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STRUCTURAL ESTIMATION ON DEMAND WITH BRAND CHOICE AND QUANTITY ADJUSTMENT: FROM NON-ORGANIC TO ORGANIC FOOD

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ABSTRACT

I estimate product demand in the vertically differentiated goods market, where consumers choose brand and quantity. I develop a two-stage decision model where consumer chooses both discrete brand and continuous quantity. Using Nielsen Homescan data, I estimate consumer demand in the markets of organic and non-organic bagged carrots.

I modify Dixit-Stiglitz preferences by adding linear combination of brands and preference weights of each brand in order to capture quality-quantity trade-off. In my model, the quantity decision is brand dependent and it is derived from underlying optimization. As Hanemann (1984) points out, optimal discrete choice depends on optimal continuous choice and vice versa. While Hanemann (1984) does not focus on quality-quantity trade-off, my model sheds light on vertically differentiated goods market. I estimate individual demand using maximum likelihood method and conduct counterfactual experiments of price and income changes.

The policy experiments are conducted for two scenarios with plausible values of price elasticity of demand. For a 10% drop in prices of organic carrots, for instance, producers of organic carrots can expect 42.9% rise in quantity demanded and 7.8% increase in supplier revenue in organic carrots market. As consumers switch from non-organic to organic carrots in response to price fall for the latter, they could make a downward adjustment in overall quantity demanded of carrots; the total consumption in the carrot markets (organic and non-organic) would fall by 1.8%, with the fall in the supplier revenue by 2.5%.

Consumption of carrots depends also on income elasticity of demand. With a 10% increase in household income, our experiments show, consumption of organic carrots would increase 19.7% while that of non-organic carrots would fall 3.1%. With increase in income, the quantity demanded overall in the carrot markets would fall by 1.7% and the supplier revenue by 2.8%. Given our data and the underlying

pattern of carrot consumption, a downward quantity adjustment in total carrot consumption (organic and non-organic) could well be expected. That segment of the consumers who switch from non-organic to organic carrots will see their carrot consumption fall (given their budget constraints). If these consumers play a more potent role in the carrot market (i.e., they dominate the carrot demand in the market), their role in reducing total carrot consumption may outweigh that of organic consumers who now increase the consumption of the same (organic carrots).

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Dedication

I dedicate my dissertation work to my wonderful family who have supported me all the way since the beginning of my study. Particularly to my patient husband, Seunggyu Sim and my baby, Joon Young Sim. I must also thank my loving parents who wake up at the dawn every day and pray for me.

Chapter 1

Introduction and Research Objectives

1.1 Introduction

In markets with differentiated products such as yogurt or vegetables, consumers have to decide between several brands. Furthermore, consumers decide how much they purchase as well as which products they buy. One of the features of the market for vertically differentiated products, where hierarchy exists between product qualities, is that the better quality products tend to be sold in smaller units at higher (per unit) prices. When consumers switch from low (conventional) quality products to better quality products, they tend to cut down their consumption but pay more (per unit). Given these quality-price-quantity interactions, it is nontrivial to estimate the own and cross price elasticities for each product and to measure the effect of price and income changes. This paper estimates demand for organic and non-organic branded carrots.

Estimating demand for differentiated products has been a key part of recent research in the fields of industrial organization, marketing science, public economics, macroeconomics, and so on. Hanemann (1984) suggests a theoretical model to estimate the unified demand of discrete brand and continuous quantity choice. Although he suggests a coherent approach based on the random utility model, few empirical papers have analyzed both decisions together. This might be due to an historical lack of rich micro-level data or an insufficiency of computation power.

However, since this technical restriction has been relaxed, this paper attempts to estimate the structural model with both decisions using Nielsen Homescan panel data.

Another string of important literature is Berry (1994) and Berry, Levinsohn, and Pakes (1995) who propose a method for estimating random-coefficients discrete-choice models of demand. Since this method can be applied to market-level price-sales data in the absence of micro-level data, it has become a canonical framework for estimating demand for (horizontally) differentiated products.[1]

However, their methodology is not applicable to the market for vertically differentiated products, i.e. the market for organic and non-organic products, given that consumers are allowed to consume only one unit regardless of their brand choice. [2] The main purpose of this paper is to estimate the 'brand-dependent individual demand' using individual consumer-level data.

It is useful to point out that consumers consume a continuum of 'goods' in their everyday lives, which leads us to incorporate Dixit-Stiglitz preferences into the discrete (brand) choice framework.[3] Given that an individual 'brand' is usually a perfect substitute for another, I assume that consumers utility function is consist with the composite good which is a linear combination of each brand. Consumers respond to each brand characteristic depending on their own demographic characteristics. This specification of fundamentals enriches the implication of the model since, besides enabling me to estimate price elasticities, it also enables me to conduct counterfactual experiments, in order to measure such factors as the effect of price promotion and economy-wide income shocks.

In the market for food, organic products are considered to be higher quality products and therefore tend to be more expensive[4]. In general, when consumers switch from non-organic products to organic products, they tend to cut down on

[1]For details , Nevo (2000) provides a good summary of Berry (1994) and Berry, Levinsohn, and Pakes (1995). See Nevo (2000).

[2]Note that they apply their method to the automobile industry, where each consumer purchases one car.

[3]Nowadays, Dixit-Stiglitz preferences are quite popular in the applied micro economics as well as macro economics because it enables us to derive aggregate demands for infinitely many goods from individual preferences. See Dixit and Stiglitz (1977).

[4]Smith, Huang, and Lin (2009) point out organic produce has a significant price premium.

their consumption. Private label products (also called store brands) complicate the organic price premium. Given these price-brand-quantity interactions, the purpose of the empirical analysis in this paper is to answer the following questions regarding the (organic and non-organic) food market: (i) What characterizes typical organic product consumers in terms of income, education, and other relevant demographic characteristics? (ii) When consumers switch from non-organic products to organic ones, how much do they cut down their consumption (and vice versa)? (iii) To what extent do the sales of organic food increase through price promotion and aggregate income shock due to economic growth? I focus on the "carrots market", where organic products comprise more than 10% of market share in transaction frequency, according to Nielsen 2009 homescan data. The market for carrots is the second largest market in terms of transaction volume, and the fourth largest market in terms of total dollar expenditure on single vegetable and fruit product modules.

Recently, there has been a growing literature analyzing consumer purchasing behavior in the food market. Bell, Chiang, and Padmanabhan (1999) design a model of both quantity and brand choice and report the decomposition of total price elasticity across 13 different product categories. Smith, Huang, and Lin (2009) argue that both price and income have significant effects on consumers' purchase of organic products. They also argue that price elasticity becomes more sensitive as organic foods become more popular. Regarding the effect of price promotion, Gupta (1988) uses coffee data to report that price promotion impacts mostly brand choice (84%), purchase incidence (14%), and stockpiling (2%).

This paper considers an oligopoly differentiated-product market where consumers not only choose the brand but also adjust their consumption depending on their brand choice. It suggests a structural approach to estimate the individual brand-dependent demand and conducts counterfactual experiments on the effect of price and income changes. In particular, I extend the random utility model offered by Hanemann (1984) and apply it to the market for (organic and non-organic) food. Although the previous literature finds and confirms important empirical facts following other econometric methodologies, researchers have yet to develop a satisfying structural model that is both distinct and relevant to the food market. To the best of my knowledge, this dissertation project constitutes the first attempt to develop such a model.

The rest of the dissertation proceeds as follows. In Chapter 2, I provide a survey of the previous literature on consumer demand in the vertically differentiated product market. In particular, as I keep track of four different strings of literature, I separately summarize studies on vertically differentiated markets, quality and quantity interaction, demand with brand and quantity choice, and price promotion effects. In Chapter 3, I summarize the previous literature on the organic food market, and present an overview of the carrot industry. Also, in this chapter, I rely on statistical analysis to respond to the first research question as to what characterizes typical organic product consumers in terms of income, education, and other relevant demographic characteristics. Chapter 4 builds up the theoretical model and predicts the implications for the model of the second research question about how much consumers cut down their consumption when they switch from non-organic products to organic ones. Chapter 5 provides dataset construction, estimation method, and empirical results. In Chapter 6, I conduct policy experiments for several scenarios and show empirical elasticity in order to answer the final question as to what extent the sales of organic food increase through price promotion, aggregate income shock. Finally Chapter 7 concludes.

1.2 Conclusion and Research Objectives

The objective of my dissertation is to investigate household purchasing behavior in vertically differentiated markets. Vertically differentiated markets have distinct features from the product markets examined in previous literature. I provide an extensive review of the relevant literature and develop a unified theoretical model of consumers' brand and quantity choice. Then, I empirically examine the impact of possible policy changes and income growth by simulating the proposed model with organic carrot market data. This research has important implications for the scholarship on demand estimation as well as for the producers of vertically differentiated markets.

1. Literature Review on the vertically differentiated goods market

2. Survey of organic foods market

3. Theoretical model of the brand dependent demand

   (a) Develop unified decisions of brand and quantity choice.

   (b) Modify Dixit-Stiglitz preferences by adding linear combination of brands and preference weights on each brand.

   (c) Derive individual consumer demand and likelihood for estimation of the model.

   (d) Discuss model implication on quality-quantity trade-off.

4. Structural Estimation of demand using carrots market data

   (a) Use 2009 Nielsen homescan data.

   (b) Present data construction.

   (c) Estimate the model using maximum likelihood.

5. Application on policy experiments

   (a) Present goodness of fit by reproducing observed data.

(b) Find the impact of decrease in organic price premium.

(c) Find the impact of increase in income.

Chapter 2

Survey on Estimating Demand in Vertically Differentiated Markets

Estimating demand for differentiated products has been a key part of recent research in industrial organization, marketing science, public economics, macroeconomics, and so on. This chapter reviews previous literature, and in particular, follows three avenues of thought. Separately, the chapter summarizes vertically differentiated markets and demand estimations, unified decisions for brand and quantity, and price promotion effects. The final consideration is the contribution of this research to the body of relevant literature.

2.1 Vertically Differentiated Markets

Firms can differentiate their products horizontally (variety) or vertically (quality). In contrast to horizontal differentiation in which the perception is that products have equivalent quality, products achieve vertical differentiation when one product's quality rank higher than another. In particular, vertical product differentiation has had extensive study in both economics and marketing ([Gabszewicz and Thisse (1979)], [Shaked and Sutton (1982)], [Moorthy (1990)], [Lancaster (1990)], [Choi and Shin (1992)], [van Denbosch and Weinberg (1995)], [Wauthy (1996)], [Lauga and Ofek (2011)]).

A seminal study by Gabszewicz and Thisse (1979) analyzed product equilibrium in which two firms sell products of different qualities. In this duopoly, firms are competing to sell similar products with different qualities to a large number of consumers representing households whose characteristics are the same except for the income level. Consumers, informed of the quality and price offerings of the two firms, differ in their reservation price for quality due the income inequality. The assumptions are that production costs for the different qualities are the same, and all consumers have identical preferences or assign the same rank to products. With this simple setting, the income dispersion among consumers gives rise to incentives for firms not only to produce products of different qualities but also maximize the products' differentiation. The rationale of this implication is that as the quality of two goods become too close, price competition between the increasingly similar products becomes too intense and reduces the profit of both firms. The role of income dispersion would be more pronounced after considering the different cost conditions. The results of differentiating two products separate the markets into rich households, which consume a high quality product at a high price and poor households, consume a low quality product at a low price. An additional, noteworthy consideration is, whether or not the differentiations according to product quality is better for social welfare.Gabszewicz and Thisse (1979) claim that a sufficient degree of income inequality is required to achieve an optimal solution for welfare.

Shaked and Sutton (1982) further developed the model of Gabszewicz and Thisse (1979) by including the market entry with the assumption of vertical differentiation. Shaked and Sutton (1982) also assumes a large number of consumers with identical preferences but different incomes and zero production costs. The model analyzes a three stage non-cooperative game, in which firms decide their entries, quality of products and then prices, sequentially. The core finding is that competition of quality leads to firms to choose the highest quality permitted with zero profits unless only two firms enter the industry. Shaked and Sutton (1982) asserted that price competition after choosing the level of quality limits the maximum number of firms that can obtain positive market shares, because firms with high quality products compete according to price to the point that even poorest consumer does not want to obtain a free, lower quality product. Following the Shaked and Sutton (1982) model, the only, perfect equilibrium is one in which exactly two firms enter, produce distinct products, and earn positive profits at equilibrium.

Moorthy (1990) extends the basic model by incorporating the existence of a quadratic cost function for quality. Assuming a higher quality product more costly than a lower quality product, they analyze two different types of product competitions. The first type of competition assumes two identical firms choose their qualities and prices simultaneously; whereas, the second type of competition has an incumbent firm in the market that chooses its quality and price first and the second entrant decides its policy sequentially. The trade-off in quality choice is that if the quality decisions for products are too similar, the price competition may become too intense; whereas, if the decisions are too divergent, the profits and market shares may shrink due to high production costs. Moorthy (1990)'s results presented that, in both types of competition, firms have incentives to differentiate their products, and firms with higher quality have a higher margin in equilibrium. Secondly, the equilibrium product differentiation is inefficient in the aggregate unless the market is monopolistic. Last, in the second type of competition, the incumbent market leader can preempt the most desirable product position and effectively discourage later entrants.

2.2 Unified Decision of Brand and Quantity

Extensive literature investigated households' purchasing behaviors for brand and quantity choices. Before the seminal work by Hanemann (1984), previous studies restricted investigation to consumers' choices of brands and quantity, separately, or assumed that decision of brand and quantity are independent ([Guadagni and Little (1983)], [Krishnamurthi and Raj (1988)], [Neslin, Henderson, and Quelch (1985)], [Gupta (1988)]). Many studies use logit models for decision for brands and regression models for decisions of quantity. However, this approach does not ensure that observed consumers' decisions are the outcome of maximizing utility within a household, and does not provide unbiased, consistent, and efficient regression parameters due to omitted or ignored relevant information.

Initially, Hanemann (1984) proposed a generalized random utility model with discrete choices for brand and continuous choices for quantity by providing a theoretical framework in which households' decisions for consumptions are combinations, based on a single utility function. By choosing a brand among a finite number of alternatives and continuously adjusting quantity, consumers maximize their utility, which depends on observed characteristics and unobserved heterogeneous preferences. Later, Dubin and McFadden (1984) showed how to apply the Hanemann (1984) model to their empirical study analyzing possessions and consumption of residential electric appliance. In addition to this, following the Hanemann framework, many studies investigated households' purchasing behavior with the unified model, based on the utility function of a single household. ([Krishnamurthi and Raj (1988)], [Tellis (1988)], [Bucklin and Lattin (1991)], [Chiang (1991)], [Chintagunta (1993)], [Bell, Chiang, and Padmanabhan (1999)]).

In particular, Krishnamurthi and Raj (1988) focused on the role of price in the decisions for brand and quantity with a model, which establishes brand and quantity as interdependent but with a sequence. Krishnamurthi and Raj (1988) model asserts that, consumers choose a brand by comparing all available brands primarily according to price, and then, consequently, decide the quantity of a purchase based on budget constraints and the price of the chosen brand. By employing ADTEL diary panel data and a two-stage estimation procedure, Krishnamurthi and Raj investigated price sensitivity in between choosing a brand and a quantity, along with empirical examination of competitive prices' main effect on the choice of brand without significant effect on the quantity of brand purchased.

Chintagunta (1993) also adopted and calibrated the framework suggested by Hanemann (1984) and investigated the impact of marketing variables such as price promotion, advertisements of features, and special displays on households' purchasing decisions. Chintagunta (1993) provided a unified model of household's decision, and the model accounts for the three options in a decisions, including purchasing incidences in addition to choice of brand and quantity purchased. This study's model estimated parameters by employing Nielsen scanner data for the purchase of yogurt in Springfield, MO. Chintagunta (1993) compared the approach and a nested logit model of purchasing incidence and choices of brands in a holdout sample. Similar to the framework of Chintagunta (1993), a number of studies in Marketing proposed a model of estimation for demand. In particular, Dube (2004) allowed consumers to purchase a bundle of products in a category as an extension to the extant literature. ([Neslin, Henderson, and Quelch (1985)], [Gupta (1988)], [Bucklin and Lattin (1991)], [Walsh (1995)]). Dube (2004) separated the time of purchase and the time of consumption by assuming that occasions of consumption for a trip follows a Poisson distribution.

Chiang (1991) built a similar model and calibrated it using scanner panel data. Later, Bell, Chiang, and Padmanabhan (1999) decomposed total price elasticity into brand switching and purchase acceleration.

In recent literature, the demand estimation with a framework with maximization of joint utility evolved in different ways. First, another relevant thread in the literature arose after Berry (1994) and Berry, Levinsohn, and Pakes (1995). In particular, Berry, Levinsohn, and Pakes (1995) proposed a method of estimating random-coefficients, discrete-choice models of demand. Their method has become a canonical framework to estimate demand because: i) It can be applied to market-level price-sales data in the absence of micro-level data. ii) It deals with the endogeneity problem of prices. And iii) it produces a more realistic indication of elasticity of demand. Nevo (2000) provided a valuable summary for theory, estimation, numerical implementation, and promising applications for the framework.

After research, Nair, Dube, and Chintagunta (2005) derived the aggregate demand system, which corresponds to a discrete/continuous household-choice, which allows consumers to purchase more than one unit of the goods. The study of Nair, Dube, and Chintagunta (2005) achieved improvement in the fit of aggregate sales in the model, applying store-level data of refrigerated orange juice with limited data, calibrated by an aggregate.

Allenby, Shively, Yang, and Garratt (2004) investigated a demand model including choice of brand and quantity using scanner data of light-beer. In that model, the choice of quantity is discrete. The assumption does not include different brand-size combinations as a different choice, instead, one brand has several size options, evaluation considers each feasible solution. The model examines nonlinear pricing on large packages (quantity discount), so the assumption is that unit prices change according to quantity.

Other recent literature extended and employed a direct utility function approach to modeling the multiple-discrete choices from optimization with corner solutions. Some of these extensions appear in other disciplines: such as Environmental economics and Transportation, for which Bhat (2008) formulated an econometric approach for the multiple discrete-continuous, extreme value model. VasquezLavin and Hanemann (2008) developed the Bhat (2008) approach to investigate further with a non-additively-separable utility function.

A growing number of researchers studied households' purchasing behavior with dynamic models. ([Pesendorfer (2002)], [Hendel and Nevo (2006)], [Erdem, Imai, and Keane (2003)]). Differing from other studies using static models, their research provide models in which consumers are forward-looking and optimize timing of purchases, based on expectations for future prices. Pesendorfer (2002) investigated the relationship between the consumer's expectation for future prices and the effect of promotion. They showed that current demand is higher when consumers experienced higher price in the past; therefore, the effect of sales promotion has a greater impact when the gap in time between current promotion and the previous one is greater. Hendel and Nevo (2006) suggested a dynamic model for decision of brand

and quantity and examined whether or not choices for brands are independent of past inventory holdings of brands. In Erdem, Imai, and Keane (2003), the stochastic price fluctuation and consumers' expectations for future prices affect decisions of quantity. Erdem, Imai, and Keane (2003) investigated differing price promotion affects demand with various scenarios of price change. By estimating price elasticity, they identified the effect of duration and frequency of price promotions on both purchase-acceleration and probability of switching brands.

Last, an influential body of research discussed the quality-quantity trade-off for purchasing behavior, particularly in relation to change in incomes. Theil (1952-1953) and Houthakker (1952-1953) initially proposed a framework to explain the quality problem and studied the joint influence with income. Houthakker (1952-1953) argued that consumers adjust their choices for quality and quantity, and thus, an increase in the premium for quality does not necessarily reduce the choice for quality because quantity may change as well. Nelson (1990), Nelson (1991), and Nelson (1994) discussed the quality-quantity trade-off by emphasizing the implication for the method for estimating elasticities of price and income. These studies identified that a method for estimating elasticities of price and income employed by Deaton (1988) might contain a problem if many dimensions exist in which goods categorized in the same group are heterogeneous. Furthermore, in this case, the unweighted sum of physical quantities may mislead the actual influence of income elasticity of demand. Deaton particularly presented substituting behavior from physical quantity to quality with increases in income among U.S. consumers. With regard to the issue of quality, a current study by Yu and Abler (2009) highlighted that as income increases consumers shift toward more expensive foods or higher-quality products, with offsetting quantity increase.

2.3 Price Promotion Effects

The current study is useful for counterfactual experiments of the impact of price promotion, growth of income, tax cuts and so on. The effect of price promotions on consumers' responses has had wide study. Gupta (1988) began to investigate decomposition of a brand's total price elasticity. The impact of promotion on purchase-acceleration consists of: purchase-incidence(14%) and stockpiling(2%), where the effects are relatively small, and brand-switching, which accounts for 84% of elasticity. Bell, Chiang, and Padmanabhan (1999) generalized this decomposition for 173 brands among 13 different product categories using price elasticity. They found that 75% of elasticity is due to switching brand and 25% due to purchase-acceleration.

While previous research reports the majority of promotional response comes from brand switching, van Heerde (2005) suggested the size of effects calculated from elasticity is exaggerated. That study proposed a decomposition of unit sales instead of elasticity providing evidence that one third of the bump from sales promotion is due to switching brands.

While the previous studies have a basis in logit model (or nested logit model), structural approaches have grown with increasing computational capability. Sun, Neslin, and Srinivasan (2003) asserted that elasticities from switching brands derived from logit-type models can be overestimated. Sun, Neslin, and Srinivasan (2003) demonstrated that a structural approach, focusing on a waiting motive for the next promotion is a requirement for capturing the promotion's effect rather than simple, static, (nested) logit models. Sun, Neslin, and Srinivasan (2003) predicted sales from a 50% increase in frequency of promotion. Erdem, Keane, and Sun (2008), using scanner panel data of ketchup, proposed and estimated a structural model focusing on stock-piling motive and implied intertemporal purchasing behavior.

Chan, Narasimhan, and Zhang (2008) developed a dynamic structural model with flexible consumption and they decomposed the effects of promotions. They suggested explicitly allowing for consumers' heterogeneity for preferred brands and consumptive needs.

2.4 Contribution to the Literature

The current research develops unified decisions for choices of brands and quantities using the Dixit-Stiglitz utility function, which considers heterogeneous preferences. The study estimates consumers' demand for both brand and quantity in a vertically differentiated market where consumers choose different quality of products. The suggestion is for a structural approach to estimate individual's brand-dependent demand and conducts policy experiments for the effect of changes in price and income. In particular, the study extends the random utility model of Hanemann (1984) and applies it to the market for (organic and non-organic) food.

Several differences exist when comparing the current research with previous studies. First, estimated demand derives from underlying optimization. The model of Bell, Chiang, and Padmanabhan (1999) also synchronized a discrete model for choice and quantity; however the choice of quantity is not from optimization.

Second, the current research estimates key structural parameters rather than fixing them at seemingly reasonable values for parameters. Chiang (1991) built a similar model and calibrated it using scanner panel data. However, that study has a limitation in the sense that it is not a precise estimation, but a calibration.

Third, current model assigns brand-dependency to the decision of quantity. As Hanemann (1984) suggested, optimal discrete choice depends on optimal continuous choice and vice versa. However, in Chintagunta (1993), the model is different from the one proposed in this study in the sense that the decision for quantity in Chintagunta (1993) is not brand-dependent. For Chintagunta (1993), each consumer's intrinsic preferences regardless of choice of brand determines the quantity. This interpretation cannot explain the common consumption reduction, which may occur when switching from non-organic to organic.

Fourth, the current model can utilize panel data, which contains richer information than aggregate data. In Berry (1994) and Berry, Levinsohn, and Pakes (1995) the main contribution is providing an econometric model with reasonable estimates due to a lack of micro-level data. In other words, Berry (1994) and Berry, Levinsohn, and Pakes (1995), in addition to estimating demand without adjustment for quantity, provided an alternative rather than exploiting a rich data set as the current study does. Notably, Berry (1994) and Berry, Levinsohn, and Pakes (1995) applied their method to the automobile industry, in which each consumer purchases one car.

Last, the proposed model focuses on switching behavior rather than attending to nonlinear pricing or storage costs. Allenby, Shively, Yang, and Garratt (2004) investigated a demand model with choices for brand and quantity using scanner data of light-beer. In that model, quantity choice is discrete, while the current study uses a framework of continuous choice for quantity to allow for using first order conditions. Allenby, Shively, Yang, and Garratt (2004) do not assume different brand-size combinations as different choices, instead, one brand has several size options, and evaluation is for each feasible solutions. Their model focused rather on discount for quantity (nonlinear pricing on large packages), assuming pricing changes according to quantity. From the assumption of choices for discrete quantities, price schedules become piecewise-linear with the budget constraint. In fact, discounts for large quantities are important for analyzing purchasing behavior of packaged products. While the proposed model uses per-unit prices, it also considers the effect of large per package discounting through empirical analysis, which estimates the coefficients of a dummy variable representing large package.[1] In the case of perishable, fresh produce, the packaged goods are not storable for long periods of time. For this reason, the model deemphasizes discounts for quantities, although the model does capture this aspect. Since Allenby, Shively, Yang, and Garratt (2004) analyzed the light-beer market, in which consumers usually buy multiple units rather than one unit, nonlinear pricing plays significant role.

In Erdem, Imai, and Keane (2003), quantity derives from storage costs and shopping costs rather than brand-dependency. In the absence of such costs, the current research still observes a brand-dependent demand in the market for food. Modeling decision rules for brand-dependent quantities and estimating the model is the main purpose of this research.

[1] See Model Variation part.

Chapter 3

The Market for Organic Foods

This chapter discusses the market for organic foods, which is vertically differentiated in the sense that customers perceive a hierarchy or quality difference between organic and non-organic products. The first area of discussion is a review of the previous literature regarding consumers' behavior in an organic food market, followed by a summary of the carrot industry. Finally, this study presents consumers' demographic characteristics categorized by organic and non-organic food purchases using 2009 Nielsen homescan data of carrots in a Midwestern metropolitan area. The investigation considers who the typical consumers of organic products are in terms of income, education, and other relevant demographic characteristics.

3.1 Consumers in the Organic Food Market

The organic food market in the U.S. has expanded significantly after early 1990s, meeting the increased demand for healthy and organic food. According to research of United States Department of Agriculture (USDA) by Dimitri and Greene (2002), which reported growth patterns in the U.S. organic food market, retail sales have grown more than 20 percent annually since 1990. Congress legislated the Organic Food Production Act of 1990 to establish national standards for organic products, the USDA implemented a uniform standard for organically produced agricultural products in October 2002. The standards specify methods, practices, and substances in production and handling of crops, livestock, and processed products. The USDA organic seal applies to agricultural products that are "100 percent organic" or "organic"[1](Dimitri and Greene (2002)).

According to Smith and Lin (2009), retail sales of organic food increased from $3.6 billion in 1997 to $18.9 billion in 2007, accounting for over 3 percent of total U.S. food sales. The global organic food market grew rapidly up to a value of $59.3 billion, with a growth rate of 12.4% in 2010. Recent estimates place the value of the organic food market in the US at 49% of the global total recently (Organic Food: Global Industry Guide 2010). [2]

Markets for organic products have special characteristics and along with markets for conventional product, markets show a hierarchical structure in the sense that customers perceive organic products to be of higher quality than conventional products. Accordingly, as several studies and report indicate, organic produce carries a significant price premium. Sok and Glaser (2001) tracked wholesale prices for organic broccoli, carrots, and mesclun and reported that price premiums for organic carrots were clearly present in the Boston market in 2000 and 2001. Prices for conventional carrots ranged from $9.50 to $14 per container (sacks of 24 count, 2lb film bags) and averaged $11.27. Prices for organic carrots show a comparatively volatile price pattern, varying between $17.50 and $35, with a premium, at wholesale, for organic carrots to be $14 per container, on average, which is 25 percent higher than conventional carrots' prices.

Not only wholesale prices, but also retail prices for organic products have significant price premiums. Huang and Lin (2007) investigated that the premium consumers are willing to pay for organic tomatoes using actual consumer purchase data. To account for variation of price premiums in consumers' socio-demographic characteristics and market area, they estimated a hedonic price model using Nielsen homescan data. The results indicated that consumers value the organic and packag-

[1]Products labeled "organic" must consist of at least 95- percent organically produced ingredients. (Organic Standards and Certification, Dimitri and Greene (2002))

[2]The detail of information is available at the web site of "Organic Food: Global Industry Guide 2010": `http://www.datamonitor.com/store/Product/organicfoodglobalindustryguide2010?productid=C9A72F75-510A-4CC7-AA28-9DE6FE209E1A`

ing attributes positively and consistently among major markets. For example, the study suggested that the organic feature contributes $0.41 per pound to the price of fresh tomatoes that consumers paid in the Northeast market. For other markets, estimates place organic premiums at $0.38 per pound in the North Central, and $0.26 per pound in the Southeast and West.

Along with this market feature, many researchers investigated the identities of typical consumers for organic products in terms of demographic characteristic. Smith, Huang, and Lin (2009) showed price and income affect consumers' purchases of organic produce and divided consumers into three groups according to purchases of organic products: devoted, casual, and nonuser. That research employed an ordered logit model to quantify the effects of economic and demographic factors on purchases of organic products. Smith, Huang, and Lin (2009) showed the profile of organic food users are typically a Hispanic household residing in the Western US with children under 6 years old and a head-of-household, older than 54 years, with a college degree.

Dettmann and Dimitri (2007) applied a logit model and a Heckman two-step model to Nielsen homescan data. Their research analyzed the relationship among demographic variables and the purchases of organic vegetables: pre-packaged salads, carrots, and spinach. Dettmann and Dimitri (2007) showed that race, education level, and household income influence the probability of buying organic vegetables.

Using the same dataset, Dettmann (2008) demonstrated that households with higher educations and incomes are more likely to buy organic pre-packaged produce. Also, the odds of purchasing organic fruits and vegetables decreases among African-Americans.

On the other hand, Zhuang, Dimitri, and Jaenicke (2009) investigated consumers' choice between private label and national brands using the Nielsen data for organic and non-organic milk. They established a two-stage model in the first stage of which, consumers choose organic or non organic milk and in the second stage, consumers select private label or national brand. Estimation used two-stage sample selection and demonstrated that relative prices, promotion, consumption patterns, and demographic variables, such as income, education, working hours, race of head-of-household significantly affect the purchase of organic milk and non-organic milk. Given organic or non-organic milk purchases, the presence of children in the household, marriage, and availability of coupons, significantly affect the choice between private label and national brands. Zhuang, Dimitri, and Jaenicke (2010) investigated pricing interactions among private label and national brands and organic price premiums using a Nielsen data set of 52 organic and non-organic milk markets in the United States.

In modeling the market for organic food, Onozaka, Bunch, and Larson (2007) emphasized that both state dependence and heterogeneous preference should be considerations when analyzing consumers' purchasing behavior. Onozaka, Bunch, and Larson (2007) also applied a mixed nested logit model to household-level panel data using organic and conventional red leaf lettuce.

The previous literature analyzed the characteristics of organic food consumers based on observed data; however, the analyses are not based on optimization. The current research focuses on fundamental preferences, and decisions, and reviews the issues mentioned earlier.

3.2 Carrot Industry in the US

Carrots are one of the major vegetables in fresh vegetable markets along with tomatoes, potatoes, lettuce and onions. Estimates place the value of the total U.S. carrot production at $311 million, and this represents an increase of more than 20% annually from 1997 to 2005 (Reynolds (2010)). Scherer and David (2000) asserts that substantial expansion of the market for carrots associates with growing consumption and improved production technology. Consumers' desire for fresh and convenient vegetables has driven the growth for consumption of carrots. In particular, the introduction of prepared carrots, pre-cut and peeled, is an influence on the trend. Large retail super market chains, enabled centralizing large carrot producers who expanded the acreage devoted to planting carrots. Furthermore, those carrot producers have effectively increased yields and quality by using hybrid varieties of carrots, air seeders, fungicides and irrigation.

The suppliers to U.S. fresh vegetable markets are largely producers in California, and this is the case for the market for fresh carrots. California has maintained approximately 75% of the market for fresh carrots in the U.S., with Michigan, Washington, and Florida producing 5.1%, 4.7%, and 4.6%, respectively. (Koo and Taylor (1999)) Producers in Michigan, Washington, New York, Ohio, and Minnesota grow one crop per year due to constraints of weather; whereas, growers can produce multiple crops per year in California. Provided that fresh carrots maintain their quality for six to nine months with proper storage procedures, California has a strong, relative advantage from weather for production of carrots.

Another noticeable phenomenon in modern industry for carrots is the extensive growth for markets for baby carrots. The short-cut or baby carrots, introduced in recent years, are capturing a larger share of the market for fresh carrots, as compared to regular fresh carrots. Baby carrots display a nearly double average retail unit price of conventional carrots, with $1.40 per pound ($ 0.088 per oz) compared to whole carrots at $0.77 per pound ($0.048 per oz), on average. (Stewart, Hyman, Buzby, Frazao, and Carlson (2011))

Along with the growth of the market for organic fresh vegetables, the market for organic carrots has also increased substantially. Carrots are a fresh vegetable that with a significant share of the market for organic products. This research defines "carrots" and "organic carrots" as follows. Throughout the study, "carrot" includes only normal and unprocessed products. Since "baby carrot", "carrot dip", "shredded carrot", or "carrot chip" are imperfect substitutes for normal carrots, the study excludes those. "organic carrots" are defined as USDA organic sealed carrots or organic claimed carrots.[3] According to USDA, USDA organic sealed products must consist of at least 95 percent organically produced ingredients, and an organic claim requires at least 50 percent organic ingredients, which are certified organic by QAI (Quality Assurance International Organic Certification).

The product category of carrots provides several advantages for analyzing purchasing behavior organic food and brand dependency. First, fresh vegetables and fruits have been top-selling food categories among organic foods. Dimitri and Greene (2002) documented that the size of market for organic fruits and vegetables was $200 million in 1990 became more than $2500 million in 2000, and the top ten organic products purchased were strawberries, lettuce, carrots, other fresh fruit, broccoli, apples, other fresh vegetables, grapes, bananas, and potatoes. According to Dimitri and Oberholtzer (2009), the retail sales of fresh produce has grown, on average, 15 percent per year from 1997 to 2007. Increasing consumer concern for health is a reflection of the rapid growth growth of the market for organic vegetables and carrots.

Second, top production companies represent a fairly intense concentration for both organic and non-organic carrots. Table 3.1 presents the market shares of each brand in the Midwestern metropolitan area in 2009. For both frequency of chosen brands and total demand (total quantity purchased), leading brands comprise more than 99.5% of the market. The non-organic brands represent 85.4% of the market's volume and organic brands represent 14.6%. This study restricts data to 4 organic brands and 4 non-organic brands and eliminates observations for other brands.

In the sample, the leading producer of the entire market for carrots is the non-organic brand 1 which has a market share of 56.43%. Non-organic, private labeled products follow and represent 18.24% of the market. Organic carrots, in the dataset

[3]Nielsen data considers two organic definitions; USDA organic sealed and organic claimed. The dataset codes, non-organic carrots as OrganicClaim = 1 or 2 or 4.

Table 3.1. Market Shares of the Carrot Market

Brand Name	Organic	Brand frequency	Total demand	Market share
1	No	1350	2764	56.43%
2(Private Label)	No	592	895	18.27%
3	No	245	456	9.31%
4	No	8	68	1.39%
5	Yes	154	429	8.76%
6 (Private Label)	Yes	43	79	1.61%
7	Yes	29	41	0.84%
8	Yes	38	166	3.39%
Total		2459	4898	100%

represent, 264 purchases, or 10.74% of the transactions involving carrots. The leading brand of organic carrots is brand 5, which has a market share of 8.76% and a 60% share of the market for organic carrots. Again, organic, private-label products have the second largest portion of the market for organic carrots. Brand 8 is a carrot-specialized organic brand with a market share of 3.39% in dataset. It is noticeable that average offered price of brand 8 is \$1.87 per pound, and the average accepted price is \$1.21 per pound. In the case of organic brand 5, its average offered price is \$1.28 per pound, and the average accepted price is \$1.26, showing a smaller gap. This implies that organic brand 8 may have more frequent price promotion than brand 5.

This study considers organic private-label brands and non-organic private-label brands as separate brands. Table 3.2 reports the private labeled carrots with the highest purchasing frequency in the dataset.

Table 3.2. Major Private Label Brands

Store Name	Private Label (N-OG)	Private Label Organic	Total
V	534	24	558
W	31	0	31
X	4	17	21
Y	9	0	9
Z	4	0	4

Table 3.3 represents availability of a brand of carrot in major stores in the study's sample. The table shows two to seven brands of carrots are available in each store. For example, in store "W," brands 1, 2, 3, 4, and 6 are available. [4]

Table 3.3. Availability of Brands in Major Stores

Brand	1	2	3	4	5	6	7	8
V	O	O	O	O	-	O	-	-
W	O	O	-	-	-	-	-	-
X	O	O	O	-	-	O	-	-
Y	O	O	O	O	O	-	O	O
Z	O	O	O	-	O	-	-	O

Note: "O" means the corresponding brand is available in the store.

Panel A in Table 3.4 reports availability and price premiums for a given brand. Notably, brand 1 is dominant in the market in terms of availability. Consumers can find non-organic carrots supplied by brand 1 in 98.2% of stores; whereas, the organic brand 8, is available only in 34.2% of stores. This table also shows a substantial price premium for organic products, as summarized in Panel B of Table 3.4. For non-organic carrots, the average offered price per pound is \$0.70, while organic carrots command \$1.33 per pound, with organic price premium of \$0.63 (90% in percentage terms). The accepted price is the price paid by consumers when the time of purchase. Even though the actual price paid for organic carrots is lower than the average price, Panel B in Table 3.4 indicates that the average accepted price for organic carrots is still higher than that for non-organic carrots as \$0.32 (46.38% in percentage). Interestingly, the organic price premium of \$0.63 cannot account for the huge difference in the actual expenditure without considering income effect. Although the substitution effect lowers consumption for expensive products, the income effect encourages wealthier households to consume more units.

[4]In fact, organic brands' availability is restricted than conventional carrot brands, the store choice issue may potentially cause problem in the estimation results.

Table 3.4. Availability and Price Premium

Panel A. Availability and average prices of each brand			
Brand	Availability	Average offered price ($) per LB	Average accepted price ($) per LB
1	98.2%	0.75	0.70
2 (Private Label)	65.0%	0.80	0.87
3	70.7%	0.67	0.57
4	54.7%	0.55	0.57
5	48.7%	1.28	1.26
6 (Private Label Organic)	30.3%	1.14	1.13
7	37.5%	1.08	1.09
8	34.2%	1.87	1.21
Total	-	0.92	0.78
Panel B. Availability and price premium for organic carrots			
Non-organic	72.2%	0.70	0.69
Organic	37.7%	1.33	1.01
Premium	-	0.63	0.32

3.3 Consumer Characteristics of the Market for Carrots

This section describes demographic characteristics of carrot's consumers. Table 3.5 summarizes the demographic characteristic of households whose members purchase organic carrots. The average income of consumers of organic carrots is above that of non-organic carrots. The sizes of household are similar between two groups, but consumers of organic carrots have younger children. This accords with the accepted notion that parents with younger children may be more sensitive to the quality of food. Last, the table shows that consumers of organic carrots are more educated than consumers of non-organic carrots. In general, these demographic statistics show that consumers regard organic carrots as a high quality product, and significant differences are apparent in purchasing behavior among households for this vertically differentiated product.

Table 3.6 provides more details of the relationship between females' educational levels and purchasing behavior for organic carrots. Although the average quantity purchased for each incident does not vary according to categories, the data shows a

Table 3.5. Demographic Characteristics of Consumers of Organic Carrots

	HH Size (number)	Presence of Children under 12(=1)	Females' Education (yr)	HH Income ($)
Non-Organic	2.728	0.165	14.624	76,589
Organic	2.640	0.273	14.909	81,316
Total	2.718	0.177	14.655	77,096

clear variation in the frequency of purchasing organic carrots according to educational level. Households with college graduates represent 13.32% of purchasers of organic carrots; whereas those who do not have high school diploma accounts for below 3% of organic carrots purchases.

Table 3.6. Females' Education and Purchase of Organic Carrots

Category	Description	Year	Frequency of organic purchase	Average quantity purchased
1	Grade School	9	0.00%	1.25
2	Some High School	10	2.63%	2.05
3	Graduated High School	12	9.49%	1.77
4	Some College	14	9.60%	1.90
5	Graduated College	16	13.32%	2.25
6	Post College Grad	18	10.77%	2.00
Total	-	-	10.74%	1.99

Table 3.7 presents the variation in frequency of purchasing organic carrots depending on the presence of young children in households. Households without children under 12 choose organic carrots for 9.49% of the group, whereas those with child under 12 choose organic carrots account for 16.55% in the same group. Again, this statistic is consistent with the notion that members of households with younger children may display greater sensitivity to choosing quality food.

Table 3.7. Presence of Young Children in Households and Purchases of Organic Carrots

Category	Description	Frequency of organic purchase	Average quantity purchased
1	No child under 12	9.49%	1.95
2	Children under 12	16.55%	2.18
Total	-	10.74%	1.99

Table 3.8 shows the relationship between female household members' working

hours per week and frequency of purchasing organic carrots. The expectation is that working hours relate to educational level and households' income. This table does not provide indication of a consistent relationship between females' working hours and purchases of organic carrots. However, it shows that the frequency of purchasing organic carrots is significantly higher if a female head-of-household works more than 35 hours per week.

Table 3.8. Females' Working Hours Per Week and Purchase of Organic Carrots

Category	Description	Frequency of organic purchase	Average quantity purchased
1	Less than 30 hours	7.69%	2.06
2	30-34 hours	6.16%	1.76
3	35+ hours	14.05%	2.02
9	No Employment	9.82%	1.98
Total		10.74%	1.99

Table 3.9 contains data for the relationship between ethnicity and purchasing organic carrots, and shows that black consumers choose organic carrots most frequently in our sample. White and black consumers purchase organic carrots 10.37% and 17.80%, respectively. Contrastingly, Asian consumers purchase the highest quantity produce but are least likely to buy organic carrots.

Table 3.9. Ethnicity and Purchase of Organic Carrots

Category	Description	Frequency of organic purchase	Average quantity purchased
1	White	10.37%	1.91
2	Black	17.80%	2.32
3	Asian	9.42%	2.67
9	Others	6.67%	2.04
Total	-	10.74%	1.99

3.4 Concluding Remarks

In this chapter, I summarize the previous literature on the organic food market, and present an overview of the carrot industry. Also, in this chapter, using 2009 Nielsen Homescan data, I rely on statistical analysis to respond to the first research question as to what characterizes typical organic product consumers in terms of income, education, and other relevant demographic characteristics.

Chapter 4

Theoretical Model

In this chapter, I model a consumer's demand function which contains both brand choice and quantity decision. This study represents a Dixit-Stiglitz type utility function and derives quantity demanded and likelihood function. Using presented model, the current research analyzes implication on income and price elasticities of demand. Later, this study introduces the variation of model to show the possibility of model extension which could capture several attributes of products such as promotion or non-linear pricing.

4.1 Basic Model

In everyday life consumers consume a continuum of different consumption goods, and in the market for each consumption good there are multiple differentiated products, say 'brands'. Consumers choose a brand among multiple alternatives and adjust how much to consume. After the seminal work by Berry (1994) and Berry, Levinsohn, and Pakes (1995), there is an extensive literature estimating discrete brand choice behavior. However, since this research is based on the automobile industry in which consumers usually purchase one car at a time, it is not directly applicable to the organic and non-organic food markets where continuous quantity decision should be considered as well. Simply, it's hard to say that a consumer keeps the same consumption level when she switches from a non-organic brand to an organic brand. Following from Hanemann (1984), this chapter analyzes the incorporated decision on both quality choice and quantity choice in the market for bagged carrots.

Throughout the paper, each consumer, brand, and product category are indexed by i, j and z, respectively. Consumer i maximizes

$$\Big[\int_{z\in Z}\{\Sigma_{j=1}^{J(z)}e^{M_{ij}(z)}q_{ij}(z)\}^{\frac{\rho-1}{\rho}}dz\Big]^{\frac{\rho}{\rho-1}}, \tag{4.1}$$

subject to the budget constraint

$$\int_{z\in Z}\{\Sigma_{j=1}^{J(z)}p_j(z)q_{ij}(z)\}dz = I_i, \tag{4.2}$$

where $q_{ij}(z)$ and $p_j(z)$ represent the quantity and price of brand j in good z, I_i is her income, and $0 \neq \frac{\rho-1}{\rho} < 1$. $M_{ij}(z)$ is a preference weight of consumer i on brand j, or an indication of quality of brand j perceived by consumer i. When $e^{M_{i1}(z)}$ is normalized to one, $e^{M_{ij}(z)}q_{ij}(z)$ is interpreted as the *effective units* of brand j measured by the unit of the first brand ($j = 1$). In the market, there are brand $j = \{1, 2, ...J(z)\}$, total number of brands is denoted by $n_j(z)$. Note that since the number of brands varies across markets, $n_j(z)$ and $J(z)$ depends on z.

In general, a brand is a perfect substitute for another brand so that each consumer chooses one brand (Hanemann (1984)). This is assumed to have a discrete choice for all consumers. An individual consumer can get a corner solution even under convex preferences, but it is not the case if we allow for heterogeneity. Thus, perfect substitution between brands is simplifying assumption. Here, the original Dixit-Stiglitz preferences are based on 'love of variety'. Hence it is not allowed to directly interpret their various goods as different brands. Given that consumers usually choose only one brand to consume, I modify Dixit-Stiglitz preferences to add a composite good, the linear combination of all brands in the same category.

Denote by z^* the consumption good of my interest, say, 'carrots'. For expositional convenience, I use q_{ij}, M_{ij}, and J instead of $q_{ij}(z^*)$, $M_{ij}(z^*)$ and $n_j(z^*)$ respectively, when it is innocuous. It is assumed that the individual i's preference weight for brand j is given by

$$M_{ij} = X_j \beta_i + \zeta_{ij}, \tag{4.3}$$

where

$$\beta_i = \alpha Y_i + \varepsilon_i. \tag{4.4}$$

X_j in (4.3) is the $(1 \times K)$-dimensional vector of observed product characteristics in brand j, and Y_i in (4.4) is the $(L \times 1)$-dimensional column vector of the observed characteristics of consumer i such as income, education, and so on. The K-dimensional random coefficient vector β_i represents the individual consumer's heterogeneous taste on or response to the product characteristics. The $(K \times L)$ matrix α captures the partial effect of individual characteristics on individual taste. The error term ε_i is K-dimensional column vector which consists of independent, and identically distributed random variables ε_{ik}. Here ε_{ik} is individual i's random component for product characteristic X_k (k-th column of product characteristic X for every brand), which is not captured by observed characteristics Y_i. It is assumed that errors are distributed normally.

$$\varepsilon_{ik} \ \sim \ i.i.d.\, \mathcal{N}(0, \sigma) \tag{4.5}$$

Last, ζ_{ij} represents the consumer i's taste on brand j which is unrelated to the observed product characteristics X_j of brand j. For example, it includes the level of satisfaction from her personal experience of it or similar one, [1] which does not depend on the consumer's observed characteristics Y_i as well. Since this is unobservable to the researcher, it is assumed to follow the type I extreme value distribution.

As Koppelman and Bhat (2006) points out, extreme value distribution has computational advantages in the choice model. It can also closely approximates the normal distribution and derive a "closed-form probabilistic choice model". Alter-

[1] This might come from the past experience on the brand or advertisement (commercial or personal advertisement), or liking of the package design.

natively, if error distributions are assumed to be normally distributed, it leads to "multinomial probit model", where normal distribution assumptions for both type of errors ε_i and ζ_{ij} produces severe computational burden in practice.

In fact there are two forms of Type I extreme value distribution (Gumbel distribution), minimum and maximum Gumbel distributions. [2] Gumbel distribution is the distribution of an extreme order statistic, where minimum Gumbel distribution is the distribution of minimum random variables while maximum Gumbel distribution is that of maximum ones. In my choice model, maximum distribution is more suitable, since consumers choose the most preferred one (the largest extreme) among many options. The probability density function of the (maximum) Gumbel distribution has the probability density function of

$$g(\zeta_{ij}) = \frac{1}{\eta} \exp\Big\{ -\frac{\zeta_{ij}-\mu}{\eta}\Big\} \exp\Big\{ -\exp\{-\frac{\zeta_{ij}-\mu}{\eta}\}\Big\} \tag{4.6}$$

where $-\infty < \zeta_{ij} < \infty$ and $\eta > 0$. μ is the location parameter and η is the scale parameter of Type I extreme value distribution.

Now, consider the utility maximization problem by consumer i. I think of the 2-stage decision problem. That is, consumer i chooses brand at stage 1 and quantity at stage 2. The two-stage optimization is simply understood as conditional probability. Denote by d_i the index of the brand chosen by consumer i at stage 1. Then, the value of $p.d.f.$ with $d_i = j$ and $q_{ij} = q$ conditional on $(X, p, Y_i, \varepsilon_i, \Theta)$ is given by

$$\begin{aligned} & l(d_i = j \text{ and } q_{ij} = q \,|X, p, Y_i, \varepsilon_i, \Theta) \\ = \;& f(d_i = j|\, X, p, Y_i, \varepsilon_i, \Theta) \times g(q_{ij} = q|\, X, p, Y_i, \varepsilon_i, \Theta \text{ and } d_i = j), \end{aligned} \tag{4.7}$$

where $X := \{X_j\}_{j=1}^J$ and $p := \{p_j\}_{j=1}^J$. In what follows, I proceed backward.

Suppose that consumer i with income I_i chooses a particular brand j at stage 1 as following decision rule. Between two alternatives j and j', consumer i prefers

[2] NIST/SEMATECH e-Handbook of Statistical Methods, the website address is http://www.itl.nist.gov/div898/handbook/eda/section3/eda366g.htm, April 2012.

brand j to j' if and only if

$$q_{ij}e^{M_{ij}} \geq q_{ij'}e^{M_{ij'}}. \tag{4.8}$$

The quantity demanded by the consumer at stage 2 is obtained by

$$q_{ij} = (e^{M_{ij}(z)})^{\rho-1} I_i P^{\rho-1} p(z)^{-\rho} \text{ where } P \equiv \Big[\int_{z\in Z} (\frac{p(z)}{e^{M_{ij}(z)}})^{1-\rho} dz\Big]^{\frac{1}{1-\rho}}. \tag{4.9}$$

where P is defined as "preference-adjusted aggregate price".

4.1.1 Proof of Derivation of Quantity Demanded

In this subsection, I derive the quantity demanded in detail. Consumer i solves the utility maximization problem.

$$\Big[\int_{z\in Z} \{\Sigma_{j=1}^{J(z)} e^{M_{ij}(z)} q_{ij}(z)\}^{\frac{\rho-1}{\rho}} dz\Big]^{\frac{\rho}{\rho-1}}, \tag{4.10}$$

subject to

$$\int_{z\in Z} \{\Sigma_{j=1}^{J(z)} p_j(z) q_{ij}(z)\} dz = I_i, \tag{4.11}$$

In stage 1, a consumer chooses a brand, and in stage 2, quantity demanded. Then, by backward induction, for the choice brand j, I can pin down the problem of consumer i into the problem of choosing function $q_{ij}(z)$, simply denoted by $q_i(z)$. That is,

$$\begin{aligned} V \;\; := \;\; & \max_{q(\cdot)} \Big[\int_{z\in Z} (e^{M_{ij}(z)} q_i(z))^{\frac{\rho-1}{\rho}} dz\Big]^{\frac{\rho}{\rho-1}} \\ & s.t. \int_{z\in Z} p(z) q_i(z) dz = I_i, \end{aligned}$$

where $p(z) = p_{d_i(z)}$. From the first order condition with Lagrange multiplier λ,

$$\Big[\int_{z\in Z} (e^{M_{ij}(z)} q_i(z))^{\frac{\rho-1}{\rho}} dz\Big]^{\frac{1}{\rho-1}} (e^{M_{ij}(z)} q_i(z))^{\frac{-1}{\rho}} e^{M_{ij}(z)} = \lambda p(z) \tag{4.12}$$

Multiplying $q_i(z)$ on both sides and integrating over z yields

$$\Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\frac{\rho}{\rho-1}} = \lambda\int_{z\in Z}p(z)q_i(z)dz = \lambda I_i \tag{4.13}$$

Therefore, I get

$$\lambda = \frac{1}{I_i}\Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\frac{\rho}{\rho-1}} = \frac{V}{I_i} \tag{4.14}$$

Plugging (4.14) into (4.12) leads to the following.

$$\frac{V}{I_i}p(z) = \Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\frac{1}{\rho-1}}(e^{M_{ij}(z)}q_i(z))^{\frac{-1}{\rho}}e^{M_{ij}(z)} \tag{4.15}$$

$$\iff \Big(\frac{V}{I_i}\Big)^{\rho}p(z)^{\rho} = \Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\frac{\rho}{\rho-1}}(e^{M_{ij}(z)}q_i(z))^{-1}e^{M_{ij}(z)\rho} \tag{4.16}$$

$$\iff e^{M_{ij}(z)}q_i(z) = \Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\frac{\rho}{\rho-1}}\Big(\frac{V}{I_i}\Big)^{-\rho}e^{M_{ij}(z)\rho}p(z)^{-\rho} \tag{4.17}$$

$$\iff e^{M_{ij}(z)}q_i(z) = e^{M_{ij}(z)\rho}V^{1-\rho}I_i^{\rho}p(z)^{-\rho} \tag{4.18}$$

From the definition of V,

$$\begin{aligned}
V^{1-\rho} &= \Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{-\rho} \\
\iff & V^{1-\rho}I_i^{\rho}p(z)^{-\rho} = \Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{-\rho}I_i^{\rho}p(z)^{-\rho} \\
\iff & e^{M_{ij}(z)\rho}I_i^{\rho}p(z)^{-\rho} = e^{M_{ij}(z)}q_i(z)\Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\rho} \\
\iff & e^{M_{ij}(z)\rho-1}I_i^{\rho-1}p(z)^{1-\rho} = (e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}\Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\rho-1} \\
\iff & I_i^{\rho-1}\Big[\int_{z\in Z}e^{M_{ij}(z)\rho-1}p(z)^{1-\rho}dz\Big] = \int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\rho-1} \\
\iff & I_i^{-1}\Big[\int_{z\in Z}(\frac{p(z)}{e^{M_{ij}(z)}})^{1-\rho}dz\Big]^{\frac{1}{1-\rho}} = \Big[\int_{z\in Z}(e^{M_{ij}(z)}q_i(z))^{\frac{\rho-1}{\rho}}dz\Big]^{\frac{\rho}{1-\rho}} = V^{-1}.
\end{aligned}$$

Finally, I get

$$V = I_iP^{-1}, \text{ where } P = \Big[\int_{z\in Z}(\frac{p(z)}{e^{M_{ij}(z)}})^{1-\rho}dz\Big]^{\frac{1}{1-\rho}}. \tag{4.19}$$

Plugging (4.19) into (4.18) derives the result,

$$q_i(z) = (e^{M_{ij}(z)})^{\rho-1} V^{1-\rho} I_i^{\rho} p_j(z)^{-\rho} = (e^{M_{ij}(z)})^{\rho-1} I_i P^{\rho-1} p_j(z)^{-\rho}.$$

Given optimal quantity demanded for each choice of brand j, consumer i chooses brand j^* if and only if

$$q_{ij^*} e^{M_{ij^*}} \geq q_{ij} e^{M_{ij}}, \forall\, j \in \{1, ...J(z)\}. \tag{4.20}$$

4.1.2 Likelihood Function Derivation

From (4.9), the probability that consumer i purchases less than or equal to q units of brand j conditional on $(X, p, Y_i, \varepsilon_i, \Theta)$ and $d_i = j$ is given by

$$\begin{aligned} & Pr(q_{ij} \leq q |\ X, p, Y_i, \varepsilon_i, \Theta \text{ and } d_i = j) \\ = \ & Pr\Big(I_i P^{\rho-1} p_j^{-\rho} [\exp(\rho - 1)\{X_j(\alpha Y_i + \varepsilon_i) + \zeta_{ij}\}] \leq q \Big). \end{aligned} \tag{4.21}$$

Then, the corresponding likelihood that consumer i who chooses brand j purchases the exact q units is defined by the probability density function of ζ.

$$\begin{aligned} & g(q_{ij} = q |\ X, p, Y_i, \varepsilon_i, \Theta) \\ = \ & g(\zeta_{ij} = \frac{\log(q I_i^{-1} P^{1-\rho} p_j^{\rho})}{(\rho - 1)} - X_j(\alpha Y_i + \varepsilon_i) |\ X, p, Y_i, \varepsilon_i, \Theta) \end{aligned} \tag{4.22}$$

Given the optimal demand for each j at stage 2, consumer i chooses the brand best for her. Between two alternatives j and j', she prefers brand j to j' if and only if

$$q_{ij} e^{M_{ij}} \geq q_{ij'} e^{M_{ij'}}. \tag{4.23}$$

Plugging (4.3), (4.4), and (4.9) into (4.23), taking logarithm, and reordering yields that consumer i prefers brand j to j' if and only if

$$M_{ij} - \log p_j \geq M_{ij'} - \log p_{j'}$$

$$\iff \quad \zeta_{ij'} - \zeta_{ij} \leq (X_j - X_{j'})(\alpha Y_i + \varepsilon_i) - \log\left(\frac{p_j}{p_{j'}}\right). \tag{4.24}$$

Note that ζ_{ij} follows a type I extreme value distribution by construction. Since

$$q_{id_i} e^{M_{id_i}} \geq \max_j q_{ij} e^{M_{ij}}, \tag{4.25}$$

the probability that consumer i chooses brand j among J alternatives is obtained by

$$f(d_i = j | \, X, p, Y_i, \varepsilon_i, \Theta) = \frac{\exp\left\{X_j(\alpha Y_i + \varepsilon_i) - \log p_j\right\}}{\sum_{j'=1}^{J} \exp\left\{X_{j'}(\alpha Y_i + \varepsilon_i) - \log p_{j'}\right\}}. \tag{4.26}$$

The derivation of likelihood f is presented in appendix A.

Putting (4.22) and (A.4) together into (4.7) yields the likelihood that consumer i purchases q units of brand j.

$$\begin{aligned} &L(X, p, Y_i, \varepsilon_i, \Theta) = \\ &\quad f(d_i = j | X, p, Y_i, \varepsilon_i, \Theta) g(q_{ij} = q | X, p, Y_i, \varepsilon_i, \Theta \text{ and } d_i = j). \end{aligned} \tag{4.27}$$

Since ε_i is orthogonal to Y_i by construction, I get

$$\begin{aligned} &L(X, p, Y_i, \Theta) = \\ &\quad \int f(d_i = j | X, p, Y_i, \Theta, \varepsilon_i) g(q_{ij} = q | X, p, Y_i, \Theta, \varepsilon_i \text{ and } d_i = j) d\Phi(\varepsilon_i), \end{aligned} \tag{4.28}$$

where $\Phi(\varepsilon_i)$ is the K-dimensional multivariate normal distribution with common variance σ and zero covariance. Finally, from the whole sample, I get

$$\begin{aligned} &L(\Theta) = \\ &\quad \prod_{i=1}^{I} \int f(d_i = j | X, p, Y_i, \Theta, \varepsilon_i) g(q_{ij} = q | X, p, Y_i, \Theta, \varepsilon_i \text{ and } d_i = j) d\Phi(\varepsilon_i) \end{aligned} \tag{4.29}$$

Finally, taking logarithm yields

$$\log L(\Theta) = \tag{4.30}$$

$$\sum_{i=1}^{I} \log \Big[\int f(d_i = j | X, p, Y_i, \Theta, \varepsilon_i) g(q_{ij} = q | X, p, Y_i, \Theta, \varepsilon_i \text{ and } d_i = j) d\Phi(\varepsilon_i) \Big].$$

4.2 Model Variation

My basic model can be extended in many ways, I use the following model for my empirical study. In the basic model, individual weight M_{ij} for brand j is given by (4.3), it is now extended to

$$M_{ij} = X_j\beta_i + \sum_n D_{jn}\gamma_n + \zeta_{ij} \tag{4.31}$$

where

$$\beta_i = \alpha Y_i + \varepsilon_i. \tag{4.32}$$

X_j in (4.31) is the $(1 \times K)$-dimensional vector of observed product characteristics in brand j, and D_{jn} is a dummy variable of product characteristic in brand j. Y_i in (4.32) is the $(L\times\ 1)$ dimensional vector of the observed characteristics of consumer i such as income, education, and so on. In the extended model, γ_n is a coefficient to be estimated. Since the K-dimensional random coefficient vector β_i represents the individual consumer's heterogeneous taste on or response to the product characteristics, thus the $(K \times L)$ matrix α captures the partial effect of individual characteristics on 'individual' taste. While, the coefficient γ_n captures 'common' response to the product characteristic which is not conditional on consumer's heterogeneous demographic characteristics. It can be used as a constant term in the empirical study.

Assumptions on distributions are maintained without changes. The error term ε_i is K-dimensional column vector which consists of independent, and identically distributed random variables ε_{ik}. It is assumed that

$$\varepsilon_{ik} \sim i.i.d.\, \mathcal{N}(0, \sigma). \tag{4.33}$$

Also, ζ_{ij}, consumer's taste on brand j which is not related to the observed product characteristic, follows the type I extreme value distribution with probability density function of

$$g(\zeta_{ij}) = \frac{1}{\eta} \exp\big\{ -\frac{\zeta_{ij}-\mu}{\eta}\big\} \exp\big\{ -\exp\{-\frac{\zeta_{ij}-\mu}{\eta}\}\big\} \tag{4.34}$$

with location parameter μ and scale parameter η.

Therefore, the corresponding likelihood that consumer i who chooses brand j purchases the exact q units is defined by the probability density as follows. Note that it is now conditional on $(X, p, D_{jn}, Y_i, \varepsilon_i, \Theta)$.

$$\begin{aligned} & g(q_{ij} = q|\ X, p, Y_i, D_{jn}, \varepsilon_i, \Theta) \qquad (4.35) \\ = g(\zeta_{ij} \quad = \quad & \frac{\log(qI_i^{-1}P^{1-\rho}p_j^{\rho})}{(\rho-1)} - X_j(\alpha Y_i + \varepsilon_i) - \sum_n D_{jn}\gamma_n|\ X, p, D_{jn}, Y_i, \varepsilon_i, \Theta) \end{aligned}$$

Next, the probability that consumer i chooses brand j among J alternatives is obtained by

$$\begin{aligned} & f(d_i = j|\ X, p, Y_i, D_{jn}, \varepsilon_i, \Theta) = \qquad (4.36) \\ & \frac{\exp\left\{X_j(\alpha Y_i + \varepsilon_i) + \sum_n D_{jn}\gamma_n - \log p_j\right\}}{\sum_{j'=1}^{J} \exp\left\{X_{j'}(\alpha Y_i + \varepsilon_i) + \sum_n D_{jn}\gamma_n - \log p_{j'}\right\}}. \end{aligned}$$

Putting those probabilities into (6) yields the likelihood that consumer i purchases q units of brand j.

$$\begin{aligned} & L(X, p, Y_i, D_{jn}, \varepsilon_i, \Theta) = \qquad (4.37) \\ & f(d_i = j|X, p, Y_i, D_{jn}, \varepsilon_i, \Theta) g(q_{ij} = q|X, p, Y_i, D_{jn}, \varepsilon_i, \Theta \text{ and } d_i = j). \end{aligned}$$

Since ε_i is orthogonal to Y_i by construction, I get

$$\begin{aligned} & L(X, p, Y_i, D_{jn}, \Theta) = \qquad (4.38) \\ & \int f(d_i = j|X, p, Y_i, D_{jn}, \Theta, \varepsilon_i) g(q_{ij} = q|X, p, Y_i, D_{jn}, \Theta, \varepsilon_i \text{ and } d_i = j) d\Phi(\varepsilon_i), \end{aligned}$$

where $\Phi(\varepsilon_i)$ is the K-dimensional multivariate normal distribution with common variance σ and zero covariance. Finally, from the whole sample, I get

$$L(\Theta) = \prod_{i=1}^{I} \int f(d_i = j|X, p, Y_i, D_{jn}, \Theta, \varepsilon_i) g(q_{ij} = q|X, p, Y_i, D_{jn}, \Theta, \varepsilon_i \text{ and } d_i = j) d\Phi(\varepsilon_i) \tag{4.39}$$

Finally, taking logarithm yields

$$\log L(\Theta) = \sum_{i=1}^{I} \log \Big[\int f(d_i = j|X, p, Y_i, D_{jn}, \Theta, \varepsilon_i) g(q_{ij} = q|X, p, Y_i, D_{jn}, \Theta, \varepsilon_i \text{ and } d_i = j) d\Phi(\varepsilon_i) \Big]. \tag{4.40}$$

4.3 Discussion

In this section, I explore the implications of the model analytically. I will discuss the strengths and the weaknesses of using a Dixit-Stiglitz type utility function through investigation of issues of elasticity and homotheticity. After looking at the general characteristics of the Dixit-Stiglitz preference, I will continue on to discussing my model, which is a modified version of the Dixit-Stiglitz model. I will discuss why empirical elasticity is necessary and how homotheticity is moderated in my theoretical framework and estimation model. Finally, I will examine the relation between quality and quantity, and present testable implications in a vertically differentiated market.

4.3.1 Dixit-Stiglitz Preference

In this study, a modified version of the Dixit-Stiglitz is used. Dixit-Stiglitz preference model is extensively used in the field of Industrial organization, International trade and Macroeconomics, as a general form of the utility function. In Dixit and Stiglitz (1977), widely used form of the Dixit-Stiglitz preference is the constant elasticity case. (CES utility function). Various forms of utility functions, from Leontief functions to linear utility functions, are in the category of CES functions. Cobb-Douglas function is a special form of CES Dixit-Stiglitz preferences as well. Dixit-Stiglitz in the discrete case and the continuum case are represented as follows:

$$U = (\sum_{z=0}^{n} q(z)^{\sigma})^{\frac{1}{\sigma}},$$

$$U = (\int_{z \in Z} q(z)^{\sigma} dz)^{\frac{1}{\sigma}}$$

where $\sigma = \frac{\rho-1}{\rho}$, which is the parameter for love of variety, or elasticity of substitution between any two varieties. σ is assumed to be less than 1 for concavity. When $\rho \to 0$ ($\sigma \to -\infty$), Dixit-Stiglitz utility function converges to a Leontief utility function with perfect complements. When $\rho \to 1$ ($\sigma \to 0$), it converges to a Cobb-Douglas utility function and when $\rho \to \infty$ ($\sigma \to 1$), it converges to a linear utility with perfect substitutes. [3]

This preferences model is useful in dealing with composite goods. Except for the good in focus, I can include all other goods in the budget into the composite good. I can treat the composite good as if it is a single good. In this paper, since I are focusing on consumer decisions on carrots category, Dixit-Stiglitz type model is employed.

I modified the Dixit-Stiglitz preference model into a decision model of brand and quantity. Every commodity category forms a composite good, where the linear combination of all brands are in the same category. In this framework, consumers decide which brand to consume and how many units to buy. Extensive part of the literature that utilize discrete brand choice models, fail to include quantity decisions. If the quantity choices set is discrete as well as the brand choice set, the problem becomes a discrete choice model. If both brand and quantity choices are made from a continuous set, the model becomes difficult to estimate practically. Thus, I assume that consumers make brand choices from a discrete set while quantity choices from a continuous set. Since brands are perfect substitutes to each other, I can avoid the multiple discreteness problem. Each brand alternatives are linearly connected, so consumer chooses only one brand. Since the choice of brand and the choice of quantity will depend on each other, especially if brands are vertically differentiated, I model two stage model of choosing brand and quantity. By adding preference weight for each brand, it can capture quality differences and the preference weight has a structure to examine underlying quality-quantity interaction mechanism.

4.3.2 Elasticities

One caveat of the Dixit-Stiglitz preference is that the elasticity of substitution is equal to the price elasticity of demand and it is constant for all categories. The elasticity of substitution is the relative change of two varieties to the relative change of prices, and is constant to ρ in the Dixit-Stiglitz. Own-price elasticity (price elasticity of demand) is also ρ, and can be derived as following. The optimal quantity demand

[3] $\sigma : I \to J$ is continuous where $\sigma = \frac{\rho-1}{\rho}$, $I = \{x \in \mathbf{R} | 0 < x < \infty\}$ and $J = \{x \in \mathbf{R} | -\infty < x < 1\}$.

derived from FOC is

$$q(z) = I(\int_{z \in Z} p(z)^{1-\rho} dz)^{-1} p(z)^{-\rho}$$

where I is the consumer's income. By taking logs on both sides, I obtain

$$\frac{\partial q_z}{\partial p_z} \frac{p_z}{q_z} = -\rho.$$

I can derive the own-price elasticity for my model in a similar fashion. With the addition of the preference weight term, the own price elasticity for my model is

$$q_{ij}(z) = (e^{M_{ij}(z)})^{\rho-1} I_i P^{\rho-1} p(z)^{-\rho}.$$

From (4.9), I get

$$\log q_{ij} = -\rho \log p_j + \log I_i + (\rho - 1)(\log P + M_{ij}) \tag{4.41}$$

Before deriving elasticity, I can define own-price elasticity in several ways. One possible method would be to consider the price effects on quantity and switch probabilities separately as in Krishnamurthi and Raj (1988). I differentiate the quantity and brand choice probability function f with respect to p_j, respectively. Since M_{ij} contains stochastic terms, by assuming that ε_i and ζ_{ij} are not correlated with price p_j, I can differentiate them.

First, the quantity change due to price change is

$$\frac{\partial q_{ij}}{\partial p_j} \frac{p_j}{q_{ij}} = -\rho. \tag{4.42}$$

Second, the switching probability is the function of brand choice probability. Brand choice probability is given by (4.24). By differentiating brand choice probability with respect to price p_j,

$$
\begin{aligned}
\frac{\partial f}{\partial p_j} &= \frac{\exp\{X_j(\alpha Y_i+\epsilon_i)-\log p_j\}}{\sum_{j'=1}^{J}\exp\{X_{j'}(\alpha Y_i+\epsilon_i)-\log p_{j'}\}}\cdot\frac{-1}{p_j}-\frac{(\exp\{X_j(\alpha Y_i+\epsilon_i)-\log p_j\})^2}{(\sum_{j'=1}^{J}\exp\{X_{j'}(\alpha Y_i+\epsilon_i)-\log p_{j'}\})^2}\cdot\frac{-1}{p_j}\\
&= \frac{\exp\{X_j(\alpha Y_i+\epsilon_i)-\log p_j\}}{\sum_{j'=1}^{J}\exp\{X_{j'}(\alpha Y_i+\epsilon_i)-\log p_{j'}\}}\cdot\frac{1}{p_j}\Big(\frac{\exp\{X_j(\alpha Y_i+\epsilon_i)-\log p_j\}}{\sum_{j'=1}^{J}\exp\{X_{j'}(\alpha Y_i+\epsilon_i)-\log p_{j'}\}}-1\Big)\\
&= \frac{f}{p_j}(f-1)
\end{aligned}
$$

Thus

$$\frac{\partial f}{\partial p_j}\frac{p_j}{f}=f-1. \tag{4.43}$$

(4.41), (4.42) and (4.3.2) imply that if brand switching were prohibited, the negative value of $\hat{\rho}$ could be the estimated price elasticity. If not, it should suffer from serious downward bias. Therefore, rather than directly interpreting ρ as the own price elasticity, I should conduct a counterfactual experiment. I can calculate the counterfactual quantity of the other brands for consumer i based on the parameter estimates. Then, I determine whether she switches to another brand or not. By doing this, I can get an "empirical own-price elasticity" which could be more precise price elasticity.

4.3.3 Homotheticity and Income Elasticity

The general form of the Dixit-Stiglitz preference is a homothetic preference because it is a monotonic transformation of the utility function with the degree of homogeneity 1. Homothetic preference has an additional property that as the consumer's income increases, the demand of goods increases in the same proportion, if they face same prices. It implies the income elasticity of a Dixit-Stiglitz utility function is 1 as shown below.

$$
\begin{aligned}
q(z) &= I(\int_{z\in Z} p(z)^{1-\rho}dz)^{-1}p(z)^{-\rho}\\
\log q(z) &= \log I-\log(\int_{z\in Z} p(z)^{1-\rho}dz)-\rho\log p(z)
\end{aligned}
$$

$$\therefore \quad \frac{\partial \log q(z)}{\partial \log I} = 1$$

Similarly, going back to my model, the quantity demand is

$$q_{ij} = I_i P^{\rho-1} e^{(\rho-1)M_{ij}} p_j^{-\rho} \quad \text{where} \quad P \equiv \Big[\int_{z \in Z} (\frac{p(z)}{e^{M_{ij}(z)}})^{1-\rho} dz \Big]^{\frac{1}{1-\rho}}.$$

If individual i's preference weight on brand j, M_{ij}, is independent of income, as is the case in the general Dixit-Stiglitz or CES utility function, income elasticity is same as 1 and the change in switching probability will be 0.

However, if I assume an individual's preference changes with income, i.e. M_{ij} is a function of income, then quantity demand and brand choice will change with income changes. For convenience, we assume that income is l-th row of demographic characteristic vector Y_i and α is $K \times L$ matrix. Purchasing probability of brand j is given by (4.24). Assuming that ε_i and ζ_{ij} are not correlated with price p_j, I can differentiate them. By differentiating (4.24) with respect to income I_i,

$$\begin{aligned}
\frac{\partial f(d_i = j)}{\partial I_i} &= \frac{\exp\{X_j(\alpha Y_i + \varepsilon_i) - \log p_j\}}{\sum_{j'=1}^{J} \exp\{X_{j'}(\alpha Y_i + \varepsilon_i) - \log p_{j'}\}} \cdot (\sum_{n=1}^{K} X_{jn}\alpha_{nl}) \\
-\frac{\exp\{X_j(\alpha Y_i + \varepsilon_i) - \log p_j\}}{(\sum_{j'=1}^{J} \exp\{X_{j'}(\alpha Y_i + \varepsilon_i) - \log p_{j'}\})^2} &\cdot [\sum_{j'=1}^{J} (\exp\{X_{j'}(\alpha Y_i + \varepsilon_i) - \log p_{j'}\}) \cdot (\sum_{n=1}^{K} X_{j'n}\alpha_{nl})] \\
&= f(d_i = j) \cdot (\sum_{n=1}^{K} X_{jn}\alpha_{nl}) - f(d_i = j) \cdot [\sum_{j'=1}^{J} f(d_i = j') \cdot (\sum_{n=1}^{K} X_{j'n}\alpha_{nl})].
\end{aligned}$$

On the other hand, the effect of income change on quantity demanded is

$$\begin{aligned}
\frac{\partial \log q_{ij}}{\partial \log I_i} &= 1 + (\rho - 1)[\frac{\partial M_{ij}}{\partial I_i}] \\
&= 1 + (\rho - 1)[\sum_{n=1}^{K} X_{jn}\alpha_{nl}].
\end{aligned}$$

Thus, by introducing preference weight, M_{ij}, which depends on income, unit income elasticity can be relaxed and the magnitude of change depends on the sign and size of α. To get a more plausible income elasticity, I conduct counterfactual experiments by increasing incomes. That experiments enable us to investigate how consumers switch brands and adjust quantities for the change of income.

4.3.4 Model Implications

As the study has shown above, the value of α captures the effects of demographic characteristics on consumer i's brand preference and quantity choice through brand specific quality.

X vector represents quality, so better quality has bigger value of X. If there is an increase in individual i's income, if ($\alpha(1,2)$) is negative, according to my specification (4.4), β_i will drop, and preference on organic brand j (M_{ij}) also drops along (4.3). Then according to consumer's quantity decision rule, (4.9), the quantity demanded decreases if β_i is negative. Brand decision follows (4.23), so relative size of M_{ij} and new optimal consumption of quantity q_{ij} determine optimal brand. Thus as income increases twofold, quantity demanded does not increase two times, rather optimal quantity demanded could decrease more than the quantity without the change of income. That decrease in quantity demanded may relate to the decision of switching brand to a better-quality one.

4.4 Concluding Remarks

By analyzing individual consumer's demand, this study examines model implication on quality-quantity trade-offs which could occur when switching brands. I modifies Dixit-Stiglitz preference by adding an assumption of linear combination of brands and preference weight on each brand, to capture possible quality-quantity interaction. In the current model, quantity decision is brand-dependent and the closed form solution of quantity demanded is derived from individual optimization. As Hanemann (1984) indicated, optimal discrete choice depends on optimal continuous choice and vice versa. While Hanemann (1984) does not focus on quality-quantity trade-off, this model shed light on predicting demand in a vertically differentiated goods market. My framework suggests a structural approach to estimate the individual brand-dependent demand and conduct policy experiments for the effect of price and income changes.

Chapter 5

Estimation

This chapter derives the maximum likelihood function from the proposed model in the previous chapter. In this chapter, I specify data construction and econometric model. Here the study discusses identification of model parameters and report two sets of parameters for two possible price elasticity values of ρ. By identifying key parameters in the model, I can figure out consumer decision rule via data simulation. The current study demonstrates that as a consumer's income increases, quantity demanded decreases for plausible value of ρ that theory suggests. The result suggests that as consumers' income increase, they reduce consumption of carrot purchases by switching from non-organic carrots to organic carrots. The evidence to support this quality quantity trade off is provided in the next chapter through policy experiments. With parameter estimates, this study can reproduce and simulate how consumers respond to change of price or income.

5.1 Construction of the Data

1. (2009 Nielsen Homescan data) Dataset is constructed from Nielsen homescan data purchased by USDA ERS. The Nielsen homescan data is a panel data set of households who record their grocery purchases on a weekly basis. It consists of approximately 40,000 household in 48 continental states. I restrict my analysis to fresh carrots purchases at one Midwest metropolitan city area

in year 2009. There are 7,397 observations and 22 carrots brands in the sample.

2. (Excluding Processed Carrots) In this research, I focus on the whole carrots, excluding some forms of processed carrots. I eliminated the observation if the chosen type of carrot is "mini peeled carrot" or "carrot chip", "baby carrot", "shredded carrot", "petite carrot", "carrot matchstick", "carrot dip", "julienne-cut carrot", "coin-cut carrot". I assume whole carrot markets and the processed carrot markets are segregated. It is hard to say that the processed carrots are perfect substitutes of the whole carrot. Among 7,397 observations, 4,647 observations are dropped. Among the dropped, 16 brands appeared and 230 observations are organic carrots. This leaves 2,750 observations and 12 brands. 282 out of 2,750 are organic carrots.

3. (Dropping small number of observations) If the number of observations of one brand is less than 20, the observations corresponds to the brand are dropped. Among the dropped brands, P brand has 5 observations which is the largest number as one brand. In total, 6 brands are dropped. Most of dropped brands have one to two observations, thus total 13 observations have been dropped, leaving 2737 observations in the sample. Additionally, I dropped brand 4's processed carrots with small package (3oz package) products. This leaves 2,676 observations.

4. (Promotion Variable) Nielsen data has promotion variable with 4 categories. Store feature promotion is most frequent in my dataset with 657 observations. There are 4 observations using manufacturer coupons and 35 observations using store coupons. Among 35 observations, 19 of them are private labels. 5 other deals are non-price promotion and all of them are private label.

   (Promotion dummy) For later use, I define promotion dummy variable as in Table 5.1. If the observation comes under any of promotion category, I coded 1.

Table 5.1. Promotion types

Category	Description	Number of Observations
1	Store feature	657
2	Store coupon	35
3	Manufacturer coupon	4
4	Other deals	5

5. (Definition of Quantity) Package size purchased are various, my sample contains 7, 16 (1Lb), 20, 32 (2Lbs), 48 (3Lbs), 80 (5Lbs), 160 (10Lbs) Oz bagged carrots. I use total quantity purchased at each transition as consumer's quantity choice, which is defined as unit package size times number of units. Quantity is coded by unit of pound. Table 5.2 shows carrot quantity purchased per package size(unit) for total and organic and non-organic carrots, respectively. The top table is for both non-organic and organic carrots. 16oz (1Lb) and 32oz (2Lbs) bagged carrots are mostly chosen according to table. In the case of 7Lbs and 20Lbs carrots, there is a single observation respectively, I dropped this two cases in the estimation and counterfactual analysis. The table in the middle is for only organic carrots, and the bottom one is for only non-organic carrots. The tables reports quantity purchased in terms of transaction volume and total weights.

   (Large package dummy) In each observation, if the total quantity purchased is bigger than 80Oz, it is defined as a large package. This is to partly capture nonlinear pricing in large package purchase. So I include the case that package size is small but the total quantity is more than 80Oz.

   (5Lbs, 10Lbs dummy) If the quantity purchased is above 80Oz and less than 160Oz, I define 5Lbs dummy assigning value 1. If the quantity is above 160Oz, I also define 10Lbs dummy.

6. (Demographic Characteristics) I define consumers' demographic characteris-

Table 5.2. Organic and Non-organic Carrots Quantity Purchased

Unit Oz/Quantity	1	2	3	4	5	6	7	8	10	Total transactions	Total Oz
7	1									1	7
16	1,137	251	77	30	4	2	1	1	1	1,504	24,064
20	1									1	20
32	677	35	6		1					719	23,008
48	65	11	1							77	3,696
80	125	3								128	10,240
160	26									26	4,160
Total	2,032	300	84	30	5	2	1	1	1	2,456	69,355

Unit Oz/Quantity	1	2	3	4	5	6	Total transactions	Total Oz
7	1						1	7
16	119	15	4	2	1	1	142	2,272
32	62	5	1				68	2,176
80	33						33	2,640
160	20						20	3,200
Total	235	20	5	2	1	1	264	10,295

Unit Oz/Quantity	1	2	3	4	5	6	7	8	10	Total transaction	Total Oz
16	1,018	236	73	28	3	1	1	1	1	1,362	21,792
20	1									1	20
32	615	30	5		1					651	20,832
48	65	11	1							77	3,696
80	92	3								95	7,600
160	6									6	960
Total	1,797	280	79	28	4	1	1	1	1	2,192	54,900

(i) Organic and Non-organic (top) (ii) Organic (middle) (iii) Non-Organic (bottom) tics as follows:

(a) (Education) I use education level of female head variable, because in many cases, female household heads make a decision in food purchase. Nielsen data provides the level of female head education as a categorical variable, I converted it to year of education. I dropped 208 observations in cases where female head's education does not exist or education level is unknown. This leaves 2461 observations in my sample. Education distribution is shown in Table5.3.

Table 5.3. Female education variable

Category	Description	Year
1	Grade School	9
2	Some High School	10
3	Graduated High School	12
4	Some College	14
5	Graduated College	16
6	Post College Grad	18
0	No Female Head or Unknown	0

(b) (Income) Table 5.4 reports the income distribution in my sample. Nielsen data coded household income in 19 income brackets, I define income as a median of each category. For the truncated values at the top, I use \$250,000. [1]

(c) (Household size) Household size is the number of members in the household including children.

(d) (Child dummy) I define a young child variable as follows in Table 5.5. Nielsen data have AC(Age and Presence of Children) variable which contains presence of children in the household and the age information. If household have at least one children under age of 12, I coded 1.

(e) (Working hours) I look at female employment and working hours. Nielsen data has a Female Working Hours variable as in Table 5.6, which is the

[1] Robustness check on choosing this value will be available in the later version.

Table 5.4. Household income variable

Income	Organic Users					Non-organic Users				
	-9th yr	-12th yr	-16th yr	+16th yr	total	-9th yr	-12th yr	-16th yr	+16th yr	total
Under $5000	0	0	0	0	0	5	8	1	4	18
$5000-$7999	0	0	0	0	0	0	7	0	0	7
$8000-$9999	0	0	0	0	0	0	5	0	0	5
$10,000-$11,999	0	1	0	0	1	0	6	1	5	12
$12,000-$14,999	0	1	0	0	1	3	16	3	0	22
$15,000-$19,999	0	9	1	0	10	3	24	12	0	39
$20,000-$24,999	0	1	0	0	1	0	34	28	5	67
$25,000-$29,999	0	3	7	0	10	5	56	2	1	64
$30,000-$34,999	1	14	2	0	17	0	67	12	5	84
$35,000-$39,999	0	1	0	3	4	4	96	3	4	107
$40,000-$44,999	0	5	16	0	21	0	85	27	0	112
$45,000-$49,999	0	11	1	0	12	0	107	39	16	162
$50,000-$59,999	0	15	5	2	22	1	130	90	22	243
$60,000-$69,999	0	21	7	5	33	13	143	63	44	263
$70,000-$99,999	0	30	29	5	64	7	248	161	78	494
$100,000 - $124,999	0	15	17	10	42	0	127	109	53	289
$125,000 - $149,999	0	0	6	4	10	0	15	40	21	76
$150,000 - $199,999	0	0	1	2	3	0	8	25	19	52
$200,000 +	0	0	6	8	14	0	11	23	46	80
total	1	127	98	39	265	41	1193	639	323	2196

Table 5.5. Young Child dummy variable

Category	Description	New variable
1	Under 6 only	1
2	6-12 only	1
3	13-17 only	0
4	Under 6 & 6-12	1
5	Under 6 & 13-17	1
6	6-12 & 13-17	1
7	Under 6 & 6-12 & 13-17	1
9	No Children Under 18	0

number of hours per week a female head is employed. I create a dummy variable as follows: if female working hours are more than 35 hours a week, I code 1, and 0 otherwise. I dropped observations with no information on female head working hour, this reduces my sample size from 2461 to 2456.

Table 5.6. Working hour dummy variable

Category	Description	New variable
1	Less than 30 hours	0
2	30-34 hours	0
3	35+ hours	1
9	Not employed for pay	0
0	No female head	0

(f) (Low income dummy) If household income is less than $20,000(income category value is smaller than 12), I define it as low income class and coded 1. There are 115 observations in this range.

(g) (Race dummy) If race of household head is white, race dummy variable has 0 value. Otherwise, race dummy is coded as 1. (Table 5.7)

7. (Construction of Missing Price Vectors) Nielsen homescan data contains only the price of the items purchased, so I need to construct price vectors of alternatives that each household are facing. In constructing price vectors, I use

Table 5.7. Race dummy variable(White=0)

Category	Description	New variable
1	White	0
2	Black	1
3	Oriental	1
4	Others	1

prices in adjacent weeks, following previous literature such as Keane (1997) and Gupta(1988). Here is the procedure that I recover the missing prices for every transaction.

Firstly, the number of alternatives that consumers face is determined by the number of brands appeared in the data in the same store during 2009. In my theory model, the assumption of Type I extreme value distribution leads to the probability that consumer i chooses j brand as in the equation A.4, where the denominator is additive forms of all available options. In calculating this likelihood, the set of brands which is available to the consumer are only considered. For example, if two options were observed in the data for the grocery store, the likelihood is the probability to choose between those two options.

Secondly, for the items bought, I use the unit carrot price per pound which is actually paid (realized), and interpolate the price for the same store. For example, at one store, if the observed prices of brand j are same for some period, the price is used to fill in missing prices. Otherwise, I extrapolate the adjacent data with the closest week of similar units.

Third, if the closest reference price is the promotion price, I use the price just for short period (3 days) forward or backward,because generally the promotion price does not last for a longer period.

Fourth, to capture unobserved heterogeneity in brand premium, I also collect price information as a quality proxy. In calculating quality proxy, I use regular price not a promotion price. So if consumer bought the item using coupon, I add coupon amount to the dollars paid and use the price before applying coupon.

5.2 Estimation Procedure

5.2.1 Estimation

I use maximum likelihood method to estimate the model proposed above, this fulfills a main research objective. The objective function and the target parameter vector is presented in (4.30). Then, I solve for estimates $\hat{\Theta}$ such that

$$\hat{\Theta} \in \arg\max_{\Theta} \; \log L(\Theta), \tag{5.1}$$

where $\log L(\Theta)$ is defined in (4.30). The estimates $\hat{\Theta}$ include $(\hat{\alpha}, \hat{\rho}, \hat{\sigma}, \hat{\eta}, \hat{\mu})$.

In the estimated model, X will have two elements, x_{j1} and x_{j2}, that reflect an organic attribute and a quality-differential. Let x_{j1} be an indicator such that

$$x_{j1} = \begin{cases} 1 & \text{if brand } j \text{ is organic} \\ 0 & \text{otherwise} \end{cases} \tag{5.2}$$

Then, β_{i1} can be interpreted as consumer i's sensitivity to an organic attribute and $\hat{\alpha}$ reflects how consumers are responsive to quality evaluation when their demographic characteristic changes.

Next, variable x_{j2} is defined as follows.

$$x_{j2} = \begin{cases} \bar{p}_j - \bar{p}_o & \text{if brand } j \text{ is organic} \\ \bar{p}_j - \bar{p}_{no} & \text{otherwise} \end{cases} \tag{5.3}$$

where $\bar{p}_j$ means average price of brand j and $\bar{p}_o$ and $\bar{p}_{no}$ denote the average price of organic products and the average price of non-organic products, respectively. This is the proxy variable for the product characteristics unobserved by econometricians. Berry (1994) and Berry, Levinsohn, and Pakes (1995) point out that the product characteristics observed not by econometrician but by sellers and buyers create 'omitted variable bias' in estimation. In particular, the product with a more appealing color, or design of the container may charge a higher price than others, which create 'price endogeneity' in their regression analysis.[2] My structural approach is free from the 'price endogeneity' in the sense that individual preferences cannot not depend price by theory. Price can affect 'choice' through the budget constraint but cannot through utility function.[3] However, I should be aware of the potential omitted variable bias in the sense that the unobserved characteristics may appeal to individual consumer in different ways. So, to mitigate the potential omitted variable bias, I adopt the relative price gap as a proxy for the unobserved (brand) characteristics. It reflects the idea that if an organic (non-organic) product has more appealing characteristics observed by buyers and sellers, it will be sold at a higher price than other organic (non-organic) product. It captures brand price premium and perceived quality difference. I call it 'brand premium' here.

5.2.2 Bootstrapped Standard Error

I calculate bootstrapped standard errors following Eaton, Kortum, and Kramarz (2011). From my sample s, using bootstrap technique, I resample with replacement each bootstrap b with 2459 bins, $N_b = 30$ times. I solve for estimates $\hat{\Theta}_b$ such that

$$\hat{\Theta}_b \in \arg\max_{\Theta} \ \log L(\Theta_b), \tag{5.4}$$

where $\log L(\Theta_b)$ is defined in (4.30).

Then the bootstrap variance is

$$V(\Theta) = \frac{1}{N_b} \sum_{b=1}^{N_b} (\hat{\Theta}_b - \hat{\Theta})(\hat{\Theta}_b - \hat{\Theta})' \tag{5.5}$$

[2] In their regression analysis, the normal equations imply that

$$\begin{aligned} \mathbb{E}[\hat{\beta}|X] &= \mathbb{E}[(X'X)^{-1}X'Y|X] = \mathbb{E}[(X'X)^{-1}X'(X\beta + \epsilon)|X] \\ &= \beta + (X'X)^{-1}\mathbb{E}[X'\epsilon|X], \end{aligned}$$

where the last term shows that $\hat{\beta}$ is biased when $\mathbb{E}[X'\epsilon|X] \neq 0$. In their regression analysis, prices are included in X and the unobserved characteristics such as product design may create 'omitted variable bias' as above, which is called by 'price endogenity' by the authors.

[3] I estimate individual preferences described (4.3) and (4.4). In general, it is hard to see that consumers get some (dis)utility just from the amount of money that they pay.

I can get the standard errors by taking a square roots on the diagonal elements of variance matrix. Standard errors are reported at each parameter estimates table.

5.2.3 Definition of Income and Engel's Law

In Nielsen data, income is a categorical variable as described in the Table 5.4. This might bring out measurement error issues. Recovering income distribution by nonparametric estimation will be a way to resolve it, but it is postponed for later research here. Another issue is that the annual income reported in the dataset is not consistent with the income in my model because the former includes many durable goods consumption such as housing, car, electronics, furniture and clothes expenditures. Instead, I restrict my attention to food expenditure inferred from Engel's Law. The marginal propensity of food expenditure subject to additional dollar is not linear but significantly concave. Banks, Blundell, and Lewbel (1997), through nonparametric analysis of consumer expenditure patterns, show that the ratio of food expenditure to income yields a concave curve of the logarithm of expenditure. Following their empirical findings, I employ log transformation of income to get the total food expenditure.

5.3 Empirical Results

5.3.1 Identification

Before estimating the model, I need to check whether all parameters are identifiable. As Erdem, Imai, and Keane (2003) point out, a formal identification analysis is hard to apply for this kind of non-linear model. Thus I discuss intuitively how the structural parameters are identified. I estimate $(\alpha, \rho, \sigma, \eta, \mu, P)$. My key parameters are in the $(K \times L)$ matrix α, which captures the partial effect of individual characteristics to the preference and quantity, where K is the dimension of observed product characteristic vector X_j and L is the dimension of consumer i's demographic characteristic vector Y_i. ρ is the elasticity of substitution parameter and it is also an own-price elasticity parameter. η and μ are the scale parameter and the location parameter of Maximum Type I extreme value distribution (Gumbel distribution). σ is the standard deviation of mean zero normal distribution that ε_i follows. P is the price index or aggregate price for all the composite goods.

Table 5.8 reports that μ and P are not separately identified. I fix $P = 0.1$, $P = 0.5$, and $P = 1.0$ in Panel A, B, and C, respectively. Then, in each panel, I calculate the maximum likelihood given $\rho \in \{0.1, 0.5, 3.0, 5.0\}$. Regardless of P, one can see that given ρ the maximum likelihood values are same across different panels and the candidate estimates are identical except μ. That is, there are a lot of different pairs of (μ, P) at the maximum point. For this highly complex non-linear model, it is difficult to derive neutrality conditions regarding μ and P. [4] Moreover, since there is no good analogy of P in reality, I fix $P = 0.1$ in what follows and check the robustness of my choice later.[5] Table 5.8 also advises us that I don't need to care about the robustness too much except μ.

Another interesting point in Table 5.8 is that different values of the parameter ρ affect all estimates of the other parameters and it lead to non-monotonic patterns. The parameter ρ is so called parameter for love of variety, or elasticity of substitution

[4] By starting my estimation procedure from many different initial points, I confirm that there is a unique maximum values given (ρ, P).

[5] The Consumer Price Index might be a good proxy. But Table 5.8 tells that it does not generate much difference.

Table 5.8. Identification Issue on μ and P

Panel A ($P = 0.1$)	$\rho = 0.1$	$\rho = 0.5$	$\rho = 3.0$	$\rho = 5.0$
η (scale parameter of Gumbel Dist.)	0.757	1.312	0.528	0.433
μ (location parameter of Gumbel Dist.)	<u>4.191</u>	<u>5.973</u>	<u>0.584</u>	<u>1.196</u>
σ (s.d. of Nomal Dist.)	0.697	0.803	1.323	1.027
$\alpha(1,1)$ (education effect on organic)	0.026	0.027	0.058	0.048
$\alpha(1,2)$ (HH income effect on organic)	-0.116	-0.152	-0.170	-0.128
Log-Likelihood	5838.507	7163.157	5186.599	4706.681

Panel B ($P = 0.5$)	$\rho = 0.1$	$\rho = 0.5$	$\rho = 3.0$	$\rho = 5.0$
η (scale parameter of Gumbel Dist.)	0.757	1.312	0.528	0.433
μ (location parameter of Gumbel Dist.)	<u>2.581</u>	<u>4.364</u>	<u>-1.025</u>	<u>-0.413</u>
σ (s.d. of Nomal Dist.)	0.697	0.803	1.323	1.027
$\alpha(1,1)$ (education effect on organic)	0.026	0.027	0.058	0.048
$\alpha(1,2)$ (HH income effect on organic)	-0.116	-0.152	-0.170	-0.128
Log-Likelihood	5838.507	7163.157	5186.599	4706.681

Panel C ($P = 1.0$)	$\rho = 0.1$	$\rho = 0.5$	$\rho = 3.0$	$\rho = 5.0$
η (scale parameter of Gumbel Dist.)	0.757	1.312	0.528	0.433
μ (location parameter of Gumbel Dist.)	<u>1.888</u>	<u>3.671</u>	<u>-1.718</u>	<u>-1.106</u>
σ (s.d. of Nomal Dist.)	0.697	0.803	1.323	1.027
$\alpha(1,1)$ (education effect on organic)	0.026	0.027	0.058	0.048
$\alpha(1,2)$ (HH income effect on organic)	-0.116	-0.152	-0.170	-0.128
Log-Likelihood	5838.507	7163.157	5186.599	4706.681

between commodity categories. When $\rho \to 0$, my utility function converges to Leontief utility function with perfect complements. When $\rho \to 1$, it converges to Cobb-Douglas utility function, and when $\rho \to \infty$, it converges to linear utility with perfect substitutes. When it converges to a Leontief preference, consumers with positive income shock (or changing education level) hardly switch to organic food from non-organic food. When it converges to Cobb-Douglas utility function, my estimation results show non-monotonic pattern. The first order condition of likelihood function with respect to ρ, the issue rests on the coefficient $(\rho - 1)$. On the boundary with $\rho = 1$, the effects on other key parameters is opposite and it brings the non-monotonicity mentioned. Analytical approach also suggest ρ cannot be pinned down because the first order condition has an irrational solution of $\rho = \infty$ as well. As the Figure 5.1 displays, likelihood function has U-shape as ρ changes in $(0, \infty)$, so ρ is not pinned down at one value as it converges to 0 and ∞.

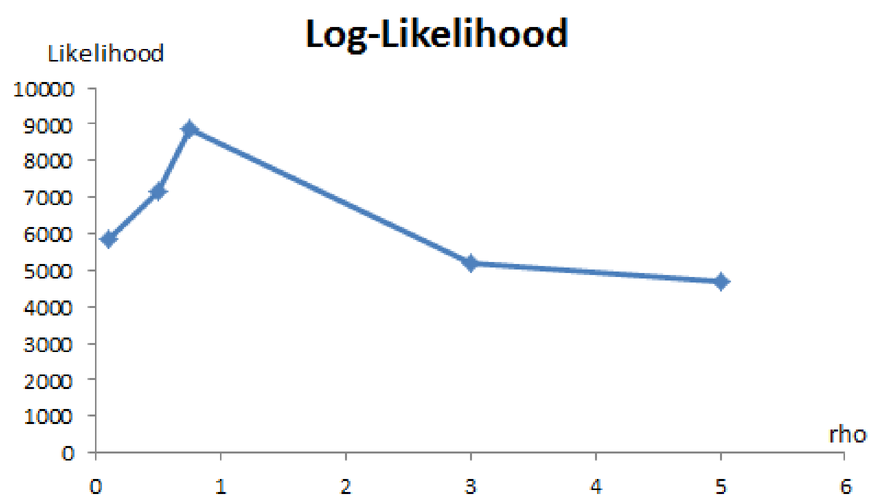

Figure 5.1. Changes of log likelihood function to ρ

To resolve it, I fix ρ and check sensitivity. As I have shown in the theory part, ρ is the own-price elasticity of each category. While my brand specific price elasticity cannot be derived from the theoretic model due to its high nonlinearity, I can find the price elasticity of the carrot industry in the literature. The USDA Economic Research Service provides price and income elasticities for the most commodities and food, collected from literature. In the carrots category, reported overall own price elasticity is in the range of [-1.653, -0.0388]. The minimum own price elasticity is -1.653 and this is from Henneberry, Piewthongngam, and Qiang (1999)'s linear approximation of an almost ideal demand system model (LA/AIDS) on the consumption of 14 fresh produce categories in the United States for 1970-1992. The maximum own price elasticity is -0.0388 by Huang (1999). This is from the linear expenditure demand system (LES) in the United States for the period of 1953-1983. Thus in the result section, I report two sets of parameters for $\rho \in \{1.653, 0.0388\}$ and sort them according to the criterion that theory implies.

If we restrict domain of ρ in a compact space, key parameter α can be identified as a function of ρ, i.e., inference of function $\alpha(\rho)$ is possible. To support this, I conduct estimation of our key parameters for every value of ρ in the domains of [0.1, 0.9] and [1.1, 5.0], respectively. Figure 5.2 and Figure 5.3 show parameter estimates of $\alpha(1,1)$ and $\alpha(1,2)$ in a baseline model I if ρ is in the set [0.1, 0.9]. As the figures represent, there exists a unique α which maximizes likelihood of proposed model given fixed value of ρ. All my attempts with different initial values converge to the same point, which numerically shows that there is a unique maximum point. Figure 5.4 and Figure 5.4 also show parameter estimates of $\alpha(1,1)$ and $\alpha(1,2)$ in a baseline model I if ρ is in the set [1.1, 5.0], implying that key parameters are pinned down at a unique point conditional on ρ in a compact set.

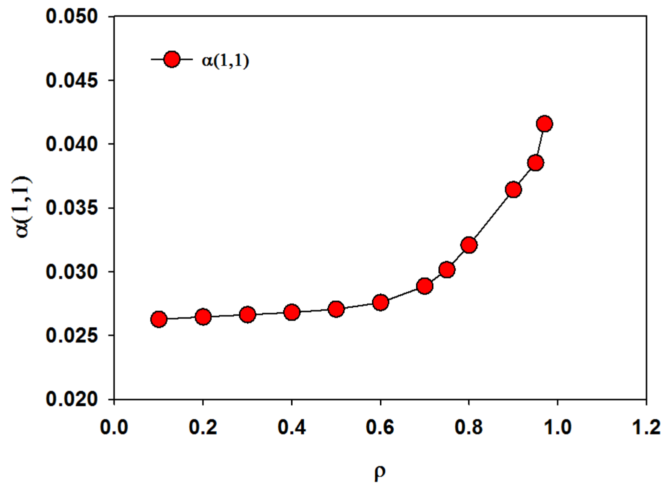

Figure 5.2. Baseline I: Parameter Estimates of $\alpha(1,1)$: ρ<1

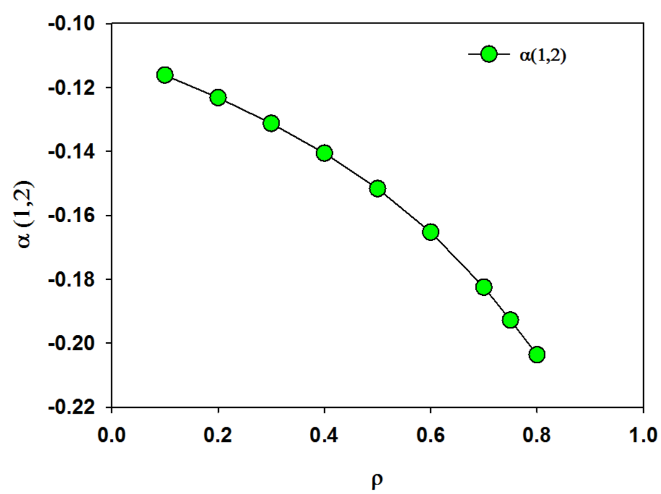

Figure 5.3. Baseline I: Parameter Estimates of $\alpha(1,2)$: ρ<1

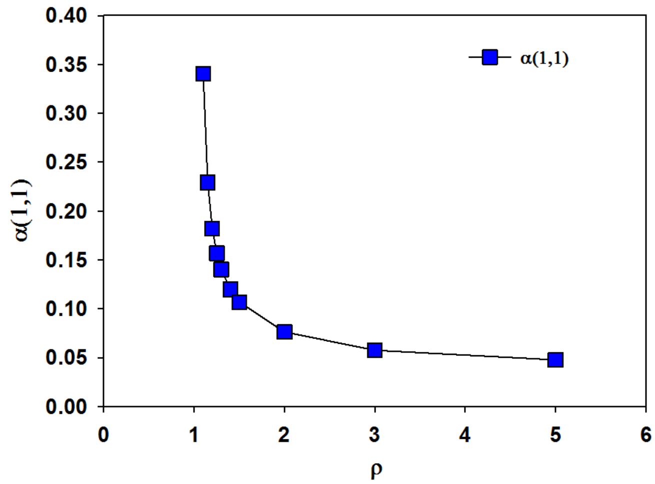

Figure 5.4. Baseline I: Parameter Estimates of $\alpha(1,1)$: ρ>1

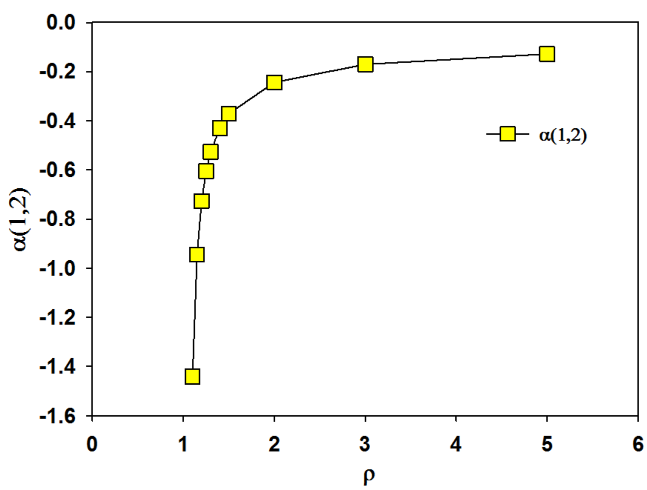

Figure 5.5. Baseline I: Parameter Estimates of $\alpha(1,2)$: ρ>1

5.3.2 Results

Table 5.9 shows the baseline I model. Estimates are $\{\hat{\alpha}, \hat{\eta}, \hat{\mu}, \hat{\sigma}\}$. α is a $(K \times L)$ matrix containing my key parameters, which captures the effects of demographic characteristics on consumer i's brand preference and quantity choice depending on brand specific quality. In baseline I model, brand specific quality, or brand j's characteristic is whether a certain brand is organic or conventional (non-organic). Brand characteristic vector X_j is an indicator variable and it has value of 1 if brand j is organic, and 0 if non-organic. [6] Demographic attributes Y_i include years of female education and log of household income. As my theory model suggests, according to demographic characteristics such as education or income level, consumer's preference changes.

I fixed price the elasticity of carrots demand (at industry level) ρ at 1.653 and 0.0388. The results below are conditional on the two chosen ρ values. In both cases, Table 5.9 shows that the signs of parameters are same.

When ρ is 1.653, income effect coefficient ($\alpha(1,2)$) is -0.314. To be specific, it measures how income affects preference weight and quantity for organic carrots. If there is an increase in individual i's income, since ($\alpha(1,2)$) is negative, β_i drops, and

[6] Individual i's preference weight for brand j is given by

$$M_{ij} = X_j \beta_i + \zeta_{ij},$$

where

$$\beta_i = \alpha Y_i + \varepsilon_i.$$

X_j is the $(1 \times K)$-dimensional vector of observed product characteristics in brand j, and Y_i is the $(L \times 1)$-dimensional column vector of the observed characteristics of consumer i such as income, education, and so on. The K-dimensional random coefficient vector β_i represents the individual consumer's response to the product characteristics. The error term ε_i is K-dimensional column vector which consists of independent, and identically distributed random variables ε_{ik}.

$$\varepsilon_{ik} \sim i.i.d.\, \mathcal{N}(0, \sigma)$$

Last, ζ_{ij} follows the type I extreme value distribution. The (maximum) Gumbel distribution is

$$g(\zeta_{ij}) = \frac{1}{\eta} \exp\Big\{ -\frac{\zeta_{ij} - \mu}{\eta} \Big\} \exp\Big\{ -\exp\{-\frac{\zeta_{ij} - \mu}{\eta}\} \Big\}$$

where $-\infty < \zeta_{ij} < \infty$ and $\eta > 0$. μ is the location parameter and η is the scale parameter of Type I extreme value distribution.

Table 5.9. The Baseline Model I

Model Parameters	Initial Values								$\rho = 1.6530$ $(S.E)$	$\rho = 0.0388$ $(S.E)$
η	1.00	1.00	2.00	1.00	1.00	2.00	1.00	0.60	0.982**	0.714**
(scale parameter of the Gumbel distribution)									(0.08)	(0.04)
μ	1.00	1.00	2.00	2.00	1.00	1.00	2.00	3.50	-1.981**	4.046**
(location parameter of the Gumbel distribution)									(0.10)	(0.00)
σ	1.00	2.00	0.03	1.00	0.01	0.05	0.01	0.02	2.297**	0.687**
(standard deviation of normal distribution)									(0.24)	(0.13)
$\alpha(1,1)$	0.10	0.05	0.02	0.10	0.03	0.05	0.05	0.05	0.09**	0.026
(education effect on quantity through organic)									(0.04)	(0.03)
$\alpha(1,2)$	0.10	0.10	0.05	0.05	0.03	0.05	-0.01	0.02	-0.314*	-0.112**
(HH income effect on quantity through organic)									(0.21)	(0.06)
Log-likelihood Function									6730.437	5702.590

Note: Single asterisk (*) denotes significance at 10% level, double asterisks (**) denote significance at 5% level.

preference on organic brand j (M_{ij}) also drops following (4.4)and (4.3), respectively. Then according to consumer's quantity decision rule, (4.9), organic carrots demand decreases if β_i is negative. Brand decision follows (4.23), so relative size of M_{ij} and new optimal consumption of quantity q_{ij} determines optimal brand. Thus while income increases twofold, new demand not only does not increase two times, but can even decrease. In Chapter 6, I will show that there is quality-quantity trade-off if income increases by 10%, observing consumers switch from non-organic to organic carrots rather than increase the consumption of non-organic carrots.

Conditional for the case that ρ is 1.653, education effect coefficient ($\alpha(1,1)$) is 0.09. As consumer's education level increases, positive $\alpha(1,1)$ pushes M_{ij} up and increases consumption of organic carrots. For the switching behavior, detailed analysis is also available in next Chapter.

Parameter σ is the standard deviation of multivariate normal distribution, in my model, error term ε_i is a K-dimensional column vector. I repeatedly apply Nelder Meade method to achieve maximum likelihood until the computation code converges. In particular, in order to (numerically) ensure the global maximum, I test with eight different initial parameter vectors. The initial parameter vectors chosen are reported from column 2 through column 9.

One potential problem in the baseline I model is that brand specific quality only includes the information on whether the carrot is organic or non-organic. This means that within organic carrot brands (or non-organic brands), price and random components determine optimal brand. If a certain brand is non-organic, M_{ij} is just equal to ζ_{ij}, which is unobserved by econometrician, so I assumed it to follow Type I extreme value distribution. Then only the price plays a significant role in choosing quantity and brand choice. In a similar fashion, if brand j is organic, deterministic part of M_{ij} is same for all organic carrots, again the price difference and random term determine optimal quantity and brand. Since the value of X_j is constant at 1 for all organic brands, M_{ij} does not capture the difference between brand specific qualities.

The baseline II model employs the average brand price deviations from its group (organic or non-organic) mean prices as a proxy of quality or 'brand premium'. In

Table 5.10. The Baseline Model II

Model Parameters				Initial Values					$\rho = 1.653$ $(S.E)$	$\rho = 0.0388$ $(S.E)$
η	1.00	2.00	1.00	0.50	1.00	0.40	0.46	0.76	0.782**	0.631**
(scale parameter of the Gumbel distribution)									(0.03)	(0.05)
μ	1.00	2.00	2.00	1.00	1.00	1.60	1.07	0.11	-2.501**	3.767**
(location parameter of the Gumbel distribution)									(0.04)	(0.03)
σ	1.00	1.00	1.00	0.10	2.00	0.00	0.05	1.28	5.063**	2.400**
(standard deviation of normal distribution)									(0.34)	(0.32)
$\alpha(1,1)$	0.40	0.10	0.10	0.40	0.10	0.05	-0.06	-0.18	0.233**	0.111**
(education effect on quantity through organic)									(0.07)	(0.04)
$\alpha(2,1)$	0.10	0.10	0.05	1.00	0.10	-0.07	1.09	3.39	0.114	-0.124
(education effect on quantity through quality proxy)									(0.15)	(0.11)
$\alpha(1,2)$	0.05	0.10	0.10	0.01	-0.01	-0.01	0.02	0.46	-0.817**	-0.389**
(HH income effect on quantity through organic)									(0.09)	(0.06)
$\alpha(2,2)$	0.05	0.10	0.05	0.01	-0.01	0.04	-0.19	-0.51	0.589**	0.551
(HH income effect on quantity through quality proxy)									(0.19)	(0.16)
Log-likelihood Function									6254.444	5456.216

Note: Single asterisk (*) denotes significance at 10% level, double asterisks (**) denote significance at 5% level.

reality, consumers care about freshness, display, atmosphere, and/or design as well as organic qualification. So, I need to think of so called 'unobserved brand specific quality', which is observed by buyers and sellers but not by econometricians. The parameter estimates are reported in Table 5.10. Interestingly, the parameter estimates obtained in Table 5.10 are similar to those in Table 5.9. The Likelihood value is improved slightly. All my attempts with eight different initial values converge to the same point, which numerically shows that there is a unique maximum point. Household income effect on preference and quantity for organic carrots is negative, which is the same result as the baseline I model.

Potentially there is an omitted variable bias problem such that the omitted variable is positively correlated with income but negatively correlated with error terms. By omitting those variables, I might have underestimated the income effect. This is similar reasoning with 'price endogeneity' in Berry (1994).

To resolve the potential omitted variable bias problem, I look at household size effect. In fact, household size and income are positively correlated, as labor market experience is positively correlated with age. So, in Table 5.11, I control the household size. The coefficient of household size ($\alpha(1,3)$) is negative, larger household size may not increase the consumption of organic carrots. But positive coefficient of household size depending on quality proxy ($\alpha(2,3)$) implies that household size encourages to buy a better quality brand more.As expected, after controlling household size, the income effect coefficient increases from -0.817 to -0.770. I try this with four different initial values here.

In the similar reasoning, I add a young child dummy. I create a dummy variable if a household has at least one child under age of 12. Table 5.12 reports my estimates. Table 5.12 reveals that having young children under age 12 increases the quantity of organic brands a lot, the coefficient is 1.728 in the case of $\rho = 1.653$.

Adding female employment status leads to Table 5.13. If a female head-of-household works more than 35 hours per week, the indicator variable has value of 1. It shows that female employment also increases organic carrot preference and quantity. It can be interpreted, for example, female household head working longer hours cares for organic qualification, but brand specific qualities such as freshness, package design do not affect brand and quantity decisions.

Table 5.11. The Model with Household Size Effect

Model Parameters	Initial Values				$\rho = 1.653$ $(S.E)$	$\rho = 0.0388$ $(S.E)$
η	1.00	1.00	2.00	2.00	0.781**	0.6314**
(scale parameter of the Gumbel distribution)					(0.03)	(0.05)
μ	1.00	2.00	1.00	1.00	-2.503**	3.768**
(location parameter of the Gumbel distribution)					(0.04)	(0.03)
σ	1.00	1.00	2.00	1.00	5.083**	2.392**
(standard deviation of normal distribution)					(0.34)	(0.31)
$\alpha(1,1)$	0.01	0.02	0.01	0.10	0.218**	0.113**
(education effect on quantity through organic)					(0.07)	(0.04)
$\alpha(2,1)$	0.01	0.01	0.02	0.10	0.124	-0.127
(education effect on quantity through quality proxy)					(0.15)	(0.11)
$\alpha(1,2)$	0.01	0.02	0.01	0.01	-0.770**	-0.375**
(HH income effect on quantity through organic)					(0.12)	(0.06)
$\alpha(2,2)$	0.01	0.01	0.02	0.01	0.483	0.614
(HH income effect on quantity through quality proxy)					(0.19)	(0.13)
$\alpha(1,3)$	0.01	0.02	0.01	-0.02	-0.110	-0.066
(HH size effect on quantity through organic)					(0.14)	(0.07)
$\alpha(2,3)$	0.01	0.01	0.02	-0.02	0.389**	-0.244*
(HH size effect on quantity through quality proxy)					(0.12)	(0.18)
Log-likelihood Function					6251.841	5453.589

Note: Single asterisk (*) denotes significance at 10% level, double asterisks (**) denote significance at 5% level.

Table 5.12. The Model with Household Having Young Children

Model Parameters	Initial Values				$\rho = 1.653$ $(S.E)$	$\rho = 0.0388$ $(S.E)$
η	1.00	1.00	2.00	2.00	0.782**	0.630**
(scale parameter of the Gumbel distribution)					(0.03)	(0.05)
μ	1.00	2.00	1.00	1.00	-2.505**	3.762**
(location parameter of the Gumbel distribution)					(0.04)	(0.03)
σ	1.00	1.00	2.00	1.00	5.045**	2.416**
(standard deviation of normal distribution)					(0.33)	(0.32)
$\alpha(1,1)$	0.01	0.02	0.01	0.10	0.177**	0.083**
(education effect on quantity through organic)					(0.06)	(0.04)
$\alpha(2,1)$	0.01	0.01	0.02	0.10	0.116	-0.125
(education effect on quantity through quality proxy)					(0.14)	(0.11)
$\alpha(1,2)$	0.01	0.02	0.01	0.01	-0.775**	-0.373**
(HH income effect on quantity through organic)					(0.09)	(0.06)
$\alpha(2,2)$	0.01	0.01	0.02	0.01	0.588**	0.558**
(HH income effect on quantity through quality proxy)					(0.18)	(0.16)
$\alpha(1,3)$	0.01	0.02	0.01	-0.02	1.728**	0.841**
(young children effect on quantity through organic)					(0.39)	(0.18)
$\alpha(2,3)$	0.01	0.01	0.02	-0.02	0.213	-0.011
(young children effect on quantity through quality proxy)					(0.64)	(0.38)
Log-likelihood Function					6244.360	5448.1287

Note: Single asterisk (*) denotes significance at 10% level, double asterisks (**) denote significance at 5% level.

Table 5.13. The Model with Female Employment Effect

Model Parameters	$\rho = 0.0388$ $(S.E)$	$\rho = 1.653$ $(S.E)$
η	0.630**	0.783**
(scale parameter of the Gumbel distribution)	(0.03)	(0.05)
μ	3.762**	-2.501**
(location parameter of the Gumbel distribution)	(0.04)	(0.03)
σ	2.416**	5.060**
(standard deviation of normal distribution)	(0.34)	(0.33)
$\alpha(1,1)$	0.083	0.223**
(education effect on quantity through organic)	(0.08)	(0.04)
$\alpha(2,1)$	-0.125	0.120
(education effect on quantity through quality proxy)	(0.15)	(0.11)
$\alpha(1,2)$	-0.373**	-0.833**
(HH income effect on quantity through organic)	(0.11)	(0.07)
$\alpha(2,2)$	0.558**	0.553**
(HH income effect on quantity through quality proxy)	(0.18)	(0.14)
$\alpha(1,3)$	0.841**	1.107**
(female employment(35+ hrs) effect on quantity through organic)	(0.24)	(0.15)
$\alpha(2,3)$	-0.011	0.773
(female employment effect on quantity through quality proxy)	(0.47)	(0.63)
Log-likelihood Function	5448.129	6247.390

Note: Single asterisk (*) denotes significance at 10% level, double asterisks (**) denote significance at 5% level.

5.4 Concluding Remarks

This chapter specifies the estimation methodology and show the results. The study estimates key parameters of the model using maximum likelihood estimation. I present intuitive discussion on identification procedures of key parameters and report two sets of parameters for two values of elasticity parameters suggested in the literature. The result suggests that as consumers' income increases, they reduce consumption of carrot purchases by switching from non-organic carrots to organic carrots. The evidence to support this quality-quantity trade off is provided in the next chapter through counterfactual experiments. With parameter estimates, I can reproduce and simulate consumer response to the several scenarios.

Chapter 6

Applications

Structural estimation enables us to conduct scenario analysis. Substituting parameter estimates into the proposed model, I simulate consumers' choices on brand and quantity. In the first section, I examine how the proposed model fits with observed data by comparing sample data with simulated data. Then by perturbing a demographic characteristic (or price), I can answer the research question of how the overall demand for carrots and the firms' revenues change. Here, I simulate and examine two possible policy experiments: (1) a 10 % price drop in organic carrot brands and (2) a 10% increase in household incomes. By doing this, I can get a more plausible brand-specific price (or income) elasticity of demand. Policy experiments suggest that there tends to be a quality-quantity trade-off in the carrot markets. These experiments accomplish the research objectives.

6.1 Goodness of Fit

In this section, I investigate whether the proposed model properly explains households' purchasing behavior using several moments. This simulation is based on parameter estimates of Baseline model I when the elasticity of substitution ρ is 1.653.

Table 6.1. Goodness of fit: Size and Brand

Panel A. Brand choice in transaction frequency(%) in sample data

	Brand								
Size (lb)	1	2	3	4	5	6	7	8	Size Total
1	22.53	14.03	4.84		3.50	0.53	0.81		46.24
2	22.53	9.03	3.05		1.34	1.14	0.33	0.33	37.74
3	4.11	0.24	1.22	0.04	0.16				5.77
4	1.30	0.33	0.73		0.28				2.64
5	3.38	0.41	0.04	0.04	0.04	0.08	0.04	1.22	5.25
6	0.65	0.04			0.08				0.77
7	0.04								0.04
8			0.04						0.04
9	0.04								0.04
10	0.33		0.04	0.24	0.85				1.46
Brand Total	54.90	24.07	9.96	0.33	6.26	1.75	1.18	1.55	100.00

Panel B. Brand choice in transaction frequency(%) in simulated data

	Brand								
Size (lb)	1	2	3	4	5	6	7	8	Size Total
1	24.32	6.38	6.14	2.16	2.03	0.61	0.53	0.33	42.50
2	10.86	4.72	6.83	5.33	0.20	0.33	0.28		28.55
3	3.62	2.32	2.77	5.08	0.24	0.12	0.12	0.04	14.31
4	1.46	0.98	1.34	3.13	0.20		0.04	0.04	7.20
5	0.61	0.12	0.89	1.59	0.28	0.08	0.04		3.62
6	0.33	0.08	0.73	0.37			0.12		1.63
7	0.12	0.04	0.49	0.12					0.77
8	0.12	0.04	0.16	0.04		0.08	0.04		0.49
9	0.08		0.20	0.08					0.37
10	0.24		0.12		0.12		0.04	0.04	0.57
Market Share	41.76	14.68	19.68	17.89	3.09	1.22	1.22	0.45	100.00

Note: Brands 1-4 are conventional carrots and 5-8 are organic carrots.

Table 6.1 reports the comparison of the sample choice frequencies and simulated choice frequencies for all brand and size combinations. Overall, the simulated model predicts patterns of carrot purchase behavior for the households similar to those in the sample data. In both Panel A and Panel B, brand 1 carrots show the highest demand among non-organic carrot brands, and brand 5 is the most popular among organic carrot brands. The probability that a household purchases brand 1 is 55% in the sample data and 42% in the simulated data, respectively. On the other hand, only 6% of the households purchase brand 5 organic carrots in the sample data and 3% of the households purchase brand 5 in the simulated data. It is noticeable that the proposed model overestimates the consumption of brand 4. Even though brand 4 is rarely chosen in the sample data, the model predicts that 18% of the households purchase brand 4. Overestimation of quantity demanded for brand 4 results in underestimation of that for other brands.

In the decision of quantity, it is observed in both Panel A and Panel B that carrot purchases are concentrated on 1lb and 2lbs. The sample data shows that 46% of consumers purchase 1lb of carrots in a single purchase and 38% of consumers purchase 2lbs of carrots. Consistent with this pattern, the model predicts 42% of consumers make 1lb carrot purchases and 29% make 2lb carrot purchases.

Table 6.2. Goodness of fit: Organic and Non-organic purchase frequency(%)

	Sample data			Simulated data		
Size (lb)	Organic	Non-organic	Total	Organic	Non-organic	Total
1	4.84	41.40	46.24	3.50	39.00	42.50
2	3.13	34.61	37.74	0.81	27.73	28.55
3	0.16	5.61	5.77	0.53	13.79	14.31
4	0.28	2.36	2.64	0.28	6.91	7.20
5	1.38	3.86	5.25	0.41	3.21	3.62
6	0.08	0.69	0.77	0.12	1.50	1.63
7	-	0.04	0.04	-	0.77	0.77
8	-	0.04	0.04	0.12	0.37	0.49
9	-	0.04	0.04	-	0.37	0.37
10	0.85	0.61	1.46	0.20	0.37	0.57
Brand Total	10.74	89.26	100.00	5.98	94.02	100.00

Note: This table is calculated based on transaction frequency.

Table 6.2 presents the goodness of fit of the proposed model by grouping the carrot purchases into organic and non-organic categories. It shows that the simulated model tends to underestimate smaller package of carrots, especially 2lbs of carrots. This leads to a discrepancy in the distribution of market shares between simulated data and sample data. In the sample data, 10.74% of the consumers purchase organic carrots, while the rest purchase non-organic carrots. In case of the simulated data, 5.98% and 94.02% of households choose organic carrots and non-organic carrots, respectively. The 2 pound-category is a slight exception: 6.8% of consumers choose organic carrots in the sample, and 4.8% in the simulated data, which closes the gap.

In Table 6.3, I provide the total demand of each brand and the corresponding market share. In general, brand 1 shows the highest market share among all carrot brands, consisting of more than 50% of the total carrot demand. Following brand 1, non-organic brands 2 and 3, and organic brand 5 rank high in terms of market share. Overall, the consumers' purchasing behavior tends to be consistent with the sample data as well as the result of brand choice in Table 6.1.

Table 6.3. Goodness of fit: Total demand(Lb), Market share(%) and Average price paid($/Lb)

	Sample data			Simulated data		
Brand	Demand	Market Share	Avg. Price	Demand	Market Share	Avg. Price
1	2,700	55.99	.666	1,789	33.45	.637
2	895	18.56	.845	698	13.05	.678
3	454	9.42	.570	1,232	23.04	.533
4	68	1.41	.542	1,294	24.20	.511
5	419	8.69	.938	163	3.05	.951
6	79	1.64	1.101	66	1.23	1.106
7	41	0.85	1.058	81	1.51	1.000
8	166	3.44	1.121	25	0.47	1.564
Total	4,822	100.00	.738	5,348	100.00	.613

Note 1: Brands 1-4 are conventional carrots and 5-8 are organic carrots.
Note 2: Market shares are calculated based on total quantity demanded.

However, the demands of those brands are underestimated in my simulated data. In particular, non-organic brand 1 and organic brand 5 present 33.45% and 3.05% of market share, respectively. On the other hand, brand 3 and 4 show a substantially overestimated demand in my simulated data. It is possible that unobserved attributes of brands 3 and 4, which are not controlled by the proposed model in this paper, may give rise to this discrepancy between the sample data and the simulated data. I also include the average unit price consumers paid in each transaction. Interestingly, in the simulated data, the average price paid for non-organic carrots is higher than the average price paid for organic carrots. This issue may be related to the underestimation of quantities demanded for organic brands, and I save this for the discussion in a later section.

6.2 Policy Experiments

Using the structural framework in this paper, I simulate and examine two possible policy experiments: (1) a 10 % price drop in all organic carrot brands and (2) a 10% increase in household income. I evaluate the impacts of those experiments on total quantity demanded, brand choice frequency in transaction, and the revenue of each firm. This simulation is based on parameter estimates of Baseline model I when the elasticity of substitution ρ in the model is 1.653. For the robustness check, I simulate and examine the policy experiments with different key parameters with the value of ρ at 0.0388.

6.2.1 Effects of a 10% Price Drop in Organic Carrots

For a long time, industry observers have been curious about what would happen if the "organic price premium" shrinks. Here I conduct a policy experiments that if all the organic prices decrease by 10% so that the average organic price premium decreases from 90% to 71%.

I impose a 10% price cut for all organic carrot brands (brands 5, 6, 7, and 8) and simulate households' purchase behavior using parameter estimates when the elasticity of substitution ρ in the model is 1.653. The proposed model expects a substantial change in purchasing decisions as a result of a price change.

Table 6.4. Effect of a 10% organic price decrease on organic and non-organic carrot purchase

	Non-organic	Organic	Total
Total demand	-4.77%	42.99%	-1.78%
Brand choice	-9.82%	154.42%	0.00%
Total revenue	-3.77%	7.79%	-2.54%

In Table 6.4, organic carrots gain substantial increases in all variables from the price drop. Although the increase in brand choice frequency for the organic category is predictive in this experiment, the increases in total demand and total revenue provide us with interesting insights on this market. It shows that organic brands are chosen 154.42% more than the simulated data under observed prices while total quantity demanded of organic carrots increases by 42.9%. Compared to the increase in organic carrot transactions, the total quantity of organic carrots rises less, implying possible quality-quantity trade-off. Revenue of organic carrot firms increases by 7.79% with a decrease in organic price of 10%. On the other hand, the quantity demanded for non-organic carrots is expected to decrease by 4.77%, and total revenue by 3.77%. The result implies that when consumers switch from a non-organic carrot brand to an organic one, some consumers cut down their carrot consumption, which leads to a drop in quantity demanded in carrot markets by 1.78%. That segment of the consumers who switch from non-organic to organic carrots will see their carrot consumption fall given their budget constraints. If they play a more potent role in the carrot market overall (i.e., they are the ones who dominate the carrot demand in the market), their role in reducing total carrot consumption may outweigh the role of those who have been organic carrot consumers who now increasing consumption of organic carrots.

Table 6.5. Effect of a 10% organic price decrease on each brand

	Effect on Brand (%)								
	1	2	3	4	5	6	7	8	Total
Total Demand	-6.71	-5.59	-3.90	-2.47	46.01	54.55	33.33	24.00	-1.78
Brand Choice	-11.59	-9.42	-10.54	-5.23	146.05	160.00	170.00	154.55	0.00
Total Revenue	-6.91	-4.09	-2.07	0.21	19.16	14.27	1.73	-36.88	-2.54
Organic	No	No	No	No	Yes	Yes	Yes	Yes	-

Note: Brands 1-4 are conventional carrots and 5-8 are organic carrots. *Note*: Changes in brand choice are calculated in comparison with the simulated original market share in transaction volume.

To see the effects of a decrease in the organic price premium on each brand, I also present Table 6.5. As we verified in Table 6.4, non-organic brands lose their market shares, while organic brands gain more. To be specific, the 10% price drop of organic carrot brands results in the market share decreasing by 11.59% compared to the original market share for brand 1. [1] The transaction frequency of brand 2 decreases by 9.42%, brand 3 by 10.54%, and brand 4 by 5.23%, respectively. In the case of organic brands, the choice frequency of brand 5 increases by 146.05% compared to its original transaction frequency in the simulated model. Other organic brands get more market share in a similar fashion. Quantity gains in organic brands are

[1] Market share of brand 1 in transaction volume was 41.8% in simulated data (6.1). With a 10% drop in organic carrot prices, new market share of brand 1 is 36.9%.

smaller than substantial increases in transaction volumes. The quantities demanded in the organic brands rises by 46.01%, 54.55%, 33.33%, and 24% for brands 5, 6, 7, and 8, respectively. It is noticeable that brand 5 captures a significant portion of the revenue increase from the organic price drop, whereas brand 8 loses significant market share and revenue from the price drop.

Table 6.5 implies that different brands are affected differently by changes in the price of organic carrots. The total revenue of organic brand 8 declines by 36.88% compared with its original revenue. In this policy experiment, average paid price for brand 8 is $.805 per pound, which is smaller than the average paid price of $1.564 per pound in the simulated sample. Simulation results show that 92.86% of transactions occur with a lower price than an average price, which leads to the decrease in total revenue for brand 8. In fact, organic brand 8 shows the largest gap between the average offered price and the average accepted price in the sample. Chapter 3's Table 3.4 shows the average offered price is $1.87 per pound, and the average accepted price is $1.21 per pound for brand 8. In short, consumers often buy brand 8 when it is on a price promotion, and the simulation results reflect this fact. In the case of organic brand 5, its average offered price is $1.28 per pound, and the average accepted price is $1.26, showing a smaller gap. In addition, the restricted availability and low market share of brand 8 may be responsible for the decline in revenue. Because brand 8 have small transaction volume, and because that brand is often bought on promotion, the outcome of policy experiment can be affected by outlier sample.

6.2.2 Effects of a 10% Income Increase for Households

Policy makers and marketers are also interested in predicting the change of aggregate demand as the economy grows. It is widely accepted that the economy (the aggregate income) and the market for healthful foods grow together. However, with the income growth, if the consumers who switch from non-organic to organic carrots reduce carrot consumption, and this switching effect outweighs an income effect, then the quantity demanded overall in the carrot markets would fall.

Table 6.6. Effect of 10% income increase on organic and non-organic purchase

	Non-organic	Organic	Total
Total demand	-3.11%	19.70%	-1.68%
Brand choice	-8.35%	131.29%	0.00%
Total revenue	-2.07%	-9.13%	-2.82%

In the second experiment, I impose a 10% income increase for all households. Similar with the price drop scenario, Table 6.6 shows that the total quantity demanded and firms' revenue in the carrot markets would fall respectively by 1.68 % and 2.82%, implying potential quality-quantity trade-off. An aggregate income increase affects the organic carrot market and non-organic carrot market in opposite directions. In particular, my result shows that the quantity demanded of organic carrot brands increases by nearly 20% while that of non-organic carrot brands decreases by 3.11% as a result of a 10% income increase. This implies that the income elasticity of organic carrots and non-organic carrots is 1.97 and -0.311, respectively.

The substantial transfer of brand choice frequency from non-organic to organic brands also indicates that the carrot market is vertically differentiated, and organic carrot brands are perceived as higher quality goods. In Table 6.6, it is noticeable that total revenue decreases in both the non-organic and the organic categories. These results may come from the decrease in revenue in organic brands 6, 7, and 8 as Table 6.7 shows.

Table 6.7 reports the effects of a 10% income increase on each brand. The 10% income increase results in substantial increases in total demand for organic brands, but it is most focused on brand 5. It gets a 25.77% increase in total demand, is chosen 130% more frequently, and gets a 4.45% increase in firm's revenue. The impact of

Table 6.7. Effect of 10% income increase on each brand

	Effect on Brand (%)								
	1	2	3	4	5	6	7	8	Total
Total demand	-4.97	-4.58	-2.11	-0.70	25.77	21.21	9.88	8.00	-1.68
Brand choice	-10.32	-8.59	-8.47	-3.41	130.26	116.67	146.67	136.36	0.00
Total revenue	-5.19	-3.21	0.04	2.03	4.45	-11.15	-15.86	-45.26	-2.82
Organic	No	No	No	No	Yes	Yes	Yes	Yes	-

Note 1: Brands 1-4 are conventional carrots and 5-8 are organic carrots.
Note 2: Brand 8's small market share and low availability may be responsible for the decrease in revenue.

income growth on organic brand 5 may be due to unobserved heterogeneity that brand 5 entails. In fact, brand 5 is a dominant organic brand which sells a wide range of organic products such as salads, herbs, and other fresh vegetables. Given our data, brand 5 consists of 60% of organic carrots market share and its perceived quality would be higher. As income increases, if consumers switch to a brand which has higher perception of quality, brand 5 may enjoy the most of strong demand on organic carrots. Here, among organic brands, the result of brand 5 shows what we have expected.

On the other hand, organic brands 6, 7, and 8 get lower revenues, although they experience increases in the quantity demanded and transaction frequency. First of all, a lower accepted price is responsible for those drops in firms' revenue. The average paid prices per pound for those organic brands are \$0.80, \$0.78, and \$0.80, respectively, which are lower than their average offered prices. If consumers respond mostly when organic brands are on a price promotion, firms' revenues would decrease in spite of increases in quantity demanded and number of transaction. These patters may also be due to their restricted availability and low market shares. Small market shares render the results vulnerable to outliers and measurement errors.

Chapter 7

Conclusion

This paper develops a structural demand model that reflects the distinct characteristics of the organic and non-organic food markets in terms of hierarchical market structure, significant price differentials, and different consumer groups. I especially focus on consumers' brand choice and quantity decision behavior and quality-quantity trade-offs in switching brands. One of the features of the market for vertically differentiated products, where hierarchy exists between product qualities, is that the better quality products tend to be sold in smaller units at higher (per unit) prices. In the market for food, when consumers switch from non-organic products to organic products, they tend to cut down their consumption but pay more (per unit).

In many fields of study such as those of international trade, industrial organization, and development, quality-quantity interactions are modeled and examined. Most studies simply multiply a quality parameter (or weight) to quantity in their utility functions without further structure, and this method sometimes blurs the mechanism by which quality-quantity trade off works. In my framework, by adding a structure of quality (preference weight M_{ij}), I have been able to investigate what drives quality-quantity interaction in detail. My analysis has been possible only through the availability of the Nielsen Homescan data. This is a household level panel dataset that contains individual food purchase history along with detailed product characteristics and demographic characteristics.

The policy experiments are conducted for two scenarios with the plausible values of price elasticity of category-wide demand. For a 10% drop in prices of organic carrots, for instance, producers of organic carrots can expect 42.9% rise in consumer demand and 7.79% increase in supplier revenue in organic carrots market. As consumers switch from non-organic to organic carrots in a response to price decrease for the latter, they make downward adjustment in overall quantity demanded of carrots; consumption of carrot markets (organic, non-organic) would fall by 1.78%, and supplier revenue by 2.54%. Also, if there is a 10% increase in household income, consumption of organic carrots would increase nearly 20% while that of non-organic carrots would fall by 3.11%. With an increase in income, the quantity demanded overall in the carrot markets would fall by 1.68% and the supplier revenue by 2.82%. Given our data and the pattern of carrot consumption implicit in it, a downward quantity adjustment in the overall carrot consumption (organic and non-organic) could well be expected. That segment of the consumers who switch from non-organic to organic carrots will see their carrot consumption fall given their budget constraints. If that segment plays a more potent role in the carrot market overall (i.e., they are the ones who dominate the carrot demand in the market), their role in reducing total carrot consumption may outweigh the role of those who have been organic carrot consumers who would now increase consumption of organic carrots. In other words, the impacts of non-organic to organic switches may dominate the market.

It is noticeable that different brands are affected differently by changes in the price of organic carrots (or increase in aggregate income). In particular, brand 5 captures a significant portion of the revenue increase from aggregate income growth by 10%, which may be due to unobserved heterogeneity that brand 5 entails. In fact, brand 5 is a dominant organic brand which sells a wide range of organic products such as salads, herbs, and other fresh vegetables. Given our data, brand 5 consists of 60% market share of organic carrots and its perceived quality could be higher. As income increases, if consumers switch to a brand which has higher perception of quality, brand 5 may enjoy the most of strong demand on organic carrots.

When I interpret the results, one limitation to my analysis is that it is restricted to the consumer side. A quality-quantity trade off may also come from the supply side. One possible explanation is that as organic and non-organic carrot prices become sufficiently close, supermarkets may tend to decide not to offer non-organic products. If this is the case, quantity of non-organic carrots will drop as they become unavailable.

In future research, my model can be modified in several directions. First, I assume that the preference weight M is multiplied an exponential form. This is designed for mathematical convenience, but I am not sure of the effects of possible convexity issues. To resolve this problem, I can multiply preference weight M_{ij} to the quantity in the utility function and assume $\log(M_{ij})$ has the same underlying structure as before.

Another direction of modification is to consider dynamic decision. Even though I am using household panel data, the benefits of using panel data are not fully attained in the sense that I am treating each observation as different entities. Modeling on state dependence can lead to more precise predictions in the policy experiments.

Marketers and policy makers will find the policy experiments for the various scenarios especially useful, particularly the one that examines the impact of decrease in organic price premium. For a long time, industry observers have been curious about what would happen if the "organic price premium" shrinks. My finding suggests that if all organic prices decrease by 10% so that the average organic price premium decreases from 90% to 71%, although market shares of organic brands increase, the overall carrot demand would decrease from switching effects. The result provides us with interesting insights on carrot markets. Promoting the organic food industry might lead to an unexpected decrease in overall carrot consumption if the segment of the consumers who switch from non-organic to organic carrots play a more potent role. Marketers and policy makers may be also interested in firms' revenue. Our policy experiments also provides useful implications on the change of firms' revenue. For a 10% drop in prices of organic carrots, producers of organic carrots can expect 7.79% increase in supplier revenue, but the supplier revenue in the carrot markets overall would fall by 2.54%.

On the other hand, the experiment which examines the impact of aggregate income growth can be useful in predicting the change of aggregate demand. It is widely accepted that the economy (the aggregate income) and the market for healthful foods grow together. I can apply my method to quantify the relationship between the growth of the economy and the growth of healthful food markets other than the carrot industry.

Finally, the framework to analyze quality-quantity interaction can be applied to other products. In health economics, for instance, taxation on cigarettes is an important issue. Recent empirical studies report that once the consumption tax on cigarettes increases, smokers are more likely to switch to cheap and low quality products, which badly affects their health condition. I can find the same quality-quantity trade off issue as in the market for organic food. I also hope to quantify the magnitude of switching behavior due to tax cuts for other food markets.

Appendix A

Derivation of Likelihood f

In this appendix I describe the details of how I derive likelihood function f. I draw heavily on Kennan (2004)'s "Notes on the Type I Extreme Value Distribution".

Given monotonicity assumption, consumer i's choice rule for each category is simplified as follows. Between two alternatives j and j', she prefers brand j to j' if and only if

$$q_{ij}e^{M_{ij}} \geq q_{ij'}e^{M_{ij'}} \tag{A.1}$$

By taking log and substituting (4.3), (4.4) and the quantity demanded (4.9) into (A.1), I get

$$\begin{aligned} & M_{ij} - \log p_j \geq M_{ij'} - \log p_{j'} \\ \iff \quad & X_j(\alpha Y_i + \varepsilon_i) - \log p_j + \zeta_{ij} \geq X_{j'}(\alpha Y_i + \varepsilon_i) - \log p_{j'} + \zeta_{ij'} \end{aligned} \tag{A.2}$$

Suppose there are J alternatives, with payoffs $\tilde{v_{ij}} = v_{ij} + \zeta_{ij}$ where $\{\zeta_{ij}\}$ is a set of iid Type I extreme value random variables. Define u_{ij} by setting $\zeta_{ij} = -\log(y_{ij})$ and $y_{ij} = -\log(u_{ij})$. Then $\{u_{ij}\}$ is a set of iid random variables which are uniformly distributed on the unit interval [0,1].

Firstly, I want to derive the following multinomial choice probabilities (see Mcfadden (1974)).

$$P(\tilde{v_{i1}} = \max_j \tilde{v_{ij}}) = \frac{\exp(v_{i1})}{\sum_{j=1}^{J} \exp(v_{ij})} \tag{A.3}$$

To prove (A.3), I calculate the probability for the event that $\tilde{v_{i1}}$ is the maximal.

$$\begin{aligned}
P(v_{ij} + \zeta_{ij} &\leq v_{i1} + \zeta_{i1} | u_{i1}) \\
&= P(\zeta_{ij} - \zeta_{i1} \leq v_{i1} - v_{ij}) \\
&= P(\exp(\zeta_{ij} - \zeta_{i1}) \leq \exp(v_{i1} - v_{ij})) \\
&= P(y_{i1} \cdot \exp(v_{ij} - v_{i1}) \leq y_{ij}) \\
&= P(\log(u_{ij}) \leq \log u_{i1} \cdot \exp(v_{ij} - v_{i1})) \\
&= P(u_{ij} \leq \exp(\log u_{i1} \cdot \exp(v_{ij} - v_{i1}))) \\
&= u_{i1}^{\exp(v_{ij} - v_{i1})}
\end{aligned}$$

Therefore

$$\begin{aligned}
P(\tilde{v_{i1}} = \max_j \tilde{v_{ij}}) &= \int P(\tilde{v_{i1}} = \max_j \tilde{v_{ij}} | u_{i1}) du_{i1} \\
&= \int (\prod_{j=2}^{J} P(v_{ij} + \zeta_{ij} \leq v_{i1} + \zeta_{i1})) du_{i1} \\
&= \int u_{i1}^{\sum_{j>1} exp(v_{ij} - v_{i1})} du_{i1} \\
&= \frac{1}{1 + \sum_{j>1} exp(v_{ij} - v_{i1})}
\end{aligned}$$

By multiplying $\exp(v_{i1})$ to the nominator and denominator of the fraction, I obtain (A.3). From each side of (A.2), v_{ij} can be expressed $X_j(\alpha Y_i + \varepsilon_i) - \log p_j$. Plugging this into (A.3) derives the likelihood f. Since ε_i is known to individual i but not known to econometricians, ε_i still remains in the likelihood.

Thus the likelihood is

$$f(d_i = j|\ X, p, Y_i, \varepsilon_i, \Theta) = \frac{\exp\left\{X_j(\alpha Y_i + \varepsilon_i) - \log p_j\right\}}{\sum_{j'=1}^{J} \exp\left\{X_{j'}(\alpha Y_i + \varepsilon_i) - \log p_{j'}\right\}}. \tag{A.4}$$

Appendix B

Other Numerical Simulation Results

B.1 Policy Experiments (ρ=0.0388)

For the robustness check, I simulate and examine the policy experiments with a different key parameter and the corresponding estimation results. I calculate my estimation with a ρ of 0.0388. Then, I evaluate the impacts of organic carrot price cuts and income increase on total demand, brand choice frequency, and revenues of each producer. Overall, I obtain a robust conclusion from policy experiments with different parameters in terms of quality-quantity trade-off, but the results were varied for different brands.

B.1.1 Effects of a 10% Price Drop in Organic Carrots

Table B.1. Effect of 10% organic price decrease on organic and non-organic purchase with $\rho = 0.0388$

	Non-organic	Organic	Total
Total Demand	-13.09%	35.10%	-8.87%
Brand Choice	-9.08%	156.30%	0.00%
Total Revenue	-14.10%	15.85%	-10.30%

In Table B.1, after imposing a 10% price cut for all organic brands carrots, I show that total demand, brand choice frequency, and total revenue for organic carrots increase substantially. However, the total demand and revenue for the entire carrot market decreases by 8.87% and 10.3%, respectively. From this result, I confirm that the price cut for organic carrots induces a substantial consumer transfer of carrot purchasing from non-organic to organic.

Table B.2. Effect of a 10% organic price decrease for each brand with $\rho = 0.0388$

	Effect on Brand (%)								
	1	2	3	4	5	6	7	8	Total
Total Demand	-13.40	-16.64	-14.78	-7.95	2.12	164.10	162.22	190.91	-8.87
Brand Choice	-10.11	-11.05	-9.86	-4.75	96.67	255.00	275.00	360.00	0.00
Total Revenue	-14.17	-16.56	-16.64	-8.55	-8.69	115.84	106.06	85.93	-10.30
Organic	No	No	No	No	Yes	Yes	Yes	Yes	-

Note: Brands 1-4 are conventional carrots and 5-8 are organic carrots.

Table B.2 presents the impact of the price cut of organic carrots on each brand. Again, I show that total demand, brand choice frequency, and total revenue for organic carrots increase substantially. In particular, the brand choice frequency of each organic brand increases two or three times. Total revenue for organic brands also significantly increases in organic carrot brands 6, 7, and 8. Since organic brand 5 has higher market share, the additional increase in quantity demanded is significantly smaller than other organic brands. Moreover, as ρ is less than 1, the theoretical model predicts that an inverse relationship between preference weight M_{ij} and quantity q_{ij}, which may cause results opposite to those of Table 6.5.

B.1.2 Effects of a 10% Income Increase for Households

Table B.3. Effect of a 10% income increase on organic and non-organic purchase with $\rho = 0.0388$

	Non-organic	Organic	Total
Total demand	-9.44%	15.64%	-7.24%
Brand choice	-6.76%	116.30%	0.00%
Total revenue	-10.23%	1.72%	-8.71%

Simulation results in Table B.3 show that consumers react to a 10% income increase in a similar way to the original parameter case. Even though total demand and total revenue for the entire carrot market decreases by 7.24% and 8.71%, respectively, organic brand carrots benefit substantially from the income increase.

Table B.4. Effect of a 10% income increase on each brand with $\rho = 0.0388$

	Effect on Brand (%)								
	1	2	3	4	5	6	7	8	Total
Total demand	-10.09	-12.52	-10.19	-4.56	-8.20	115.38	97.78	145.45	-7.24
Brand choice	-7.79	-8.14	-7.10	-3.31	75.56	200.00	175.00	280.00	0.00
Total revenue	-10.50	-12.93	-11.46	-5.21	-16.78	81.54	63.44	62.10	-8.71
Organic	No	No	No	No	Yes	Yes	Yes	Yes	-

Note: Brands 1-4 are conventional carrots and 5-8 are organic carrots.

Table B.4 reports the impact of an income increase on each brand. Except for organic brand 5, organic carrot brands obtain increases in all measures. Organic brands 6, 7, and 8 shows significant growth in transaction frequency and the quantity demanded, which drives the increase in their revenues. As in the Table B.2, when ρ is less than 1, preference weight M_{ij} and quantity q_{ij} decision is reverse, which may be the reason for the opposite results.

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