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STRATEGIC MARKETING BEHAVIOR OF PRIVATE LABEL AND ORGANIC PRODUCT FIRMS: A CASE STUDY OF THE PRE–PACKAGED SALAD SECTOR

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ABSTRACT

This research studies the strategic marketing behavior of food manufacturing firms and the welfare implications of their behavior in the pre-packaged salad industry. To achieve the objectives, we examine consumers' choices among pre-packaged salad options by two alternative methods both of which study discrete choice models with unobserved product characteristics. We study the strategic behavior of food manufacturing firms by a game theoretic approach. Estimates of demand are used for obtaining firms' markups in equilibrium and conducting welfare analysis for counterfactual changes. We conduct welfare changes for both consumers and manufacturers caused by the introduction of new organic products.

Table of Contents

List of Tables

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Dedication

Chapter 1

Introduction And Research Objectives

1.1 Introduction

This research focuses on the strategic marketing behavior of food manufacturing firms and the welfare implications. Based on industry reports, analysis of the purchase data, and even casual observance of supermarket trends, several stylized facts serve as the background of this research. The facts include the following: (i) Expenditure on private label goods (store brands) are increasing faster than overall growth rate of food expenditure; (ii) Growth rates for organic food products as a whole are also above average; (iii) An increasing number of supermarkets are offering their own private label organic lines; (iv) And growth rates for organic private label organic lines are above average.

These stylized facts which serve as the background for the organic food industry are examined in more details one by one.

First of all, expenditure on private label goods is increasing dramatically faster than the growth of over all food expenditures. In Nielsen's 2009 online survey of consumers, they found 43 percent of respondents were buying more supermarket-branded products in an effort to cut their household spending. Nielsen spokesman Warren Gillmer said that by June 2008, the average Australian household had increased its weekly spending on house-brand products by $11.20 (The Daily Telegraph 2009). And growth of private label brands had outstripped branded products. Private label is also starting to gain traction in traditionally brand-dominated categories. Sales of private-label items have been growing up to twice the rate of national brands over the past 10 years, according to Nielsen (Noreen O 'Leary, Adweek 2007). Also by Nielsen, while that growth has slowed recently, private-label sales still outpaced that for national brands, rising 4.2 percent versus 3.4 percent in the 52-weeks ended in June 2007 (Noreen O 'Leary, Adweek 2007). But based on U.S. Census Survey: Advance Monthly Sales for Retail and Food Service, food and beverage sales growth rate is about only 0.5 percent from 2007 to 2008.

Second, growth rates for organic food products are also increasing faster in U.S. than other food products. Organic products and organic agriculture are expanding rapidly in the United States, as consumer interest continues to increase and new organic production and marketing systems evolve. Since 1990, retail sales in organic food products have equaled 20 percent or more annually (Dimitri & Greene 2002). According to the Organic Trade Association (OTA), growth in the U.S. organic industry has been fairly steady, averaging between 15 percent to 21 percent (Huang and Lin 2007 and OTA). Retail organic food sales in the United States increased from $3.6 billion in 1997 to totaled $24.8 billion in 2009, representing 3.7% of total U.S. food sales (NBJ, 2008 and OTA, 2010). The implementation of national organic standards by the USDA in October of 2002, which provided uniform labeling for consumer recognition, coincides with the recent expansion in this industry. Demand trends are expected to continue as more conventional retailers take up a larger portion of the organic market. Sales of organic foods are estimated to rise to $23.8 billion by 2010 (NBJ, 2004). And fresh produce is the top-selling organic category, followed by nondairy beverages, breads and grains, packaged foods (frozen and dried prepared foods, baby food, soups, and desserts), and dairy products. Organic fruits and vegetables, which represent 38 percent of total organic food sales, reached nearly $9.5 billion in sales in 2009, up 11.4 percent from 2008 sales, now representing 11.4 percent of all U.S. fruit and vegetables sales. Organic food industry continued to outpace total sales of comparable conventional food, which continued a flat to downward trend in 2010 (Agri-Pulse, 2011). While total food sales grew by less than 1% in 2010, the organic good industry grew by 7.7% (FoodBusinessNews, 2011 and OTA, 2011).

Thirdly, in response to the increasing demand of organic food products, conventional supermarkets accounted for 47 percent of organic sales in 2003 (Oberholtzer, Dimitri, and Greene, 2005). Mainstream supermarkets are expanding their offerings of private label food items and account for the largest share of the organic foods market. Since 1997, organic fruits and vegetables have continued to be the top-selling organic product (Dimitri and Oberholtzer, 2009). Consumers have started to purchase packaged and prepared foods. Organic food was available in 82 percent of retail food stores in 2007 (Food Marketing Institute, 2008). Further, retailers have begun to develop lines of private-label organic products. New organic private-label products increased from 35 in 2003 to 540 in 2007 (Driftmier, 2009). Now, nearly every large conventional supermarket has a private label for organic products. "In 2003, approximately 8 percent of organic foods were sold under a private label (Nutrition Business Journal, 2004), in comparison to 16 percent for U.S. food products in general (Nielsen, 2005). In 2008, the share of private organic label products sales was an estimated 17.4 percent in the United States (Nielsen, 2008). USDA data indicate that, in 2007, approximately 43 percent of certified organic handlers manufactured private-label products, and private-label products make up approximately 19 percent of handlers' organic sales. "(Dimitri and Oberholtzer 2009).

Fourthly, organic private label lines are a big source of growth trends for both organic and private labels. According to ACNielsen, private label sales have been growing at a faster rate than their national brand counterparts for the better part of the past 10 years (Hartman Group online newsletter, 2007). Conventional supermarkets have steadily increased their investment in organic private labels since the National Organic Program was introduced in 2002. At first, the emphasis focused on price: Typically an organic store brand might be 10% more expensive than a conventional national brand, but still 10% less than the national organic brand equivalent. During the 2007-2009 recession, industry observers credited organic private label with helping to maintain sales in the especially price-sensitive category. More recently, retailers have shifted their marketing message to quality, in hopes of retaining shopper loyalty (Supermarket News). Private label product lines, especially organic options, got a big push in 2007 as major retailers like Safeway and Meijer introduced new lines and expanded existing ones (Supermarket News, December 31, 2007). Plans also call for an organic children's meal to be added to the in-store food-service menu. Safeway launched a 40-item extension of its O Organics store-brand line in the form of O Organics for Baby and O Organics for Toddler. O Organics for Kids was another new addition. Safeway also launched a proprietary brand called Eating Right. The line's "spot your needs" packaging system lets shoppers identify healthy attributes that match up with their specific nutritional needs. (Supermarket News, December 31, 2007). Ethnic private label is a growth area, as 27 percent of retailers said they plan to enhance their private label lines with ethnic products, according to the 2007 Survey of Center Store Performance (Supermarket News, December 31, 2007). Store-brand volume was up 3 percent in food, drug and mass channels (excluding Wal-Mart) for the 28 weeks ending Sept. 6, 2007, according to Nielsen data.

The Natural Foods Merchandiser reported that sales of packaged fresh produce in natural foods supermarkets had the highest growth rate among sales of all organic products during 2003 to 2004, expanding 35.4 percent annually on average to $171.9 million. Pre-packaged salad section is one of this packaged fresh products and capture all these trends based on our observation of purchasing data. Prepackaged salad is one of the fasted-selling items in U.S. grocery stores, which was still fairly rare a decade ago. Sales of prepackaged precut fresh salad mix, led by private label growth are booming recently according to reported statistics from The Nielsen Co.. And the products with an organic claim saw sales of $233 million for the 52 weeks ended July 12 in 2007, up nearly 25%. Private label organic sales leaped nearly 149% to $98 million while branded organic sales dropped 8.5% to $135 million(21food.com, Sept. 09, 2008). Calvin etc. al. (2001) report that 55 firms sold 197 bagged salad items in mainstream supermarkets in 1993, with total sales of $197 million. In 1999, 54 firms sold 459 items with sales of $1.3 billion.

With the rapid growth of organic fresh produce and private label products, organic foods become increasingly affordable and available in conventional supermarkets, which accounted for 47 percent of organic sales in 2003 (Oberholtzer, Dimitri, and Greene 2005). Researchers found that half of the respondents who purchase organic food frequently have income below $50,000 (Hartman Group 2002).

Consumers benefit from the variety of choice and the quality of food products with the increasing concern of food safety and healthiness as well as the low price of private label product. We use Pre-Packaged salad category as an example to study firms' marketing behavior and welfare change from the introduction of private label pre-packaged salad driven by consumers' demand of quality, variety and convenience. Pre-Packaged salad products become highly differentiated. But there are only two major national brands and private labels from the observant of Nielsen Homescan data. We consider the pre-packaged salad industry is dominated by a few companies. Then the possible market conducts are numerous and collusive behavior like the leadership pricing strategy is sustainable in repeated game manner (Roberts and Samuelson 1988).

This research considers the strategic marketing behavior of food manufacturing firms and the welfare implications of their behavior in the pre-packaged salad industry. To achieve the objectives, we examine consumer choice among pre-packaged salad options by two alternative methods, both of which study discrete choice models with unobserved product characteristics. We study the strategic behavior of food manufacturing firms by a game theoretic approach. Estimates of demand are used for obtaining firms' markups in equilibrium and conducting welfare analysis under counterfactual changes. We conduct welfare changes for both consumers and manufacturers caused by the introduction of new organic products.

This research is directed by NEIO literature and game theoretic studies of manufactures' and retailers' strategic marketing behaviors. A number of earlier papers in this field provides general guidance. Mussa and Rosen (1978) analyze a monopoly pricing model of products with the same generic type but of different qualities. Lal (1990) models three firms' (two national brands with some loyal consumers, one local brand with no loyal consumers) interactions in a market of switchers and loyals, which analyzes the phenomenon of temporal price promotions where national firms promote their products alternating. Raju, Srinivasan and LAL (1990) propose a game-theoretic model that links the degree of brand loyalty to price promotion strategies. Bresnahan (1987) studies the supply-side structure movement in total quantity and quality-adjusted price in the American automobile market in 1955. Gasmi, Laffont and Vuong (1992) propose a methodology for the study of firm's strategic behavior that connects game-theoretic models and econometric approach analyzing various non-nested possible pricing and advertising behaviors of Coca-Cola and Pepsi-Cola in the U.S. soft-drink market. However, there are few studies provide empirical analysis on pre-packaged salad category. Although there are some studies on strategic interactions among different agents in the food markets (Villas-Boas, 1995; Richards and Patterson, 2005; Villas-Boas and Zhao, 2005; Richards, Acharya, and Molina, 2011), none considers structural estimation of organic private label pre-packaged salad category and none tests among non-nested models. Li and Sexton (2005) study temporary price reductions and sales in bagged salad category, but not a structural analysis. Marketing managers are faced with complicated task to implement a pricing strategy that balance competition from rivals with consumer concerns. In this study, we propose three related investigations to study firms ′ behaviors and welfare change from the introduction of private label product to help the study of public policy issues and help marketing managers make the pricing decision while taking into account their rivals. These three investigations are: (i) An estimation of discrete choice demand model of the differentiated pre-packaged salads, (ii) an estimation of supply based on non-collusive and collusive game models and apply a test of whether standard oligopoly pricing models apply in the prepackaged salad sector, and (iii) a computation of the welfare impacts associated to the introduction of a private label line of organic pre-packaged salad.

1.1.1 Methodology

We propose to use the pre-packaged salad category as an example to study firm marketing behavior and the welfare implications of their behavior. In this product category, our data show discrete purchasing pattern. Households usually purchase one brand of pre-packaged salad in each purchase trip. This is consistent of discrete choice. Therefore, a discrete choice model will be estimated for the demand side. As in recent literature on discrete-choice model, consumer's utility is based on product characteristics and some random tastes (see, e.g., McFadden (1980) and

Lancaster (1971)). Moreover, the presence of unobserved characteristics causes price endogeneity (see, e.g., Berry, Levinsohn, and Pakes (1995) and Petrin and Train (2010)), which is also an issue in our model. Without dealing with price endogeneity, it is well known in the literature that the demand estimates are biased (see, e.g., Berry (1994)). Following the literature of discrete consumer choice, we estimate the demand under two dominant approaches, namely, the BLP approach and the control function method, and compare the results induced by these two different methods.

We also consider the supply side. To understand the supply function, an interesting question comes out: what is the nature of market competition structure? Without addressing this question properly, we would be unable to estimate the supply function correctly. We consider two alternative competition structures: Bertrand-Nash competition and Stackelberg price leader model with collusive behavior. We apply the method developed by Vuong (1989), called likelihood ratio test for non-nested models, to select between the competing models. We solve for new equilibrium price system under the counterfactuals as if there were no private label product based on the demand and supply estimates. Then we calculate the consumer welfare change by compensating variation and the change of producer profits. More specifically, the empirical studies we conduct in this paper are as following:

(i) An estimation of discrete choice demand model of the differentiated pre-packaged salads. This model is derived from consumer preference theory and consumer utility depends on product characteristics and individual random tastes. We apply two different estimation methods, the BLP method (Berry, Levinsohn and Pakes 1995) and the control function method (Petrin and Train 2010) and compare the results.

(ii) An examination of two pricing models and a test of which standard oligopoly pricing model should be adopted in the prepackaged salad sector.

From the pattern of our Homescan Panel data, we find that US organic prepackaged salad industry is highly concentrated, two major brands hold more than 80 percent volume share. So our conjecture of market structure is one of the oligopoly forms, but the exact form is unknown. Knowing market structure is important for two reasons: first, it is crucial for researchers to adopt the right structure to analyze even when there is not much well documented information about market structure, for a misspecification structure would not give us consistent estimators and induce a misleading welfare analysis. Second, in the game theory context, the equilibrium solution could be totally different under different game structures. There is no use to analyze a Bertrand-Nash equilibrium when the indeed equilibrium is the Stackelberg leader type.

(iii) A computation of the welfare impacts associated to the introduction of a private label line of organic prepackaged salads.

As private label product lines expanding, consumers gain from more variety of products and the increased competition between both manufacturers. We can expect private label products increase the bargaining power of retailers and reduce the price of competing brands. For the suppliers of national brands, the possible reduction of retail price and the loss of sales led by the purchases switching from national brands to store brand may hurt the manufacturers' profit. So, total welfare change is not clear without a full analysis of both consumer and manufacturer.

We use compensating variation to measure the change of consumer welfare caused by the introduction of private label pre-packaged salad. Compensating variations measure the loss of income, taking place after the fall in price, which would make the consumer no better off than he was before the fall took place (Hicks 1946). The welfare change from the introduction of new private label products can be represented as two parts of variation: quantity-compensating variation ('variety effect') and price-compensating variation ('price effect'). 'Variety effect' measure consumer welfare change from more choices of products. 'Price effect' measures consumer welfare change due to the changes in price of existing brands. Thus, in prepackaged salad industry, consumers' compensating variation is the dollar value that a former consumer need to be compensated to achieve the same utility level before the introduction of private label pre-packaged salad. Because private label products will compete closely to national brands, the prices of national brands are likely to fall. Consumer welfare is expected to increase for the availability of more variety and the price reduction of existing brands. We compute the profits for each firm in the environment without new brand by solving new equilibrium prices and compare the profits in the environment with new brands. The suppliers' surplus is defined as the total sum of profit changes.

1.1.2 Results

Given the private label organic pre-packaged salad is more accepted by consumers and the reduction of national brand sales from Nielsen Co.'s report, we can expect consumers gain from the larger choice set and the increased competition between both manufacturers with manufacturers and with retailers for private label products may increase the bargaining power of retailers and reduce the price of competing brands. But for the suppliers of national brands, the possible reduction of retail price and the loss of sales led by the purchases switching from national brands to store brand may hurt the manufacturers' profit. And for the retailers, the introduction of store brand will attract more consumers into the prepackaged salad category who previously did not buy. But the price sensitive consumers may switch to store brand or become more sensitive to price. Retailers may need to lower the national brand price or sell more store brand to get a lower margin. So, total welfare change is not clear if just analyzing one aspect. An accurate welfare measure of packaged salad industry will be our interest of research in this study.

1.2 Research Objectives

This paper studies the strategic marketing behavior of food manufacturing firms and the welfare implications of their behavior. The research objectives of this paper consist of the comparison of two alternative methods to examine households' choices among pre-packaged salad options and the study of strategic behavior of food manufacturing firms as well as the counterfactual welfare analysis caused by their behavior in highly concentrated market. Therefore, estimating demand function is needed for obtaining firms' markups in equilibrium and conducting welfare analysis for counterfactual changes. The thesis will be composed of three major chapters studying pre-packaged salad industry.

The proposed objectives are as follows:

1. To examine market demand derived from a discrete-choice model of consumer preferences. The utility of consumers are based on product characteristics and random consumer tastes. In this case, the estimated effects of observed factors are correlated with the effects of those unobserved factors, which reintroduces endogeneity and heterogeneity (Berry 1994 and BLP 1995) . The first chapter applies two methods proposed by Berry(1994) and BLP (1995) and Petrin and Train (2010) to estimate the structure parameters and address the endogeneity problem.

1a. prepare data for estimation of demand parameters. We have information on the characteristics of products and households' choices among the alternatives. But we do not require to observe all the product characteristics. A.C Nielsen's Home scan Panel data provides household purchasing history which means consumer level data is available. This data set also provide purchasing price, coupon value and main attributes of all the products like flavor, product size, organic or not etc..

1b. estimate a random-coefficients discrete-choice demand model allowing price endogeneity by BLP method which is a consumer level data extension of the method proposed by Berry(1994) and BLP (1995) that recover the mean utility by matching the observed market shares to the predicted market shares and applies the instruments to control endogeneity;

1c. estimate the same random-coefficients discrete-choice model of demand for differentiated products allowing price endogeneity by a Control Function method (CF) proposed by Petrin and Train (2010), which uses a control function derived from economic theory and observed variables to control the endogeneity between the endogenous variable and demand error. We use an alternative pricing equation derived from economic theory that contains information on unobserved characteristics to control the endogeneity.

Both methods are extensions of random coefficient logit model. We estimate both for comparison.

2. estimate and compare different market structures and choose the model that fits the data best. We focus on two price competition structures: (i) Bertrand competition; (ii) Stackelberg price leader.

2a. prepare data for supply side estimation. We need the price of each product and the cost information. We use fresh vegetables' price, such as the price of carrot, lettuce and spinach, as proxy of cost. A.C Nielsen's data set provide all the purchase prices for these products.

2b. two game theoretical models of price competition are concerned: Bertrand and Stackelberg leader. We will derive the equilibrium outcome from different supply side model assumptions and use maximum likelihood estimation to estimate the parameters.

2c. we apply likelihood ratio test proposed by Vuong (1989) for two competing hypothesis.

3. To quantify a comparative static welfare change associated to the introduction of Private Label pre-packaged salad category based on the demand estimation and the firms' strategic behavior model that fits the data best. We construct a supply-and-demand equilibrium analysis on empirical models of differentiated products in pre-packaged salad industry.

3a. The data available for this study is similar to the data we use in the above two sections.

3b. do a counterfactual analysis to see the welfare change caused by introduction of private label pre-packaged salad.

Chapter 2

Literature Review

Estimating demand and supply is the key of many empirical studies to examine the market power, strategic behavior and counterfactual welfare analysis etc.. The so-called "new empirical industrial organization" (NEIO) was proposed in late 1980s and widely used today to the demand and supply estimations. This approach applies economic theory to individual choice and firm decision carefully to guide specification and inference in empirical models. The stylized model has three sets of unknown parameters: costs, demands and firm conducts. (Bresnahan 1989). This study estimates the structural parameters and conducts a welfare analysis on introduction of new private label pre-packaged salad.

In the recent literature on structural IO models, another important feature is the wide adoption of game theoretical concept and solution to capture the strategic behavior among firms (see, e.g., Bresnahan and Reiss (1991)), especially in a concentrated market as the one we studied here. In our supply analysis, we use the concepts like Nash Equilibrium from game theory. The market prices chosen by firms are interpreted as strategic behavior under particular market competition structure, an essential idea in the classical Bertrand model.

2.1 Literature Incorporating Strategic Behavior in Product Pricing

The increase in the number of studies in industrial organization and marketing literature now emphasizes on applying economic theory to guide inferences and estimating the models using market data. A variety of theoretic models of price or quantity competition has been well developed in the past several decades especially in highly concentrated market which will help our empirical analysis.

Mussa and Rosen (1978) analyzes a monopoly pricing model of products with the same generic type but of different qualities. Lal (1990) models three firms' (two national brands with some loyal consumers, one local brand with no loyal consumers) interactions in a market of switchers and loyals, which analyzes the phenomenon of temporal price promotions where national firms promote their products alternating. This paper shows that if there are sufficiently large number of switchers, the demand parameter is within in a feasible range and the firms do not discount their future values too heavily, then, national firms provide a price promotion alternatively in a infinite horizon repeated game while the local firm holds its price constant is a perfect Nash equilibrium. Raju, Srinivasan and LAL (1990) proposes a game-theoretic model that links the degree of brand loyalty to price promotion strategies. This paper analyzes how loyalties influence the decision of firms on whether or not using a price promotion and how loyalty differences lead to the depth and frequency of different brands in the same product category based on the unique perfect equilibrium in a finitely repeated game. Their model predicts price promotions increase with an increase of the number of competing brands and the brands with larger brand loyalty promote less often than the brands with relatively smaller loyalty. These results are also empirically tested and are found consistent with the data.

The development of the "new empirical industrial organization" (NEIO) builds a bridge between theoretical pricing models and econometric studies. Several important papers based on NEIO approach are highly relevant to our work.

Bresnahan (1989) provides a review of the economic theories that have been applied and the way in which economic inferences have been drown from the empirical work. Most of the work reviewed in this chapter of the handbook have been focused on monopoly power and oligopoly interaction. The author also shows the theoretical and empirical arguments for why it is a monopoly power is in fact being tested and shows that the hypothesis of market power is identified on reasonable data. This handbook chapter also takes up the question of measuring market power in the product-differentiated industry. Bresnahan (1981, 1987) are empirical examples of using spatial model of the demand for automobiles by type as demand system. Bresnahan (1987) studies the supply-side structure movement in total quantity and quality-adjusted price in the American automobile market in 1955. The author sets up the models making assumptions on cost, demand and product type and then solve the equilibrium under two hypotheses: competitive and collusive. This paper tests four different equilibrium models (Collusive, Nash-competitive, hedonic and so-called products model) of oligopoly in differentiated product market by Cox tests of hypothesis and finds the oligopoly behavior change from collusion to a competitive Nash equilibrium , while the collusive behavior hold in 1954 and 1956. In the final section of the handbook chapter, the author points out the causes of market power, in particular, the topics of entry, predation, entry deterrence and strategic competition are interesting topics for future research.

With the development of NEIO, more and more empirical studies have been referred to structural models. Richards, Acharya and Molina (2011) use a structural model of demand and pricing in organic and non-organic apple market to test the hypothesis of organic suppliers enjoy more market power. Richards and Hamilton (2006) and Richards and Patterson (2006) investigate the roles of price and variety in manufacturers' competition and supermarket retailers' strategic interactions respectively in a model of nested constant elasticity of substitution and a dynamic game. Richards and Patterson (2005) extend Green and Porter (1984) to fresh produce prices in U.S. retail and wholesale markets to determine whether a non-cooperative pricing model explains observed retail and wholesale pricing interactions. Villas-Boas (1995) is one of the first attempts to test the complete equilibrium structure of price promotions which focus on Varian (1980) model. Villas-Boas and Zhao (2005) study a structural model that include discrete choices of consumers and manufacturers and retailers interacting as a Stackelberg model with retailers pricing follow wholesale prices. Berry (1994), Berry Levinsohn, and Pakes (1995 BLP) develop a structure to empirically analyze the demand and supply system in differentiated products market allowing price endogeneity in discrete consumer choices. Nevo (2000, 2001) extend BLP method and apply the approach into Ready-to-Eat cereal industry. Petrin and Train (2010) propose a control function method to take care of endogeneity problem in choice models which is a compositionally easier alternative to BLP product-market controls for unobserved product characteristics.

The variety of the theoretic models give us guides on empirical studies. Most of the above researches hypothesize from one of the strategic interaction models and test the explanations. One exception is Nevo (2001) using the estimated elasticities to compute different price cost margins under different conduct models. So which model reveals the data is a question to ask. A misspecified model will bias the econometric inference. There are some papers propose the techniques for model selection which help us to determine which model fits the data best for empirical analysis. Vuong (1989) proposes a likelihood ratio test to suggest a method to test appropriate firms' strategic behaviors among possible alternative non-nested game models. We will follow the procedure by Vuong (1989) and Gasmi, Laffont, and Vuong (1992) to test the competing models in U.S. pre-packaged salad industry in 2005.

Vuong (1989) provides a test method for pairwise comparison between candidate non-nested game theoretic models. His test method which we will apply to help model selection in this paper, is based on likelihood ratio principle and is used to compare null hypothesis that two models are fitting the data equally well to alternatives that one is better than the other. After we get the normalized likelihood ratio which is normally distributed, we can figure out which model fits the data better if the test statistics is less or greater than the negative and positive critical value.

There are some applications in various industries especially those in food industries use Vuong (1989)'s likelihood ratio test to help model selection which show us the detailed procedures of how to apply this test in empirical work. The first one is Gasmi, Laffont and Vuong (1992), which proposes a methodology for the study of firm's strategic behavior that connects game-theoretic models and econometric approach. They analyze various possible pricing and advertising behaviors of Coca-Cola and Pepsi-Cola which is the duopoly in the soft-drink market over the 1968-1986 period. The framework is based on game theoretical models. They specify the demand function for each product both on rival's price and advertising.

Marginal cost is a linear function of input prices. Using the demand and cost, they build the relationship and derive the first order conditions for each firm in both price and advertising. Then the parameters in these equations are imposed different restrictions in different oligopoly games and are simultaneously estimated by full information maximum likelihood estimation, they determine the best fitted game by Vuong (1989)'s tests. The result shows some tacit collusive behavior in advertising between Coca-cola and Pepsico Inc. prevailed and collusion of prices does not seem to be supported by the data.

Kadiyali, Vilcassim and Chintagunta (1996) examine the retail liquid laundry competition between P&G and Lever Brothers in the detergent product category using store-level sales and price data from Sioux Falls, South Dakota markets. They develop linear demand functions and seven different equilibrium conditions based on different game theoretical assumptions. The parameters are estimated by 3SLS and choose the best fitted model by the criterion of choosing the minimum of minimized error of sums of squares, which is equivalent to Vuong's (1989) likelihood ratio test. The result shows that both firms are price leaders in their major products and price follower in their miner products.

Vasilis G. Mihalopoulos and Michael P. Demoussis (2001) study the consumption of food away from home (FAFH) by Greek households using cross-sectional data from 1993 to 1994 Household Budget Survey carried out by the National Statistical Service of Greece (NSSG). They use Vuong's test (Vuong 1989) to compare double hurdle model, purchase infrequency models and a Inverse Hyperbolic Sine (HIS) Tobit model and find HIS double-hurdle participation model fits the data best. Dhar, Chavas, Cotterill, and Gould (2005) investigate market structure and strategic pricing for Coca-Cola and Pepsico. Their estimation result consists of two parts: first, use Gasmi etc. al. (1992) non-nested test to detect the market structure is Collusion or the other three competition models. If the Collusion structure is rejected, then Wald tests can be used for the other three competition structures in a nested model. Second, this is the first study to use the Almost Ideal Demand System (AIDS) within a structural model of firm conduct to get the estimates. They find support for a Nash-Bertrand or Stackelberg Leadership equilibrium in the brand-level pricing game. Dong, Marsh and Stiegert (2006) examine a dual two state enterprises market structure of global malting barley market which is dominated by two STEs to help the choice of trade policy. Because the trade policy is crucially dependent on the strategic variable, they follow GLV (1992) to test competing models of different market structures including both quantity and price-setting strategies.

2.2 Literature on Estimating Discrete Choice Models of Demand for Differentiate Product

Estimation of demand is one of the important parts of estimating valuation of new product introduction in differentiated-product industries. The main streams are divided into two classes: one is to estimate an almost ideal demand system and the other is discrete choice model. This paper will apply a methodology that belongs to the second class. Estimating discrete choice models when the utility depends on product characteristics, the presence of unobserved characteristics, which enter the demand non-linearly, brings the econometric problem of endogeneity. There are several methods focusing on resolve this problem. One is called Control Function method. The other is BLP fashion.

2.2.1 Literature on application of "Control Function" method

Petrin and Train (2010) propose a control function method to take care of endogeneity problem in choice models. This approach is an alternative to widely used Berry, Levinsohn, Pakes (1995 BLP) product-market controls for unobserved product characteristics, which is easier to estimate and compute as well as is available under the conditions in which BLP estimator is not valid. Such condition includes where there are zero, one, or sample error. Researchers have shown that unobserved or unmeasured factors in discrete choice demand models, like unobserved product characteristics which not only affect cost but also consumer choice, are correlated with some of the observed factors in the models violating the standard independent assumptions and cause inconsistency of the estimates. The authors describe a control function approach to deal with this endogeneity problem. This approach uses observed variables and economic theory to derive controls for dependence between the endogenous variable and the part of demand error that are not independent of the endogenous variable.

To be more specific, this method begins with a commonly used discrete choice model, assuming consumer $n's$ utility from alternative j is

$$U_{nj} = V(y_{nj,}x_{nj,}\beta_n) + \varepsilon_{nj}$$

Where y_{nj} is the observed endogenous variable, x_{nj} is a vector of observed exogenous variables that affect utility of choosing j, β_n are parameters of consumer $n's$ tastes, and ε_{nj} is unobserved part of utility which is correlated with y_{nj}.

The basic idea of control function is to derive a proxy variable that conditions out the part of y_{nj} that depends on ε_{nj}.Then the remaining variation in the endogenous variable will be independent of the demand error and the traditional estimation method could be used.

In discrete choice model, y_{nj} can be written as a function of exogenous variables in utility function and a group of instruments, and a vector of unobserved terms μ_{nj}:

$$y_{nj} = W(x_{nj}, z_{nj,}\mu_{nj}).$$

Where μ_{nj} and ε_{nj} are not independent of each other but independent of x_{nj} and z_{nj}. This function illustrates the source of dependence of y_{nj} and ε_{nj} as μ_{nj} affects y_{nj} and not independent of ε_{nj}. And conditional on μ_{nj}, ε_{nj} is independent of y_{nj}. If one can derive μ_{nj}, it can be conditioned on when estimate the parameters. ε_{nj} can be decomposed into two parts

$$\varepsilon_{nj} = CF(\mu_{nj};\lambda) + \widetilde{\varepsilon}_{nj},$$

where $CF(\mu_{nj};\lambda)$ denotes the control function with parameter λ.

Then we have

$$U_{nj} = V(y_{nj,}x_{nj},\beta_n) + CF(\mu_{nj};\lambda) + \widetilde{\varepsilon}_{nj}.$$

Conditional on μ_{nj}, the probability that consumer n chooses alternative i is

$$P_{ni} = \int I(U_{ni} > U_{nj}\ \forall\ j \neq i)\ f(\beta_n, \widetilde{\varepsilon}_{nj})d\beta_n\ d\widetilde{\varepsilon}_{nj}$$

where $f(\cdot)$ is the joint density of β_n and $\widetilde{\varepsilon}_{nj}$ and $I(\cdot)$ is the indicator function. Thus, what left is just to make assumptions on the distributions and we will get likelihood function. Then standard estimation methods can be used to estimate.

The model is estimated in two step. First, regress the endogenous variables on the observed characteristics and the instruments. Maintain the residual. Second, use the residual as an extra variable to estimate the choice model. The control function approach can be estimated with standard software packages.

The authors also provide some parametric functional forms examples for the errors in both equations. Under these different distributional assumptions, the model leads to probit and mixed logit models. They also take price as the endogenous variable and use some variant of the controls in the above examples to investigate control function method under the condition of both marginal cost and monopoly pricing behavior. They apply their method to households' choice among television options. The specification and the data are similar to those used in Goolsbee and Petrin (2004), who applied the BLP method. Thus the results are compared. Households have four alternatives of TV and the sample consists of 11,810 households in 172 geographically district markets. Each market has one cable franchise that offers basic, extended, and premium packages with some multiple system operator own several franchises. The price and other attributes of the cable options vary over markets. The first step is to estimate pricing functions to recover the residuals entering the control functions in the choice model. The instrument is the average prices in other markets that are served by the same multiple system operators. The second step is the residuals entering without transformation in the mixed logit model to correct the endogeneity. The empirical results show that the corrected estimates from both BLP and Control Function method are quite similar and produce much more realistic demand elasticities. This implies that Control Function approach is an alternative to the BLP method and individual level data can be applied by this method when there is both endogeneity and heterogeneity. Kim and Petrin (2010) expands on the approach from Petrin and Train (2010) and provides the conditions on demand and supply such that the pricing functions can be inverted to recover controls that is a one-to-one function of the unobserved product attribute, and then use this control to condition out the dependence of the demand error on price.

2.2.2 Literature on Berry (1994) and BLP (1995) method

Berry (1994) and Berry, Levinsohn, and Pakes (1995 BLP) develop a structure to empirically analyze the demand and supply system in differentiated products market allowing price endogeneity in discrete choice models, which will not suffer from some strong assumptions (e.g. IIA, "independence of irrelevant alternatives") and has huge advantage in the counterfactual welfare analysis, especially the evaluation of the impact of the new product on market. They also develop a simulated moment method for the demand-supply equation system, which can be applied to both aggregate level and consumer-level data (For the household-level data, their estimates work easier and have a better asymptotic performance.) avoiding non-linear instruments difficulty. BLP apply the model and techniques to the U.S. automobile markets and obtain cost and demand parameters for all auto-models markets over a twenty year period using market level data. Later, there are lots of develops based on BLP to analyze different industries and applications to micro level data, for instance, Goolsbee and Petrin (2004) and Chintagunta, Dubė and Goh (2005) carry out some exercises using individual level data.

Berry (1994) considers the problem of "supply-and-demand" analysis on a cross section of oligopoly markets with differentiated product assuming discrete-choice demand model and that prices are endogenous determined by price-setting firms. Because the utility of consumers depend on both observed characteristics and unobserved characteristics, the fundamental problem is the correlation between price and unobserved characteristics. In discrete-choice models, both price and unobserved characteristics enter the utility in a non-linear fashion which makes the straightforward application of instrumental variable method invalid. This paper introduces a method that consists of two–step estimation procedure: (1) inverting the function of market shares to uncover mean utility levels of various products. These mean utility level of product j are a linear function of price of product j, product j's observed characteristics and its unobserved characteristics. (2) use instrument method to estimate the mean utility level functions. The author provides two examples in the inversion step: Vertical Differentiation and Nested Logit. The random coefficient model's market share is more difficult to calculate, but the general idea of solving mean utility does not substantially change. With the estimates of demand side, we get the demand elasticities and thus supply side parameters are also estimated if assume price is the result of price-setting strategies. The author also compares the method he proposed with "fixed effect" or to "integrate out" over some exogenous distribution for the unobserved characteristics. The former is not identified and the latter does not work because the unobserved characteristics vary with price. The proposed method is also compared with solving for the reduced form of the model which need the uniqueness of equilibrium. The Monte Carlo simulation results show that the method introduced in this paper provides more reasonable coefficients and more close to the true parameter value.

Berry, Levinsohn and Pakes(1995 BLP) introduce a method to estimate discrete choice demand model allowing unobserved characteristics correlated with price.

The model of BLP consists of two parts: the demand side and the supply side.

First, the way to specify demand function is to derived a choice of consumer from the utility function which is a function of both individual characteristics and product characteristics:

$$U_i^j = U(\zeta_i, p_j, x_j, \xi_j; \theta)$$

where i is the identity of consumer, j is the j-th choice of differentiated product, or say product j. p_j is the price and ζ_i is individual characteristics. x_j and ξ_j are, respectively, observed and unobserved (by econometrician) product attributes. Further, a specification of this U function is assumed:

$$U(\zeta_i, p_j, x_j, \xi_j; \theta) = (y_i - p_j)^{\alpha} G(x_j, \xi_j, \nu_i) e^{\epsilon_{i,j}}$$

where y_i is income, and ν_i is consumer taste, $\epsilon_{i,j}$ is independent shock with a known distribution. Take a monotone transformation to the utility function: $u_{i,j} = \log U_i^j$ and assume further $G(\cdot)$ is linear in logs and has the standard random coefficient specification in the literature, then

$$u_{i,j} = \alpha \log(y_i - p_j) + x_j\beta + \xi_j + \sum_k \sigma_k x_{j,k} v_{i,k} + \epsilon_{i,j}$$

for $j = 1, ..., J$. Assume the outside option, means when consumer i doesn't choose anything from $1, ..., J$.

$$u_{i,0} = \alpha \log(y_i) + \xi_0 + \sigma_0 v_{i,0} + \epsilon_{i,0}$$

Let ν_i conforms to a parametrized distribution.(which means we can simulate its value even we don't have data on it.)

In all, from above analysis, we can have a demand function (aggregate consumer characteristics to obtain market share.)

$$s_j(p, x, \xi; \theta) = \int_{\zeta \in A_j} P_0(d\zeta)$$

where

$$A_j = \{\ \zeta : U(\zeta_i, p_j, x_j, \xi_j; \theta) \geq U(\zeta_i, p_r, x_r, \xi_r; \theta),\ \text{for } r = 0, 1, ..., J\ \}$$

Second, given demand function, they will model how oligopolies maximize profit.

$$\max \Pi_f = \max \sum_{j \in F(f)} (p_j - mc_j) M s_j(p, x, \xi; \theta)$$

F.O.C

$$p = mc + \Delta^{-1}(s(p, x, \xi; \theta)) s(p, x, \xi; \theta)$$

where $\Delta(s)$ is a function of s, which only depends on how these K ($K \leq J$) firms own the J products and $s(p, x, \xi; \theta)$.

Assume

$$\log mc_j = w_j \gamma + \omega_j$$

where w_j and ω_j are the observed and unobserved product characteristics. Hence, we obtain the demand-supply system:

$$s = s(p, x, \xi; \theta) \tag{2.1}$$

$$\log(p - b(p, x, \xi; \theta)) = w\gamma + \omega \tag{2.2}$$

where $b(p, x, \xi; \theta) = \Delta^{-1}(s(p, x, \xi; \theta))s(p, x, \xi; \theta)$.

Given (1), (2), the equilibrium price and market share(quantity) are functions of those exogenous (the observed and unobserved product characteristics, note here, only product characteristics involves in and no consumer characteristics.)

Estimation strategy. Assume

$$\begin{aligned} E(\xi_j|z) &= 0 \\ E(\omega_j|z) &= 0 \end{aligned}$$

Then use GMM method to estimated it.

Nevo (2000) describes the methods for estimating random-coefficients discrete-choice models of demand proposed by Berry (1994) and Berry Levinsohn and Pakes

(1995) with the intent of increasing the understanding and reducing the difficulty of using them for the researchers who have never used them. This paper carefully discusses the model the estimation including the data required, the algorithm, instrumental variables offered in the literature, adding in brand-specific dummy variables and also provide the detailed estimation algorithm in an appendix.

The BLP approach, originally applied to automobile market, has been widely applied to various food industries. Nevo (2001) estimates the economic price-cost margins (PCM) in the Ready-to-Eat cereal industry and empirically distinguishes between the three sources: (i) margin due to product differentiation; (ii) margin due to multi-product firm pricing; and (iii) margin due to price collusion by comparing with a crude measure of actual PCM. The estimation strategy is to estimate brand-level demand and then use the estimates jointly with pricing rules implied by different models of firm conduct to recover PCM. The demand system is estimated following Berry, Levinsohn, and Pakes (BLP 1995), which uses a random coefficient discrete choice model to estimate demand parameters but with three major differences: the instrumental variables are different; do not specify a functional form for the supply side; using the richness of the panel data to control for unobserved product characteristics by using brand fixed effects. The estimated elasticities are used to compute three different price cost margins under different conduct models. These models are tested by comparing the crude measures of margins. The empirical results rule out an extreme version of cooperative pricing, one in which all firms jointly maximize profit. Reimer (2004) focuses on U.S. cereal firms ′ strategic interactions on pricing and estimates the size and significance of conduct parameters in this industry by using Nevo's demand elasticities in Nevo (2001) when constructing price-cost margin estimates under different scenarios. Chintagunta, Dube, and Goh (2005) extend Berry (1994) to estimate consumer choice by maximum likelihood estimation using household scanner panel data of margarine category in Denver market from January 1993 to March 1995. The purpose of this paper is to investigate the role of potential unobserved product characteristics which not only affect the mean price response but also lead to larger estimates of the variance in the heterogeneity distribution of preferences and price sensitivities across household. Allender and Richards (2010) analyzes whether egg producers use export to improve their market power using the data of the California egg market. The demand side estimation follows BLP (1995) and Nevo (2001). The supply side is estimated by a structural model that producers first set the prices that are paid by retailers who set prices to consumers. Any deviation from the margins implied by Bertrand-Nash competition is assumed due to market power. Mojduszka, Caswell, and Harris (2001) apply BLP (1995) to prepared frozen meals to estimate consumer preferences with regard to product characteristics to evaluate price competition in this industry and the effect of the new mandatory labeling policy. Chidmi and Lopez (2007) applies BLP to estimate a discrete-choice random coefficients logit demand model using supermarket chain level data to examine consumer choices and retail competition for thirty-seven brands of breakfast cereals in Boston. Kim (2008) estimates the demand and pricing relationship in the U.S. margarine industry following BLP (1995). Rennhoff (2008) applies BLP (1995) to estimate a structural model of merchandising allowances in ketchup industry in the U.S..

2.3 Literature on Comparative Static Welfare Change Associated to The Introduction of New Product

The development and introduction of new products is an important way to improve consumers ′ standard of living and may yield large profits for the innovators. Estimation of demand is the key of many studies to examine the question of valuation of new products in differentiated-products industries. There are some applications trying to measure how much consumers benefit from a greater variety of choice and infer the changes in producer surplus with estimates of combining demand for discrete choice models and a model of strategic competition which fits the data best.

Several important papers are highly relevant to our work. Each of them make some methodology contributions and apply BLP to a variety of industries to analyze welfare change. These papers show the detail techniques that will help our study of valuation of new pre-packaged salad product introduction.

Petrin (2002) estimates the changes in consumer and producer welfare from the introduction of the minivan in the United States. This paper uses BLP approach but supplement their moments with a new set of moments for estimating demand more precisely when consumer level data is not available. The author suggests to relate the market-level data with information relating demographic averages of consumers to the characteristics of the products they purchased. In particular, he divides U.S. population into three equal sized groups by income level and match the model's probability of purchasing new vehicle for different groups to observations from data of conditional probability of purchase. And he also matches model predictions for average family size for purchasers of different vehicles to real data. The supply side is exactly follow BLP by assuming Nash-Bertrand competition. Petrin applies this method to U.S. automobile industry from year 1981 to 1993. He uses compensation variation to measure changes in consumer welfare from the introduction of the minivan. Counterfactual analysis without minivans is doing by solving equilibrium first-order conditions dropping minivan. Putting producer surplus and consumer welfare change together, the results of this paper show that overall gains from the introduction of minivan were large. Consumer and the innovator gain large welfare at the expense of the producers who are not well prepared for the introduction of new good.

Nevo (2003) constructs a price index that takes account of new-product introductions and quality changes. A structural estimation is required to conduct the welfare equivalent analysis. This paper builds a discrete choice model to estimate demand system allowing for the introduction of new goods and for quality change. However, the interpretation of the estimation results to construct welfare measure and thereafter price index heavily depends on a set of assumptions: time dummy and error terms. Due to lack of information that which assumption is proper, Nevo suggests a comprehensive method: construct price index under every possibility of these different assumptions, then give a range of price index. Hence, the paper consists of two parts: first is a structural estimation of discrete choice model. Second, under different assumptions, he interprets the estimates and constructs price index.

Because our data set is household choice data, Goolsbee and Petrin (2004) is a good example for us to apply BLP to micro level data. This paper examines the effect of introduction of direct broadcast satellites on basic cable. The authors apply BLP method to control for price endogeneity when estimating demand system with micro level data on television choices. The method is following Berry (1994) and BLP (1995) which consists of two steps. The first step is a MLE procedure to recover the mean utility δ using household level data. The second stage is to regress mean utility on price and product characteristics, and instrument the price with a cost shifter to control for correlation with the unobserved characteristics. The results indicate that there is a significant welfare gain by the introduction of DBS.

Hausman and Leonard (2002) analyze the competitive effects of a new product introduction in US bath tissue industry. This paper demonstrates a method on how to estimate consumer welfare effects and compare the direct method which requires a more complete data set in both pre-introduction and post-introduction of new product with the indirect method just requires a post-introduction period data. This paper estimates the net benefit to consumers associated with the introduction of the Kimberly-Clark bath tissue product “Kleenex Bath Tissue” (KBT). Using retail scanner data from before and after the introduction, the authors employ a two-stage demand system based on Gorman’s two-stage budgeting method which has been used in Hausman, Leonard, and Zona (1994) and Hausman (1997) to estimate consumer surplus associated with the price effects and the variety effect directly. However, this method needs the restrictions of substitution patterns and hard to incorporate micro information. In addition, the authors also use the estimated post-introduction demand structure, along with an assumed firms competition model to estimate the price effects indirectly.

Large number of applications of using discrete-choice models to analyze welfare change in food industry appears with the widely influence of BLP approach. Kim (2004) uses the standard BLP (1995) method to estimate the effects of new low-fat segment brands in U.S. processed cheese market and the associated welfare analysis. Basically, the structure of model, the estimation procedure, the instrument choice and the computation algorithm are extensions of BLP (1995) and Nevo (2000). The author incorporates the new data and new industry to the classical BLP method and find that the observed increase in consumer welfare was attributable mainly to an increase in the number of brands in the sample market, while the price competition from new brands decreases welfare as the prices of existing brands increased. The author also decompose the consumer welfare increase into two parts: observed product characteristics and idiosyncratic error terms. The decomposition indicates that the welfare gain mainly comes from the first part (62.5%). Kim and Cotterill (2008) estimates a mixed logit demand system in the U.S. processed cheese market under Nash-Bertrand pricing and collusive pricing assumptions with the method similar to BLP (1995) and Nevo (2001). These estimates are used to simulate pass-through rates under different market conduct and associated welfare analysis. Xiao (2008) in his job market paper follows BLP (1995) and Berry et al. (2004) to investigate the competition effects of the introduction of Crystal Pepsi in U.S. soft drink industry. Albuquerque and Bronnenberg (2009) extends BLP (1995) and Nevo (2001) combining different aggregate-level data to evaluate the launch of new brands in frozen pizza category in Houston, Texas market. This approach aims to improve the estimation of demand, consumer heterogeneity and the overall size of outside good using market-level data by adding in a different moment conditions based on aggregate-level time-series data with brand penetration and purchase set size data.

Organic agricultural production is typically more cost intensive than conventional agriculture (Stevens-Garmon, Huang and Lin 2007). Consumers usually pay high premium for organic products. Demand for organic products in the U.S has growing fast in recent years and even faster than supply so that organic price premiums for most fresh produce remained relatively high. The price premiums vary from 9% for oranges to 78% for potatoes in 2004 (Stevens-Garmon, Huang and Lin 2007). With increasing introduction of private label organic agricultural products, organic food can become more and more affordable and available for consumers in main stream grocery stores. Consumers' welfare is expected to increase with introduction of new private label organic food products. There are several researches studying organic food demand, organic food market and the trend of this market.

Stevens-Garmon, Huang and Lin (2007) uses Nielsen Homescan data from 2001 and 2004 to analyze the consumer purchase patterns of organic fresh produce. They study organic consumers' demographic characteristics such as income, age, education, region and race which affect their purchases of organic fresh products. Their descriptive statistics also show what the consumers buy, how much they spend and the price premiums they pay. They do not find any positive relation between income and expenditure on organic produce. This study is mainly a statistic report and lack a rigorous empirical analysis. Huang and Lin (2007) and Lin, Smith and Huang (2008) estimate hedonic price models to examine the effects of product attributes, market factors and consumer characteristics focusing on organic attributes on the price of U.S fresh produce. Li, Zepeda and Gould (2007) use maximum likelihood estimation method to estimate a two-stage model that examines factors affect whether consumers purchase organic food and consumers' expenditure conditional on the first stage choices. They use 2003 University of Wisconsin's Study of Food Buying data and found that income is not a direct influence of households' selection of organic food, but that the most factor is the indirect effect of searching cost. Zhang, Huang, Lin and Epperson (2008) use generalized double hurdle model to identify how consumer demographic characteristics affect the consumption of fresh organic produce by using Nielsen Homescan data. The estimated results show positive effects of income and education. Nielsen Homescan data is also used to examine U.S consumer purchase patterns for fresh fruit and vegetables (Smith, Huang and Lin 2009). This research examines the effects of price and income as well as some other demographic characteristics on the consumer decision of purchasing organic fresh produce by estimating an ordered logit model. They find a significant positive income effect and a marginal price effect of demand of organic fresh fruit and vegetable products. Age, education, region and race also matter.

Chapter 3

Econometric Model of Demand and Supply

This chapter describes our demand and supply models obtained from discrete choice models of individual consumer behavior and firms ′ strategic interactions. We will conduct a welfare analysis relying on demand and supply estimates in a later chapter. Previous literature finds that welfare change is sensitive to the estimates of demand and the specification of supply. So in this chapter, we will apply two different methods (BLP and Control Function, later called CF) to examine households' choices among pre-packaged salad products. Demand parameters and the own- and cross-price elasticities are estimated and compared by two different estimation methods and will be used to estimate the price-cost margins of pre-packaged salad industry. Supply side models are derived based on different firms ′

behaviors assumptions and will be selected by likelihood ratio test. The rest of this chapter is organized as follows. Section 1 discusses the utility and demand. Section 2 presents the demand model and estimation approaches. Section 3 introduces supply models, the estimation method and model selection procedure.

3.1 Demand

This section discusses the models for consumer decisions that we will apply to our empirical analysis. We follow traditional discrete-choice models projecting products onto a characteristics space to reduce the high dimension when we have a large number of products, see Lancaster (1971), Berry (1994), Berry et al. (1995) and Nevo (2001). We also allow the correlation between price and unobserved characteristics following Berry et al. (1995) and Petrin and Train (2010).

3.1.1 Utility And Demand Model

The demand system we apply in this chapter is following traditional discrete-choice model of individual choices in the literature. In our model, consumers make decisions (on pre-packaged salad) among differentiated products in the market and choose the product that bring them the highest utility level. Here the market means in a fixed location and at a specified time period. We also implicitly assume that each time a consumer only pick at most one product and no storage consideration in our model. The utility for each consumer is a function of the vector of observed product characteristics, as well as unobserved product characteristics (x_j, ξ_j), the vector of individual demographic characteristics (D_i) and unobserved error terms (ε_{ij}). Consumers with different individual demographics, which include household size, income, age, education, employment et al., would make different choices: for example, the high income individuals would favor organic pre-packaged salad more than non-organic ones. The observed product characteristics are price, volume, organic claim promotion in our data and unobserved product characteristics are other facts that may capture the value of product differentiation, for instance the brand premium which are unobserved by researchers. Consumer loyalty, taste, among others are included in unobserved individual heterogeneity, which will affect each individual to choose a preferred brand differently. We assume that the researchers are not accessible to these data but we have a distribution of these variables. (See the literature of random-coefficients logit model, for instance, Cardell and Dunbar, 1980, Boyd and Mellman, 1980; Tardiff, 1980; and Cardell, 1989.) The utility of consumer i chooses product j is as follows,

$$U(D_i, x_j, \xi_j; \theta),$$

where θ is the parameters to be estimated.

Consumer i chooses product j if and only if

$$U(D_i, x_j, \xi_j; \theta) \geq U(D_i, x_k, \xi_k; \theta), \quad \text{for } k = 0, 1, ..., J,$$

where $k = 0, 1, ..., J$ represent the competing alternative differentiated products. Product 0 is outside option.

We will discuss two functional forms for the consumer decisions problem and present two different estimation approaches for the full model.

3.1.2 Logit Model

The logit model (MacFadden, 1973) reduces the dimension of parameters by projecting the products onto a characteristic space. BLP (1995) and Nevo (2001) both include a Logit demand model as a useful tool to get a feeling of data (Nevo, 2001). Due to computational simplicity, we first use a Logit model to examine the effects of the instrumental variable we will apply in this chapter.

$$u_{ijk} = x_{jk}\beta - \alpha p_{jk} + \xi_{jk} + \varepsilon_{ijk} = \delta_j + \varepsilon_{ijk}$$

$$\delta_j = x_{jk}\beta - \alpha p_{jk} + \xi_{jk}$$

where x_{jk} is the observed product characteristics of product j in market k, α and β are consumer taste parameters, ε_{ijk} is mean zero individual shock of household i related to product j at market k, ξ_{jk} is the unobserved product characteristics that affects consumers choice and correlated with price, which are independent across markets and products, and δ_j is the mean utility of product j.

We first estimate a Logit model assuming the error term has type I extreme distribution. The utility function is as following,

$$u_{ijk} = x_{jk}\beta - \alpha p_{jk} + \xi_{jk} + \varepsilon_{ijk} = \delta_j + \varepsilon_{ijk}$$

$$\delta_j = x_{jk}\beta - \alpha p_{jk} + \xi_{jk}$$

We assume ε_{ijk} conforms to type I extreme distribution. We further normalize δ_0 to zero. Then loglikelihood function obtains as follows

$$\sum_{k=1}^{K}\sum_{i=1}^{N_k}\sum_{j=1}^{J} y_{ijk}\delta_j - \sum_{k=1}^{K}\sum_{i=1}^{N_k}\sum_{j=1}^{J} y_{ijk} \log\left(1 + \sum_{\ell=1}^{J} \exp(\delta_\ell)\right)$$

The demand parameters can be obtained by maximizing above loglikelihood function.

3.1.3 Random Coefficient Model

The Logit model, although computational easier, suffers from unrealistic substitution patterns due to the restriction of consumer heterogeneity. The substitution is totally driven by market share instead of the differences in the product and demographic characteristics. Random-coefficient model allows each individual has different taste for different characteristics, which avoid IIA problem. This model is widely used in the literature, for example, Berry (1994), Berry et al. (1995), Nevo (2001) and Petrin and Train (2010). In our study, households are assumed to have different preference and just purchase one unit of the pre-packaged salad that gives the highest utility. It should be noted that because we have micro-level data for the demographics (but not for the consumer tastes.), instead of drawing them by computer from a known distribution, our estimation method is slightly different from the literature.

We follow the tradition in the literature assuming the indirect utility function of household i at market k of purchasing product j is:

$$u_{ijk} = x_{jk}\beta_i - \alpha_i p_{jk} + \xi_{jk} + \varepsilon_{ijk}$$

$$i = 1, ..., I_k, \quad j = 1, ...J_k, \quad k = 1, ...K,$$

where x_{jk} is the observed product characteristics of product j in market k. β_i and α_i are the individual-specific coefficients of the consumer i. p_{jk} is the price of product j in market k. ε_{ijk} is mean zero individual shock of consumer i related to product j at market k. ξ_{jk} is the unobserved product characteristics that affects consumer's choice and are correlated with price which are independent across markets and products.

Assume consumers's taste parameters for the characteristics as standard normal. Let

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

$$v_i \sim N(0, I_k)$$

where v_i conforms to standard normal distribution and independent across i.

Then, the utility function can be rewritten as

$$u_{ijk} = \delta_j + \eta_{ijk} + \varepsilon_{ijk}$$

where

$$\eta_{ijk}(\theta) = \left[-p_{jk}, x_{jk}\right] \cdot (\Pi D_i + \Sigma v_i)$$

$$\delta_j = x_{jk}\beta - \alpha p_{jk} + \xi_{jk}$$

where D_i is the observed demographic characteristics (in our data, they are not random draws like in BLP (1995), Π is the matrix of coefficients that measure how consumers ′ tastes vary with demographics, v_i is unobserved demographics conforms to standard normal distribution, Σ is the scaling matrix, and δ_j is the mean utility from choosing product j and $\eta_{ijk} + \varepsilon_{ijk}$ is a random deviation from that mean. Note that we normalize one brand's mean utility to zero to achieve identification.

3.1.4 Estimation

This section presents the two different methods we apply for estimating the demand parameters in a discrete choice model allowing unobserved product characteristics and consumer tastes. We estimate both Logit and random coefficient models by two different methods: Control function method, which is computationally easier but relies on some distributional assumptions; and BLP method which requires some more complicated computational techniques. Fixed coefficient model like standard Logit model does not require simulation based computation techniques but suffers from unrealistic substitution patterns. But we can still use this model to get a feeling of our data and estimates. Random coefficient model gives more flexible and realistic substitution pattern but computationally challenging, especially in the case with high dimension. Basically, the same estimation method can be used to obtain the parameters in both fixed coefficient and random coefficient models. In a random coefficient discrete choice model, assuming β_i is fixed across individuals as β leads to a Logit model. Estimating discrete choice models with unobserved product characteristics and unobserved taste heterogeneity needs to deal with price endogeneity in nonlinear models, which means standard instrumental variable method addressing the same problem in linear models does not apply here. In the literature, there are several ways to circumvent this problem. Given our data is individual level: there are I_k households choices and the demographics be observed in market k., there are two methods both of which are applicable in our empirical application. We first discuss the control function approach by Petrin & Train (2010), then Berry(1994) & BLP(1995). Because we have micro-level data for the demographics (but not for the consumer tastes.), instead of drawing them by computer from a known distribution, our estimation method are slightly different from the literature.

Control function method

This method is introduced by Petrin and Train (2010), which is computationally easy for estimating discrete choice models allowing unobserved product characteristics and consumer taste heterogeneity. But this method need some specific model assumptions. Same as before, the consumer's utility function is

$$u_{ijk} = x_{jk}\beta_i - \alpha_i p_{jk} + \xi_{jk} + \varepsilon_{ijk}$$

The main problem is the correlation between p_{kj} and ξ_{kj}.

Assume a control function

$$p_{jk} = W(x_{jk}, z_k, \mu_{jk}; \gamma)$$

where z_k is the instrument variables that is independent of ξ_{kj}. μ_{kj} is the error term in the control function and is correlated with ξ_{kj}. $W(x_{jk}, z_k, \mu_{kj}; \gamma)$ is a function of x_{jk}, z_k and μ_{jk} parametrized by γ. To obtain a theory foundation for the control function, we need to assume firm's pricing behavior. Assume

$$p_{jk} = MC(x_{jk}, z_k, \mu_{jk}; \gamma)$$

and further assume MC can be written as

$$\begin{aligned} \ln p_{jk} &= \ln MC(x_{jk}, z_k; \gamma) + \mu_{jk} \\ &= x_{jk}\gamma_1 + z_k\gamma_2 + \mu_{jk} \end{aligned}$$

where z_{kj} is the cost characteristics which don't effect demand. Hence

Assume further ξ_{kj} and μ_{kj} are joint normal distributed, then

$$\xi_{jk} = \lambda\mu_{jk} + \tilde{\xi}_{jk}$$

where $\tilde{\xi}_{kj}$ is i.i.d. normal distributed. Then we obtain

$$u_{ijk} = x_{jk}\beta - \alpha p_{jk} + \lambda\mu_{jk} + \eta_{ijk}(\theta) + \tilde{\xi}_{kj} + \varepsilon_{ijk}$$

where

$$\mu_{jk} = \ln p_{jk} - x_{jk}\gamma_1 - z_k\gamma_2$$

$$\eta_{ijk}(\theta) = \left[-p_{jk}, x_{jk}\right] \cdot (\Pi D_i + \Sigma v_i)$$

In above utility function, $\tilde{\xi}_{kj}$, ε_{ikj}, v_{ik} and ς_{ik} are i.i.d. stand normal distribution. The unknown parameters are β, α, λ, γ and θ. Given value of x_{jk}, p_{jk} and z_k, the choice probability of household i for product jk could be derived from $u_{ijk} \geq u_{ijk'}$. In other words, by using control function, the consumer choice problem can be transformed as a standard random coefficient model where the new error term is independent of observed variable (x_{jk}, z_k, p_{jk}) and the new error term conditions out the part that the price is correlated with the unobserved characteristics.

Then rewrite the utility with control function as follows;

$$u_{ijk} = V_{ijk} + \eta_{ijk}(\theta) + \tilde{\xi}_{kj} + \varepsilon_{ijk}$$

where

$$V_{ijk} = x_{jk}\beta - \alpha p_{jk} + \lambda \mu_{jk}$$

Therefore, the choice probability takes the form of mixed logit with integrating out over the distribution of v and the integral is approximated by simulation estimator.

$$s_{ijk}(\alpha, \beta, \theta) = \int \frac{e^{V_{ijk} + \eta_{ijk}(\theta)}}{1 + \sum_{\ell=1}^{J} e^{V_{i\ell k} + \eta_{i\ell k}(\theta)}} dF(v_i)$$

Then the estimation procedure is a two-step approach. The first step, we regress the price in each market on the observed product characteristics, cost data and all the Hausman type instruments. We collect the residuals from these regressions and use them as a new variable in the choice model. The cost function here is called control function. This method assumes unobserved product characteristics ξ_{kj} only correlated with price in the manner of the cost function error term μ_{jk}. So when the residuals of the cost function enter the utility function as a new regressor, they condition out the part that price is correlated with the unobserved product characteristics. Then the error terms in the utility function do not correlated with the regressors any more. This method solves endogeneity problem by using the control function and suggests a computationally easier estimation procedure.

In the second step, we estimate a traditional random coefficient discrete choice model by maximum likelihood estimation. For a Logit model estimation, the only difference is just maximizing a standard loglikelihood function without any integration.

Berry(1994) & BLP(1995)

This subsection describes the method provided in Berry (1994) & BLP(1995) for estimating the random coefficient discrete choice model allowing correlation between price and unobserved characteristics with micro-level data. This method does not rely on the specific model and distributional assumptions but computationally complicated. In Berry (1994) & BLP(1995), p_{jk} is correlated with ξ_{jk}. They pool them together in the mean utility δ_{jk} to avoid the endogeneity problem. They use GMM method to estimate the demand parameters. Their approach is applied when there is only market-level data. Based on their estimation strategy, given we have micro-level household choice data, MLE or simulated maximum likelihood method is more applicable in our study. The estimation strategy is a two-stage procedure. The first stage is to estimate a random coefficient discrete choice model with a full set of mean utility (δ_{jk} in the following equations). So mean taste parameters β are not obtained in the first stage because they are not separated from mean utility δ_{jk}. The second stage is to use two-stage least square regression to solve endogeneity issue by instrumental method in traditional linear models. Because of dimensional issue in computation, we apply contraction mapping technique in BLP(1995) to assist gradient search method when maximizing our likelihood functions.

Following Berry (1994) and BLP (1995), we have the utility function for a household i in market k choosing product j as

$$u_{ijk} = \delta_{jk} + \eta_{ijk}(\theta) + \varepsilon_{ijk}$$

Where

$$\delta_{jk} = x_{jk}\beta - \alpha p_{jk} + \xi_{jk}$$

$$\eta_{ijk}(\theta) = x_{jk}\Pi D_i - p_{jk}\Pi D_i + x_{jk}\Sigma v_i - p_{jk}\Sigma v_i$$

Where x_{jk} include the observed product characteristics of product j in market k. In our study, we have three observed characteristics: size, organic claim, and promotion. β_i and α_i are the individual-specific coefficients of the consumer i and β are mean tastes for observed product characteristics. p_{jk} is the price of product j in market k. ξ_{jk} is the unobserved product characteristics that affects consumer's choice and are correlated with price which are independent across markets and products. So β is not identified in the first stage estimation because of the endogeneity problem caused by price and ξ_{jk}. D_i is the observed demographic characteristics, in our case, they are income, education, household size, age and if the individual is full-time labor or not, Π is the matrix of coefficients that measure how consumers ′ tastes vary with demographics, v_i is unobserved demographics conforms to standard normal distribution, Σ is the scaling matrix, and δ_{jk} is the mean utility from choosing product j in market k and $\eta_{ijk} + \varepsilon_{ijk}$ is a random deviation from that mean. ε_{ijk} is mean zero individual shock of consumer i related to product j at market k.

Therefore, the choice probability is as follows;

$$s_{ijk}(\alpha, \beta, \theta) = \int \frac{e^{U_{ijk}}}{1 + \sum_{\ell=1}^{J} e^{U_{i\ell k}}} dF(v_i)$$

$$U_{ijk} = \delta_{jk} + \eta_{ijk}(\theta)$$

The estimation strategy is a two-stage procedure. The first stage is to estimate a random coefficient discrete choice model by maximum likelihood estimation. In this stage, we have the log likelihood function is as follows,

$$LL = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} y_{ijk} \ln s_{ijk}$$

$$y_{ijk} \quad = \quad 1 \text{ if household } i \text{ in market } k \text{ choose product } j,$$

$$= \quad 0 \text{ otherwise,}$$

Choice probability is approximated by simulation estimator

$$s_{ijk} = \frac{1}{ns} \sum_{i=1}^{ns} \frac{e^{U_{ijk}}}{1 + \sum_{j=1}^{J} e^{U_{ijk}}}$$

We have a large number of products meaning we have a big set of alternative specific constants to be estimated in the first stage. The traditional gradient search method is, although feasible, very challenging when there are too many parameters and highly dimensional integrations. To avoid computational burden, we follow BLP (1995), incorporating MLE and contraction mapping to estimate the demand parameters.

The strategy is taking δ_{jk} as unknown parameters, given a guess of other parameters θ, we match the predicted market share with the observed market share. In market k, we have

$$\hat{\delta}_{new} = \hat{\delta}_{old} + \ln(s) - \ln(s(X, \hat{\delta}_{old}, \theta))$$

The contraction mapping procedure returns a new set of $\hat{\delta}$, which is a function of previous guess parameters θ and $\hat{\delta}_{old}$. These $\hat{\delta}_{new}$ should match the predicted market share and the real market share as close as possible. In each iteration, $\hat{\delta}_{new}$ is closer to true $\hat{\delta}$ than previous $\hat{\delta}$. These $\hat{\delta}_{new}$ enter the likelihood function and the gradient method search over the parameters θ and update the set of θ. The maximum likelihood method searches over the parameters $\theta \in \Theta$ in each iteration with the contraction mapping estimates of $\hat{\delta}$.

After we obtain $\hat{\delta}_{jk}$, the second stage estimation is traditional instrument method in linear models. We use two-stage least square method to estimate the taste parameters α and β in the following equation,

$$\hat{\delta}_{kj} = x_{jk}\beta - \alpha p_{jk} + \xi_{jk}$$

Then the mean tastes parameters β and price parameter α are unbiased estimated.

3.2 Supply

This chapter presents the estimation of supply function and the likelihood ratio test we apply for model selection among non-nested competition models.

What is the nature of market competition structure is important for two reasons: first, it is crucial for researchers to adopt the right structure to analyze even when there is not much well documented information about market structure, for a misspecification structure would not give us consistent estimators and induce a misleading welfare analysis; second, in the game theory context, the equilibrium solution could be totally different under different game structures. There is no use to analysis a Bertrand-Nash equilibrium when the indeed equilibrium is the Stackelberg leader type. From the pattern of our Homescan data, we find that US organic pre-packaged salad industry is highly concentrated, two major brands hold more than 80 percent volume share. Our conjecture of market structure is one of the oligopoly forms. But which one reveals the data is ambiguous without a rigorous examination.

The supply system we apply in this chapter focus on two competing models that are widely–used in the literature: Bertrand competition model and Stackelberg price leader model with collusive behavior. Each model involves different set of assumptions about the setup of the game played by these oligopoly firms. For the Bertrand competition model, we assume firms simultaneously choose their price. In Stackelberg price leader model with collusive behavior, we assume national brands maximize their joint profit and private label firm choose its own price given knowing national brands pricing strategy. We estimate these two models respectively by maximum likelihood estimation and also apply the method developed by Vuong (1989) to test that which model matches our data better using a Likelihood ratio test. Because we need the likelihood ratio to compare between two competing models, we need to choose MLE method other than alternative estimation methods such as 3SLS. We then make an assumption about the distribution of the error terms to get the likelihood functions for the maximum likelihood estimation. And we make a linearity assumption for the supply function system for simplifying the computation of the estimates.

Generally, the retail markets for most products are dominated by a small number of firms that interact strategically. In particular, more than 60 percent of the pre–packaged salad market are supplied by two national brands: D and F. Given the importance of public policy issues related to collusive behavior, it is our interest to investigate the collusive behavior in this market. Due to lack of observations of collusive agreements (if they exist), an important feature of this research is to apply structural approach to derive the collusive behavior from economics models.

The trend of the recent applied industrial organization literature on collusive behaviors can be broadly classified into two categories. The first category includes studies that attempt to test for tacit collusion in dynamic game models, see Porter, 1983; Slade, 1986, 1987; Roberts and Samuelson, 1988. However, the empirical works in this research line still suffer from the difficulties of dealing with the multiple equilibria issue – almost any outcome could be sustained in a markov equilibrium of a dynamic game due to the folk theorem. In the second category of research studies are pioneered by Gasmi, Laffont, and Vuong (1992), which proposes an empirical methodology for testing collusive behaviors by using simple static models. This paper follows the latter methodology, which allows us to estimate and compare different market structures directly and choose the one that fits the data best.

3.2.1 A Market Competition Structure Test

To model the supply, there are two competing models that could be used to rationalize our data: one is a competitive pricing model and the other one is a collusive model. Knowing which competition structure our data are generated from is important for understanding the supply side and answer policy questions properly.

In a competitive environment, the strategic oligopoly price behaviors can be described in the Bertrand competition model, which has been studied extensively, (see Tirole (1988) for the literature in economics and Bresnahan (1989) for a survey of empirical models). In this literature, studies are focused on the static non–cooperative game of complete information. Players are profit maximization firms, who strategically choose their prices simultaneously, given other players' prices as fixed. The solution concept is called as Nash equilibrium, known as a fixed point of such price behaviors for all firms.

Alternatively, collusive behavior could also occur in the competitive environment, but only in the long–term rivalry relationship. So Stackelberg price leader model is also considered in our analysis. As is evoked by Cournot (1938, p. 83), cartel–type collusive agreements could be maintained by "means of a formal engagement" in the long run competition. Recent game theoretic work (see, e.g. Aumann and Shapley, (1976), Chamberlin (1929), Fudenberg and Maskin (1986), Kreps and Wilson, (1982), Samuelson (1967), and Stigler (1964), among others) has suggested that the tendency toward collusion in oligopolies is enforceable by using retaliation strategies against defectors, even under the assumption of noncooperative (Nash) behavior. In the recent industrial organization literature, the possibility of collusion among producers has been a permanent concern of oligopoly theory.

Moreover, following Bernheim and Whinston (1990), multi–market contact always facilitates collusion. Because two national brand firms compete with each other in every local market and in every product category, this provides them even more incentives to come to an understanding and agree on sharing the market at the monopoly price. Although theory provides such suspicions, now we still need to rely on data for the direct and convincible evidence.

On the other hand, it is less likely for Private Label to collude with National Brand. The Private Label products target different kind of consumer group from that of the firm brands, given the fact that Private Label products tend to be less expensive than the National Brands and more flexible with respect to the price and quantity (Barsky et al. 2003).

The evidence of collusive agreements, however, is usually unavailable in most cases, which is also the case in our data. In contrast, as the outcome of a collusion if there exist, collusive behavior, e.g., the price decision, is observed by researchers.

So it is our interest to investigate that whether the collusion occurs between the two National Brands in this industry or not, which is crucially important to further policy analysis. We follow the method proposed by Gasmi, and Laffont, and Vuong (1992), and analyze two structural models that represent two distinct market competition structures: one is a Bertrand competition as a default hypothesis, and the other one is a Stackelberg price leader model with collusive behaviors. Note that the two models for various market structures considered are not nested. So after these two structures are estimated using the same data set, we then apply Vuong (1989)'s non–nested test to decide which model fits the data better using a likelihood ratio test. Kadiyali, Vilcassim, and Chintagunta (2003), among others, adopt a similar method to study the laundry detergent market whether the market structure is Bertrand competition or Stackelberg price leader for multiple products firms.

3.2.2 Two Competing Models

In the following analysis, we assume that there are three firms in the market: National Brands D, F, and P. In this paper, we assume away other small brands for simplicity because the sum of their market shares only consists of a small proportion of the whole pre–packaged salad market. In principal, there are many different market structures in terms of price or quantity competition, or both. In this paper, however, we focus on the different nature of price competition for the competing market structures. The reason is, in the whole pre–packaged salad market, products are not easy to preserve, but there is not much capacity constraint in the production, i.e., firms can always produce more than demanded from the market. So we exclude quantity competition for the nature of pre-packaged salad industry.

Firms' pricing behavior can take two forms: (i) the Bertrand competition; (ii) the Stackelberg price leader. The three firms, National Brands F, D and P, choose their prices to maximize their individual profits under these two different market structures, respectively. The strategic interactions among their choices are assumed to be well informed to the decision makers. Under the Bertrand competition, all these three firms need to “believe” what other two firms would do in equilibrium correctly and response optimally according to those. This is a standard static Nash equilibrium analysis. For the Stackelberg price leader, the two dominant National Brands F and D form a market leader collusively, and correctly “believe” how the follower (the Private Label) will response to their prices. The Private Label simply observes the prices decision made by leaders and then just best respond to that without any uncertainty. Intuitively, the price leaders might be endowed some disadvantage due to move first in pricing, however, the collusion part helps them play a role like a giant in the market.

Before we discuss these two models in more details, it should be noted out that these two price competition models are “non–nested”. Non–nested structures are defined as follows: let Y be the dependent variables in the two structures, which are the endogenous prices for three firms, and X be the regressors. Let further $f(Y|X;\theta)$ be the conditional probability density function of Y given X in the Bertrand competition model, where $\theta \in \Theta$ is the structural parameters. Similarly, let $g(Y|X;\gamma)$ be the conditional probability density function of Y given X in the Stackelberg price leader model with structural parameter $\gamma \in \Gamma$. We call these two models are non–nested if and only if there doesn't exist a pair of parameters $(\theta, \gamma) \in \Theta \times \Gamma$, such that $f(\cdot|X;\theta) = g(\cdot|X;\gamma)$ almost surely. In this paper, the two structures we considered are non–nested to each other, which can be easily verified later after we specify them in the following subsections.

Bertrand competition model

In a Bertrand competition model, the demand for these three brands is given by follows:

$$S_i = [s_i(P_F, P_D, P_P) - \mu_i] \times L$$

for $i = F, D$ and P, where s_i is i's market share and L is the market population.

Moreover, we use MC_i to denote i's marginal cost, which is a positive constant. As convention, we assume for $j = F, D, P$

$$MC_j = \tau_{0j} + \tau_{1j} W_j + \tau_{2j} V$$

where W_j is a vector of brand–specific cost factors, including the promotion cost and the volume of product, which differ across brands and markets; V is the real price of input, namely, the unit prices for carrot, lettuce and strawberry. Note that V affects all products.

Then, each firm's profit can be expressed

$$\Pi_j = (P_j - \tau_{0j} - \tau_{1j} W_j - \tau_{2j} V) \times \left[s_j(P_F, P_D, P_P) - \mu_j\right] \times L. \tag{3.1}$$

where μ_j is the error term.

Assumption 1 *In our Bertrand competition model, let Π_j be firm j's payoff function described as equation (3.1). Let three firms, National Brand D, F and private label firm P, move simultaneously by choosing their own price P_D, P_F and P_P respectively.*

The competitive equilibrium can be obtain by

$$s_F(P_F^*, P_D^*, P_P^*) + (P_F^* - \tau_{0F} - \tau_{1F} W_F - \tau_{2F} V) \times \frac{\partial s_F}{\partial P_F} = \mu_F,$$
$$s_D(P_F^*, P_D^*, P_P^*) + (P_D^* - \tau_{0D} - \tau_{1D} W_D - \tau_{2D} V) \times \frac{\partial s_D}{\partial P_D} = \mu_D,$$
$$s_P(P_F^*, P_D^*, P_P^*) + (P_P^* - \tau_{0P} - \tau_{1P} W_P - \tau_{2P} V) \times \frac{\partial s_P}{\partial P_P} = \mu_P.$$

We can solve above equation system numerically,

$$P_F^* = h_F(MC_F, MC_D, MC_P, \mu_F, \mu_D, \mu_P)$$

$$P_D^* = h_D(MC_F, MC_D, MC_P, \mu_F, \mu_D, \mu_P)$$

$$P_P^* = h_P(MC_F, MC_D, MC_P, \mu_F, \mu_D, \mu_P)$$

However, as shown by Gasmi, Vuong, and Laffont (1992), such a closed–form solution is both tedious and unnecessary. Applying an alternative method proposed by Gasmi, Vuong, and Laffont (1992), we derive the likelihood function later for the joint distribution of (P_F^*, P_D^*, P_P^*) and estimate structure using maximum likelihood (ML) method.

Stackelberg price leader model with collusive behavior

As cooperative behavior, collusion could occur tacitly or explicitly. In the repeated game literature, the collusion is tacit and treated as a subgame perfect equilibrium. The dynamic part of such a game is to ensure the collusion behavior could be implemented and the short run deviation incentive would be prohibited by the punishment in terms of the long run cooperative profit. To simplify the discussion, in contrast, we treat the collusion as a static game and assume that the implement of the cooperation has been guaranteed explicitly.

We assume that the collusion occurs between the two national brands, for which the reason could be long–run competition(see, e.g., Kreps and Wilson, (1982)), or multi–market contact (see, e.g., Bernheim and Whinston (1990)). Because it is less likely for Private Label to collude with National Brand, so we assume Private Label is a follower, that makes its price decision shortly after the two national brands. We describe the collusion between national brands and the competition between the national brands and the Private Label as a two stage game model: Following Gasmi, Laffont and Vuong(1992), two national brands maximize the joint profit together in the first stage,, i.e.,

$$(P_F^c, P_D^c) = \underset{P_F, P_D}{\arg\max}\ \pi_F(P_F, P_D, P_P) + \pi_D(P_F, P_D, P_P),$$

where P_P is a function of P_F^c and P_D^c deriving from the second stage profit maximization of Private Label. Namely,

$$\arg\max_{P_P} \pi_P(P_F^c, P_D^c, P_P).$$

Assumption 2 *In our Stackelberg price leader model with collusive behavior, let National Brand D and F move first by choosing their own price P_D, P_F to maximize the joint profit $\Pi_F + \Pi_D$; Observing P_D and P_F, private label firm P chooses its own price P_P to maximize its own profit Π_P.*

As it is well–known, the two–stage game can be solved using backward induction: First, we solve the optimal pricing, $P_P^c = h(P_F^c, P_D^c)$, for Private Label, i.e., f.o.c.

$$s_P(P_F^c, P_D^c, P_P^c) + (P_P - \tau_{0P} - \tau_{1P} W_P - \tau_{2P} V) \times \frac{\partial s_P}{\partial P_P} = \mu_P.$$

Thus, we are ready to solve the first stage optimization for both National Brands, i.e., setting their price (P_F, P_D) together to maximize the joint profit: f.o.c.

$$s_F(P_F^c, P_D^c, P_P^c) + (P_F^c - MC_F) \times \left(\frac{\partial s_F}{\partial P_F} + \frac{\partial s_F}{\partial P_P} \times \frac{\partial h}{\partial P_F} \right) + (P_D^c - MC_D) \times \left(\frac{\partial s_D}{\partial P_F} + \frac{\partial s_D}{\partial P_P} \times \frac{\partial h}{\partial P_F} \right) = \mu_F,$$

$$s_D(P_F^c, P_D^c, P_P^c) + (P_D^c - MC_D) \times \left(\frac{\partial s_D}{\partial P_D} + \frac{\partial s_D}{\partial P_P} \times \frac{\partial h}{\partial P_D} \right) + (P_F^c - MC_F) \times \left(\frac{\partial s_F}{\partial P_D} + \frac{\partial s_F}{\partial P_P} \times \frac{\partial h}{\partial P_D} \right) = \mu_D,$$

where

$$\frac{\partial h}{\partial P_F} = -\frac{\partial s_P/\partial P_F + (P_P - \tau_{0P} - \tau_{1P} W_P - \tau_{2P} V) \times \partial^2 s_P/\partial P_P \partial P_F}{\partial s_P/\partial P_P + (P_P - \tau_{0P} - \tau_{1P} W_P - \tau_{2P} V) \times \partial^2 s_P/\partial P_P^2 + \partial s_P/\partial P_P},$$

and

$$\frac{\partial h}{\partial P_D} = -\frac{\partial s_P/\partial P_D + (P_P - \tau_{0P} - \tau_{1P}W_P - \tau_{2P}V) \times \partial^2 s_P/\partial P_P \partial P_D}{\partial s_P/\partial P_P + (P_P - \tau_{0P} - \tau_{1P}W_P - \tau_{2P}V) \times \partial^2 s_P/\partial P_P^2 + \partial s_P/\partial P_P}.$$

3.2.3 Identification

Regarding to the identification issue in both models discussed above, similar to the classical demand–supply analysis, the well–defined simultaneous equations structure can be identified when we assume the demand function s_i is linear in prices (P_F, P_D, P_P) together with additional model restrictions.

The key assumption for achieving identification is the existence of exogenous variations in each equation, which are called as instrument variables. We choose cost shifters, (W_F, W_D, W_P), as our instrument variables, such that (W_F, W_D, W_P) are independent of the error terms in our supply models and W_j ($j = F, D, P$) only affects firm j's profit maximization.

W_j is a vector of brand–specific cost factors, including the promotion cost and the volume of product, which differs across brands and markets; The summary statistics of our instrument variables are shown in the Table 4.2 and 4.3.

If the instrument variables can't provide sufficient variation to identify the structural parameters in the model, we call it as "weak identification" (see Stock, Wright, and Yogo, 2002, for a survey of this literature). When this is under concern, one can test for identification using, for example, the test proposed by Wright (2003) for nonlinear GMM models. Our sample analog of the objective function behaves well and is not flat around its maximizer, which means our choice of instruments is effective and the data provide sufficient identification power.

3.2.4 Estimation

As presented in the beginning of the supply subsection, for we use likelihood ratio test to do the model selection, we need apply maximum likelihood estimation to get the objective function value of each model and eventually get the likelihood ratio of the two models. This subsection presents the estimation and the test procedure. Results are reported in the next chapter.

Let $f(\cdot;\theta)$ and $g(\cdot;\gamma)$ be the (conditional) likelihood functions of the dependent variable conditioning on the regressors in the Bertrand and the collusion models, respectively. Let further θ^* and γ^* be the pseudo–true values of θ and γ in these two structures respectively.[1] Note that Pseudo true values θ^* and γ^* can be estimated using Pseudo ML method, i.e.,

$$\widehat{\theta} = \arg\max_{\theta\in\Theta} \frac{1}{n}\sum_{i=1}^{n} \log f(Y_i|X_i;\theta), \quad \widehat{\gamma} = \arg\max_{\gamma\in\Gamma} \frac{1}{n}\sum_{i=1}^{n} \log g(Y_i|X_i;\gamma).$$

White(1982) established the limiting distribution of above pseudo–ML estimators,

[1]Pseudo–true value θ^* is the parameter which solves $\max_{\theta\in\Theta} \mathbb{E}\log f(Y|X;\theta)$. Note that $f(Y|X;\theta^*)$ might not be the underlying (true) conditional probability density distribution of Y given X; similar notation for γ^*.

where the variance of estimates requires a sandwich form known as 'White correction'. However, the estimates themselves are not of our interest — what is useful for our test is the log–likelihood functions evaluated at estimated values, $\frac{1}{n}\sum_{i=1}^{n}\log f(Y_i|X_i;\widehat{\theta})$ and $\frac{1}{n}\sum_{i=1}^{n}\log g(Y_i|X_i;\widehat{\gamma})$.

To compute the likelihood function, we make several assumptions to simplify our discussion. We first impose a parametric assumption on the joint distribution of $\mu = (\mu_F, \mu_D, \mu_P)$ for deriving a conditional probability distribution for the endogenous variables (P_F, P_D, P_P). Following the convention, we assume that μ conforms to a joint normal distribution (see, e.g., Gasmi, and Laffont, and Vuong (1992)).

Assumption 3 *Let $\mu = (\mu_F, \mu_D, \mu_P)$. Assume that μ conforms to a joint normal distribution:*

$$\mu \sim N(0, \Sigma)$$

where μ is a variance–covariance matrix.

Under Assumption 3, the endogenous prices for three firms also conform to a joint normal distribution because of the linearity of the simultaneous equation system.

Assumption 4 *Let*

$$s_F(P_F, P_D, P_P) = a_F - \beta_{11}P_F - \beta_{12}P_D - \beta_{13}P_P,$$

$$s_D(P_F, P_D, P_P) = a_D - \beta_{21}P_F - \beta_{22}P_D - \beta_{23}P_P,$$

$$s_P(P_F, P_D, P_P) = a_P - \beta_{31}P_F - \beta_{32}P_D - \beta_{33}P_P.$$

Assumption 4 is more than necessary, but it simplifies the computation of estimates a lot. The similar assumption is also made by Gasmi, and Laffont, and Vuong (1992). Under Assumption 4, each structural model has a closed–form solution for the prices, from which we can derive a (conditional) probability distribution for the prices easily.

Under Assumption 4, we derive the F.O.C. in the Bertrand competition[2]

$$a_F - 2\beta_{11}P_F^* - \beta_{12}P_D^* - \beta_{13}P_P^* + \beta_{11}(\tau_{0F} + \tau_{1F}W_F + \tau_{2F}V) = \mu_F, \tag{3.2}$$

$$a_D - \beta_{21}P_F^* - 2\beta_{22}P_D^* - \beta_{23}P_P^* + \beta_{22}(\tau_{0D} + \tau_{1D}W_D + \tau_{2D}V) = \mu_D, \tag{3.3}$$

$$a_P - \beta_{31}P_F^* - \beta_{32}P_D^* - 2\beta_{33}P_P^* + \beta_{33}(\tau_{0P} + \tau_{1P}W_P + \tau_{2P}V) = \mu_P. \tag{3.4}$$

White (1982) and Gasmi, Laffont and Vuong (1992) have derived the likelihood function for this kind of general linear simultaneous-equation system. We can simply extend their derivations to get the objective function and the limiting distribution of the estimates in our case. Note that we can only estimate $a_F + \beta_{11}\tau_{0F}$, instead of both a_F and τ_{0F}. Further we normalize $\beta_{jj} = 1$, rather than the variance of μ. Based on above assumptions, the model is nested in a general linear

[2]It is straightforward to see that there exists a (closed form) solution for (P_F^*, P_D^*, P_P^*) to the equation system, and the closed form solution is called the "reduced form", which is derived from the simultaneous equations called as the "structural model". More discussions on the notion of reduced form and structure model can be found in Heckman (2010).

simultaneous-equation model system as follows,

$$\beta_{01} - 2P_F^* - \beta_{12}P_D^* - \beta_{13}P_P^* + \tau_{1F}W_F + \tau_{2F}V = \mu_F, \tag{3.5}$$

$$\beta_{02} - \beta_{21}P_F^* - 2P_D^* - \beta_{23}P_P^* + \tau_{1D}W_D + \tau_{2D}V = \mu_D, \tag{3.6}$$

$$\beta_{03} - \beta_{31}P_F^* - \beta_{32}P_D^* - 2P_P^* + \tau_{1P}W_P + \tau_{2P}V = \mu_P. \tag{3.7}$$

Thus we follow White (1982) and Gasmi, Laffont and Vuong (1992) to derive the likelihood function for the linear system as shown above. Let the general linear simultaneous-equation system defined by $BY + \Gamma X = \epsilon$. Then the likelihood function is

$$L_n(\theta) = c_1 + n \log \|B\| - \frac{n}{2} \log |\Sigma| - \frac{1}{2} \text{tr}\{\Sigma^{-1}(BY_i' + \Gamma X_i')(Y_i B' + X_i \Gamma')\}$$

where

$$B = \begin{bmatrix} -2 & -\beta_{12} & -\beta 13 \\ -\beta_{21} & -2 & -\beta_{23} \\ -\beta_{31} & -\beta_{32} & -2 \end{bmatrix}, \quad \Gamma = \begin{bmatrix} a_F & -\tau_{1F} & 0 & 0 & \tau_{2F} \\ a_D & 0 & \tau_{1D} & 0 & \tau_{2D} \\ a_P & 0 & 0 & \tau_{1P} & \tau_{2P} \end{bmatrix},$$

and $Y = (P_F^*, P_D^*, P_P^*)'$, $X = (W_F, W_D, W_P, V)'$ and $\epsilon = (\epsilon_F, \epsilon_D, \epsilon_P)'$.

The estimation results are displayed in Tables 4.9. Note that the self–price coefficient has been normalized to be one.

We now turn to the Stackelberg price leader model with collusive behavior.

Similarly we derive the F.O.C., i.e.,

$$
\begin{aligned}
& a_F - (\beta_{11}+\delta_{11})P_F - (\beta_{12} + \delta_{12})P_D - \beta_{13}P_P \\
& \qquad\qquad + \delta_{11}(\tau_{0F} + \tau_{1F}W_F + \tau_{2F}V) + \delta_{12}(\tau_{0D} + \tau_{1D}W_D + \tau_{2D}V) = \mu_F, \\
& a_D - (\beta_{21}+\delta_{21})P_F - (\beta_{22} + \delta_{22})P_D - \beta_{23}P_P \\
& \qquad\qquad + \delta_{21}(\tau_{0F} + \tau_{1F}W_F + \tau_{2F}V) + \delta_{22}(\tau_{0D} + \tau_{1D}W_D + \tau_{2D}V) = \mu_D, \\
& a_P - \beta_{31}P_F - \beta_{32}P_D - 2\beta_{33}P_P + \tau_{0P} + \tau_{1P}W_P + \tau_{2P}V = \mu_P.
\end{aligned}
$$

where $\delta_{11} = \beta_{11} - 0.5\beta_{13}\beta_{31}/\beta_{33}$, $\delta_{12} = \beta_{21} - 0.5\beta_{23}\beta_{31}/\beta_{33}$, $\delta_{21} = \beta_{12} - 0.5\beta_{13} \times \beta_{32}/\beta_{33}$, and $\delta_{22} = \beta_{22} - 0.5\beta_{23} \times \beta_{32}/\beta_{33}$. Thus, the structural model we will estimate is

$$
\begin{aligned}
& \beta_{0F} - (1 + \delta_{11})P_F - (\beta_{12} + \delta_{12})P_D - \beta_{13}P_P + \delta_{11}\tau_{1F}W_F + \delta_{12}\tau_{1D}W_D + \gamma_F V = \mu_F, \\
& \beta_{0D} - (\beta_{21} + \delta_{21})P_F - (1 + \delta_{22})P_D - \beta_{23}P_P + \delta_{21}\tau_{1F}W_F + \delta_{22}\tau_{1D}W_D + \gamma_D V = \mu_D, \\
& \beta_{0P} - \beta_{31}P_F - \beta_{32}P_D - 2P_P + \tau_{1P}W_P + \gamma_P V = \mu_P.
\end{aligned}
$$

which subject to nonlinear constraints

$$
\delta_{11} = 1 - 0.5\beta_{13}\beta_{31}, \quad \delta_{12} = \beta_{21} - 0.5\beta_{23}\beta_{31}, \quad \delta_{21} = \beta_{12} - 0.5\beta_{13}\beta_{32}, \quad \delta_{22} = 1 - 0.5\beta_{23}\beta_{32}.
$$

For this linear system, we apply the same method to derive the likelihood function as that in the last model. The estimation results are displayed in Tables 4.10.

3.2.5 Testing Procedure

The goal of this test is to select among two different market structures: whether the market equilibrium is competitive equilibrium or a collusive equilibrium specified in above Stackelberg price leader model. Note that the two competing structures are non–nested, so the methodology we adopt here follows Vuong (1989), Gasmi, Laffont and Vuong(1990), namely, Likelihood ratio tests for model selection and nonnested hypotheses. The test procedure consists of two parts: first, we estimate the model by maximum likelihood(ML) each structure separately. Each econometric model associated with each game ; second, we apply a likelihood ratio test for two competing hypothesis. Let f and g be the (conditional) likelihood functions of the dependent variable conditioning on the regressors in the Bertrand and the collusion models, respectively. Let further θ^* and γ^* be the pseudo–true values of θ and γ in these two structures respectively.[3] Thus, in the second stage, we test

$$H_0 : \mathbb{E}\left[\log \frac{f(Y_i|X_i;\theta^*)}{g(Y_i|X_i;\gamma^*)}\right] = 0,$$

meaning two structures are equally close to the true data generating process, against alternative hypothesis

$$H_B : \mathbb{E}\left[\log \frac{f(Y_i|X_i;\theta^*)}{g(Y_i|X_i;\gamma^*)}\right] > 0$$

[3]Pseudo–true value θ^* is the parameter which solves $\max_{\theta\in\Theta} \mathbb{E} \log f(Y|X;\theta)$. Note that $f(Y|X;\theta^*)$ might not be the underlying (true) conditional probability density distribution of Y given X; similar notation for γ^*.

meaning the Bertrand competition model is superior to the Stackelberg model with collusion, or

$$H_C : \mathbb{E}\left[\log \frac{f(Y_i|X_i;\theta^*)}{g(Y_i|X_i;\gamma^*)}\right] < 0$$

meaning the Bertrand competition model is inferior to the Stackelberg model with collusion.

Follow White(1982), the pseudo–true value θ^* and γ^* can be consistently estimated by maximum likelihood (ML) estimators under regularity conditions, respectively. Thus, the LHS of above hypothesis, $\mathbb{E}\left[\log \frac{f(Y_i|X_i;\theta^*)}{g(Y_i|X_i;\gamma^*)}\right]$, can be consistently estimated by sample analog, i.e., the log–likelihood ratio (LR) statistic

$$\mathrm{LR}_N(\widehat{\theta},\widehat{\gamma}) \equiv \frac{1}{N}\sum_{i=1}^{N} \log \frac{f(Y_i|X_i;\widehat{\theta})}{g(Y_i|X_i;\widehat{\gamma})}.$$

Vuong(1989) established the asymptotic distribution of above LR statistic. Under the null hypothesis, i.e., the two competing models are equally good, LR statistic conforms to a normal distribution, i.e.,

$$\frac{N^{-\frac{1}{2}}\mathrm{LR}_N(\widehat{\theta},\widehat{\gamma})}{\widehat{w}} \xrightarrow{D} N(0,1),$$

where $\widehat{w}$ is the estimated standard deviation of the LR statistic, i.e.,

$$\widehat{w} \equiv \frac{1}{N}\sum_{i=1}^{N}\left[\log \frac{f(Y_i|X_i;\widehat{\theta})}{g(Y_i|X_i;\widehat{\gamma})}\right]^2 - \left[\frac{1}{N}\sum_{i=1}^{N} \log \frac{f(Y_i|X_i;\widehat{\theta})}{g(Y_i|X_i;\widehat{\gamma})}\right]^2.$$

Following Vuong(1989), we can specify a critique value $c_\alpha > 0$ based on the standard normal distribution, and test for model selection by: accept H_0 whenever $-c_\alpha \leq \frac{N^{-\frac{1}{2}}\mathrm{LR}_N(\widehat{\theta},\widehat{\gamma})}{\widehat{w}} \leq c_\alpha$; accept H_B whenever $\frac{N^{-\frac{1}{2}}\mathrm{LR}_N(\widehat{\theta},\widehat{\gamma})}{\widehat{w}} > c_\alpha$; accept H_C whenever $\frac{N^{-\frac{1}{2}}\mathrm{LR}_N(\widehat{\theta},\widehat{\gamma})}{\widehat{w}} < -c_\alpha$.

Thus we apply some pairwise tests for the non–nested hypotheses proposed by Vuong(1989). For these two models, we calculate the likelihood ratio statistic and normalized by

$$n^{\frac{1}{2}}\hat{w}_n = \frac{1}{2}\sqrt{\sum_{i=1}^{n}\left(\hat{\epsilon}_i'\hat{\Sigma}_i^{-1}\hat{\epsilon}_i' - \tilde{\epsilon}_i'\tilde{\Sigma}_i^{-1}\tilde{\epsilon}_i'\right)^2} = 8.9505.$$

where $\hat{\epsilon}_i$ and $\hat{\Sigma}_i$ are the estimated residuals and covariance matrix for the competitive equilibrium model, and $\tilde{\epsilon}_i$ and $\tilde{\Sigma}_i$ are the estimated residuals and covariance matrix for the collusive equilibrium model. It should be noted that θ and γ have the same dimension. If that hadn't be the case, then we would have had to apply a degrees of freedom correction.

Table 4.15 reports the model selection LR statistics, from which we conclude that both Bertrand competition model and Stackelberg price leader model are statistically indistinguishable, which means they are equally close to the true market structure among firms. The estimates of Bertrand competition model make more sense in terms of their signs.

Chapter 4

Data and Econometric Results

4.1 Data

The data we apply for the estimation of the described models in the last chapter is AC Nielsen Homescan panel data. Nielsen's Homescan panel data provides information for food product purchase. This data set contains purchase prices, product characteristics and information on market trends for these products. The data also provides consumer demographic information. Participants scan the purchased products at home using a device provided by Nielsen after each shopping trip. And the information is uploaded to NieIsen's computer system. These information paired with the household 's demographic information when the participants signed up with the program (Harris and Blisard). The Nielsen Homescan panel began in 1989 and the sample size kept increasing. The sample size was 15,000 in 1989 and rose to 100,000 households and from original 2 markets to 33 markets in late 2005 (Harris and Blisard). The demographic data records includes 21 variables providing information on Household ID, Household size, Household income, Age, Age and presence of children, Employment (interval data for the number hours worked per week), Education, Occupation, Household composition, Race, Region, Market Area etc.. Purchase data consists of 34 variables such as: Household ID, Purchase date, Product module, Brand, Product size1 and Product size 2, Multi-pack, UPC Code, Quantity, Price paid (expenditure for a sale or regular priced item), Coupon Value, Container, Store Names, Channel Type, Product Group, Department, Organic Claim, USDA Organic Seal, Store Zip Code and other Nine attributes maintained by Nielsen that describes the product which are not available for all product modules. Nielsen Homescan data is a very micro level data, which can support the analysis of heterogeneous household preferences and industrial organization studies.

In our current analysis, we use Nielsen Homescan 2005 data to analyze consumer choice and firm competition in pre-packaged salad industry. A total of 30,599 households are recorded in our pre-packaged salad category. We focus on the top sixth biggest brands accounting for more than 80% volume share and 6 markets out of 11 major markets in which these six top brands are available. Thus, we have a total of 3554 households' weekly purchases and corresponding product and demographic information. We aggregate weekly data to quarterly for tractability.

For estimation of our random coefficients discrete choice model allowing unobserved product characteristics and supply side models, we require the data contain some consumer choice and market conduct information: prices and quantities in each market, brand characteristics and consumer demographics and their purchase information. Nielsen Homescan data contains all these information in household level. This data set includes the brand characteristic variables for all alternatives each week corresponding to purchase information. We use purchased brand, purchase price, volume, organic or non-organic claim and promotion information. Market-quarter average price is calculated by total dollars paid divided by total sales for every brand in each market each quarter. So the product is defined in this study as brand-market-quarter. For the household demographics, we have household size, household income, education, full-time labor as representatives. For supply side estimation, we have market-quarter prices for all the brands. We use the brand in all other market as the proxy of cost. Summary statistics for the main variables are provided in Table 4.1, 4.2, 4.3(a), 4.3(b), 4.3(c), 4.3(d), 4.3(e), 4.3(f), and 4.4.

Table 4.1. Brands Used For Estimation of Demand

Six Brands in Pre-packaged Salad Category
A
B
C
D
E
F

Table 4.2. Statistics For Main Characteristic Variables

Variable	Description	Mean	Median	Std	Min	Max
Price	¢ per oz	32.64005	29.77583	14.89988	7.471961	71.12222
Volume	oz	11.00314	10.26603	3.634523	4.5	27.39821
Organic	0 or 1	0.2982456	0	.4588315	0	1
Promotion	0 or 1	0.3359807	0.3674419	.1960672	0	1

Table 4.3. (a) Statistics For Main Characteristic Variables For A

Variable	Description	Mean	Median	Std	Min	Max
Price	¢ per oz	23.32319	19.9	15.24055	0	103.6
Volume	oz	12.09395	10.5	6.451565	4.5	48
Organic	0 or 1	0.0020462	0	0.0451907	0	1
Promotion	0 or 1	0.4953391	0	0.4999972	0	1

(b) Statistics For Main Characteristic Variables For B

Variable	Description	Mean	Median	Std	Min	Max
Price	¢ per oz	11.58749	9.9375	5.946251	2.0625	52.52632
Volume	oz	17.83591	16	10.24784	6	48
Organic	0 or 1	0	0	0	0	0
Promotion	0 or 1	0.4361946	0	0.4959476	0	1

(c) Statistics For Main Characteristic Variables For C

Variable	Description	Mean	Median	Std	Min	Max
Price	¢ per oz	30.07231	28.42857	17.23417	0	107.8
Volume	oz	11.97036	9.25	9.329434	4.5	80
Organic	0 or 1	0.0063291	0	0.0793132	0	1
Promotion	0 or 1	0.3790166	0	0.4852013	0	1

(d) Statistics For Main Characteristic Variables For D
(D, private label store brand)

Variable	Description	Mean	Median	Std	Min	Max
Price	¢ per oz	22.89979	12.9	18.7504	0	71.28571
Volume	oz	12.3556	12	6.098619	4.9	48
Organic	0 or 1	0.0263813	0	0.1602863	0	1
Promotion	0 or 1	0.3379791	0	0.4730803	0	1

(e) Statistics For Main Characteristic Variables For E

Variable	Description	Mean	Median	Std	Min	Max
Price	¢ per oz	28.51908	26.91667	12.24097	6.6	79.8
Volume	oz	9.528242	10	2.751011	4	32
Organic	0 or 1	0	0	0	0	0
Promotion	0 or 1	0.3870968	0	0.4871388	0	1

(f) Statistics For Main Characteristic Variables For F

Variable	Description	Mean	Median	Std	Min	Max
Price	¢ per oz	48.6676	43.6875	24.15623	9.9	142.5714
Volume	oz	9.896276	5	5.395643	3.5	16
Organic	0 or 1	1	1	0	1	1
Promotion	0 or 1	0.1313783	0	0.3379127	0	1

Table 4.4. Statistics For Main Demographic Variables

Variable	Description	Mean	Median	Std	Min	Max
Household Size	the no. of individuals in household	2.466517	2	1.389976	1	9
Household Income	income intervals	20.69021	21	5.798131	3	27
Age-Female Head	age of the female head	5.987901	7	2.778252	0	9
Age-Male Head	age of the male head	4.783061	6	3.453431	0	9
Male Head Education	school level intervals	3.041362	4	2.168975	0	6
Female Head Education	school level intervals	3.821328	4	1.647482	0	6
Marital Status	marital status	1.967923	1	1.219545	1	4
Household Full-time Empl	no. hours household worked	0.1826111	0	0.3864018	0	1
Female Full-time Empl	no. hours of female head worked	0.3809792	0	0.4856958	0	1

Table 4.2 shows the statistics of our main product characteristic variables that consist of Price, Volume, Organic and Promotion. The Price variable is average unit price over all brands and all markets, which we divide the price (cents) by volume. The mean is 32.6401 cents per oz and the median is 29.7758 cents per oz. Organic and Promotion are 0,1 variables. When one product is organic, Organic variable equals one, otherwise equals zero. And when a product is on sale, Promotion equals one, otherwise, equals zero. The demographic variables are recorded by some codes. These codes are some numbers increasing with the value of the variables. The median of Household Size is 2 meaning the median of all the households' family member is two. The median of Household Income is $54,000. The median female age of all households is 52 and median age of male head is 46. The median of male head and female head educations are both some college. Median Marital Status is married. Median of Household Full-time labor and median of Female Full-time labor are both zeros meaning no full-time labor.

Table 4.3(a) to table 4.3(f) shows the main product characteristics of each brand. For the Price variable in these tables, there are some brands has zero as minimum unit price and some maximum values are much higher from their mean and median unit price value. These extreme values are reasonable because our data set is Homescan data, which means the price we get is consumer's purchase price. Consumers may use coupons to deduct their purchase price to zero. Some consumers buy pre–packaged salad in some convenient stores where the shelf price is much higher than other grocery stores. Other product characteristics of each brand like Volume, Organic and Promotion are close to the overall statistics for the main characteristics we study in this paper.

For the valid instrumental variables, we follow the method that used in Hausman (1996), which is extended in Nevo (2001) when examining the ready-to-eat industry. We also assume that prices in one market controlling for market and brand-specific effects are driven by underlying costs, which provide instrumental variables that are correlated with prices but uncorrelated with disturbances in the demand equations and cit-specific valuations are independent across cities as in Hausman (1996) and Nevo (2001). Based on this assumption, prices of the brand in different cities can be instruments for one brand excluding the market being instrumented. We use the prices of brand j in all other markets as our instruments. These variables are correlated with common marginal cost but independent with market-specific valuation.

4.2 Results and Discussion

This section, we discuss the results from two demand models using two different estimation procedures (Control Function and BLP). We also describe the estimation results for supply side and the tests between two different supply models.

4.2.1 Demand

Consumers' discrete choice models (Logit and Random Coefficient Models) are estimated by two different estimation approaches, Control Function method and BLP method, for each of them has some advantages in estimation and implications. We compare the results from both approaches.

Control Function

We apply control function method to estimate two demand models (Logit and Random Coefficient model). The estimation procedures are based on the descriptions in section 3.1.4. First, we estimate the price functions to recover the residuals which enter the choice model as new regressors. We regress the prices in each market on the observed product characteristics and the same products' brand–quarter prices in all the other markets, which follows Hausman-type instruments (see Hausman 1996). Here we assume the prices of the products from same manufacture reflect common costs information but not common market-specific shocks. We collect the residuals from the regression of the pricing functions and use them as new regressors in the choice probabilities. The second step, we estimate a traditional discrete choice model by maximum likelihood estimation.

Table 4.5 shows the estimates of Logit model by control function method. The first column gives the product attributes variables. The second column shows the means of the marginal utilities, $\beta' s$. The rest of the columns give the interactions between product attributes and consumer demographics.

The estimated price coefficient is significant but with a positive sign in the Logit model. The organic attribute enters with an unexpected negative sign in a significant level. This may be caused by the weakness of instruments or the local maximum value achieved in the estimation algorithm. Our control function pre-assumes the functional form of the correlation which may not appeal the true relation form. But the organic-income interaction term is positive and significant, which means higher income consumers value organic feature more. All the other attributes like product size and promotion are significant with expected signs. Most taste interactions with demographics are significant except the interactions between full-time labor with the product attributes and promotion with some of the demographics as well as organic-education. The income-price interaction is positive and significant meaning the higher the income, the less price sensitive. The volume-household size, organic-income and organic-women full-time labor are all statistically significant and positive, meaning marginal valuation of product size and organic claim increase with household size, income and women full-time labor.

Table 4.6 gives own- and cross-price elasticities for Logit model estimated by control function method. Because the estimated price coefficient has a positive sign. It is either a biased estimate or a mis-specification biased estimate. It causes the own- and cross-price elasticities get unexpected signs. The magnitude is reasonable which is consist with the findings in the literature in food industry, e.g., Nevo (2001), Kim (2004) and Chidmi and Lopez (2007). As mentioned before, Logit model suffers from IIA problem.

Table 4.7 presents the estimation results of random coefficient model by control function method. In table 4.7, the first column gives the product attributes variables. The second and third columns show the means of the marginal utilities, $\beta's$, and the standard deviations of the means of parameters. The rest of the columns give the interactions between product attributes and consumer demographics.

The estimated price coefficient is significant but with a positive sign. The organic attribute enters with an unexpected negative sign in a significant level. This may be caused by the weakness of instruments or the local maximum value achieved in the estimation algorithm. Or control function pre-assumes the functional form of the correlation which may not appeal the true relation form. But the organic-income interaction term is positive and significant which means higher income consumers value organic feature more. All the other attributes are significant with expected signs. Most taste interactions with demographics are significant. The income-price interaction is positive and significant meaning the higher the income, the less price sensitive. The volume-household size, organic-income and promotion-women full-time labor are all statistically significant and positive, meaning marginal valuation of product size, organic claim and promotion increase with household size, income and women full-time labor.

Table 4.8 gives the own- and cross-price elasticities for random coefficient model by control function method. For the estimated price coefficient has a positive sign. It should be a biased or a mis-specification biased estimate. The own- and cross-price elasticities also have unexpected signs. But the magnitude is reasonable. We can find similar results in the literature on food industry, e.g., Nevo (2001), Kim (2004) and Chidmi and Lopez (2007). Consumers choose indifferently between national brands with lower market shares and private label product. But the two biggest national brands A and B with the first two largest market shares have higher cross-price elasticities with each other, but with lower cross-price elasticities corresponding to price changes of all the other smaller brands. This might mean consumers have some level of loyalty for the biggest national brands in pre-packaged salad categories. We also find F, a national brand that only provides organic products has a lower cross-price elasticities between other brands. This is reasonable for consumers have some degree of loyalty for the products that have some specific features.

Table 4.5. Results From Logit Model By CF Method

Variable	β's	Interactions with Demographic Variables				
		Income	Household Size	Education	Full-Time Labor	Women Full-time Labor
Price	0.0193*	0.0906*				
	(0.3706)	(0.0123)				
Volume	0.1110*		1.4797*			
	(0.6514)		(0.1042)			
Organic	-3.0941*	0.0427*		-0.0111	0.0137	0.2404*
	(0.1458)	(0.0066)		(0.0144)	(0.0866)	(0.1145)
Promotion	1.5324*				-0.0893	0.0802
	(0.0453)				(0.0743)	(0.0956)
Residual	-0.0771*					
	(0.3106)					
Log-likelihood at convergence at			-107, 655			

Asymptotically standard errors are given in parenthese.

Table 4.6. Own and cross price elasticities

	A	B	E	D	C	F
A	0.2807	-0.0467	-0.0526	-0.0392	-0.0502	-0.0210
B	-0.1695	0.1769	-0.0526	-0.0392	-0.0502	-0.0210
E	-0.1695	-0.0467	0.4979	-0.0392	-0.0502	-0.0210
D	-0.1695	-0.0467	-0.0526	0.4028	-0.0502	-0.0210
C	-0.1695	-0.0467	-0.0526	-0.0392	0.5302	-0.0210
F	-0.1695	-0.0467	-0.0526	-0.0392	-0.0502	0.9183

Table 4.7. Results From Random Coefficient Model By CF Method

Variable	Means (β's)	Standard Deviations (σ's)	Interactions with Demographic Variables				
			Income	Household Size	Education	Full-Time Labor	Women Full-time Labor
Price	0.0195*	0.0000	0.0009*				
	(0.0037)	(0.0014)	(0.0001)				
Volume	0.1116*	-0.0000		0.0147*			
	(0.0065)	(0.0033)		(0.0010)			
Organic	-3.0980*	-0.0009	0.0427*		-0.0106		-0.0790
	(0.1437)	(0.0000)	(0.0067)		(0.0131)		(0.0531)
Promotion	1.5328*	0.0020					0.2133*
	(0.0453)	(0.0705)					(0.0715)
Residual	-0.0773*						
	(0.0031)						
Log-likelihood at convergence		-107, 658					

Asymptotically standard errors are given in parenthese.

Table 4.8. Own and cross price elasticities

	A	B	E	D	C	F
A	0.4578	-0.1533	-0.0701	-0.0651	-0.0635	-0.0164
B	-0.1533	0.3222	-0.0389	-0.0361	-0.0352	-0.0091
E	-0.0701	-0.0389	0.1684	-0.0165	-0.0161	-0.0042
D	-0.0650	-0.0361	-0.0165	0.1576	-0.0150	-0.0039
C	-0.0635	-0.0352	-0.0161	-0.0150	0.1541	-0.0038
F	-0.0164	-0.0091	-0.0042	-0.0039	-0.0038	0.0427

BLP

We also use BLP method to estimate both Logit and random coefficient models allowing correlation between price and unobserved characteristics with household level data. In Berry (1994) & BLP(1995), p_{jk} is correlated with ξ_{jk}. They pool them together in the mean utility δ_{kj} to avoid the endogeneity problem. They use GMM method to estimate the demand parameters. Their approach is applied when there is only market-level data. Based on their estimation strategy, given we have micro-level household choice data, MLE method is more applicable in our study. The estimation strategy is a two-stage procedure. The first stage is to estimate a random coefficient discrete choice model as equation by maximum likelihood estimation method. The second stage is to use two-stage least square regression to solve endogeneity issue by instrument method.

As stated in section 3.1.3, the Logit model, although computational easier, suffers from unrealistic substitution patterns due to the restriction of consumer heterogeneity. The substitution is totally driven by market share instead of the differences in the product and demographic characteristics. But Logit model is a useful tool to have a feeling of data (Nevo, 2001). Table 4.9 gives the Logit results estimated by MLE method based on BLP two-stage approach. These results are compared with the random coefficient model. The first column is observed product characteristics variables. The second column reports consumers taste parameters associated with product characteristics. Price and volume parameters are statistically significant and of the expected signs. But organic claim is of unexpected negative sign, although statistically significant. We find that Organic-Income is positive and significant which means higher income households care more about organic p[roducts. Promotion variable is insignificant. Most taste interactions with demographics are significant. The income-price interaction is positive and significant meaning the higher the income, the less price sensitive. The magnitude is in a reasonable level which does not adjust price parameter to positive. The Volume-Household size, organic-income, organic-women full-time labor and promotion-women full-time labor are all statistically significant and positive meaning marginal valuation of Volume, organic and promotion increase with household size, income and women full-time labor.

Table 4.10 indicates the estimated own- and cross-price elasticities for Logit model estimated by BLP method. The elasticities are defined as the percent change in demand of product i corresponding to a one percent change in the price of product j. The own-price elasticities range from -0.3522 to -1.8278 depending on different brands. The cross-price elasticities range from 0.0419 to 0.3374 associated to different products. All the estimated elasticities have the expected signs.

Table 4.11 shows the estimation results of random coefficient model. The sign and magnitude of the estimates from random coefficient model are similar to Logit model. But the estimate of standard deviations are insignificant. Given we have micro level data, this suggests that most of the heterogeneity is explained by the demographics.

Table 4.12 gives the own- and cross-price elasticities for random coefficient model by BLP method. The own-price elasticities range from -0.0879 to -0.9423 associated to different products. The cross-price elasticities range from 0.0078 to 0.3156 depending on different brands. All the estimated elasticities show the expected signs. The results are intuitive. The two biggest national brands are more sensitive to each other. A and B who have the largest market shares have higher cross-price elasticities with each other. They have lower cross-price elasticities corresponding to price changes of the products that have smaller market shares. Consumers do not affected by the price changes from the brands with lower market shares including private label product. This might mean consumers have developed a comparative strong degree of loyalty for the bigger national brands in pre-packaged salad industry. We also find that F, a national brand that only produces organic products has lower cross-price elasticities. This is intuitive because of the reputation effects. For the high quality products or the products with some specific features, consumers usually believe in some producers that have technology advantage. Consumers are not quite sensitive to the price change of other normal goods if they prefer some special feature of a product. In our results, Logit model leads to higher cross-price elasticities than random coefficient model. This observation is consistent with the findings in the literature on food industry, e.g., Nevo (2001), Kim (2004) and Chidmi and Lopez (2007). It should be noted that both models estimate the elasticities with expected signs and in a reasonable level in magnitude.

Table 4.9. Results From Logit Model By BLP Method

Variable	β's	Interactions with Demographic Variables				
		Income	Household Size	Education	Full-Time Labor	Women Full-time Labor
Price	-0.0384172*	0.0014*				
	(.015023)	(0.0000)				
Volume	0.0982114*		0.0195*			
	(0.0321539)		(0.0007)			
Organic	-2.518023*	0.0254*		0.0093		0.6210*
	(0.3573871)	(0.0030)		(0.0142)		(0.1655)
Promotion	-0.8060007				0.0321	0.2514*
	(0.516809)				(0.0800)	(0.1182)
Constant	0.1903293					
	(0.7858934)					
Log-likelihood at convergence	-98, 432					

Asymptotically standard errors are given in parenthese.

Table 4.10. Own and cross price elasticities

	A	B	E	D	C	F
A	-0.5587	0.0930	0.1046	0.0780	0.0999	0.0419
B	0.3374	-0.3522	0.1046	0.0780	0.0999	0.0419
E	0.3374	0.0930	-0.9910	0.0780	0.0999	0.0419
D	0.3374	0.0930	0.1046	-0.8017	0.0999	0.0419
C	0.3374	0.0930	0.1046	0.0780	-1.053	0.0419
F	0.3374	0.0930	0.1046	0.0780	0.0999	-1.8278

Table 4.11. Results From Random Coefficient Model By BLP Method

Variable	Means (β's)	Standard Deviations (σ's)	Interactions with Demographic Variables				
			Income	Household Size	Education	Full-Time Labor	Women Full-time Labor
Price	-0.0401396*	-0.0017	0.0013*				
	(0.0142038)	(0.0055)	(0.0002)				
Volume	0.0818109*	-0.0595		0.0364*			
	(0.0304005)	(0.0468)		(0.0026)			
Organic	-2.235274*	-0.0635	0.0368*		0.0085	0.2606*	0.7541*
	(0.3378982)	(0.2494)	(0.0078)		(0.0153)	(0.1070)	(0.1859)
Promotion	-0.1962347	0.0466				0.0302	0.2075*
	(0.4886265)	(0.3610)				(0.0893)	(0.1464)
Constant	0.1822311						
	(0.7430372)						
Log-likelihood at convergence		-98, 421					

Asymptotically standard errors are given in parenthese.

Table 4.12. Own and cross price elasticities

	A	B	E	D	C	F
A	-0.9423	0.3156	0.1443	0.1340	0.1307	0.0338
B	0.3156	-0.6632	0.0800	0.0743	0.0725	0.0188
E	0.1443	0.0800	-0.3467	0.0334	0.0332	0.0086
D	0.1340	0.0743	0.0340	-0.3244	0.0308	0.0080
C	0.1307	0.0725	0.0332	0.0308	-0.3172	0.0078
F	0.0338	0.0188	0.0086	0.0080	0.00078	-0.0879

4.2.2 Supply

We focus on two forms of price competition for the competing market structures: (i) the Bertrand competition; (ii) the Stackelberg price leader. The three firms, National Brands F, D and a Private Label brand, choose their prices to maximize their individual profits under these two different market structures, respectively. The goal of this study is to select among two different market structures: whether the market equilibrium is competitive equilibrium or a collusive equilibrium specified in above Stackelberg price leader model. We apply the methodology proposed by Vuong (1989), Gasmi, Laffont and Vuong (1990), namely, Likelihood ratio tests for model selection and nonnested hypotheses. The test procedure consists of two parts: first, we estimate by maximum likelihood(ML) each structure separately. Each econometric model associated with each game ; second, we apply a likelihood ratio test for two competing hypothesis.

In above estimation, the data we use is monthly data covering 6 separated local markets in 2005, and the number of observations is 72.

The estimation results of the Bertrand competition model are displayed in Table 4.13. The maximized likelihood value is equal to -139.73.

The estimation results of the Stackelberg Price Leader Model are displayed in Table 4.14. The maximized likelihood value is equal to -127.58. It should be noted that most of coefficient estimates of the Stackelberg Price Leader Model have the same sign as those of the Bertrand competition model.

Table 4.13. PARAMETERS ESTIMATES OF BERTRAND COMPETITION MODEL

	Firm F		Firm D		Firm P	
Variable	Coefficient	*t* Statistic	Coefficient	*t* Statistic	Coefficient	*t* Statistic
Price A	—	—	-2.77	-0.06	-10.35	-0.66
Price B	15.14	0.98	—	—	2.50	0.11
Price G	-41.84	-18.32	46.73	14.52	—	—
Volume	16.39	2.20	33.80	6.27	-0.47	-0.03
Promotion	14.78	34.97	-1.65	-1.55	0.24	0.61
Carrot	-8.98	-0.55	-4.31	-0.34	1.78	0.02
Lettuce	-2.20	-0.03	2.36	0.04	-1.51	-0.02
Strawberry	0.40	0.01	-1.86	-0.05	-4.57	-0.30
Constant	-6.55	-0.75	0.92	0.19	0.28	0.26
Observations	72			Likelihood	-139.73	

Table 4.15 reports the LR test statistics and p–value for Vuong–type likelihood ratio test. From the results, we fail to reject the null hypothesis. From the LR statistics we conclude that both Bertrand competition model and Stackelberg price leader model are statistically indistinguishable, which means they are equally close to the true market structure among firms. However, the overall estimates of the effects of exogenous variables and the price interaction effects appear to be economically more reasonable for Bertrand competition model.

In our future research, we can conduct similar pairwise comparisons associated to other equilibrium concepts. For example, two brands that produced by the same manufacture might collude with each other and compete with other brands from other manufacturers. Or a dynamic model that could account for firms' pricing strategy change over time can be analyzed.

Table 4.14. PARAMETERS ESTIMATES OF STACKELBERG PRICE LEADER MODEL

	Firm F		Firm D		Firm P	
Variable	Coefficient	*t* Statistic	Coefficient	*t* Statistic	Coefficient	*t* Statistic
Price A	—	—	-0.56	-0.01	-1.09	-0.02
Price B	-1.03	-0.01	—	—	0.90	0.02
Price G	-3.19	-0.02	5.28	0.03	—	—
Volume	4.63	0.16	2.42	0.01	1.17	0.03
Promotion	32.45	54.15	-3.94	-1.20	-5.54	-0.98
Carrot	0.94	0.01	0.46	0.01	-1.39	-0.04
Lettuce	-0.06	0.00	-0.32	0.00	-0.26	0.00
Strawberry	-0.77	0.04	-0.23	0.00	0.16	0.00
Constant	4.86	0.39	-8.39	-1.22	-3.09	-0.22
Observations	72			Likelihood	-127.58	

Table 4.15. LR Test Statistics for Model Selection

LR statistic	$\widehat{w}_n^2$	Test Statistics	p–Value
-12.15	8.95	-1.36	17.46%

Chapter 5

Welfare Change from The Introduction of Private Label Pre-packaged Salad

More and more mainstream supermarkets are expanding their offerings of private label food items and account for the largest share of the organic foods market: "The U.S. organic food industry crossed a threshold in 2000: for the first time, more organic food was purchased in conventional supermarkets than in any other venue" (Dimitri & Greene 2002). Supermarkets attempt to diminish the market power of manufacturers by their own line of products, and to promote the store-brand products with their own names on them. Private-label share leaders now accounting for 21.9% private label market share which is nearly double the share of retailers that focus more on national brands. Private label product lines, especially organic options, got a big push in 2007 as major retailers like Safeway and Meijer introduced new lines and expanded existing ones (Supermarket News, December 31, 2007). Given the private label prepackaged salad is more accepted by consumers and the reduction of national brand sales, we can expect consumers gain from more variety of products and the increased competition between manufacturers. We can expect private label products increase the bargaining power of retailers and reduce the price of competing brands But for the suppliers of national brands, the possible reduction of retail price and the loss of sales led by the purchases switching from national brands to store brand may hurt the manufacturers' profit. So, total welfare change is not clear without a full analysis of both consumer and manufacturer. Therefore, an accurate welfare measure will be our interest of our research.

To conduct such a welfare analysis with empirical methods, the structure of demand and supply system plays a crucial role. First, it is feasible to use the estimates to conduct a counterfactual analysis based on the structure. This means the equilibrium price of manufacturers brands and thereafter social welfare can be computed from the estimates even if the private label products were not available in the market. Amil Petrin(2002) conducts a counterfactual welfare analysis of introducing Minivan into U.S. market based on BLP(1995). And Goolsbee and Petrin (2009) do an exercise of a similar welfare analysis with micro level data following BLP(1995). Second, as pointed out by BLP(1995), consumer level studies do often interact consumer preferences with (observable and unobservable) product characteristics, sometimes in a more complicated way than traditional multinomial model. Based on the simulated moments methods proposed by Pakes(1986), BLP(1995) or Control Function method, to use a rich structure to model such an interaction between consumers and product characteristics is possible. It is important to capture all the product characteristics which are relevant to consumers' choice, for the unobservable (to researchers) product characteristics explains the significant price difference (around 10%) between the products of private label and of manufacturers brands. Third, to model supply, the cost structure of private label products embedded a similar marginal cost as manufacturers brands. However, there are unobserved brand cost characteristics which cause a difference of marginal costs: (1) branded product manufacturer always spend an significant advertisement cost. (2) Branded products always have richer variety than the private label products, which reflects a R&D cost difference. (3) Private label products' costs entail a mark-up based on retailers' bargaining power. Hence, it is necessary to decomposed the cost characteristics into a subset which are observed by the econometrician, a product-specific unobserved component and a private-label-specific unobserved component. In the last chapter, we already get the demand and supply estimates based on the estimation methods both by Petrin and Train (2009) and BLP(1995). This chapter is to quantify a comparative static welfare change associated to the introduction of Private Label pre-packaged salad category.

In the following analysis, we focus on one representative market out of six, which has the median market size. Our welfare analysis is conducted here only according to all the households in the data, but the conclusions can be easily extended to the population of the local market by a simple multiplication of the market size if our data is indeed a random sample.

Given we already have the demand and supply estimates, we can compute the new equilibrium prices without private label product. We originally have six brands in the market. If we suppose there is no private label product in the market, there will be just five brands in each market. Then the equilibrium prices will change and the market share will also change as consumers' choice probability of the particular brand will differ. We already have the estimates of all parameters. In the new demand and supply system without private label, consumers choose among five national brands. Suppliers maximize their profit given other four rivals pricing strategies. Taken prices as unknown in new equilibrium we can solve the new system of first order conditions without private label product given by below:

$$s_j(P,X;\theta) + \sum_{j=1}^{J}(p_j - mc_j)\frac{\partial s_j(P,X;\theta)}{\partial p_j} = 0.$$

where θ is replaced by $\hat{\theta}$, and mc_j is replaced by the estimates of the mark–up in the old equilibrium.

To measure consumer welfare change, we use compensating variation from the introduction of private label pre-packaged salad in six major markets in 2005. The new vector of equilibrium price can be used to compute compensating variation defined as follows:

$$CV = \int \frac{\ln\left[\sum_{j=0}^{J=6} \exp(V_{ij}(p_1))\right] - \ln\left[\sum_{j=0}^{J=5} \exp(V_{ij}(p_0))\right]}{\alpha_i} dF_{\alpha_i}$$

where $V_{ij}(p_1) = x_j\beta_i - \alpha_i p_{j1} + \xi_j$ is the utility level in the post-entry environment (with private label); and $V_{ij}(p_0) = x_j\beta_i - \alpha_i p_{j0} + \xi_j$ is the utility level under the counterfactual (without private label); moreover $\alpha_i = \alpha + \Pi_1 D_i + \Sigma_1 v_i$ where $v_i \sim N(0, I_K)$.

The new equilibrium prices are also used to compute the variable profits for each firm under counterfactual environment. From chapter 3, we get the conclusion that Bertrand competition is more reasonable. So the suppliers' surplus is defined as the total sum of profit changes.

$$\sum_{j=1}^{J=6} \left[\Pi_j(p_1, mc; \theta) - \Pi_j(p_0, mc; \theta)\right]$$

where $\Pi_j(p_1, mc; \theta)$ is firm j's post-entry profit at the initial prices and $\Pi_j(p_0, mc; \theta)$ is firm j's profit at the counterfactual equilibrium prices. Note that the profit for private label at the counterfactual equilibrium prices has been set to zero.

Table 5.1 shows new equilibrium prices without the private label products and compares them with current market prices. The table indicates that the market become much less competitive without private label products.

Table 5.2 reports the welfare loss without the private label products. Remaining firms' profit increases significantly, but is less than the welfare loss from demand side. The net loss is $264,810 per season for all these consumers in our data.

Table 5.1. New Equilibrium Prices

Brand	Current prices	Counter factual prices	Δp	(%) Change
A	22.0852	24.5325	2.4473	11.08%
C	35.1792	35.2606	0.0814	0.23%
F	53.9322	54.1247	0.1925	0.36%
E	27.2417	27.8357	0.5940	2.18%
B	12.7663	13.8454	1.0791	8.45%

Table 5.2. Total Social Welfare Changes ($ Thousands)

Total Profits Changes	Total Consumer Surplus Changes	Total Welfare Changes
237.7	-502.51	-264.81

Note: the total number of households for welfare analysis is equal to 3554.

Chapter 6

Conclusion

This dissertation examines the strategic marketing behavior of pre-packaged salad brands and the effects of introduction of new private label brand on consumer welfare and firm's profit.

Understanding market structure of an industry has three implications for policy decision makers and marketing managers. The structural model of demand and supply system and the test for the market structure help for antitrust or merger policy analysis. From the likelihood ratio test, policy makers can get evidence on antitrust cases in a highly concentrated industry. With the estimated demand parameters, one can predict pre- and post-merger equilibrium. We can analyze how a merger activity influences the level of competition among the firms. The second application of this study is to conduct a comparative static welfare analysis. Counterfactual welfare analysis relies on consistent estimates of demand parameters and correctly specified firms' strategic marketing behaviors. My analysis allows for correlation between price and unobserved product characteristics in a discrete choice model. I also test which strategic pricing model best reveals the data. Gasmi, Laffont and Vuong (1992), Dhar, Chavas, Cotterill, and Gould (2005) have applied the likelihood ratio test to soft drink industry. Mihalopoulos and Demoussis (2001) has applied the test to Greek food away from home. We can also extend our study in other agricultural industries such as dairy products or fruit industry. Policy makers can use the counterfactual analysis to regulate an industry under the concern of consumers' welfare. For example, Nevo (2001) suggests an application of the results in that paper to do a welfare analysis in Ready-To-Eat cereal industry. Petrin(2002) has applied BLP methods to evaluate the welfare change associated to the introduction of minivan and Goolsbee and Petrin (2004) valuate consumer gains from the competition of cable TV. Hausman (1996) uses demand estimates to evaluate the welfare gains from introducing a new product. He computes the virtual price of a brand prior to introduction and uses this to compute a price index. Hausman (2002) introduces a framework to estimate consumer welfare effects of new product introduction and apply it to bath tissue industry. The third application benefits marketing managers, who are faced with the complicated task of adopting a pricing strategy for maximizing the profit in a oligopoly market. Empirical evidence can help them make such a pricing decision.

Although there are some studies on strategic interactions among different agents in the food markets (Villas-Boas, 1995; Richards and Patterson, 2005; Villas-Boas and Zhao, 2005; Richards, Acharya, and Molina, 2011), none considers structural estimation of organic private label pre-packaged salad category and none tests non-nested models. Li and Sexton (2005) study temporary price reductions and sales in bagged salad category, but not a structural analysis. The pre-packaged salad industry has not been rigorously empirically studied using a structural model. This is the first attempt to test the complete equilibrium structure based on discrete choice demand models allowing unobserved product characteristics and consumer taste heterogeneity, and a model selection method on supply side.

I propose three related investigations to study firms' behaviors and welfare change from the introduction of private label product to help the study of public policy issues and help marketing managers make the pricing decision while taking into account their rivals. I estimate discrete choice demand models of the differentiated pre-packaged salads by two different estimation methods to compare and improve the welfare estimates. Given most of the previous studies on food market strategic interaction behavior pre-assume a game theoretical form and test the implication of the model, I use maximum likelihood estimation to estimate supply functions based on one non-collusive and one collusive game model and apply a test of whether standard oligopoly pricing models apply in the pre–packaged salad sector. I calculate the new equilibrium price without private label product and compare them with current prices. Then I conduct the welfare impacts associated to the introduction of a private label line of pre-packaged salad.

The empirical results of demand model show that BLP method is more applicable in our case, which relies on less restrictions. The price parameter is negative and significant using BLP method. But it is positive using the control function method. The results from random coefficient model indicate that consumers with higher income are price sensitive. Bigger house size households prefer bigger packages. Valuation of organic products increases for households with higher income, full-time labor and women full-time labor. Women full-time labor care about promotions. The insignificancy of the estimates of the standard deviations of the mean tastes means our individual level demographic data absorb most of the consumer heterogeneity. The own- and cross-price elasticities for random coefficient model by BLP method show that consumers choose indifferently between national brands with lower market shares and private label product. That means private labels have a strong competitive power among smaller brands. But the two biggest national brands A and B with the first two largest market shares have higher cross-price elasticities with each other, but with lower cross-price elasticities corresponding to price changes of all the other smaller brands. This might mean consumers have some degree of loyalty for bigger national brands in pre-packaged salad categories.

The supply side likelihood ratio test results show that Bertrand competition model and Stackelberg price leader model are statistically equally close to true market structure. But the estimates of the price interaction effects might be more economically reasonable for Bertrand model. We apply Bertrand competition model to in the welfare analysis.

Our counterfactual analysis shows that introduction of new private label pre-packaged salad decrease the market power of national brands. The new estimated equilibrium price without private label is higher than current equilibrium price in the market. Total firms' profit increase, but is less than the welfare loss without private label brand. Total welfare increase $264,810 per season in our sample markets.

In view of the limitations of our study, we have only focused on the Nash-Bertrand competition and Stackelberg price leader model in this study. Similar studies associated to other equilibrium concepts can be considered in our future research. For example, two brands that produced by the same manufacture can collude with each other and compete with other brands from other manufacturers. Or a dynamic model that allows firms' pricing strategy to change over time can be analyzed. In our current study, we have considered price endogeneity. We can also apply the same technique to control endogeneity along other marketing characteristics like advertisement. We can also exploit the panel data for our structural estimation. Nevo (2001) controls for the correlation between prices and unobserved brand–specific demand shocks in Ready–To–Eat industry by exploiting panel structure of the data. Future research would benefit by considering a larger sample of pre-packaged salad industry. More recent data can help us get more variation of product characteristics and instruments, which therefore improves the precision of our estimates.

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