1	1	1	1	1	2	1	1
Composition by channel type																
Convenience	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-	-
Defense commissary	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	-
Dollar	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-
Drug	-	-	-	-	-	-	-	-	-	-	-	-	-	1	-	1
Grocery	14	11	5	2	3	2	1	1	-	1	1	1	1	-	-	-
Mass merchandise	-	-	1	-	-	-	-	-	-	-	-	-	-	-	1	-

Table A5. Sales Information by Variety and Outlet

	Local		Small Regional		Regional		Nationwide	
Variety	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Prices (Dollars per Pound)								
Gala	0.40	0.17	0.33	0.11	0.52	0.16	0.28	0.09
Red Delicious	0.33	0.14	0.34	0.12	0.45	0.16	0.32	0.12
Fuji	0.59	0.18	0.60	0.21	0.61	0.20	0.37	0.13
Granny Smith	0.45	0.16	0.38	0.11	0.53	0.17	0.27	0.08
Honeycrisp	1.14	0.36	1.11	0.26	1.15	0.32	0.64	0.34
Golden Delicious	0.53	0.18	0.51	0.18	0.67	0.15	0.59	0.29
Pink Lady/Cripps Pink	0.78	0.22	0.77	0.20	0.83	0.22	0.39	0.13
Braeburn	0.73	0.18	0.74	0.20	0.77	0.18	0.46	0.22
Market Shares (Percent)								
Gala	3.75	5.09	4.18	4.90	1.03	1.35	0.69	0.76
Red Delicious	3.58	3.75	3.11	3.55	1.01	1.37	0.33	0.33
Fuji	1.63	2.87	0.99	1.27	1.00	2.02	0.31	0.38
Granny Smith	1.95	2.04	2.27	2.50	0.81	0.97	0.43	0.44
Honeycrisp	0.95	2.04	0.69	1.42	0.46	0.88	0.46	1.02
Golden Delicious	1.10	1.54	0.90	1.12	0.24	0.28	0.15	0.33
Pink Lady/Cripps Pink	0.45	0.64	0.45	0.70	0.23	0.31	0.27	0.43
Braeburn	0.40	0.70	0.59	1.55	0.20	0.33	0.10	0.24

Note: Prices are deflated by regional price indices from the Bureau of Labor Statistics (BLS) with the base period at 1982-84.

Table A6. IRI Cities and Terminal Markets

IRI Cities	Terminal Markets
BOS, HAS, PRO	Boston
NYC, BUF, SYR, ALB	New York
HAR	Average over Philadelphia and Pittsburgh
PHL	Philadelphia
PIT	Pittsburgh
DET, GRR	Detroit
TOL, CLE, COL	Average over Detroit and Pittsburgh
CIN, LOU	Average over St. Louis, Chicago, and Detroit
CHI, IND, MIL, GRB	Chicago
STL, KAN, WIC	St. Louis
PEO, MSP, DSM, OMA	Average over St. Louis and Chicago
BAL, RIC, ROA	Baltimore
CHL, RAL	Columbia
ATL, BIR	Atlanta
MIA, TAM, ORL, JAC	Miami
NAS, MEM, KNX	Average over St. Louis and Atlanta
DAL, NOL, HOU, SAT	Dallas
OKL, TUL, LIT	Average over St. Louis and Dallas
SLC, DEN	Average over Seattle, Los Angeles, and San Francisco
PHX, LAS	Average over Los Angeles and San Francisco
LAX, SDC	Los Angeles
SFC, SAC	San Francisco
SEA, PRT, SPK, BOI	Seattle

Note: In Figure 2, the IRI cities are denoted by shadowed areas with associated labels, while the terminal markets are marked by circles. The abbreviations are spelled out in the continued table.

Table A6. IRI Cities and Terminal Markets (Continued)

Abbreviation	IRI City	Abbreviation	IRI City	Abbreviation	IRI City
ALB	Albany, NY	IND	Indianapolis, IN	PHX	Phoenix/Tucson, AZ
ATL	Atlanta, GA	JAC	Jacksonville, FL	PIT	Pittsburgh, PA
BAL	Baltimore, MD/Washington, DC	KAN	Kansas City, KS	PRO	Providence, RI
BIR	Birmingham/Montgomery, AL	KNX	Knoxville, TN	PRT	Portland, OR
BOI	Boise, ID	LAS	Las Vegas, NV	RAL	Raleigh/Greensboro, NC
BOS	Boston, MA	LAX	Los Angeles, CA	RIC	Richmond/Norfolk, VA
BUF	Buffalo/Rochester, NY	LIT	Little Rock, AR	ROA	Roanoke, VA
CHI	Chicago, IL	LOU	Louisville, KY	SAC	Sacramento, CA
CHL	Charlotte, NC	MEM	Memphis, TN	SAT	San Antonio/Corpus Christi, TX
CIN	Cincinnati/Dayton, OH	MIA	Miami/Ft Lauderdale, FL	SDC	San Diego, CA
CLE	Cleveland, OH	MIL	Milwaukee, WI	SEA	Seattle/Tacoma, WA
COL	Columbus, OH	MSP	Minneapolis/St Paul, MN	SFC	San Francisco/Oakland, CA
DAL	Dallas/Ft Worth, TX	NAS	Nashville, TN	SLC	Salt Lake City, UT
DEN	Denver, CO	NOL	New Orleans, LA/Mobile, AL	SPK	Spokane, WA
DET	Detroit, MI	NYC	New York, NY	STL	St Louis, MO
DSM	Des Moines, IA	OKL	Oklahoma City, OK	SYR	Syracuse, NY
GRB	Green Bay, WI	OMA	Omaha, NE	TAM	Tampa/St Petersburg, FL
GRR	Grand Rapids, MI	ORL	Orlando, FL	TOL	Toledo, OH
HAR	Harrisburg/Scranton, PA	PEO	Peoria/Springfield, IL	TUL	Tulsa, OK
HAS	Hartford, CT/Springfield, MA	PHL	Philadelphia, PA	WIC	Wichita, KS
HOU	Houston, TX				

Figure 1. Annual Sales of the Honeycrisp (Million Pounds)

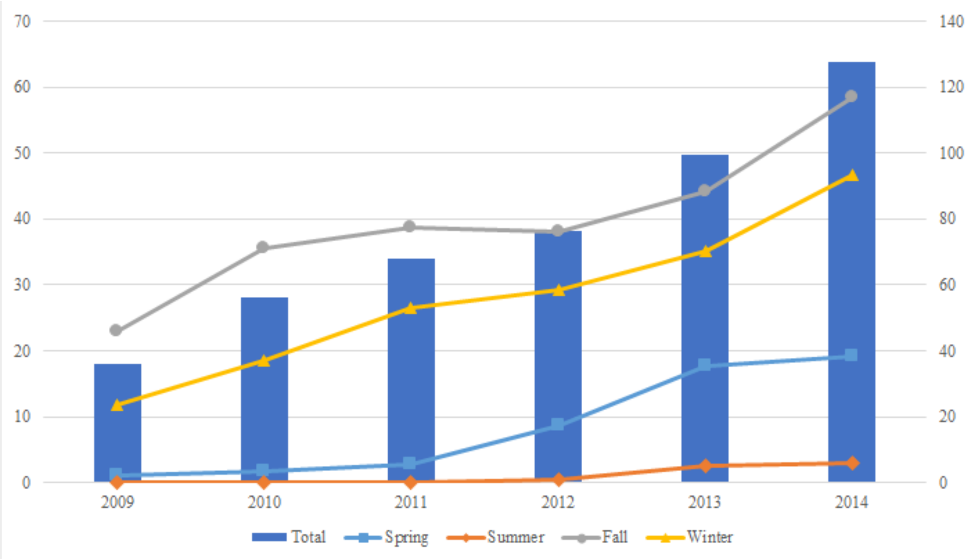


Figure 2. Map of the Cities in IRI data and Terminal Markets

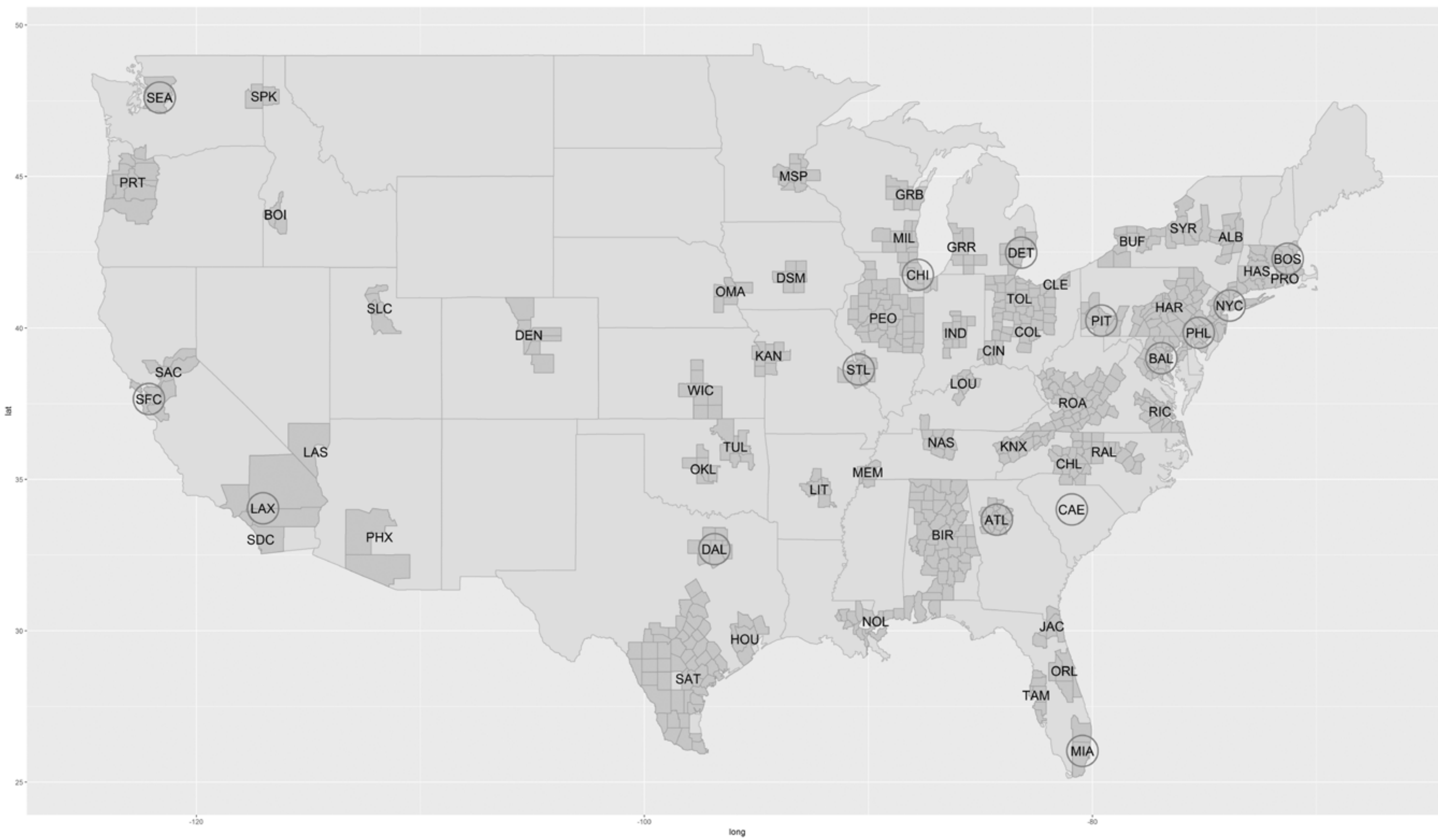
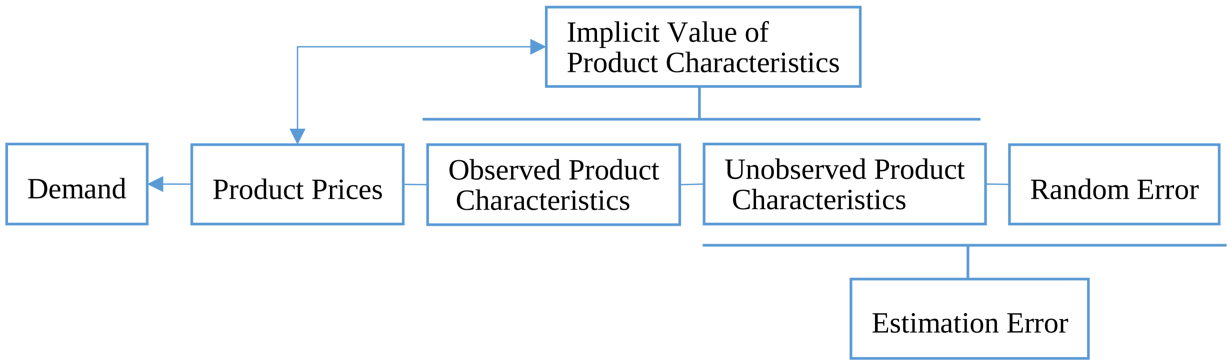


Figure 3. Correlation between Product Prices and Estimation Error



Note: Product prices represent the implicit value of product characteristics, but not all product characteristics are included in the demand estimation. Therefore, the correlation between product prices and the estimation error, which contains the consumer valuation of unobserved characteristics, raises the problem of endogeneity.