ABSTRACT

ZHAN, CONGNAN. Essays on Empirical Analysis of Price Discrimination. (Under the direction of Xiaoyong Zheng.)

This dissertation consists of two papers examining firms' price discrimination strategies. Healthy food products have experienced a rapid growth rate in recent years in the US because of the increasing consumer demand for healthier and environmental friendlier lifestyle. The first paper in the dissertation examines to what extent the high price premium enjoyed by healthy ketchup products over regular products can be attributed to price discrimination. To answer this question, I conduct a multi-step structural analysis. First, I use discrete choice methods (e.g. Berry 1994, Berry, Levinsohn and Pakes 1995) to estimate consumers' demand for different ketchup products at the Universal Product Code (UPC) level. Then, using the estimated elasticities obtained from the first step and a model on firm competition, I recover the marginal cost as well as the price-cost margin for each product. Finally, using the estimated marginal costs and margins, I quantify the price discrimination with respect to the healthy feature using a counterfactual experiment. Results show that price discrimination with respect to all differences in product characteristics between the two groups of products accounts for about 2.34% of the average price difference between healthy and regular products, with the rest accounted for by the marginal cost difference. Furthermore, only 0.46% of the average price difference can be attributed to price discrimination with respect to the healthy feature, indicating consumers pay little extra for being health and environment conscious. In addition, the paper examines the welfare effects of two policy experiments and quantifies to what extent income heterogeneity in the market allows firms to practice price discrimination with respect to the healthy feature by conducting three counterfactual experiments us-

ing the structural estimates. Results show that both banning price discrimination and imposing a tax on regular products lead to a social welfare loss. Income heterogeneity is an important source of price discrimination with respect to the healthy feature.

The second paper examines the relationship between market competition and second-degree price discrimination with respect to both the healthy feature and package size in the ketchup market. After controlling for observed as well as unobserved product, firm and market specific cost shifters using a two-way fixed effects approach and correcting the potential endogeneity bias arising from the market competition variables, results indicate that price discrimination with respect to both the healthy feature and package size increases when competition intensifies. The results are consistent with the theoretical implications of the Hernandez (2011) model and are robust to different definitions of price discrimination and different measures of market competition.

Essays on Empirical Analysis of Price Discrimination

by
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DEDICATION

To my family.

BIOGRAPHY

Congnan Zhan was born and raised in Beijing, China. She graduated from The High School Affiliated to Renmin University of China in 2002. After high school, she studied international economics and trade at Beijing Technology and Business University and obtained her bachelor degree in 2006. In August 2006, she moved to Raleigh, North Carolina to pursue her graduate degrees in economics at North Carolina State University.

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Chapter 1

Do Consumers Pay for Being Health and Environment Conscious?—An Analysis of Price Discrimination of Healthy Food Products

1.1 Introduction

The market for healthy food products such as organic food, reduced/low sugar food, reduced/low fat food and reduced/low salt food in the United States is growing rapidly. For example, the retail sales of organic foods have increased from \$3.6 billion in 1997 to \$21.1 billion in 2008 (Dimitri and Oberholtz 2009). Several factors may contribute to this trend. First, the perception that these foods are healthier and safer than conventional foods is widespread among consumers (Lohr 2001). As organic standards prohibit the use of synthetic fertilizers, pesticides, growth regulators, and livestock feed additives during production, consumers may believe organic foods are less likely to contain chemical residuals that are detrimental to human health. Indeed, Zepeda and Deal (2009) report that this is the dominant reason for the initial purchase of organic food products by consumers. The idea of environment protection and animal welfare is another reason. Producing healthier food products often involve production practices that are environmental and animal friendly. For example, avoiding the use of fertilizer reduces soil degradation. For another example, freeing egg laying hens from cages not only produce eggs that taste better, but also improve hens' welfare. Therefore, these products are especially appealing to those consumers who are environmental and animal friendly.

As a result, healthy food products are marketed as a higher quality alternative to conventional foods and usually command a price premium over conventional foods. Thompson and Kidwell (1998) report that price premiums for organic fresh produce products ranged from 40% to 175% over their conventional counterparts, based on price data they collected from two retail stores in Arizona in 1994. The traditional explanation for this price premium is that the production costs for healthy products are higher. Indeed, there is a literature on comparing organic and conventional production technologies in terms of productivity and efficiency (e.g. Tzouvelekas, Pantzios and Fotopoulus 2001a, 2001b, Oude Lansink, Pietola and Backman 2002, Kumbhakar, Tsionas and Sipilainen 2008, Mayen, Balagtas and Alexander 2010). For example, Mayen, Balagtas and Alexander (2010) find that organic dairy farms in the U.S. are 13% less productive than conventional ones.

But consumers do not purchase foods from farmers directly. Instead, they purchase foods from food manufacturers, who in turn purchase raw materials from farmers. Therefore, another potential explanation for why consumers pay high price premiums for healthy foods could be that these food manufacturers practice price discrimination. Price discrimination is a practice that firms often use to extract additional consumer surplus so that they can get a larger share of the total benefits generated by the trade. Firms can practice price discrimination against environment and health-oriented consumers, that is, the differences in production costs cannot entirely explain the price premiums these consumers pay for healthy foods over conventional foods. They pay extra for being environment and health conscious.

The goal of this article is to empirically examine this question, using data from the U.S. ketchup industry. Though conceptually simple, answering this question is challenging as costs are not observed and therefore I do not know whether the price premium is due to cost difference or price discrimination. To overcome this difficulty, I conduct a multi-step structural analysis. First, I use discrete choice methods (e.g. Berry 1994, Berry, Levinsohn and Pakes 1995) to estimate consumers' demand for different ketchup products at the universal product code (UPC) level. Then, using the elasticities obtained from the first step and a model on firm competition, I recover the marginal cost as well as the margin (difference between price and marginal cost) for each product.[1] Finally, using the estimated marginal costs and margins, I quantify the price discrimination with respect to the healthy feature using a counterfactual experiment.

Results show that price discrimination (with respect to all differences in product characteristics between the two groups of products) accounts for about 2.34% of the average price difference between healthy and regular products, with the rest accounted for by the marginal cost difference. Furthermore, only 0.46% of the difference in average prices between healthy and regular products is price discrimination with respect to the healthy feature. These results imply that food manufacturers only practice price discrimination against consumers of healthy products to a very small extent. Most of the price premium

[1]Following Tirole (1988), I define price discrimination as difference in margins.

paid by those consumers comes from higher costs of producing healthy products.

Using the structural estimates, I then conduct several counterfactual experiments to examine the welfare effects of two policy experiments and quantify to what extent income heterogeneity in the market allows firms to price discriminate with respect to the healthy feature. Results there show that both banning price discrimination and imposing a tax on regular products lead to a social welfare loss and income heterogeneity is an important source of price discrimination with respect to the healthy feature.

With the rising popularity of healthy foods, there is a growing literature studying various aspects of these products. Thompson (1998) surveys the early literature on consumer demand for organic foods, which focuses on identifying factors that influence consumers' demand for organic foods. More recently, Lusk and Briggeman (2009), James, Rickard and Rossman (2009), Hu, Woods and Bastin (2009) and Dentoni, Tonsor, Calantone and Peterson (2009) all use experimental methods to assess consumer willingness to pay (WTP) for healthy foods and examine the determinants of WTP for healthy foods. In addition, Kanter, Messer and Kaiser (2009) study how the introduction of healthy foods impact the demand for conventional foods. And as mentioned above, studies such as Mayen, Balagtas and Alexander (2010) compare organic and conventional food production technologies. This article is also related to studies in the industrial organization literature that examine price discrimination practices in various industries. A few examples include Verboven (1996) for the European auto market, McManus (2007) and Villas-Boas (2009) for the coffee market and Cohen (2008) for the paper towel industry. To the best of my knowledge, I am the first to examine price discrimination as a potential explanation for the high price premiums enjoyed by healthy foods over conventional foods.

The rest of the paper is organized as follows. The next section describes my empirical methodology. Section 3 introduces the U.S. ketchup industry and the data. Section 4 presents estimation details and discusses results. Section 5 discusses the welfare effects of two policy experiments. Section 6 examines income heterogeneity as a source of price discrimination and the final section concludes.

1.2 Empirical Strategy

My empirical analysis consists of three steps. In the first step, I estimate consumer demand for ketchup products and calculate the own and cross-price elasticities for different products. In the second step, with the elasticities obtained from the first step and a model on firm competition, I recover the marginal cost and the margin for each ketchup product. Finally, in the third step, using the estimated marginal costs and margins, I quantify the price discrimination with respect to the healthy feature using a counterfactual experiment.

1.2.1 Demand Estimation

Since I am estimating the demand for ketchup products at the UPC level, there are many products in the demand system. Estimating such a large demand system using traditional methods like AIDS (e.g. Deaton and Muellbauer 1980) requires the estimation of hundreds of parameters. To overcome this dimensionality problem, I follow the approach in the discrete choice demand analysis literature (e.g. Berry 1994, Berry, Levinsohn and Pakes 1995) and employ a random coefficients logit specification in particular.

Suppose I observe $t = 1, ..., T$ markets, each with $i = 1, ..., I_t$ consumers. In the estimation below a market will be defined as an MSA-quarter combination. There are $j = 1, ..., J_t$ products in each market available for purchase. The indirect utility of consumer

i from purchasing product j in market t is

$$u_{ijt} = w_{jt}\alpha_{it} + x_j\beta_{it} + \xi_j + \Delta\xi_{jt} + \varepsilon_{ijt}, \tag{1.1}$$

where w_{jt} is a k_1-dimensional vector containing observed market-varying product characteristics for UPC j. For example, one such characteristic is the price of the UPC in market t. x_j is a k_2-dimensional vector containing observed market-invariant product characteristics for UPC j. For example, one of such product characteristics is the package size of a UPC. ξ_j is the market-invariant unobserved product characteristic of UPC j, while $\Delta\xi_{jt}$ is the UPC-market specific unobserved demand shifter for the same UPC. ε_{ijt} is an error term *i.i.d.* with a Type I extreme-value distribution. In case that a consumer does not purchase a ketchup product, I specify the indirect utility from this outside choice as $u_{i0t} = \varepsilon_{i0t}$.

α_{it} and β_{it} are consumer i's taste parameters for product characteristics. These are assumed to be random and depend on consumer characteristics, both observed and unobserved, as follows,

$$[\alpha_{it}; \beta_{it}] = [\alpha; \beta] + \Pi D_{it} + \Sigma v_{it}, \tag{1.2}$$

where α and β are interpreted as the mean taste parameters, D_{it} denotes the $d \times 1$ vector of consumer (observed) demographic variables that are likely to influence consumer tastes in market t and v_{it} denotes the $k \times 1$ vector of random variables that constitute the random (unobserved) part of the consumer tastes, where $k = k_1 + k_2$. Π denotes a $k \times d$ matrix of parameters and Σ denotes a $k \times k$ diagonal matrix of parameters. Both need to be estimated. In this way, consumers with similar characteristics have similar preferences and are likely to choose similar products and the resulting substitution pattern is more general and reasonable.

Combining (1.1) and (1.2), the predicted market share for product j can be written as

$$s_{jt} = \int \frac{\exp\left(\delta_{jt} + \mu_{ijt}\right)}{1 + \sum\limits_{k=1}^{J_t} \exp\left(\delta_{kt} + \mu_{ikt}\right)} dP_D\left(D_{it}\right) dP_v\left(v_{it}\right), \tag{1.3}$$

where $P_D\left(\cdot\right)$ and $P_v\left(\cdot\right)$ are distributions for D_{it} and v_{it}, respectively, $\delta_{jt} = w_{jt}\alpha + x_j\beta + \xi_j + \Delta\xi_{jt}$ and $\mu_{ijt} = [w_{jt}; x_j]' * (\Pi D_{it} + \Sigma v_{it})$. The resulting own- and cross-price elasticities are

$$e_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \frac{p_{kt}}{s_{jt}} = \begin{cases} -\frac{p_{kt}}{s_{jt}} \int \alpha_{itp} s_{ijt}\left(1 - s_{ijt}\right) dP_D\left(D_{it}\right) dP_v\left(v_{it}\right), & \text{if } j = k \\ \frac{p_{kt}}{s_{jt}} \int \alpha_{itp} s_{ijt} s_{ikt} dP_D\left(D_{it}\right) dP_v\left(v_{it}\right), \text{ otherwise} \end{cases}, \tag{1.4}$$

where $s_{ijt} = \frac{\exp(\delta_{jt}+\mu_{ijt})}{1+\sum\limits_{k=1}^{J_t}\exp(\delta_{kt}+\mu_{ikt})}$ and α_{itp} is the coefficient in α_{it} that is associated with the price variable p_{jt} in w_{jt}. From (1.4), it is clear that the random coefficients logit model implies a very general substitution pattern among different products and the Independence of Irrelevant Alternatives (IIA) critique that other types of discrete choice models (i.e. the multinomial logit model and the nested logit model) suffer from no longer applies. In fact, as shown in McFadden and Train (2000), this model is general in the sense that it can approximate arbitrarily close any discrete choice model.

Due to the multi-dimensional integral in (1.3), an estimating equation that is linear in parameters cannot be obtained. Therefore, nonlinear estimation method has to be used to recover the structural parameters. Berry (1994) proved that given the parameter values and the observed market shares, the J_t-equation system (1.3) is a contraction mapping in $\delta_{\cdot t}$ and hence a unique vector of $\delta_{\cdot t}$ can be obtained using iterations. In practice, the multiple integrations in (1.3) are computed using simulations, that is,

$$s_{jt} = \frac{1}{I_t} \sum_{i=1}^{I_t} \frac{\exp\left(\delta_{jt} + \mu_{ijt}\right)}{1 + \sum_{k=1}^{J_t} \exp\left(\delta_{kt} + \mu_{ikt}\right)},$$

where $\mu_{ijt} = [w_{jt}; x_j]' * (\Pi D_{it} + \Sigma v_{it})$, D_{it} is the ith random draw of the observed consumer characteristics variables from the CPS of market t and v_{it} is the ith random draw of the unobserved consumer characteristics variables v_{it} from normal distributions. I_t is the number of simulations.

Next, using the definition of δ_{jt} and the recovered $\delta_{.t}$, I can further recover the UPC-market specific demand shifter term $\Delta\xi_{jt}$ using

$$\Delta\xi_{jt}\left(\theta\right) = \delta_{jt} - w_{jt}\alpha - x_j\beta - \xi_j, \tag{1.5}$$

where the dependence of the recovered error term on the parameters to be estimated, θ, is made explicit. I then use the moment condition $E\left[Z'\Delta\xi\left(\theta\right)\right] = 0$, where Z is a vector of instrumental variables, to form the GMM objective function

$$\Delta\xi\left(\theta\right)' Z A^{-1} Z' \Delta\xi\left(\theta\right). \tag{1.6}$$

A is an appropriately chosen weighting matrix. The GMM estimator is the vector of θ that minimizes the objective function.[2]

[2]Here, only the demand model is estimated using the GMM estimation. An alternative approach is to estimate the demand and supply models together by stacking together the moment conditions from both the demand model and the supply model and estimate both models jointly using the GMM. There are advantages and disadvantages of this alternative approach. The advantages are 1). I can specify the marginal cost function to be exponential so the estimated marginal cost is always positive. 2). There are more moment conditions used in the GMM estimation. Estimates will be more precise (with smaller standard errors) because they need to satisfy more restrictions imposed by the model. The disadvantage is the demand parameters will be influenced by the supply model specification. Hence, if the supply

1.2.2 Recovering the Margins

On the supply side, I assume food manufacturers engage in differentiated products Betrand Nash competition. Suppose the J_t products in market t are produced by F_t firms. Then, the profit maximization problem for firm f in market t is as follows,

$$Max\Pi_f = \sum_{j \in \digamma_{f_t}} (p_{jt} - mc_{jt}) M_t s_{jt} (\mathbf{p}_t) - C_{f_t},$$

where $\digamma_{f_t}$ denotes the subset of products that are produced by firm f in market t and $\digamma_{f_t}$ varies by firm and market, M_t is the potential market size of market t, $\mathbf{p}_t$ denotes the vector collecting prices for all UPCs in market t, and C_{f_t} is the fixed cost for firm f to produce and sell in market t.

The first order condition with respect to prices can be written as:

$$s_{jt} (\mathbf{p}_t) + \sum_{r \in \digamma_f} (p_{rt} - mc_{rt}) \frac{\partial s_{rt} (\mathbf{p}_t)}{\partial p_{jt}} = 0,\ j = 1, ..., J_t. \tag{1.7}$$

The margins can then be solved for explicitly by defining $S_{jrt} = -\frac{\partial s_{rt}(\mathbf{p}_t)}{\partial p_{jt}}$, $j, r = 1, ..., J_t$, $\Omega^*_{jrt} = 1$ if j and r are produced by the same firm and $\Omega^*_{jrt} = 0$ otherwise, and Ω_t is a $J_t \times J_t$ matrix with $\Omega_{jrt} = \Omega^*_{jrt} * S_{jrt}$. With these notations, the set of J_t first order conditions in (1.7) can be written in vector form as

$$\mathbf{s}_t (\mathbf{p}_t) - \Omega_t (\mathbf{p}_t - \mathbf{mc}_t) = 0. \tag{1.8}$$

model is misspecified, then demand parameters will be biased.

Hence, the margins can be calculated using

$$(\mathbf{p}_t - \mathbf{mc}_t) = \Omega_t^{-1} * \mathbf{s}_t\left(\mathbf{p}_t\right). \tag{1.9}$$

The marginal costs can be computed using

$$\mathbf{mc}_t = \mathbf{p}_t - \Omega_t^{-1} * \mathbf{s}_t\left(\mathbf{p}_t\right). \tag{1.10}$$

From (1.9), it is clear that the obtained margins depend on two critical assumptions. The first is the specification used in demand estimation, which determines the elasticities and hence the $S_{jrt} = -e_{jrt}\frac{s_{jt}}{p_{rt}}$ terms. The second is the assumption on market structure, which determines the terms in Ω^*_{jrt}.

1.2.3 Measuring Price Discrimination with Respect to the Healthy Feature

With the margins obtained from the second step, I can answer my main question of interest, that is, whether firms practice price discrimination against health and environmental conscious consumers. One candidate for the measure of price discrimination with respect to the healthy feature is the difference between the average margin for healthy UPCs across all markets and the average margin for regular UPCs across all markets, that is,

$$PD_1 = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{J_{ht}}\sum_{j=1}^{J_{ht}}\left(p_{jt} - mc_{jt}\right) - \frac{1}{T}\sum_{t=1}^{T}\frac{1}{J_{rt}}\sum_{j=1}^{J_{rt}}\left(p_{jt} - mc_{jt}\right), \tag{1.11}$$

where J_{ht} and J_{rt} are the numbers of healthy and regular UPCs in market t, respectively. However, PD_1 is a misleading measure on price discrimination with respect to the healthy feature because healthy and regular products also differ in several other dimensions. For example, they may be sold in different package sizes and Cohen (2008) shows that there is evidence in the paper towel market that firms use package size to practice price discrimination.

To isolate the price discrimination due to the healthy feature, I conduct the following counterfactual experiment. In this experiment, the healthy feature of the healthy UPCs is removed, while other characteristics of the healthy UPCs are retained. This is equivalent to setting h_j, the dummy variable indicating whether UPC j is a healthy product or not and a variable in x_j in (1.1), from 1 to 0 for all healthy UPCs in the dataset. Denote this as h_j^{cf}. One implicit assumption here is that the healthy feature is a product characteristic that is independent of other observed and unobserved product characteristics except the price variable. These variables include w_{jt} excluding the price variable, variables in x_j other than the healthy feature variable, ξ_j and $\Delta\xi_{jt}$. Hence, firms can just remove the healthy feature without changing other product characteristics (except the price).

The marginal costs for healthy UPCs also need to be adjusted as the healthy feature is an important determinant of the marginal cost. I do so using the following procedure. First, using the estimated marginal costs from (1.10), I run the following regression,

$$mc_{jt} = \gamma_0 + \gamma_1 h_j + y_{jt}\gamma + v_{jt}, \tag{1.12}$$

where y_{jt} is a set of variables that are likely to influence the marginal cost of UPC j in market t. These variables include the size of the UPC, as well as the MSA and quarterly dummy variables, the latter of which control for the cost shifters that I will use as IVs in demand estimation below. γ_1 provides an estimate for the part of the marginal cost that is due to the healthy feature. With the healthy feature is removed, the marginal cost for the healthy UPCs is adjusted using

$$mc_{jt}^{cf} = mc_{jt} - \widehat{\gamma}_1. \tag{1.13}$$

With h_j^{cf} and mc_{jt}^{cf} computed using the procedure described above, I then re-solve the first order condition (1.9) for the new set of equilibrium prices, $\mathbf{p}_t^{cf}$, for each market. I then re-compute the difference between the average margin for healthy UPCs across all markets and the average margin for regular UPCs across all markets using the new set of prices and marginal costs, that is,

$$PD_2 = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{J_{ht}}\sum_{j=1}^{J_{ht}}\left(p_{jt}^{cf} - mc_{jt}^{cf}\right) - \frac{1}{T}\sum_{t=1}^{T}\frac{1}{J_{rt}}\sum_{j=1}^{J_{rt}}\left(p_{jt}^{cf} - mc_{jt}\right). \tag{1.14}$$

Note in (1.14), the marginal costs for the regular UPCs do not change as there is no change in the characteristics of the regular UPCs. (1.14) can be regarded as the measure of price discrimination due to other features of the healthy UPCs. In this counterfactual scenario, the healthy UPCs lose their healthy feature, but retain all other features. Therefore, any difference in the average margins between the two groups now are due to differences in features other than the healthy feature. With PD_1 and PD_2 computed, the measure for price discrimination with respect to the healthy feature can be readily computed using

$$PD = PD_1 - PD_2. \tag{1.15}$$

As explained above, PD_1 measures the price discrimination due to all differences between the healthy and regular UPCs. PD_2 measures the price discrimination due to features of the healthy UPCs other than the healthy feature. Hence, the difference between PD_1 and PD_2 measures the price discrimination with respect to the healthy feature.

1.3 Industry and Data

The U.S. ketchup market is selected for my empirical analysis. I choose the ketchup market mainly because of data availability. Healthy or organic fresh produce is the top selling category of healthy foods (Dimitri and Oberholtzer 2009). However, brand or firm level price and sales data for such products are simply not available. For the ketchup market, on the other hand, brand level price and sales scanner data are collected by marketing companies and are available to researchers.

1.3.1 Ketchup Industry and Business

Ketchup is a widely used condiment in the U.S., found in 97% of all kitchens, a showing matched only by salt, pepper, and sugar (Villas-Boas and Zhao 2005). It is mainly consumed with hot dogs, French fries, hamburgers, pasta and serves as seasoning when making sauces such as salsa and other food. The total annual market sales in 2006 was approximately $5.88 billion.[3] Heinz is the leading firm whose market share has remained around 60% in volume in recent years. Hunt's, a ConAgra Foods brand, is the second largest, accounting for about 16% of the market. The rest of the market is shared by private label products, Del Monte and other local brands.

The business section of the annual reports of Heinz and ConAgra Foods provide a glimpse of the ketchup business ranging from procurement of inputs to retailing of outputs. Ketchup is made starting from developing recipes in individual company's research laboratories and experimental kitchens. Then, ingredients are inspected and transported to factories. To hedge against the spot market price volatility, major ketchup producers usually sign forward contracts with farmers growing raw materials such as tomatoes and

[3] This number was calculated by dividing Heinz's total revenue from ketchup and sauce sales in 2006 by 0.6, Heize's market share in that year.

onions. Ingredients such as sugar and sweeteners (high fructose corn syrup, a major sugar substitute in most Heinz and Hunt's products) are purchased from approved suppliers. In the factory, raw materials are manufactured into ketchup products through the following processes: sterilization, homogenization, chilling, freezing, pickling, drying, freeze drying, baking or extruding, bottling and labeling. Products are sold through their own sales organizations and through independent brokers, agents and distributors to chain, wholesale and other retailers. Wal-Mart is the number one customer of Heinz and ConAgra Foods, representing approximately 11% and 18% of the firms' total sales in 2010.

1.3.2 Cost Difference between Healthy and Regular Ketchup Products

As mentioned above, one explanation for the price difference between healthy and regular products is that the (marginal) costs for healthy products are higher. One source of such cost difference is difference in input costs as healthy ketchup products use different inputs than regular ketchup products. First of all, reduced sugar products substitute for high fructose corn syrups (HFCS) with sucralose (Splenda, a low calorie sweetener). According to the prices at Alibaba.com, an online business-to-business trading platform and wholesale merchant, the industrial wholesale price for sucralose was $231.96 per kilogram while the wholesale price for HFCS was only $0.66 dollars per kilogram in March 2011. However, according to a study in chemistry, sucralose is much sweeter than HFCS. Ophardt (2003) shows that if use sucrose as the reference and it has a sweetness score of 1, HFCS is between 1.2 and 1.6 and sucralose is 600. Suppose producing a bottle of 36 oz. ketchup uses 50 gram HFCS which costs 3.30 cents, by switching to sucralose, it only needs about 0.10 to 0.13 gram of sucralose with a cost about 2.32 to 3.09 cents to achieve the same sweetness, depending on which type of HFCS is substituted away.[4] Therefore, the input costs of reduced sugar products are slightly lower than those of regular products.

The difference between organic and regular ketchups is the quality of tomatoes and other ingredients according to organic ketchup producers H.J. Heinz and Auntie Anne's (a firm which only produces organic products). The ingredients of ketchup include tomato concentrate from red ripe tomato, vinegar, sugar, salt, onion powder, spices and natural flavoring. Organic ketchup products distinguish themselves from conventional ones by using all organic ingredients (even spices). Therefore, to evaluate the cost of producing organic ketchups, it is critical to examine the cost of producing organic tomatoes, because tomato is the major ingredient in ketchup. Unfortunately, to the best of my knowledge, there is no study comparing the production costs of organic tomatoes with those of conventional tomatoes. Generally speaking, organic farming is less efficient and has lower yield, especially at the initial stage of transition from conventional farming. Therefore, the costs of organic ketchup products are higher than the regular products.

Finally, the input cost difference between no salt ketchup products and conventional ketchup products is small. By examining the nutrition facts and ingredients of regular and no salt Heinz ketchup products, I find that the only difference between no salt ketchup and regular ketchup is the substitution of regular salt with potassium chloride. According to the prices at Alibaba.com, the wholesale price of regular salt was about \$320 per metric ton while the wholesale price of potassium chloride was about \$390 per metric ton in March 2011. Therefore, the cost difference between producing regular and

[4] According to White (2008), there is a variety of HFCSs by combining different percentages of fructose and glucose. For example, HFCS 55 (mostly used in soft drinks), approximately 55% fructose and 42% glucose; and HFCS 42 (used in beverages, processed foods, cereals and baked goods), approximately 42% fructose and 53% glucose. HFCS-90, approximately 90% fructose and 10% glucose, is used in small quantities for specialty applications, but primarily is used to blend with HFCS 42 to make HFCS 55.

no salt ketchup is fairly small.

In addition to the input cost difference, there are also other sources of cost difference between healthy ketchup products and conventional ketchup products. Most notably is the fact that healthy ketchup products still command a fairly small market share and as a result, cannot enjoy returns to scale in production and marketing. Since I do not have data on such costs, I rely on a structural model to recover the marginal costs for different ketchup products.

1.3.3 Data

The data needed to estimate the demand system presented in section 2 includes data on prices, market shares, product characteristics and consumer demographic variables. These data come from two main sources: IRI Marketing Data Set and Current Population Survey (CPS) from BLS. Prices, market shares and product characteristics were constructed from the IRI marketing dataset and consumer demographic variables were randomly sampled from the CPS.

The IRI Marketing dataset provides weekly sales information (both quantity and revenue) at the UPC level for each sampled supermarket or grocery store. These stores are randomly selected from 32 MSAs across the U.S. The 32 MSAs are divided into 4 regions following U.S. Census Bureau's Regions and Divisions Map.[5] Table 1 lists the 32 MSAs by region.

Two hundred and forty-nine ketchup products (UPCs) appeared in at least one week in at least one MSA between 2004 and 2006, the sample period. I chose to focus on 198 of them, which together accounted for about 95% of the ketchup sales (in volume) during the three-year sample period. A UPC was included in the analysis if it appeared in all 12

[5] Available at http://www.census.gov/geo/www/us_regdiv.pdf.

quarters from 2004 to 2006 in at least one MSA and had a market share, which will be defined below, larger than 0.001% in at least one market. The 198 UPCs were produced by Heinz, Hunt's, Del Monte, 39 retail chains and 15 other small firms. Table 2 lists the numbers of UPCs included in the analysis by brand and product type.

I then aggregated weekly data to quarterly data. Since the sample covers 3 years, I have 12 quarters. For each of the 198 UPCs, I computed the market share for each UPC in each market (MSA and quarter combination). The market share is in terms of volume and was calculated by dividing the quarterly sales in ounces by the potential market size in the corresponding MSA. The difference between 1 and sum of inside good shares was taken as the market share for the outside product. For each MSA, the largest quarterly total sales quantity from all 249 UPCs in the raw dataset (not just the 198 UPCs I focus on) across the 12 quarters was taken as the potential market size for that MSA. Table 3 reports the market shares (in volume) by firm over the sample period. Heinz was the obvious market leader with an average market share above 50%, followed by Hunt's with a market share about 20%. The other national brand, Del Monte, accounted for about 5% of the market. Private labels and other small firms accounted for the rest. Therefore, the ketchup market was fairly concentrated during the sample period. In addition, among the 198 UPCs, 10 UPCs are healthy products: 1 organic, 8 reduced/no sugar and 1 no salt. Table 4 reports their market shares over years. Together, they accounted for 0.78% of the total sales in 2006.

Average price was calculated by dividing deflated dollar sales by sales quantity in ounces.[6] The obtained price is essentially the unit retail price, taking into account retailer coupons but excluding manufacturer coupons or any other discount offered by the retailer. An example of the latter is that a retailer offers a $5 discount if a consumer purchases

[6]The regional yearly CPI for all urban consumers from BLS was used as the deflator.

more than \$200 during a trip. Since not all UPCs appeared in all MSAs in all quarters and I only kept those UPC-market observations where the UPC had a market share larger than 0.001%, in the end, I have 13,553 UPC-market observations from 384 (32 MSAs*12 quarters) markets. 1,552 out of these 13,553 observations are from the healthy products. Table 5 reports the summary statistics for the price and market share variables. It is clear that healthy products commanded a price premium during the sample period. On average, healthy products were 4.14 cents per ounce, or 110.26% more expensive than the conventional products. In more detail, reduced/no sugar products were 5.59 cents (149.20%) more expensive than conventional products, while no salt and organic products were 1.05 cents (28.00%) and 3.62 cents (96.58%) more expensive, respectively.

Product characteristics data also come from the IRI Marketing Dataset. For each product, I created four variables. The first one is a dummy variable indicating whether the product is a healthy product or not. The second one is product package size, which is a continuous variable. Table 6 reports the summary statistics for these two variables. The third and fourth variables are two variables on advertising activities. IRI provides weekly display and promotion information at the UPC-store level. The variable Display describes whether a UPC was in display and how it was displayed in a certain store during a certain week. The variable Promotion describes whether a UPC was in promotion and how it was promoted in a certain store during a certain week. See Table 7 for details on how these two variables were created. Both variables were then aggregated to UPC-market level by averaging across all stores in the MSA and all weeks in the quarter. Table 5 includes summary statistics of these two variables. Among the 13,553 observations in the sample, 5,133 (38%) have non-zero display values and 4,501 (33%) have non-zeros promotion values.

Finally, consumer demographic variables were randomly drawn from the CPS of the corresponding year. The IRI's MSA definition is close to that of the CPS. For each MSA in each of the three years, 100 individuals were randomly drawn and their demographic variables were used in estimation. The demographic variables used include income per person, education attainment and household size. Income per person was calculated using total deflated household income divided by the number of persons in the household. Table 8 reports summary statistics for these demographic variables. Note that the average income per person is lower than the national average income reported by BLS because I didn't exclude individuals under 16 years old in the household when calculating the income per person variable.

1.4 Estimation Details and Results

This section provides details of my empirical strategy and it presents and discusses estimation results. I first discuss my identification strategy and then present and discuss the results.

1.4.1 Identification

To estimate the demand system described above, several issues need to be resolved. First, the ξ_j variable in (1.1) is not observed in the data. To solve this problem, I include a set of UPC dummy variables in the regression in place of the term $x_j\beta + \xi_j$, that is,

$$UPC_j = x_j\beta + \xi_j. \tag{1.16}$$

The second issue is that the key variable in (1.1), the price variable in w_{jt}, might be endogenous. This is because firms often make pricing decisions based on product and market characteristics. Though I have included market-invariant UPC dummy variables in the regression, there may still be UPC-market specific factors that influence firms' pricing decisions but unobserved to the econometrician. These factors are captured by the error term $\Delta\xi_{jt}$ in (1.1), leading to the endogeneity problem. To correct for the potential endogeneity bias, I first include a set of MSA and quarterly dummy variables in the regression (they are included in w_{jt}) to control for the market specific factors as much as possible and then use instrumental variable regression techniques.

A valid instrumental variable needs to satisfy two conditions. First, it needs to be highly correlated with the endogenous variable. Second, it needs to be uncorrelated with the error term. With these two criteria in mind, I created 4 groups of IVs. The first group of IVs are two variables describing the average product characteristics of the UPCs in the same market. The second group of IVs are 18 variables counting the numbers of UPCs by firm ownership and product category in the same market. Berry, Levinsohn and Pakes (1995), Bresnahan, Stern and Trajtenberg (1997), Sudhir (2001) and Petrin (2002) use similar ideas to create IVs in their studies. The argument here is that firms make pricing decisions based on how many competing products their products face in the same market and how similar the competing products are to their own products. When a firm's products are quite different from their competitors or there are fewer competing products in the same market, the firm tends to charge higher prices for its products. Therefore, the first two groups of IVs are likely to be correlated with the price variable. On the other hand, these two groups of IVs are not likely to be correlated with the error term $\Delta\xi_{jt}$, which is defined as a market (MSA and quarter combination)-UPC specific unobserved demand influencing factor. Product design, introduction and exit is a time consuming process and hence the number of products in a market and their features are not likely to respond to demand changes within the same quarter (market).

The third group of IVs constructed are the average prices of the same UPC in other MSAs of the same region in 12 quarters, following Hausman (1997a) and Nevo (2001). See Table 1 for the lists of MSAs in different regions. As these are the prices for the same UPC in other markets, these average price variables are correlated with the endogenous price variable. And they are not correlated with the error term $\Delta\xi_{jt}$ under the assumption that the unobserved UPC-market specific demand shifting factors are independent across different markets. Bresnahan (1997) points out that this assumption may not hold if the demand shocks are correlated across different markets. For example, regional or national advertising campaigns can shift demand in different markets at the same time. To lessen this concern, following Hausman (1997a, 1997b), I also control for advertising activities at the UPC-market level. The two advertising variables, described above in section 3.3, are included in w_{jt} in the estimation.

The last group of IVs are several supply shifters, again following Nevo (2001). Specifically, I use regional dummies and population density to control for the land cost of retailing and hourly wage in the supermarket sector to control for the labor cost of retailing. As cost is an important determinant of price, the supply shifters are correlated with price. Also, as they are supply shifters, they are not likely to be correlated with demand shifters.

Table 9 provides the detailed definitions and the correlation coefficients between the constructed IVs and the endogenous price variable. For most of the IVs, the correlation coefficient is quite large. This implies that the IV under consideration is highly correlated with the price variable, satisfying the first desired property of a valid IV. Whether the second desired property of a valid IV is satisfied or not will be checked using the overidentification test after the GMM estimation. A potential problem with these IVs is that there is little variation across different observations for some IVs, especially for the average regional price variables. The demand parameters may not be well identified when there is little variation in IVs.

1.4.2 Estimation Details

For the GMM estimation, w_{jt} is specified to include the following variables: price, Display, Promotion, the MSA dummies and the quarterly dummies. As mentioned above, $x_j\beta + \xi_j$ is replaced UPC_j. D_i is specified to include three variables: income per person, education and household size. For computational reasons, each demographic variable d is scaled using $\frac{d_i}{Range_d}$, where $Range_d$ is the observed range for the demographic variable. Finally, not all parameters in Π, the coefficient matrix for product and household characteristics interaction terms, are estimated. I only estimate those coefficients for which I have a prior expectation that they are important determinants of the utility. The interaction terms for which the associated coefficients are estimated include the price-income interaction term, as people with higher income are less price sensitive, the income-healthy and education-healthy interaction terms, as people with higher income and education are more likely to prefer healthy products, and the household size-package size interaction term, as households with more people are more likely to purchase products packaged in bigger containers. The Σ coefficient matrix is also restricted to be diagonal, meaning that the unobserved consumer preference for different product characteristics are independent from one another. Restricting some of the parameters in Π and Σ to be 0 reduces the number of parameters to be estimated in the GMM estimation, alleviating the computational burden of the estimation significantly.

Since the parameters α and coefficients for product, MSA and quarterly dummies appear linearly in (1.5), the estimation is simplified as the first order condition of (1.6) with respect to these linear parameters implies that the linear parameters are functions of the remaining nonlinear parameters, that is, parameters in Π and Σ. As a result, (1.6) is essentially a function of the remaining nonlinear parameters only, significantly reducing the dimensionality of the estimation problem.

In my specification, I have 8 parameters in Π and Σ. Therefore, I need at least 9 IVs to conduct the GMM estimation and the overidentification test. From the list of 38 constructed IVs in Table 9, I tried different sets of IVs with each set had at least 9 IVs. The results reported here are based on a set of 10 IVs, 6 from group II and 4 from group III. The last column of Table 9 lists the IVs selected. This set of results is selected because the specification passes the overidentification test. Also, a two-step GMM approach is used, with the identity matrix used as the weighting matrix A in the first step and the optimal weighting matrix (constructed using the first step estimates) in the second step.

Finally, after the GMM estimation, I use the estimated coefficients for the UPC dummies as the dependent variable in an OLS regression to obtain the estimates for β in (1.16).

1.4.3 Results

Table 10 collects results from the GMM estimation. Several results are worth mentioning. First, the value of the J statistic, the test statistic for the overidentification test, is 4.20. The critical values for the χ^2 distribution with 2 degrees of freedom (difference between the number of IVs and the number of nonlinear parameters) at the 10%, 5% and 1% significance levels are 4.61, 5.99 and 9.21, respectively. Therefore, I cannot reject the hypothesis that the instruments used satisfy the two conditions discussed above at conventional statistical significance levels. Second, the price parameter is negative and statistically significant at 1% level, which is consistent with the law of demand. Third, all the estimated coefficients for consumer demographic and product characteristic interaction terms have the correct signs and are statistically significant. People with higher income and more education prefer healthy products and larger households prefer products packaged in larger containers. Also, people with higher income are less sensitive to price. Fourth, advertising variables are estimated to have a positive effect on demand, though the estimates are not statistically significant.

Using the estimates on utility parameters, I then computed the own- and cross-price elasticities using (1.4). For each UPC, I computed its own-price elasticity for all the markets it appeared. For each pair of UPCs, I computed the cross-price elasticity between the two UPCs for all the markets the two UPCs appeared together. This allows me to create a median elasticity matrix for the 198 UPCs in the sample. This matrix is available upon request. In this matrix (198×198), each diagonal element is the median of own-price elasticities for one UPC across all the markets the UPC appeared. Each off-diagonal element is the median of cross-price elasticities between two UPCs across all the markets they appeared together. Table 11 reports the summary statistics of the numbers in this median elasticity matrix. From this table, the median own-price elasticities for different UPCs range from -37 to -2, with an average of -7.53. This implies that the demand for an individual UPC is quite price elastic. This is not surprising for such a disaggregate demand analysis as mine because the demand curve tends to become more price elastic when the product under consideration is defined more narrowly. Gordon, Goldfarb and Li (2012) estimate ketchup elasticities at the brand level and report an average own-price elasticity of -2.66. My result is also consistent with the notion that profit-maximizing firms will never operate along the inelastic portion of the demand curve.

The cross-price elasticity estimates are also reasonable. For example, the cross-price elasticity estimates between UPC 1 and other products range from 5.58E-08 to 0.9274. UPC1 is a 14 oz. regular product from a small firm named Mcilhenny. UPC 5 is a Heinz 114 oz. regular product. Their cross-price elasticity is 5.58E-08, which implies that the price change of UPC1 does not affect the quantity demanded of UPC 5. On the other hand, the cross-price elasticity between UPC 1 and UPC 38, a 14 oz. Heinz regular product, is 0.9274. This implies that a consumer is more likely to substitute to a product with similar package size when the price of UPC 1 increases. For another example, the cross-price elasticities between in-category products are larger than between cross-category products. The elasticity between the 12 oz. Walden Farms reduced sugar product (UPC 28) and the 14 oz. reduced sugar Heinz product (UPC 44) is 0.1319, while the number between the former (UPC 28) and the 14 oz. regular Hunt's product (UPC 18) is only 0.0011. This is consistent with the idea that healthy product consumers are less likely to substitute to regular products.

Using the obtained elasticity estimates and the assumed Betrand Nash competition market structure, I then computed the marginal costs and the margins for all UPC-market observations. Table 12 summarizes marginal cost and margin estimates. The difference in average margins between healthy and regular products is 0.04 cents per ounce.

To further isolate the price discrimination with respect to the healthy feature, I followed the procedure described in section 2.3, which requires the calculation of the counterfactual prices from the experiment where the healthy feature of the healthy products is removed. I only did this for the 238 markets where all the estimated marginal costs are positive. As can be seen from Table 12, 196 out of the 13,553 UPC-market observations in the sample have a negative estimated marginal cost. Negative marginal costs may lead to misleading estimates of the counterfactual prices and hence markets where there are observations with negative estimated marginal costs were dropped from the experiment.[7] Table 13 reports results from this calculation. Within these 238 markets, the difference in average prices between healthy and regular products is 4.28 cents per ounce and the price discrimination with respect to all differences in product characteristics and the healthy feature are, 0.10 cents and 0.02 cents per ounce, respectively. Therefore, I can conclude that price discrimination (with respect to all differences in product characteristics between the two groups of products) accounts for about 2.34% of the price difference and only 0.46% of the difference is price discrimination with respect to the healthy feature.

1.4.4 Collusion

The results obtained so far depend on the assumption that the firms in the ketchup industry engage in non-cooperative Betrand Nash competition. The 57 competitors are Heinz, Hunt's, Del Monte, 39 retail chains and 15 other small firms To assess the robustness of the results, I also repeated the analysis assuming the 57 competitors collude with one another. Under this market structure assumption, 51% of the recovered marginal costs are negative. These results are obviously not realistic, indicating that the Betrand Nash competition market structure is more consistent with the data than the full collusion model.

1.5 Effects of Government Policies

My results above show that price discrimination only accounts for a small percentage of the observed price difference between healthy and regular products. This result is driven

[7] Of course, using 0 rather than other numbers like 0.0001 as the cutoff point for valid marginal cost estimates is arbitrary.

by the fact that demands for individual ketchup products are quite price elastic and hence firms price their products close to the marginal costs. As a result, price margins are quite small for all products and the difference in average margins between the two groups of products, my price discrimination measure, is small. This implies that price discrimination is not a big concern in this market. However, price discrimination may be a cause of concern in other markets and the government may want to consider policies that aim to reduce the price discrimination practice by the firms. Therefore, it is worthwhile to examine the effects of such a policy.

Also, my results show that healthy products command a price premium over regular products mainly due to the fact that they cost more to produce. Higher costs lead to higher prices and as a result, fewer people consume such products. A policy governments often use to promote healthy behavior or discourage unhealthy behavior is to impose a tax on unhealthy behavior. For example, cigarettes are heavily taxed to discourage smoking. It is also worthwhile to examine the effects of such a policy in the ketchup market.

In the rest of this section, I report results from two policy experiments. I did the experiments only for the first market in the sample, that is, the market for Atlanta MSA in the first quarter of 2004, for two reasons. First, in this market, the estimated marginal costs for all products are positive and hence there is no bias in the estimated counterfactual prices caused by negative marginal costs. Second, focusing on one market rather than summarizing results from many markets allows me to discuss the results in more detail and more clearly. In this market, there are 40 UPCs, 5 healthy and 35 regular. Heinz, Hunt's, Del Monte, 2 retail chains and 9 other small firms produce 11, 9, 2, 9 and 9 of the 40 products, respectively. Heinz, Hunt's, one retail chain and 2 other small firms each produces one healthy product.

1.5.1 Uniform Margins

The first policy the government may use to combat the price discrimination practice by the firms is to require all firms to charge the same margins for all its products in one market. With this policy, firm f's profit function in market t becomes,

$$\Pi_{f_t} = \sum_{j \in \digamma_{ft}} \psi_{ft} M_t s_{jt}(\mathbf{mc}_t + \Psi_t) - C_{ft}, \tag{1.17}$$

where the scaler ψ_{ft} is firm f's uniform margin in market t and the vector Ψ_t contains the margins of all products by all firms in market t. The decision variable for firm f now is the uniform margin, rather than the prices for all its products. The first order conditions for all firms in market t can be written as,

$$\sum_{j \in \digamma_f} \left(s_{jt} + \psi_{ft} \frac{\partial s_{jt}}{\partial \psi_{ft}} \right) = 0, \ f = 1, ..., F_t, \tag{1.18}$$

where F_t is the number of firms in market t. Denoting $\Psi_t^* = (\psi_{1t}^*, \psi_{2t}^*, ..., \psi_{Ft}^*)'$ as the solution to (A.9), the new equilibrium prices in this counterfactual experiment are simply $\mathbf{p}_t^{cf} = \mathbf{mc}_t + \Psi_t^*$.

With the new equilibrium prices $\mathbf{p}_t^{cf}$, the effects of this government policy can be quantified. The profit change for firm f in market t is,

$$\Delta profit_{f_t} = \sum_{j \in F_{ft}} M_t[p_{jt}^{cf} s_{jt}(\mathbf{p}_t^{cf}) - p_{jt} s_{jt}]. \tag{1.19}$$

The expected change in consumer surplus for a representative consumer in market t is,

$$E[E(CS_t^{CF}) - E(CS_t)] = E\Bigg(\frac{1}{\alpha_{itp}}[\ln(\sum_{j=1}^{J_t}\exp(\delta_{jt}(\mathbf{p}_t^{cf}) + \mu_{ijt}(\mathbf{p}_t^{cf}))) \\ - \ln(\sum_{j=1}^{J_t}\exp(\delta_{jt}(\mathbf{p}_t) + \mu_{ijt}(\mathbf{p}_t)))]\Bigg), \tag{1.20}$$

where the expectation can be computed using simulations.

As a benchmark, Table 13 is replicated for market 1 and Table 14 reports the results. Price discrimination is a more serious problem in market 1 than an average market. Price discrimination with respect to the healthy feature is 0.14 cents, which is about 4% of the observed difference in average prices between the healthy and regular products in this market. I now turn to the results from the counterfactual experiment. Table 15 reports the summary statistics of the counterfactual prices from the experiment. With the uniform margin policy, the prices for healthy and regular UPCs both decrease on average, but the prices for healthy products decrease more. Actually, price decreases for all of the 5 healthy UPCs, but only 11 of the 35 regular UPCs. Associated with the price changes are the quantity changes, which are collected in Table 16. As healthy products now become less expensive relative to the regular products, sales of healthy products increase and sales of regular products decrease on average.

Finally, Table 17 reports results on the welfare effects of this policy. The producers, as a whole, lose \$871. This result conforms to my prior expectation as the policy turns a firm's unconstrained profit maximization problem into to a constrained one. For the consumers, an average consumer loses $\$1.2313{*}10^{-5}$ per ounce of ketchup consumed. The potential market size for market 1 is 4,498,894.5 ounces. Therefore, the total consumer surplus loss for this market is about \$55. The negative welfare effect for consumers needs some discussion. Though the average prices decrease for both healthy and regular products, the prices increase for 24 out of the 35 regular products in this market. Therefore, 60% of the products actually see a price increase because of this policy. Also, Table 15 shows that the mean and the median prices both decrease, but the minimum price increases with the policy. This implies that price increases for those products with a low price. As low price products sell more, they have a bigger impact on consumer welfare, leading to a negative consumer welfare number for the average consumer.

Therefore, I conclude that this policy is social welfare decreasing as it decreases the welfare for both producers and consumers.

1.5.2 Tax on Regular Products

In 2009, a soda tax law was proposed in the State of New York. The law proposes to impose a one cent per ounce tax on all sugar-sweetened beverages. See Hartocollis (2009) and Brownell and Frieden (2009) for more details about the proposed law. Though the law was never passed, it is interesting to study its effects. In this experiment, I impose one cent per ounce tax to all regular products.

With such a law, firm f's profit function in market t becomes:

$$\Pi_{ft} = \sum_{j \in F_{ft}} \left\{ (p_{jt}^{cf} - mc_{jt}) * M_t * s_{jt}(\mathbf{p}_t^{cf} + \psi) \right\}, \tag{1.21}$$

where $\psi_j = 0.01$ if j is a regular product and 0 otherwise. The mandatory tax creates a wedge between the price firms receive and the price consumers pay. Table 18 reports the summary statistics of the counterfactual prices from this experiment. From this table, prices for the healthy products roughly remain unchanged on average. Consumer prices for the regular products, on the other hand, increase for about 0.99 cent. This implies that firms pass 99% of the tax to the consumers. As a result, as Table 19 shows, healthy products become relatively less expensive than before and sales of healthy products increase significantly, while sales of regular products decrease significantly.

Table 20 reports results on the welfare effects of this policy. The producers, as a whole, lose \$6,489. This result conforms to my prior expectation as taxes make products more expensive. As a result, sales and profits decrease. For the consumers, the total consumer surplus loss in this market is about \$43,189, largely due to the price increase of the regular products. This implies that the harmful effects of the tax policy are probably tilted toward lower-income households who do not buy healthy ketchup. As for the total social welfare, the tax raises \$17,654 for the government, which can then re-distribute the tax revenue back to its citizens in terms of services and products. As a result, the total social welfare decreases for \$32,034, less than the sum of consumer and producer welfare loss. It is also important to bear in mind that this consumer welfare and hence the total social welfare numbers do not take into account the fact that some consumers switch from regular products to healthy products due to the price changes and the resulting health benefits.

Finally, I also recomputed the price discrimination measure using the counterfactual prices and Table 21 reports these results. It shows that with the additional tax on regular products, price discrimination with respect to the healthy feature now accounts for 4.5% of the difference in average prices, a slight increase in terms of the percentages compared with the case without the tax. Therefore, the tax allows the producers to price discriminate more against the healthy feature. This is not surprising as the tax leads to a slight reduction in the prices firms charge for their regular products and almost no reduction in the prices for healthy products.

1.6 Sources of Price Discrimination

Having established the fact that firms practice price discrimination against health and environment (to a very small extent), a natural question to ask is what are the sources of price discrimination. The GMM estimation results in Table 10 clearly indicates that people with higher income and more education prefer healthy products. Probably, the healthy products were introduced to meet these people's preference at the first place. Therefore, the presence of such people or consumer heterogeneity (both observed and unobserved) is a source for firms to be able to price discriminate. My analysis so far has not quantified to what extent the price discrimination is due to the presence of consumer heterogeneity in the market. With the structural model estimated out, I can conduct counterfactual experiments to answer this kind of questions. As an illustration, in this section, I discuss results from an experiment where the income for all consumers in the market is set to be the same. Again, this experiment is conducted for market 1.

Table 22 reports the summary statistics of the counterfactual prices from this experiment where all consumers' income are set at the mean income level. As we can see, prices for the healthy products decrease, while prices for regular products remain roughly the same. As there are no longer high-income people in the market, sales of healthy products decrease significantly. At the same time, low income people have higher income now and they consume more ketchup products, leading to an increase in the sales of regular products. Table 23 summarizes the quantity changes.

Finally, the price discrimination measures under this uniform income scenario are computed and Table 24 collects these results. Results show that with uniform income, the price discrimination with respect to the healthy feature is -0.07 cents, that is, without high-income people, the difference in average margins between the healthy products and the regular products actually decreases 0.07 cents when the healthy feature is present. As a reminder, results from Table 14 shows that when high-income people are present, the price discrimination with respect to the healthy feature is 0.14 cents. Therefore, the presence of high-income people in the market allows firms to price discriminate 0.21 cents more with respect to the healthy feature. Income heterogeneity, as a result, is a significant source of price discrimination with respect to the healthy feature. Indeed, when I calculate the PD measure (1.15) for each of the 238 markets without observations with negative marginal costs, I find the average PD for the top 20% highest income markets is 0.0017, significantly higher than the average PD across all observations, which is 0.0002 as reported in Table 13.

1.7 Concluding Remarks

This article examines the extent to which the price premium of healthy ketchup products can be attributed to price discrimination with respect to the healthy feature. Using the multi-step structural analysis, I show that only 0.46% of the observed price premium can be explained by price discrimination with respect to the healthy feature.

The examination of price discrimination of healthy products in the food industry has important implications for public policies advocating a healthy diet. A policy removing the price discrimination component of the high price premium of healthy products will reduce the unit price of healthy products and as a result, consumers will be more likely to switch from regular products to more healthy products. My results show that price discrimination is not a serious concern in the ketchup markets and policies that aim to ban price discrimination or promote the consumption of healthy ketchup products lead to social welfare loss.

Despite the fact that a flexible demand specification and two supply side structures have been examined, the results of this study are subject to several caveats. First, no product level cost data are available to assess the accuracy of the recovered margins. Second, my analysis assumes implicitly that supermarkets or retailers play a passive role in the pricing decision and manufacturers set retail prices directly. This is equivalent to assuming that retailing cost and retailers' margin are constant and part of marketing expenses of the manufacturer. This assumption is often used in the literature (e.g. Hausman and Leonard 2002; Nevo2001) on modeling market power or price competition using scanner data. However, recent studies by Villas-Boas (2007, 2009) show that it was retailers, rather than manufacturers, who have the pricing power in the manufacturer-retailer vertical relationship. Therefore, my results may change if the supply side model takes into account the role of retailers. I leave these for future research.

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Table 1.1: Lists of MSAs in Each Region

Northeast	South	West	Midwest
Boston, MA	Atlanta, GA	Los Angeles, CA	Minneapolis/ St. Paul, MN
Buffalo/Rochester, NY	Charlotte, NC	Portland, OR	Chicago, IL
New York, NY	Dallas, TX	Sacramento, CA	Cleveland, OH
Philadelphia, PA	Houston, TX	Salt Lake City, UT	Detroit, MI
	Mississippi	San Diego, CA	Indianapolis, IN
	New Orleans, LA	San Francisco, CA	Kansas City, MO
	Raleigh/Durham, NC	Seattle/Tacoma, WA	Milwaukee, WI
	Richmond/Norfolk, VA	Spokane, WA	St. Louis, MO
	South Carolina	Phoenix, AZ	
	Tulsa, OK		
	Washington DC		

Notes: 1. Region divisions follow Regions and Divisions of the United States by U.S. Census Bureau, available at http://www.census.gov/geo/www/us_regdiv.pdf.

2. IRI dataset doesn't provide names of the MSAs in South Carolina and Mississippi.

Table 1.2: Number of UPCs used in Estimation by Brand and Product Type

Regular	# of UPCs	Healthy	Brand (# of UPCs)
Heinz	12	Organic	Heinz (1)
Hunt's	9	Reduced/No Sugar	Heinz (1), Private Labels (5), Others (2)
Del Monte	5	Low Salt	Hunt's (1)
Private Labels	144		
Others	18		
Total	188		10

Table 1.3: Annual Volume Market Shares (%) by Firm

	2004	2005	2006
Heinz	52.00	48.68	57.53
Hunt's	17.82	22.42	13.97
Del Monte	5.74	8.10	4.77
Private Labels	17.53	16.51	18.09
Other firms	0.85	0.59	0.53
Total	93.94	96.30	94.89

Table 1.4: Annual Volume Market Shares (%) by Healthy Category

Year	Total Healthy	Reduced/No Sugar	Organic	No Salt
2004	0.76	0.41	0.03	0.32
2005	0.58	0.31	0.03	0.24
2006	0.78	0.42	0.10	0.26

Table 1.5: Summary Statistics of Market-varying Product Characteristics by Product Type

		Mean	Std. Dev.	Median	Min	Max
Price ($/oz.)	**Healthy**	0.0789	0.04	0.0729	0.0172	0.2020
	Regular	0.0375	0.02	0.0326	0.0084	0.2558
Display	**Healthy**	0.0342	0.15	0	0	1.8333
	Regular	0.0835	0.20	0	0	2
Promotion	**Healthy**	0.0166	0.09	0	0	1.8571
	Regular	0.0867	0.18	0	0	3
Market Share	**Healthy**	0.1281	1.48×10^{-3}	0.0889	0.0010	1.2601
(%)	**Regular**	1.9401	0.04	0.5753	0.0010	54.0235

Note: sample size: 13,553.

Table 1.6: Summary Statistics of Market-invariant Product Characteristics

	Mean	Std. Dev.	Median	Min	Max
Size (oz.)	37.6881	19.64	36	5	114
Healthy	0.0505	0.22	0	0	1

Note: sample size: 198.

Table 1.7: Definitions of Promotion and Display Variables

Values	Display	Promotion
0	No Display	No Promotion
1	Minor Display	Small advertisement, usually 1 line of text
2	Major Display (This includes displaying at lobby and end-aisle)	Medium size advertisement
3	N/A	Large size advertisement
4	N/A	Issue retailer coupon or rebate

Table 1.8: Summary Statistics of Consumer Demographic Variables

	Income/person ($)	Household Size	Education
Mean	13,503.0488	3.2720	0.2675
Std. Dev.	12,788.04	1.60	0.44
Median	10,236	3	0
Min	0	1	0
Max	129,546	16	1

Notes: 1. Income per person is deflated by the regional non-seasonally adjusted yearly CPI series for all urban consumers from BLS.
2. Education=1 if the person has a Bachelor or higher degree.
3. Sample size: 9,600, that is, 100 individuals from each of the 32 MSAs.

Table 1.9: Correlations between IVs and the Price Variable

Instrumental Variables	Correlation	Selected
Group I		
Average package size of all other UPCs in the same market	0.0468	
Average package size of UPCs by other firms in the same market	0.0376	
Group II		
# of UPCs by the same firm in the same market	-0.0353	
# of UPCs by other firms in the same market	-0.0530	
# of UPCs in the same market	-0.0694	
# of healthy UPCs by the same firm in the same market	-0.2384	
# of healthy UPCs by other firms in the same market	-0.4008	
# of healthy UPCs in the same market	-0.4298	
# of UPCs in the same healthy subgroup by the same firm in the same market	-0.2524	yes
# of UPCs in the same healthy subgroup by other firms in the same market	-0.4065	yes
# of UPCs in the same healthy subgroup in the same market	-0.4339	yes
# of UPCs in the same size segment by the same firm in the same market	-0.0636	
# of UPCs in the same size segment by other firms in the same market	-0.3061	
# of UPCs in the same size segment in the same market	-0.3150	yes
# of UPCs in the same healthy group and size segment by the same firm in the same market	-0.3196	
# of UPCs in the same healthy group and size segment by other firms in the same market	-0.4429	
# of UPCs in the same healthy group and size segment in the same market	-0.4604	
# of UPCs in the same healthy subgroup and size segment by the same firm in the same market	-0.3479	yes
# of UPCs in the same healthy subgroup and size segment by other firms in the same market	-0.4541	
# of UPCs in the same healthy subgroup and size segment in the same market	-0.4720	yes
Group III		
Average regional prices in 12 quarters	0.9456 --- 0.9672	4 of them selected
Group IV		
y	-0.0648 --- 0.0660	
Population density in 2000	-0.0116	
Hourly wage in the supermarket sector	0.0309	

Note: There are two healthy groups: regular and healthy. There are three healthy subgroups: organic, reduced/no sugar and low salt. There are three size groups: small (4-24oz), medium (24-100oz) and large (>100oz).

Table 1.10: Random Coefficients Logit Estimation Results

Variable	Mean	Std. Dev.	Income	Education	Household Size
Price	-235.0162***	6.0689***	125.3499 ***	---	---
	(25.53)	(1.33)	(0.71)	---	---
Display	7.2556	---	---	---	---
	(9.18)	---	---	---	---
Promotion	0.4164	---	---	---	---
	(7.49)	---	---	---	---
Healthy	-104.7400***, [a]	29.7003***	63.8974***	47.8790***	---
	(0.33)	(5.29)	(1.16)	(1.33)	---
Size	-28.2638***, [a]	6.6146	---	---	146.4151***
	(0.41)	(7.60)	---	---	(2.80)
Constant	12.2826***, [a]	1.4016	---	---	---
	(0.16)	(4.22)	---	---	---
J statistic			4.20		
Critical Value (D.F.)			5.99 (2)		
Excluded IVs	Average regional prices, number of UPCs				

Notes: 1. a denotes estimates from the OLS regression using estimated UPC dummy coefficients from the GMM estimation as the dependent variable. R squared of the OLS regression is 0.83.
2. Values in parentheses are standard errors.
3. *** indicates statistical significance at 1%.
4. Coefficient estimates for MSA and quarter dummy variables are omitted for brevity purpose.

Table 1.11: Summary Statistics of Median Elasticities

Elasticity	Mean	Std. Dev.	Median	Min	Max
Own	-7.5304	4.78	-6.2292	-37.3490	-2.0592
Cross	0.0984	0.27	0.0138	5.3162×10^{-16}	5.1836

Note: The summary statistics are computed from the median elasticity matrix of the 198 UPCs. In this median elasticity matrix (Table A in the Appendix), each diagonal element is the median of own-price elasticities for one UPC across all the markets the UPC appeared. Each off-diagonal element is the median of cross-price elasticities between two UPCs across all the markets they appeared together.

Table 1.12: Marginal Cost and Margin Estimates

	Marginal Cost ($)		**Margin ($)**	
	Healthy	Regular	Healthy	Regular
Mean	0.0713	0.0303	0.0077	0.0073
Std. Dev.	0.04	0.02	4.27×10^{-3}	5.68×10^{-3}
Median	0.0637	0.0255	0.0063	0.0048
Min	-0.0494	-0.0855	0.0039	0.0038
Max	0.1976	0.2498	0.0677	0.1102

Note: 196 out of 13,553 (1.45%) of the estimated marginal costs are negative.

Table 1.13: Price Discrimination with Respect to the Healthy Feature in 238 Markets.

Average Price Difference ($)	0.0428
$\boldsymbol{PD_1}$ **($)**	0.0010
$\boldsymbol{PD_2}$ **($)**	0.0008
$\boldsymbol{PD}$ **($)**	0.0002

Note: The calculation is based on 8,841 UPC-market observations (993 healthy and 7,841 regular) from 238 markets with no negative estimated marginal costs.

Table 1.14: Price Discrimination With Respect to the Healthy Feature in Market 1.

Average Price Difference ($)	0.0350
$\boldsymbol{PD_1}$ **($)**	0.0013
$\boldsymbol{PD_2}$ **($)**	-0.0001
$\boldsymbol{PD}$ **($)**	0.0014

Note: The calculation is based on 40 UPC-market observations (5 healthy and 35 regular) from market1.

Table 1.15: Summary Statistics of Prices for the Experiment: Uniform Margin in Market 1.

	Healthy ($)		**Regular** ($)		**Overall** ($)	
	$\boldsymbol{p^{obs}}$	$\boldsymbol{p^{CF}}$	$\boldsymbol{p^{obs}}$	$\boldsymbol{p^{CF}}$	$\boldsymbol{p^{obs}}$	$\boldsymbol{p^{CF}}$
Mean	0.0760	0.0750	0.0409	0.0407	0.0453	0.0450
Std.	0.04	0.04	0.02	0.04	0.03	0.03
Median	0.0728	0.0717	0.0338	0.0333	0.0349	0.0346
Min.	0.0340	0.0319	0.0188	0.0191	0.0188	0.0191
Max.	0.1343	0.1343	0.1307	0.1307	0.1343	0.1343
#obs.	5		35		40	

Table 1.16: Summary Statistics of Quantity Changes for the Experiment: Uniform Margin in Market 1.

	Healthy (oz.)		Regular (oz.)		Overall	
	Observed	**Counter-factual**	**Observed**	**Counter-factual**	**Observed**	**Counter-factual**
Mean	7,162	9,074	77,632	75,784	68,823	67,445
Std.	8,687	11,779	141,260	129,213	134,018	122,756
Median	2,580	2,781	23,184	20,816	20,237	16,299
Min.	160	145	286	22	160	22
Max.	20,902	28,116	752,664	643,293	752,664	643,293

Note: sample size: 40.

Table 1.17: Summary Statistics of Consumer Surplus and Producer Surplus Changes for the Experiment: Uniform Margin in Market 1.

	Mean
Δ CS ($ per person per ounce)	-1.2313×10^{-5}
Δ CS ($)	-55
Δ Profit ($)	
Heinz	-953
Hunt's	99
Del Monte	68
2 retail chains	-39
9 other firms	-1
Δ Total Profit ($)	-871
Δ Welfare ($)	-926

Table 1.18: Summary Statistics of Counterfactual Prices for Experiment: Tax on Regular Products in Market 1.

	Healthy		Regular			Overall		
	p^{obs}	$p^{CF}=p^{c}$	p^{obs}	p^{CF}	p^{c}	p^{obs}	p^{CF}	p^{c}
Mean ($)	0.0760	0.0760	0.0409	0.0408	0.0508	0.0453	0.0452	0.0539
Std.	0.04	0.04	0.02	0.02	0.02	0.03	0.03	0.02
Median ($)	0.0728	0.0716	0.0338	0.0338	0.0438	0.0349	0.0351	0.0446
Min. ($)	0.0340	0.0349	0.0188	0.0188	0.0288	0.0188	0.0188	0.0288
Max. ($)	0.1343	0.1345	0.1307	0.1307	0.1407	0.1343	0.1345	0.1407
#obs.	5		35			40		

Note: p^{c} is consumer-faced counter-factual price. p^{CF} is firm-faced counter-factual price.

Table 1.19: Summary Statistics of Counterfactual Quantity for Experiment: Tax on Regular Products in Market 1

	Healthy (oz.)		Regular (oz.)		Overall	
	Observed	**Counter-factual**	**Observed**	**Counter-factual**	**Observed**	**Counter-factual**
Mean	7,162	10,406	77,632	50,441	68,823	45,437
Std.	8,687	11,579	141,260	82,989	134,018	78,726
Median	2,580	5,139	23,184	16,893	20,237	16,324
Min.	160	265	286	110	160	110
Max.	20,902	28,097	752,664	426,699	752,664	426,699
#obs.	5		35		40	

Table 1.20: Summary Statistics of Consumer Surplus and Producer Surplus Changes for Experiment: Tax on regular products in Market 1

	Mean
Δ CS ($ per person per ounce)	-0.0096
Δ CS ($)	-43,189
Δ Profit ($)	
Heinz	-4,289
Hunt's	-1,486
Del Monte	-424
2 private label retailing chains	-134
9 other firms	-3
Δ Total Profit($)	-6,489
Tax Revenue ($)	17,654
Δ Welfare ($)	-32,024

Table 1.21: Price Discrimination with Respect to the Healthy Feature for Experiment: Tax on Regular Products in Market 1

Average Price Difference ($)	0.0352
$\boldsymbol{PD_1}$ **($)**	0.0015
$\boldsymbol{PD_2}$ **($)**	-0.0001
$\boldsymbol{PD}$ **($)**	0.0016

Note: The calculation is based on 40 UPC-market observations (5 healthy and 35 regular) from market1.

Table 1.22: Summary Statistics of Counterfactual Prices from the Uniform Income Experiment

	Healthy		**Regular**		**Overall**	
	$\boldsymbol{p^{obs}}$	$\boldsymbol{p^{CF}=p^{c}}$	$\boldsymbol{p^{obs}}$	$\boldsymbol{p^{CF}}$	$\boldsymbol{p^{obs}}$	$\boldsymbol{p^{CF}}$
Mean ($)	0.0760	0.0732	0.0409	0.0409	0.0453	0.0449
Std.	0.04	0.04	0.02	0.04	0.03	0.03
Median ($)	0.0728	0.0688	0.0338	0.0338	0.0349	0.0351
Min. ($)	0.0340	0.0321	0.0188	0.0189	0.0188	0.0189
Max. ($)	0.1343	0.1315	0.1307	0.1285	0.1343	0.1315
#obs.	5		35		40	

Table 1.23: Summary Statistics of Counterfactual Quantities from the Uniform Income Experiment

	Healthy (oz.)		Regular (oz.)		Overall	
	Observed	**Counter-factual**	**Observed**	**Counter-factual**	**Observed**	**Counter-factual**
Mean	7,162	1,699	77,632	78,165	68,823	68,607
Std.	8,687	2,822	141,260	143,042	134,018	135,995
Median	2,580	69	23,184	23,369	20,237	19,711
Min.	160	0	286	17	160	0
Max.	20,902	6,535	752,664	761,511	752,664	761,511
#obs.	5		35		40	

Table 1.24: Price Discrimination with Respect to the Healthy Feature from the Uniform Income Experiment

Average Price Difference ($)	0.0323
PD_1 **($)**	-0.0014
PD_2 **($)**	-0.0007
PD **($)**	-0.0007

Note: The calculation is based on 40 UPC-market observations (5 healthy and 35 regular) from market1.

Table 1.25: Regression Results of Marginal Cost on Products Characteristics

Variable	**Estimates**
Healthy	0.0318
	(0.0006)
Size	-0.0464
	(0.0009)
MSA Dummy	Included
Quarter Dummy	Included
R squared	0.39
# obs.	13,553

Chapter 2

Market Competition and Price Discrimination: The Case of Ketchup

2.1 Introduction

Price discrimination is a practice firms often use to extract consumer surplus from high-valuation customers. Though its effect on total welfare can be either positive or negative, it usually benefits the producers at the cost of the consumers. Economists have long been interested in this phenomenon (e.g. chapter 3 of Tirole 1988, Stole 2007). One of the main issues in this literature is the relationship between market structure and the ability or the incentives of firms to practice price discrimination. The conventional wisdom is that a competitive firm cannot price discriminate because it is a price taker and a firm with market power can price discriminate as long as it can segment consumers.

However, both theoretical studies by Katz (1984), Borenstein (1985), Holmes (1989) and Dana (1998) and empirical studies by Shepard (1991) and Graddy (1995) show that price discrimination can exist in quite competitive markets. And more recently, Hernandez and Wiggins (2008), Yang and Ye (2008) and Dai, Liu and Serfes (2010) study second-degree price discrimination models where the relationship between market competition and price discrimination is positive and nonlinear, respectively, instead of negative. Finally, McAfee, Mialon and Mialon (2006) show that the same relationship can be either positive or negative using a third-degree price discrimination model. Hernandez (2011) explains the intuition for why price discrimination may actually increase when firms face more competition. In his model, when competition intensifies, the prices of both low- and high-quality products fall as firms have less market power, but the price of a low-quality product decreases proportionately more than that of a high-quality product, that is, firms compete more intensively for the low-valuation customers. This is because in his model, firms have to concede to high-valuation consumers higher informational rents when they purchase the high-quality product than when they purchase the low-quality product (so that they purchase the high-quality product). With increased competition, firms worry less about providing additional rents to high-valuation consumers as the rents they enjoy increase with competition. As a result, they cut price less for the high quality product.

Because theoretical studies do not produce a clear prediction, the relationship between market structure and price discrimination is fundamentally an empirical question. Several studies have examined this issue in different industries and the results are mixed. Busse and Rysman (2005) find that more competition leads to less price discrimination in the yellow pages advertising market. In contrast, Stavins (2001), Hernandez and Wiggins (2008), Asplund, Eriksson and Strand (2008) and Borzekowski, Thomadsen and Taragin (2009) find the relationship to be positive in the airline industry, the newspaper industry and the market for mailing lists. Finally, Clerides and Michis (2006) study the detergent market in six countries and find the relationship to be positive in some countries, while negative in others. Another strand of the literature examines the relationship between market structure and price dispersion with the assumption that price discrimination is the main driver of price dispersion. Again, the results are mixed. Borenstein and Rose (1994) find that more competition leads to more dispersion, while Gerardi and Shapiro (2009) and Dai et al. (2010) find the relationship to be negative and nonlinear, respectively. All of the three studies use data from the U.S. airline industry.

This paper offers another piece of empirical evidence on this important relationship. Specifically, using a two way fixed effects approach, I examine how the price discrimination ketchup producers practice against consumers of healthy ketchup products changes as market competition conditions change. Healthy food products such as organic food, reduced/low sugar food, reduced/low fat food and reduced/low salt food have become increasingly popular in the United States (Dimitri and Oberholtz 2009). They are marketed as higher quality alternatives to conventional foods and usually command a price premium over conventional foods (Thompson and Kidwell 1998). Recent experimental studies such as Lusk and Briggeman (2009), James, Rickard and Rossman (2009), Hu, Woods and Bastin (2009) and Dentoni, Tonsor, Calantone and Peterson (2009) also show that consumers are willing to pay more for healthy food products. However, to the best of my knowledge, to date, no one has examined how this price premium changes as market competition condition changes. In addition to examining the price discrimination with respect to the healthy feature, I also examine firms' price discrimination behavior with respect to the other important product feature, the package size.

Another contribution of this study comes from the data and the econometric model used. The dataset used is a panel dataset. This allows me to use a two-way fixed effects approach, which controls for both the product fixed effects which are invariant across different markets, as well as the firm and market interaction fixed effects, which are invariant across products by the same firm in the same market, in the regression analysis.[1] Examining price discrimination empirically has been a difficult task because price discrimination is defined as price-cost margins or markups between different products, while usually only price data are observed. Therefore, how credible the results of a study are depends on whether the researcher does a good job of controlling for cost factors in the regression analysis. The two-way fixed effects approach I use control for unobserved product, firm and market specific cost shifters, in addition to controlling for the observed ones. Therefore, my study is less likely to suffer from the omitted variable bias problem. None of the empirical price discrimination studies cited above employs such an approach.

The results indicate that price discrimination with respect to both the healthy feature and package size increases when competition intensifies in the ketchup market. The results are robust to different definitions of price discrimination and different measures of market competition. This implies that the change in market competition has effects on both price levels and the relative price structure of high- and low-quality ketchup products. These results are consistent with the theoretical implications of the Hernandez (2011) model.

The rest of the paper is organized as follow. Section two describes the data, while Section three details the empirical strategy. Results are presented and discussed in Section four and the final Section concludes.

[1]Note that the firm and market interaction fixed effects are more general than controlling for firm and market fixed effects individually.

2.2 Industry and Data

The US ketchup market is selected for analysis because of data availability. Healthy or organic fresh produce is the top selling category of healthy foods (Dimitri and Oberholtzer 2009). However, brand or firm level price and sales data for such products are simply not available. For the ketchup market, on the other hand, brand level price and sales scanner data are collected by marketing companies and are available to researchers.

Ketchup is a widely used condiment in the US, found in 97% of all kitchens, a showing matched only by salt, pepper, and sugar (Villas-Boas and Zhao 2005). It is mainly consumed with hot dogs, French fries, hamburgers, pasta and serves as seasoning when making sauces such as salsa and other food. Heinz is the leading firm whose market share remains stable around 60% in volume in recent years. Hunt's, a ConAgra Foods brand, is the second largest, accounting for about 16% of the market. The rest of the market is shared by Del Monte, private label products, and other local brands.

The business section of the annual reports of Heinz and ConAgra Foods provide a glimpse of the ketchup business ranging from procurement of inputs to retailing of outputs. Ketchup recipes are developed in individual company's research laboratories and experimental kitchens. Then, ingredients are procured, inspected and transported to factories. To hedge against the spot market price volatility, major ketchup producers usually sign futures contracts with farmers growing raw materials such as tomatoes, cucumbers and onions. Ingredients such as sugar and sweeteners (high fructose corn syrup, a major sugar substitute in most of Heinz and Hunt's products) are purchased from approved suppliers. In the factory, raw materials are manufactured into ketchup products using the following sequence of processes: sterilization, homogenization, chilling, freezing, pickling, drying, freeze drying, baking or extruding, bottling and labeling. Products are sold through their own sales organizations and through independent brokers, agents and distributors to chain, wholesale and other retailers. Wal-Mart is the number one customer of Heinz and ConAgra Foods, representing approximately 11% and 18% of the firms total sales in 2010.

2.2.1 Raw Data

The data set used in this paper is the Information Resources, Inc. (IRI)'s Marketing Dataset. The data set provides weekly sales information at the Universal Product Code (UPC) level for all ketchup products from 1,913 stores, which were randomly selected from 50 Metropolitan Statistical Areas (MSAs) across the US, for the year 2006. These stores include regional chain stores, local grocery stores and drug stores such as CVS and Rite aid. The aggregate sales of raw data represents about 6% of the US ketchup market[2].

Each observation in the raw data set summarizes the transactions for one UPC in one store during one week. In total, there are 1,167,980 such observations. For each observation, I have information on the number of units sold, total sales revenue and promotion and display activities. Using the reported information on promotion and display activities, I created two categorical variables, one for promotion and one for display, to describe the advertising intensity for each UPC in each store during each week. See Table 1 for detailed definitions of these two variables.

In addition, the raw data set provides product characteristics data on all UPCs. The reported characteristics include package size (in ounces), sugar content, flavor style, brand name and producer name. Table 2 lists all of the flavor styles and sugar content variations

[2]According to New York Times (1990), US ketchup market is a half billion industry. This is the only figure I can find about the market size of the US ketchup market. Annual ketchup sales in 2006 were $29.5 million.

that appear in the raw data set. I define healthy products to be those UPCs with flavor styles of organic, one carb and low carb and/or with sugar content of no sugar, low sugar, reduced sugar, sugar free, unsweetened, Splenda and low salt. With this criterion, 37 out of the 668 unique UPCs (including 565 private label UPCs) in the raw data set are healthy products and together they account for about 7.6% of the 1,167,980 observations in the raw data set.

2.2.2 Creating Variables

Using the raw data, I created the variables that can be classified into three groups: dependent variable, competition measure and control variables. They are described in the following sections below. Regressions include observations from only 8 MSAs because the computation is intensive and it is very time consuming to work with observations from all 50 MSAs. The 50 MSAs are grouped into 4 regions according to the US Census Bureau's Regions and Divisions Map[3]. Two MSAs (one big and one small) are selected from each region. Table 3 lists all the MSAs selected.

Dependent Variable

The dependent variable is the average unit price (price per ounce) for a UPC in a market.[4] The raw data set reports the number of units sold and sales revenue for each UPC in each store during each week. Therefore, to obtain the dependent variable, data aggregation is needed. The procedure used to obtain the dependent variable for one UPC in one market (a month and MSA combination) is as follows. First, week-store level dollar sales revenue for the UPC was deflated by the regional non-seasonally adjusted yearly CPI for all urban

[3] Available at http://www.census.gov/geo/www/us_regdiv.pdf.

[4] A market is defined as a month and MSA combination throught the entire article.

consumers from BLS so the revenue is in terms of 1982-1984 dollars. Next, the average unit price for the UPC in each store during each week was calculated by dividing the sales revenue of the UPC by the corresponding number of units sold (in ounces). Then, I computed the weighted average of the unit price for the UPC in each store across all weeks in the particular month. The weight used is $\frac{q_{sw}}{\sum\limits_{w=1}^{W} q_{sw}}$, where q_{sw} is the sales volume (in ounces) of the particular UPC in store s during week w, and W is the total number of weeks in the particular month. Finally, using the average unit prices of the UPC in each store during the particular month from the previous step, I computed the weighted average of the unit price for the UPC across all stores in the particular market (in the particular MSA during the particular month). The weight used has the same formula as the weight used in the previous step.

Competition Measure

The key explanatory variable in the regression analysis is the competition measure. I use the Herfindahl Hirschman Index (HHI). HHI is a well known measure of market concentration/competition. It ranges from $1/N$ to 1, where N is the number of firms in a market. When the HHI is smaller than 0.01 for a market, it indicates the market is highly competitive without dominant players. According to Section 5.3 of the 2010 US Department of Justice Merger Guidelines, when the HHI is below 0.15, the market is unconcentrated and an HHI between 0.15 and 0.25 and above 0.25 indicates the market is moderately concentrated and highly concentrated, respectively.[5] The HHI variable was constructed using the formula,

$$HHI_t = \sum_{i=1}^{N_t} s_{it}^2, \tag{2.1}$$

[5] The 2010 US Department of Justice Merger Guidelines is available at: http://www.justice.gov/atr/public/guidelines/hmg-2010.html

where s_{it} is the market share of firm i in market t and N_t is the number of firms in market t. The market share variable s_{it} was calculated as,

$$s_{it} = \frac{q_{it}}{Q_t} \tag{2.2}$$

where q_{it} is the total sales volume (in ounces) of ketchup products in market t by firm i and Q_t is the total sales volume in market t by all firms including the retailers who sell their own private labels.

Control Variables

Control variables include display level and promotion level. They are product market level variables. Both of them are likely to influence the price of a UPC in a market. Firms often offer low prices on those products that they are promoting and hence a product with a high display and/or promotion level often comes with a low price. In the raw data, the display and promotion information is available for each UPC in each store during each week. In regressions, I need those variables for each UPC at the market level. Hence, I aggregated them in the same way as the price variable described above.

2.2.3 Summary Statistics

Table 4 reports the summary statistics for the data that will be used in the regression analysis below. In total, there are 4,725 observations. The unit of observation is one UPC in one market. Since one market is a month and MSA combination and there are 8 MSAs, I have 96 markets (8*12) in total. In these 8 MSAs, there are 238 unique UPCs, including 70 non-private labels from 28 firms and 168 private labels from 30 retailers.

Among the 238 UPCs, 15 (9 non-private labels and 6 private labels) are healthy ones and together they account for 11% of the 4,725 observations. On average, the deflated unit price for a ketchup product is about 4 cents per ounce. The average unit price for a healthy product is 7.51 cents per ounce, which is 114% higher than the average unit price for a regular product. As for the market competition measure, the average HHI value is 0.43, indicating the ketchup market is a fairly concentrated market. This is consistent with the fact that this industry is dominated by the three main players: Heinz, Hunt's and Del Monte.

2.3 Empirical Strategy

The main objective of this paper is to examine how a firm's price discrimination strategy with respect to the healthy feature changes as market competition condition changes. To do so, I first need to define price discrimination. In the literature, there are multiple definitions of price discrimination. Some define price discrimination as differences in price-cost margins (price cost differences) (e.g. Tirole 1988), while others define it as differences in price-cost markups (price cost ratio) (e.g. Varian 1989). Clerides (2004) shows that the two definitions are qualitatively different as the two definitions can lead to opposite conclusions and recommends empirical studies to report results with both measures. The two definitions also have different implications for empirical specifications, to which I now turn.

2.3.1 Differences in Price-Cost Margins

Suppose two products are produced by the same firm and have exactly the same product characteristics except one product is healthy and the other one is regular. The two products are sold in two markets. The two markets are also identical to each other (e.g.

relative demand preference for healthy versus regular products) except that competition is more intense in one market than the other. Denote the healthy product as product h, the regular product as product r, the market with less competition as market m (stands for monopoly) and the market with more competition as market d (stands for duopoly). When price discrimination is defined as differences in price-cost margins, the relationship one is interested in testing is

$$[P_m(h) - C_m(h)] - [P_m(r) - C_m(r)] \gtreqless [P_d(h) - C_d(h)] - [P_d(r) - C_d(r)]\,, \tag{2.3}$$

where $P_m(h)$ denotes the price of product h the firm charges in market m and $C_m(h)$ denotes the marginal cost for the firm to supply product h to market m. Other price and cost terms are similarly defined. Here, I assume implicitly that supermarkets or retailers play a passive role in the pricing decision and firms set retail prices directly. This is equivalent to assuming that retailing cost and retailers' mark-up are constant and part of marketing expenses of the firm. This assumption is often used in the literature (e.g. Hausman and Leonard 2002; Nevo 2001) on modeling market power or price competition using scanner data.

If I further assume that the cost differences for the firm to supply healthy and regular products to different markets are the same, that is,

$$C_m(h) - C_m(r) = C_d(h) - C_d(r), \tag{2.4}$$

then (2.3) is reduced to be

$$[P_m(h) - P_m(r)] \gtreqless [P_d(h) - P_d(r)]\,. \tag{2.5}$$

The cost for the firm to supply products to markets mainly consists of three parts: production cost, transportation cost and marketing cost. Hence, (2.4) can be re-written as

$$\begin{aligned} & C_m^p(h) + C_m^t(h) + C_m^m(h) - C_m^p(r) - C_m^t(r) - C_m^m(r) \\ = \; & C_d^p(h) + C_d^t(h) + C_d^m(h) - C_d^p(r) - C_d^t(r) - C_d^m(r), \end{aligned} \tag{2.6}$$

where the superscripts p, t and m denote production cost, transportation cost and marketing cost, respectively. The production costs for the firm to supply the same products to markets with different competition conditions are the same if the products are produced in the same manufacturing plant, that is,

$$C_m^p(h) = C_d^p(h) \text{ and } C_m^p(r) = C_d^p(r). \tag{2.7}$$

The transportation costs for the firm to supply different products to the same market are the same as the same distance is travelled, that is,

$$C_m^t(h) = C_m^t(r) \text{ and } C_d^t(h) = C_d^t(r). \tag{2.8}$$

With (2.7) and (2.8), assumption (2.6) is reduced to :

$$C_m^m(h) - C_m^m(r) = C_d^m(h) - C_d^m(r), \tag{2.9}$$

that is, the firm's marketing cost differences for healthy and regular products in markets with different competition conditions are the same.

With these assumptions, testing (2.3) is reduced to testing (2.5), which can be conducted by running the following regression,

$$price_{jit} = \beta_0 + \beta_1 Healthy_{ji} + \beta_2 HHI_t + \beta_3 (Healthy_{ji} \times HHI_t) + \varepsilon_{jit}, \tag{2.10}$$

where $price_{jit}$ is the price of UPC j produced by firm i in market t. $Healthy_{ji}$ is a dummy variable indicating whether the product is healthy or not. HHI_t is the HHI value for market t, which describes the competition intensity of the market and ε_{jit} is an error term. The coefficient β_1 represents the price premium healthy products enjoy over regular products and β_3, the key parameter of interest, tells us how this price premium varies as market competition condition changes.

The observations in the sample, however, are from products that differ from one another in many dimensions other than the healthy feature and from markets that differ from one another in many dimensions other than the competition condition. In this case, more variables need to be added to the right hand side of (2.10) to control for such differences so that the resulting estimate for β_3 is not confounded by other factors. Therefore, I estimate the following regression,

$$\begin{aligned} price_{jit} \quad = \quad & \beta_0 + \beta_1 Healthy_{ji} + \beta_2 HHI_t + \beta_3 (Healthy_{ji} \times HHI_t) + \beta_4 MarketShare_{it} \\ & + \beta_5 Display_{jit} + \beta_6 promotion_{jit} + \beta_7 size_{ji} + \beta_8 \left(size_{ji} \times HHI_t \right) \\ & + \eta_{ji} + v_{it} + \varepsilon_{jit}. \end{aligned} \tag{2.11}$$

Here, the market share, display, promotion and size variables control for observed differences in product characteristics other than the healthy feature. η_{ji} controls for the unobserved differences in product characteristics. v_{it} controls for differences in market conditions other than the competition condition. The control for differences in market conditions also makes assumptions (2.4) and (2.9) more likely to hold. One factor I don't have data to control for is the coupons issued by the firms. IRI price data does not take into account coupons issued by firms. If firms issue more coupons in a more competitive market to promote its healthy products than in a market with less competition, but issue similar amount of coupons for regular products in the two markets, then assumption (2.9) is likely to be violated.

(2.11) is essentially a panel data regression model with unobserved UPC and market heterogeneity. Following Wooldridge (2002), I use the following dummy variable estimator,

$$\begin{aligned} price_{jit} &= \beta_0 + \beta_3(Healthy_{ji} \times HHI_t) + \beta_5 Display_{jit} + \beta_6 promotion_{jit} \\ &\quad + \beta_8 \left(size_{ji} \times HHI_t\right) + UPCDummy + FirmMarketDummy \\ &\quad + \varepsilon_{jit}. \end{aligned} \tag{2.12}$$

Once the UPC dummy is controlled for, $Healthy_{ji}$, $size_{ji}$ and η_{ji} are dropped from the regression to avoid multicollinearity. For the same reason, once the firm-market dummy is controlled for, HHI_t, $MarketShare_{it}$ and v_{it} are dropped from the regression. It is worth noting that with the dummy variable regression (2.12), the estimates for the coefficients for the UPC and firm-market dummy variables are unbiased but inconsistent. However, estimates for other parameters in the model including the key parameter of interest, β_3, remain to be consistent.

2.3.2 Differences in Price-Cost Markups

When price discrimination is defined as differences in price-cost markups, the relationship I am interested in testing becomes

$$\frac{\frac{P_m(h)}{C_m(h)}}{\frac{P_m(r)}{C_m(r)}} \gtreqless \frac{\frac{P_d(h)}{C_d(h)}}{\frac{P_d(r)}{C_d(r)}} \tag{2.13}$$

and assumption (2.4) becomes

$$\frac{C_m(h)}{C_m(r)} = \frac{C_d(h)}{C_d(r)}. \tag{2.14}$$

With (2.14), (2.13) is reduced to be

$$\frac{P_m(h)}{P_m(r)} \gtreqless \frac{P_d(h)}{P_d(r)}, \tag{2.15}$$

or equivalently,

$$[\log P_m(h) - \log P_m(r)] \gtreqless [\log P_d(h) - \log P_d(r)]\,. \tag{2.16}$$

Equation (2.16) implies that when price discrimination is defined as differences in price-cost markups, the dependent variable used in regression analysis should be the logarithm of price variable rather than the price variable itself. Therefore, in this case, I estimate the following regression instead of (2.12),

$$\begin{aligned} \log(price_{jit}) \quad = \quad & \beta_0 + \beta_3(Healthy_{ji} \times HHI_t) + \beta_5 Display_{jit} + \beta_6 promotion_{jit} \\ & + \beta_8\,(size_{ji} \times HHI_t) + UPCDummy + FirmMarketDummy \\ & + \varepsilon_{jit}. \end{aligned} \tag{2.17}$$

2.3.3 Identification

In both (2.11) and (2.17), the market competition measure HHI_t and the HHI and healthy and size interaction variables are likely to be endogenous. This is because by definition, the HHI is a function of market shares, including the producer's own market share in the market. The producer's own market share is likely to be endogenous, that is, the producer's market share is likely to be correlated with the error term in the regressions. For example, the error term may capture demand influencing factors (e.g. advertising campaigns) that are important to consumers in the market but are unobserved to the econometrician. These unobserved demand factors influence both the sales of the product and hence the firm's market share and the price of the product at the same time.

I use the instrumental variable (IV) regression method to correct for the potential endogeneity bias. As the source of the endogeneity problem in the regressions is the fact that the producer's own market share is endogenous, I construct an IV for this variable first and then use this IV to further construct IVs for the HHI and healthy and size interaction variables in the regressions. Specifically, I use the firm's average market share in other MSAs among 50 MSAs in the same month as the instrument for firm's own market share in the market under consideration. A good IV has to satisfy two conditions. First, it needs to be correlated with the endogenous variable and second, it needs to be uncorrelated with the error term in the regression. A firm's market share in one MSA is likely to be highly correlated with its average market share in other MSAs in the same month. This is driven by the fact that if consumers in one market like certain products of a firm, consumers in other markets are likely to have the same preference.

Also, the second condition is satisfied if the unobserved demand factors are MSA specific and are not correlated across different MSAs. This is because if the unobserved demand factors are MSA specific, then the firm's average market share in other MSAs is determined by unobserved demand factors in other MSAs and hence this variable is uncorrelated with the unobserved demand factors in this MSA, that is, the error term in the regressions. Of course, this is an assumption and it is likely to be violated if the firm launches a national advertising campaign which involve such as a TV advertising campaign and issuing coupons. Those activities are not captured by the display and promotion variables in my regressions.

Using the average market share in other MSAs, I then constructed an IV for the HHI variable, called $IV2$, following Borenstein (1989) and Borenstein and Rose(1994), as follows,

$$IV2_{it} = \hat{s}_{it}^2 + \sum_{j \neq i} \hat{s}_{jt}^2. \tag{2.18}$$

From (2.1) and (2.18), it is clear that $IV2_{it}$ takes the same form as HHI_t, with the only difference that s_{it} and s_{jt}s are replaced with $\hat{s}_{it}$ and$\hat{s}_{jt}$s. $\hat{s}_{it}$ is the fitted value of the market share variable obtained from a first stage regression. In this first stage regression, the firm's market share was regressed on firm's average market share in other MSAs, that is, the instrument for the market share variable, and firm, month and MSA dummies. $\hat{s}_{jt}$ is constructed as follows,

$$\hat{s}_{jt} = s_{jt} \frac{1 - \hat{s}_{it}}{1 - s_{it}}, \tag{2.19}$$

such that the adjusted market shares still sum to 1, that is, $\hat{s}_{it} + \sum_{j \neq i} \hat{s}_{jt} = 1$.[6] Since $IV2_{it}$ takes the same form as HHI_t, $IV2$ is correlated with the HHI variable by construction. $IV2$ is uncorrelated with the error term in the regressions as long as the unobserved demand factors ε_{jit} is uncorrelated with $\hat{s}_{it}$ and $\hat{s}_{jt}$s. As $\hat{s}_{it}$ is the predicted value of

[6]Plugging (2.19) into (2.18) yields $IV2_{it} = \hat{s}_{it}^2 + \frac{HHI_t - s_{it}^2}{(1-s_{it})^2}(1 - \hat{s}_{it})^2$, which is the formula used in Borenstein (1989) and Borenstein and Rose(1994).

s_{it} from a regression of it on the instrumental variable and other control variables, it is uncorrelated with ε_{jit} by construction. ε_{jit} being uncorrelated with $\hat{s}_{jt}$s, on the other hand, is an assumption. This essentially assumes that unobserved demand factors and hence the firm's pricing strategies for its own products in a market do not affect the allocation of consumers it doesn't get among its competitors, that is, s_{jt}s.

2.4 Results

Table 5 collects estimation results. The first two columns present the results from the price level regression (2.12) and the third and fourth columns present the results from the log price regression (2.17). All reported standard errors are robust and clustered by firm-market combination, which means I allow the errors for observations within the same market by the same firm to have arbitrary correlations. Each specification is estimated using both the ordinary least squares (OLS) approach, which ignores the potential endogeneity bias from the HHI and healthy and size interaction variables, and the two-stage least squares (2SLS) instrumental variable approach, which corrects for the potential endogeneity bias. Table 6 reports the first stage regression results of 2SLS. In addition, in both (2.12) and (2.17), I use the UPC dummy to control for $Healthy_{ji}$, $size_{ji}$ and η_{ji} variables in the regressions, that is,

$$UPC_{ji} = \beta_1 Healthy_{ji} + \beta_7 size_{ji} + \eta_{ji}. \tag{2.20}$$

Using the estimated coefficients for the UPC dummy variables, I also estimate (2.20). Table 7 reports results from this regression. As discussed above, the estimated coefficients for the UPC dummy variables are inconsistent but unbiased estimates of the UPC fixed effects. As a result, estimates for β_1 and β_7 might be biased.

As the results from OLS and 2SLS are quite similar, I focus my discussion on 2SLS results. In the price level regression, all the coefficients are significant at the 1% level. The results show that the price for healthy products decreases with market concentration and the price for products in larger containers increases with market concentration. From Table 7, it is clear that healthy products enjoy a price premium and products in larger containers are cheaper. Together, these results imply that both the price premium for healthy products and the discount for products in larger containers decrease with market concentration and hence I can conclude price discrimination increases with market competition in this market. This implies that as the market becomes more competitive, both price levels of high- and low-quality products and the relative price structure of high- to low-quality products change. This is consistent with the prediction of the Hernandez (2011) model. In terms of magnitude, the estimated effects are also nontrivial. For example, the price level regression results show that healthy products enjoy a price premium of 1.68 cents per ounce, which is about 47.86% of the average unit price for regular products. When the HHI value in the market decreases by 0.1, the premium increases by about 0.21 cents per ounce, which is about 5.25% of the difference between the average unit price for healthy products and the average unit price for regular products. The log price regression results are almost identical with the only exception that the estimate for the coefficient on the healthy-HHI interaction variable is statistically insignificant.

Some other results are also worth discussing. First, both the Angrist and Pischke (2009) and Kleibergen and Paap (2006) tests reject the hypotheses that the IV regression is either unidentified or weakly identified. This indicates that the chosen instruments are highly correlated with the endogenous variables, satisfying the first condition for the instruments to be good-quality instruments. Second, the adjusted R^2 in the main regression is 0.96 for both the price level regression and the log price regression, indicating I have included the most important variables affecting ketchup price in my regression analysis. Third, products on display or being promoted are sold for a lower unit price. This is consistent with our daily observation that products on promotion and display in supermarkets often come with a lower price. Finally, comparing the OLS and 2SLS results show that OLS overestimates the effect of the healthy-HHI variable on price and underestimates the effect of the size-HHI variable. This indicates the error term is positively correlated with the healthy-HHI variable and negatively correlated with the size-HHI variable. As both healthy and small package size products are more expensive, they can be considered as higher quality products. The results here basically imply the error term is positively correlated with the interaction variable between an observed quality variable and the HHI variable. Also, by construction, the error term is uncorrelated with the observed quality variables. These two facts confirm HHI is correlated with the error term, which is the reason for the IV regressions.

2.4.1 Robustness Checks

The analysis so far uses the HHI as the measure for market competition. There are also other widely used competition measures. One of them is concentration ratio, with top-4 firm and top-8 firm concentration ratios being the most widely used ones. As there are only three major firms in the ketchup market, I use the top-2 firm concentration ratio ($s_{1t} + s_{2t}$, the sum of market shares for the top-2 firms in market t) as an alternative measure for market competition. The corresponding IV is $\hat{s}_{1t} + \hat{s}_{2t}$, where $\hat{s}_{1t}$ and $\hat{s}_{2t}$ are available from the first stage regression in the process of creating the $IV2_{it}$ variable above. Results using this alternative competition measure are reported in Tables 8–10.

Results are identical, both in terms of statistical significance and the sign of the coefficient estimates, to the results in Tables 5–7, where HHI is used as the competition measure.

Also, so far, price discrimination is specified to be a parametric and linear function of the market competition variable. Recently, Dai, Liu and Serfes (2010) show that market competition has a non-monotone (non-linear) effect on price dispersion. This result could be driven by the fact that the effect of market competition on price discrimination is nonlinear. To consider this possibility, instead of using the HHI variable as a continuous variable, I use a set of HHI quartile dummy variables to measure market competition. I create 4 dummy variables, one for each quartile. For each dummy variable, the variable equals 1 if the HHI value falls into the corresponding quartile. The four quartiles are [0.24, 0.31); [0.31, 0.48); [0.48, 0.56) and [0.56, 0.72]. The dummy variable for the first quartile is omitted to avoid multicollinearity problem. Correspondingly, I also replace the $IV2_{it}$ with its quartile dummy variables. Using quartile dummies can be thought as a less parametric approach to specify the relationship between price discrimination and market competition.

Results are collected in Tables 8–11. Again, I focus on the 2SLS results. The price level regression results show that indeed, the relationship between price discrimination and market competition is nonlinear. For the price discrimination with respect to the healthy feature, as the HHI in the market increases from the first quartile to the fourth quartile, the price premium first decreases for 2.68 cents per ounce, then increases for 2.01 cents per ounce (2.68-0.67=2.01) and then finally decreases for another 1.09 cents per ounce (1.76-0.67=1.09). For the price discrimination with respect to package size, as the HHI in the market increases from the first quartile to the fourth quartile, the price discount first decreases for 0.0004 cents per ounce, then decreases for 0.0159 cents per ounce (0.0163-0.0004=0.0159) and then finally increases for another 0.0062 cents per ounce

(0.0163-0.0101=0.0062). The log price regression results show the same pattern. Though results here show the relationship between price discrimination and market competition is non-monotone, the results also show that when the HHI in a market increases from the first quartile to any of the other three quartiles, price discrimination is less. This is consistent with my main conclusion, that is, price discrimination increases when the market competition intensifies.

2.5 Conclusions

This paper empirically examines the relationship between market competition and a firm's price discrimination strategy in the U.S. ketchup industry. Price discrimination is defined in terms of both the difference in price-cost margins and the difference in price-cost markups. Competition is measured by the Herfindahl Hirschman Index (HHI) or top-2 firm concentration ratio. After correcting the potential endogeneity bias arising from the market competition variables, results show that as the market becomes more competitive, price discrimination with respect to both the healthy feature and package size increases.

Though the results are consistent with the implications of recent theoretical models, it is important to bear in mind that the results were obtained under several assumptions. One of the assumptions is that firm's marketing cost differences for different products in markets with different competition conditions are the same. Though using a two-way fixed effects approach and controlling for marketing variables like display and promotion make this assumption more likely to hold, it is still an assumption. With more detailed data on firm's marketing costs of different products in different markets, one can relax this assumption and obtain more precise results on the relationship between price discrimination and market competition condition. This is left for future research.

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Table 2.1: Definitions of Promotion and Display Variables

Values	Display	Promotion
0	No Display	No Promotion
1	Minor Display	Small advertisement, usually 1 line of text
2	Major Display (This includes displaying at lobby and end-aisle)	Medium size advertisement
3	NA	Large size advertisement
4	NA	Issue retailer coupon or rebate

Note: The raw data doesn't provide more detailed information of these definitions. For example, it doesn't provide the definition of medium size advertisement.

Table 2.2: Sugar Content and Flavor Style Variations

Sugar Content		Flavor Style		
3 GR/4GR	No Sugar	All Natural	From Concentrate	One Carb
Fructose	Reduced Sugar	Cajun	Gourmet	Organic
Fruit Sweetened	Regular	California Style	Grade A Fancy	Premium
Honey Sweetened	Splenda	Classic	Kosher	Regular
Low Sugar	Sugar Free	Country Style	Low Carb	Rich and Tangy
Natural Sweetened	Unsweetened	Fancy	Southwestern	Salsa
		Southern	Old Fashioned	

Note: IRI data set doesn't provide more specific explanations on terms such as premium, classic and fancy.

Table 2.3: Lists of MSAs included in Regressions

Northeast	South	West	Midwest
New York, NY	Knoxville, TN	Los Angeles, CA	Chicago, IL
Pittsfield, MA	Washington DC	Spokane, WA	Eau Claire, WI

Table 2.4: Summary Statistics

Variable	Mean	Std	Min	Median	Max	# of Unique Obs.
Price (cent/oz.)	3.96	2.80	0.56	3.03	25.43	4,725
--- Healthy (cent/oz.)	7.51	3.49	1.67	6.95	20.40	532
--- Regular (cent/oz.)	3.51	2.35	0.56	2.87	25.43	4,193
Healthy	0.06	0.24	0	0	1	238
Size (oz.)	35.06	22.05	5	24	132	238
Competition Measure:						
HHI	0.43	0.12	0.24	0.45	0.72	96
Control Variables:						
Display	0.14	0.33	0	0	2.00	4,725
Promotion	0.18	0.46	0	0	3.10	4,725
Instrumental Variables:						
Avg. Market Share (%)	8.29	0.15	0.0005	3.03	59.79	1,157
IV2	0.44	0.11	0.22	0.46	0.71	1,157

Table 2.5: Regression Results

Variables	Dependent Variables			
	Price		Log(price)	
	OLS	**2SLS**	**OLS**	**2SLS**
Healthy* HHI	-1.7198***	-2.1028***	-0.0447	-0.0575
	(0.3771)	(0.5736)	(0.0272)	(0.0413)
Size* HHI	0.0139***	0.0278***	0.0007	0.0018***
	(0.0053)	(0.0062)	(0.0005)	(0.0006)
Display	-0.2171***	-0.2238***	-0.0357***	-0.0362***
	(0.0343)	(0.0347)	(0.0041)	(0.0041)
Promotion	-0.2750***	-0.2758***	-0.0458***	-0.0458***
	(0.0288)	(0.0291)	(0.0035)	(0.0035)
Constant	11.3562***	11.2685***	1.0521***	1.0472***
	(0.2348)	(0.2351)	(0.0117)	(0.0120)
OLS/2SLS 2nd stage Adj.$\boldsymbol{R^2}$	0.96	0.96	0.96	0.96
Instruments	---	Healthy*IV2, Size*IV2	---	Healthy*IV2, Size*IV2
Under identification test				
Kleibergen-Paap rk LM statistic	---	59.86 Chi-sq(1) P-val=0.0000	---	59.86 Chi-sq(1) P-val=0.0000
Weak identification test				
Kleibergen-Paap rk Wald F statistic	---	165.20	---	165.20
# observations	4,725			

Note: Values in parentheses are standard errors, which are robust and clustered by firm-market combination. All regressions include UPC dummies and market dummies, where market is a month MSA combination. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

Table 2.6: First Stage of 2SLS Regression Results

	Dependent Variables	
Variables	**Healthy* HHI**	**Size*HHI**
Healthy*IV2	1.5002***	-4.3009***
	(0.0594)	(0.5923)
Size*IV2	-0.0006**	1.3343***
	(0.0003)	(0.0735)
Display	-0.0032***	0.0980
	(0.0011)	(0.0997)
Promotion	-0.0011*	-0.0269
	(0.0006)	(0.0378)
Constant	0.0029	-2.6054***
	(0.0063)	(0.3322)
Adj.$\boldsymbol{R^2}$	0.99	0.99
Angrist-Pischke multivariate F test of excluded instruments	F(1, 95) = 653.11 P-value= 0.0000	F(1, 95) = 330.11 P-value= 0.0000
# observations	4,725	

Note: Values in parentheses are standard errors, which are robust and clustered by firm-market combination. All regressions include UPC dummies and market dummies, where market is a month MSA combination. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

Table 2.7: UPC Regression Results

	Dependent Variables			
	UPC dummy Coefficients from OLS regressions for price	**UPC dummy Coefficients from IV regressions for price**	**UPC dummy Coefficients from OLS regressions for log price**	**UPC dummy Coefficients from IV regressions for log price**
Healthy	1.5137***	1.6814***	0 .0548*	0.0604**
	(0 .2584)	(0.2593)	(0 .0294)	(0.0294)
Size	-0.0277***	-0.0335***	-0.0034***	-0.0039***
	(0.0026)	(0.0026)	(.0003)	(0.0003)
Constant	-1.8972**	-1.8157**	-0.0367	-0.0307
	(0 .8307)	(0.8336)	(0 .0946)	(0.0945)
Adj.$\boldsymbol{R^2}$	0.96	0.95	0.89	0.87
# observations	238			

Note: Values in parentheses are standard errors. All regressions include firm dummy variables. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

Table 2.8: Robustness Check: Regression Results using C_2 index as Competition Measure

	Dependent Variables			
	Price		Log(price)	
Variables	**OLS**	**2SLS**	**OLS**	**2SLS**
Healthy* C_2	-1.2490**	-1.9899***	0.0145	-0.0260
	(0.5044)	(0 .5863)	(0.0345)	(0.0367)
Size*C_2	0.0275***	0.0291***	0.0022***	0.0022***
	(0.0051)	(0.0068)	(0.0005)	(0.0007)
Display	-0.2155***	-0.2170***	-0.0358***	-0.0359***
	(0.0344)	(0 .0345)	(0.0041)	(0.0041)
Promotion	-0.2718***	-0.2731***	-0.0455***	-0.0456***
	(0.0292)	(0.0292)	(0.0036)	(0.0035)
Constant	11.2273***	5.0568***	1.0436***	0.6652***
	(0.2327)	(0.3431)	(0.0121)	(0.0164)
OLS/2SLS 2nd stage Adj.R^2	0.96	0.96	0.96	0.96
Instruments	---	Healthy*IV_{C_2}, Size*IV_{C_2}	---	Healthy*IV_{C_2}, Size*IV_{C_2}
Under identification test				
Kleibergen-Paap rk LM statistic	---	48.58 Chi-sq(1) P-val=0.0000	---	48.58 Chi-sq(1) P-val=0.0000
Weak identification test				
Kleibergen-Paap rk Wald F statistic	---	112.75	---	112.75
# observations	4,725			

Note: Values in parentheses are standard errors, which are robust and clustered by firm-market combination. All regressions include UPC dummies and market dummies, where market is a month MSA combination. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

Table 2.9: First Stage of 2SLS Regression Results using C_2 index as Competition Measure

	Dependent Variables	
Variables	**Healthy* C_2**	**Size*C_2**
Healthy*IV_{C_2}	0.8903***	-1.6633***
	(0 .0517)	(0 .3580)
Size* IV_{C_2}	0.0001	0.7833***
	(0 .0001)	(0.0522)
Display	0.0003	0.0935*
	(0 .0007)	(0 .0501)
Promotion	-0.0005	-0.0244
	(0 .0004)	(0 .0430)
Constant	-0.0512***	0.5469
	0 .0074	(0 .4265)
Adj.R^2	0.99	0.99
Angrist-Pischke multivariate F test of excluded instruments	F(1, 95) = 296.33 P-value= 0.0000	F(1, 95) = 225.74 P-value= 0.0000
# observations	4,725	

Note: Values in parentheses are standard errors, which are robust and clustered by firm-market combination. All regressions include UPC dummies and market dummies, where market is a month MSA combination. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

Table 2.10: UPC Regression Results using C_2index as Competition Measure

	Dependent Variables			
	UPC dummy Coefficients from OLS regressions for price	**UPC dummy Coefficients from IV regressions for price**	**UPC dummy Coefficients from OLS regressions for log price**	**UPC dummy Coefficients from IV regressions for log price**
Healthy	1.7324***	2.3114***	0.0237	0.0554*
	(0.2576)	(0.2579)	(0.0293)	(0.0294)
Size	-0.0431***	-0.0443***	-0.0048***	-0.0048***
	(0.0026)	(0.0026)	(0.0003)	(0.0003)
Constant	-1.7218**	-1.7050**	-0.0181	-0.0183
	(0.8283)	(0.8288)	(0.0945)	(0.0945)
Adj.$\boldsymbol{R^2}$	0.97	0.94	0.91	0.86
# observations		238		

Note: Values in parentheses are standard errors. All regressions include firm dummy variables. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

Table 2.11: Robustness Check: Regression Results using HHI dummy as Competition Measure

	Dependent Variables			
	Price		Log(price)	
Variables	OLS	2SLS	OLS	2SLS
Healthy* HHI_Dummy1[1]	0.0204 (0 .1041)	-2.6801** (1.1144)	0.0100 (0.0069)	-0.1359** (0.0677)
Healthy* HHI_Dummy2	-0.1534 (0.1386)	-0.6762 (0.5006)	0.0099 (0.0092)	0.0058 (0.0315)
Healthy* HHI_Dummy3	-0.4944*** (0.1193)	-1.7633*** (0.4825)	-0.0142* (0.0084)	-0.0811*** (0.0302)
Size* HHI1_Dummy1	0.0019 (0.0014)	0.0004 (0.0064)	0.0002* (0.0001)	0.0007 (0.0007)
Size* HHI_Dummy2	0.0054*** (0.0015)	0.0163*** (0.0037)	0.0004*** (0.0001)	0.0017*** (0.0004)
Size* HHI_Dummy3	0.0046*** (0.0015)	0.0101*** (0.0035)	0.0003* (0.0002)	0.0011*** (0.0004)
Display	-0.2176*** (0.0340)	-0.2372*** (0.0355)	-0.0359*** (0.0041)	-0.0378*** (0.0041)
Promotion	-0.2738*** (0.0291)	-0.2822*** (0.0296)	-0.0457*** (0.0035)	-0.0461*** (0.0036)
Constant	5.3583*** (0.3357)	10.8903*** (0.2745)	0.6845*** (0.0156)	1.0349*** (0.0166)
OLS/2SLS 2nd stage Adj.$\boldsymbol{R^2}$	0.96	0.95	0.96	0.95
Instruments	---	Healthy*IV2_Dummy1[2] Healthy*IV2_Dummy2 Healthy*IV2_Dummy3 Size*IV2_Dummy1 Size*IV2_Dummy2 Size*IV2_Dummy3	---	Healthy*IV2_Dummy1 Healthy*IV2_Dummy2 Healthy*IV2_Dummy3 Size*IV2_Dummy1 Size*IV2_Dummy2 Size*IV2_Dummy3
Under identification test Kleibergen-Paap rk LM statistic	---	8.777 Chi-sq(1) P-val= 0.0031	---	8.777 Chi-sq(1) P-val=0.0031
Weak identification test Kleibergen-Paap rk Wald F statistic	---	1.319	---	1.319
# observations	4,725			

Note: 1. HHI_Dummy1=1 if HHI$\in[0.31, 0.48)$; HHI_Dummy2=1 if HHI$\in[0.48, 0.56)$; HHI_Dummy3=1 if HHI$\in[0.56, 0.72]$.
2. IV2_Dummy1=1 if IV2$\in[0.34, 0.46)$; IV2_Dummy2=1 if IV2$\in[0.46, 0.53)$; IV2_Dummy3=1 if HHI$\in[0.53, 0.71]$. Values in parentheses are standard errors, which are robust and clustered by firm-market combination. All regressions include UPC dummies and market dummies, where market is a month MSA combination. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

Table 2.12: First Stage of 2SLS Regression Results using HHI dummy as Competition Measure

	Dependent Variables					
Variables	**Healthy* HHI_ Dummy1[1]**	**Healthy* HHI_ Dummy2**	**Healthy* HHI_ Dummy3**	**Size* HHI_ Dummy1**	**Size* HHI_ Dummy2**	**Size* HHI_ Dummy3**
Healthy_IV2_ Dummy**1[2]**	0.1576 (0 .1032)	0.2513*** (0.0527)	0.1760*** (0.0427)	1.6218 (1.2696)	-0.8686 (0 .5760)	-1.0842* (0 .5530)
Healthy_IV2_ Dummy2	-0.1133 (0.1063)	0.5234*** (0.1166)	0.3861*** (0.1170)	0.8863 (1.1568)	-1.8421 (1.3297)	-0.8436 (1.2443)
Healthy_IV2_ Dummy3	-0.1942** (0.0949)	-0.0417 (0.1005)	1.0283*** (0.1057)	1.0437 (0.9857)	0.7203 (1.6677)	-3.0569* (1.7149)
Size_IV2_ Dummy1	0.0004 (0.0002)	0.0001 (0.0001)	-0.0002** (0.0001)	0.1584* (0.0847)	0.1746*** (0 .0410)	0.1482*** (0 .0370)
Size_IV2_ Dummy2	0.0003 (0.0004)	-0.0006 (0.0005)	0.0002 (0.0004)	-0.1055 (0.1084)	0.4418*** (0.1115)	0.3224*** (0 .1018)
Size_IV2_ Dummy3	0.0002 (0.0003)	-0.0001 (0.0006)	0.00003 (0.0005)	-0.2145** (0.0881)	0.0967 (0.1458)	0.7830*** (0 .1451)
Display	0.0004 (0.0056)	0.0026 (0.0057)	-0.0135** (0.0052)	0.2751 (0.4621)	0.4245 (0.5538)	0.6193 (0 .4840)
Promotion	0.0004 (0.0042)	0.0019 (0.0036)	-0.0061* (0.0032)	0.1051 (0.2921)	-0.3657 (0.2974)	0 .1283 (0.2357)
Constant	-0.1585*** (0.0470)	-0.1362*** (0.0416)	-0.0240 (0.0301)	-2.0166*** (0.5894)	-1.8707*** (0.5451)	-1.4636*** (0.4666)
Adj.$\boldsymbol{R^2}$	0.53	0.57	0.66	0.82	0.82	0.84
Angrist-Pischke multivariate F test of excluded instruments	F(1, 95) = 8.58 P-value= 0.0043	F(1, 95) = 26.99 P-value= 0.0000	F(1,95)= 112.13 P-value= 0.0000	F(1, 95) =10.10 P-value= 0.0020	F(1, 95) =27.16 P-value= 0.0000	F(1, 95) =42.93 P-value= 0.0000
# observations	4,725					

Note: 1. HHI_Dummy1=1 if HHI$\in[0.31, 0.48)$; HHI_Dummy2=1 if HHI$\in[0.48, 0.56)$; HHI_Dummy3=1 if HHI$\in[0.56, 0.72]$.
2. IV2_Dummy1=1 if IV2$\in[0.34, 0.46)$; IV2_Dummy2=1 if IV2$\in[0.46, 0.53)$; IV2_Dummy3=1 if HHI$\in[0.53, 0.71]$. Values in parentheses are standard errors, which are robust and clustered by firm-market combination. All regressions include UPC dummies and market dummies, where market is a month MSA combination. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

Table 2.13: UPC Regression Results using HHI dummy as Competition Measure

	Dependent Variables			
	UPC dummy Coefficients from OLS regressions for price	**UPC dummy Coefficients from IV regressions for price**	**UPC dummy Coefficients from OLS regressions for log price**	**UPC dummy Coefficients from IV regressions for log price**
Healthy	0.9452***	2.0217***	0.0355	0.0878***
	(0.2587)	(0.2600)	(0.0294)	(0.0294)
Size	-0.0246***	-0.0279***	-0.0033***	-0.0039***
	(0.0026)	(0.0027)	(0.0003)	(0.0003)
Constant	-1.9470**	-2.0010**	-0.0382	-0.0378
	(0.8315)	(0. 8356)	(0.0947)	(0.0946)
Adj.$\boldsymbol{R^2}$	0.93	0.96	0.82	0.89
# observations	238			

Note: Values in parentheses are standard errors. All regressions include firm dummy variables. Estimates marked with ***, ** and * are statistically significant at 1%, 5% and 10% significance levels, respectively.

APPENDIX

Appendix A

Mathematical Derivations of Counter-Factual Experiments

A.1 Uniform Margin

$$Max\ \Pi_{ft} = \sum_{j \in F_{ft}} \psi_{ft} M_t s_{jt}(\mathbf{mc}_t + \Psi_t) - C_{ft} \tag{A.1}$$

,where the scaler ψ_{ft} is the profit margin of all products of firm f in market t, and vector Ψ_t contains margins of all products in market t.

The F.O.C. is:

$$\begin{aligned}
\frac{\partial \Pi_{ft}}{\partial \psi_{ft}} &= \frac{\partial \sum_{j \in F_{ft}} \psi_{ft} s_{jt}(\mathbf{mc}_t + \Psi_t)}{\partial \psi_{ft}} \\
&= \sum_{j \in F_{ft}} s_{jt} + \psi_{ft} \sum_{j \in F_{ft}} \frac{\partial s_{jt}(\mathbf{mc}_t + \Psi_t)}{\partial \psi_{ft}} = 0 \\
&= \sum_{j \in F_{ft}} \left[s_{jt} + \psi_{ft} \frac{\partial s_{jt}(\mathbf{mc}_t + \Psi_t)}{\partial \psi_{ft}} \right] = 0 \qquad \text{(A.2)}
\end{aligned}$$

In equation A.2

$$\begin{aligned}
s_{jt}(\mathbf{mc}_t + \Psi_t) &= \frac{1}{ns}\sum_{i=1}^{ns} s_{ijt}(\mathbf{mc}_t + \Psi_t) \\
&= \frac{1}{ns}\sum_{i=1}^{ns}[\frac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J_t}\exp(\delta_{kt} + \mu_{ikt})}] \qquad (A.3)
\end{aligned}$$

,where

$$\delta_{jt} = x_j\beta + (mc_{jt} + \psi_{ft})\alpha + \xi_j + \Delta\xi_{jt} \qquad (A.4)$$

and

$$\mu_{ijt} = [(mc_{jt} + \psi_{ft}); x_j]' * (\Pi D_i + \Sigma v_i) \qquad (A.5)$$

.

According to A.3, A.4 and A.5

$$\begin{aligned}
\frac{\partial s_{jt}(\mathbf{mc}_t + \Psi_t)}{\partial \psi_{ft}} &= \frac{1}{ns}\sum_{i=1}^{ns}\left\{ s_{ijt}[\alpha + (\Pi D_i + \Sigma v_i)_p] - \exp(\cdot)\frac{1}{\left[1 + \sum_{k=1}^{J_t}\exp(\delta_{kt} + \mu_{ikt})\right]^2}\right. \\
&\left.\left[\sum_{k=1}^{F_{ft}}\exp(\cdot)(\alpha + (\Pi D_i + \Sigma v_i)_p)\right]\right\} \\
&= \frac{1}{ns}\sum_{i=1}^{ns}\left\{ s_{ijt}[\alpha + (\Pi D_i + \Sigma v_i)_p][1 - \frac{\sum_{k=1}^{F_{ft}}\exp(\delta_{kt} + \mu_{ikt})}{1 + \sum_{k=1}^{J_t}\exp(\delta_{kt} + \mu_{ikt})}]\right\} \qquad (A.6)
\end{aligned}$$

By plugging A.6 into A.2, A.2 becomes:

$$\sum_{j\in F_{ft}}\left\{s_{jt}+\psi_{ft}\frac{1}{ns}\sum_{i=1}\left\{s_{ijt}[\alpha+(\Pi D_i+\Sigma v_i)_p][1-\frac{\sum_{k=1}^{F_{ft}}\exp(\delta_{kt}+\mu_{ikt})}{1+\sum_{k=1}^{J_t}\exp\left(\delta_{kt}+\mu_{ikt}\right)}]\right\}\right\}=0 \tag{A.7}$$

$$\sum_{j\in F_{ft}}\left\{\frac{1}{ns}\sum_{i=1}s_{ijt}+\psi_{ft}\frac{1}{ns}\sum_{i=1}\left\{s_{ijt}[\alpha+(\Pi D_i+\Sigma v_i)_p][1-\frac{\sum_{k=1}^{F_{ft}}\exp(\delta_{kt}+\mu_{ikt})}{1+\sum_{k=1}^{J_t}\exp\left(\delta_{kt}+\mu_{ikt}\right)}]\right\}\right\}=0 \tag{A.8}$$

$$\sum_{j\in F_{ft}}\left\{\frac{1}{ns}\sum_{i=1}s_{ijt}\left\{1+\psi_{ft}[\alpha+(\Pi D_i+\Sigma v_i)_p][1-\frac{\sum_{k=1}^{F_{ft}}\exp(\delta_{kt}+\mu_{ikt})}{1+\sum_{k=1}^{J_t}\exp\left(\delta_{kt}+\mu_{ikt}\right)}]\right\}\right\}=0 \tag{A.9}$$

In A.9, there are F unknowns, $\psi_{1t},...,\psi_{Ft}$, where F is the number of firms in the market t. Also, there are F equations, one for each firm. (A.9) is just one such equation. So F equations with F unknowns. This is a nonlinear system of equations.

The Equation System:

$$\sum_{j\in F_{1t}}\left\{\frac{1}{ns}\sum_{i=1}s_{ijt}\left\{1+\psi_{1t}[\alpha+(\Pi D_i+\Sigma v_i)_p][1-\frac{\sum_{k=1}^{F_{1t}}\exp(\delta_{kt}+\mu_{ikt})}{1+\sum_{k=1}^{J_t}\exp\left(\delta_{kt}+\mu_{ikt}\right)}]\right\}\right\}=0 \tag{A.10}$$

$$\sum_{j \in F_{2t}} \left\{ \frac{1}{ns} \sum_{i=1} s_{ijt} \left\{ 1 + \psi_{2t}[\alpha + (\Pi D_i + \Sigma v_i)_p][1 - \frac{\sum_{k=1}^{F_{2t}} \exp(\delta_{kt} + \mu_{ikt})}{1 + \sum_{k=1}^{J_t} \exp(\delta_{kt} + \mu_{ikt})}] \right\} \right\} = 0 \tag{A.11}$$

$$\sum_{j \in F_{3t}} \left\{ \frac{1}{ns} \sum_{i=1} s_{ijt} \left\{ 1 + \psi_{3t}[\alpha + (\Pi D_i + \Sigma v_i)_p][1 - \frac{\sum_{k=1}^{F_{3t}} \exp(\delta_{kt} + \mu_{ikt})}{1 + \sum_{k=1}^{J_t} \exp(\delta_{kt} + \mu_{ikt})}] \right\} \right\} = 0 \tag{A.12}$$

...

$$\sum_{j \in F_{Ft}} \left\{ \frac{1}{ns} \sum_{i=1} s_{ijt} \left\{ 1 + \psi_{Ft}[\alpha + (\Pi D_i + \Sigma v_i)_p][1 - \frac{\sum_{k=1}^{F_{Ft}} \exp(\delta_{kt} + \mu_{ikt})}{1 + \sum_{k=1}^{J_t} \exp(\delta_{kt} + \mu_{ikt})}] \right\} \right\} = 0 \tag{A.13}$$

In the equation system above, there are F unknowns $\psi_{1t}, \psi_{2t}, \psi_{3t}, ...\psi_{Ft}$.

The profit change of firm f in market t is as follows:

$$\Delta profit_{ft} = \sum_{j \in F_{ft}} p_{jt}^{CF} q_{jt}^{CF}(P^{CF}) - p_{jt} q_{jt} \tag{A.14}$$

,where p_{jt}^{CF} is the solved counter-factual price for product j in market t ; p_{jt} is the observed market price of the same product and q_{jt} is the observed quantity sold. $\Delta profit_{ft}$ is 384×F matrix. q_{jt}^{CF} is the quantity demand depending on the vector of prices when margins are the same and q_{jt} is the observed quantity demand.

The expected change of consumer surplus is as follows:

$$\begin{aligned}
E[E(CS_t^{CF}) - E(CS_t)] &= \frac{1}{ns}\sum_{i=1}^{ns}\left\{\frac{1}{\alpha_i}[\ln(\sum_{j=1}^{J_t}\exp(\delta_{jt}(P_t^{CF}) + \mu_{ijt}(P_t^{CF})))\right. \\
&\quad \left. - \ln(\sum_{j=1}^{J_t}\exp(\delta_{jt}(P_t) + \mu_{ijt}(P_t)))]\right\} \\
&= \frac{1}{ns}\sum_{i=1}^{ns}\left\{\frac{1}{\alpha_i}\ln(\frac{\sum_{j=1}^{J_t}\exp(\delta_{jt}(P_t^{CF}) + \mu_{ijt}(P_t^{CF}))}{\sum_{j=1}^{J_t}\exp(\delta_{jt}(P_t) + \mu_{ijt}(P_t))})\right\} \qquad (A.15)
\end{aligned}$$

,where P_t^{CF} is the vector of prices of products in market t when products of a firm have same margin. $E(CS_t)$ is a $ns \times 1$ vector in each market t and $E[E(CS_t^{CF}) - E(CS_t)]$ is a scaler for market t.

$$\alpha_i = \alpha + (\Pi D_i + \Sigma v_i)_p .$$

A.2 Tax on Regular Products

In the second counter-factual analysis, I propose a one cent one ounce tax policy to all regular products. Government tax one cent per ounce on regular ketchup products. Firm will resolve for a new optimal price p_{jt}^{CF} for each product. $(p_{jt}^{CF} + \psi_j)$ is the price consumers receive, where ψ_j is the tax levied on produce j. Firm's optimization problem becomes as follows:

$$
\begin{aligned}
F &= \underset{P^{CF}}{Max} \sum_{j \in F_{ft}} \left\{ (p_{jt}^{CF} - mc_{jt}) * M_t * s_{jt}((p_t^{CF} + \psi)) \right\} && \text{(A.16)} \\
, where\ \psi_j &= \begin{cases} 0.01 & if\ j \text{ is regular product} \\ 0 & if\ j \text{ is healthy product} \end{cases} && \text{(A.17)} \\
, s_{jt}((p_{jt}^{CF} + \psi_j)) &= \frac{1}{ns} \sum_{i=1}^{ns} \frac{\exp(\delta_{jt}(p_{jt}^{CF} + \psi_j) + \mu_{ijt}(p_{jt}^{CF} + \psi_j))}{1 + \sum_{k=1}^{J_t} \exp(\delta_{kt}(p_{kt}^{CF} + \psi_k) + \mu_{ikt}(p_{kt}^{CF} + \psi_k))} && \text{(A.18)} \\
, \delta_{jt}(p_{jt}^{CF} + \psi_j) &= \alpha(p_{jt}^{CF} + \psi_j) + X_{1j\_others}\theta_{1\_others}, && \text{(A.19)} \\
, \mu_{ijt}(p_{jt}^{CF} + \psi_j) &= (p_{jt}^{CF} + \psi_j)(\Pi D_i + \Sigma v_i)_p + X_{2j\_others}(\Pi D_i + \Sigma v_i)_{others} && \text{(A.20)}
\end{aligned}
$$

$$
\frac{\partial F}{\partial p_{jt}^{CF}} = M_t s_{jt} + (p_{jt}^{CF} - mc_{jt}) M_t \frac{\partial s_{jt}}{\partial p_{jt}^{CF}} + \sum_{k \in F_{ft}, k \neq j} \left\{ (p_{kt}^{CF} - mc_{kt}) M_t \frac{\partial s_{kt}}{\partial p_{jt}^{CF}} \right\} = 0 \quad \text{(A.21)}
$$

$$
s_{jt} + (p_{jt}^{CF} - mc_{jt}) \frac{\partial s_{jt}}{\partial p_{jt}^{CF}} + \sum_{k \in F_{ft}, k \neq j} \left\{ (p_{kt}^{CF} - mc_{kt}) \frac{\partial s_{kt}}{\partial p_{jt}^{CF}} \right\} = 0 \quad \text{(A.22)}
$$

, where

$$
\begin{aligned}
\frac{\partial s_{jt}}{\partial p_{jt}^{CF}} &= \frac{1}{ns}\sum_{i=1}^{ns}\left\{\frac{\exp(\delta_{jt}+\mu_{ijt})\left[\alpha+(\Pi D_i+\Sigma v_i)_p\right]}{1+\sum\limits_{k=1}^{J_t}\exp(\delta_{kt}+\mu_{ikt})}\right. \\
&\quad \left. -\frac{\exp(\delta_{jt}+\mu_{ijt})}{[1+\sum\limits_{k=1}^{J_t}\exp(\delta_{kt}+\mu_{ikt})]^2}\exp(\delta_{jt}+\mu_{ijt})[\alpha+(\Pi D_i+\Sigma v_i)_p]\right\} \\
&= \frac{1}{ns}\sum_{i=1}^{ns}\left\{s_{ijt}[\alpha+(\Pi D_i+\Sigma v_i)_p]-s_{ijt}^2[\alpha+(\Pi D_i+\Sigma v_i)_p]\right\} \\
&= \frac{1}{ns}\sum_{i=1}^{ns}[\alpha+(\Pi D_i+\Sigma v_i)_p]*s_{ijt}*(1-s_{ijt}) \qquad \text{(A.23)}
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial s_{kt}}{\partial p_{jt}^{CF}} &= \frac{1}{ns}\sum_{i=1}^{ns}\left\{(-1)\frac{\exp(\delta_{kt}+\mu_{ikt})}{[1+\sum\limits_{k=1}^{J_t}\exp(\delta_{kt}+\mu_{ikt})]^2}\exp(\delta_{jt}+\mu_{ijt})[\alpha+(\Pi D_i+\Sigma v_i)_p]\right\} \\
&= \frac{1}{ns}\sum_{i=1}^{ns}\left\{(-1)[\alpha+(\Pi D_i+\Sigma v_i)_p]*s_{ijt}*s_{ikt}\right\} \qquad \text{(A.24)}
\end{aligned}
$$

Therefore, the F.O.C becomes:

$$
\begin{aligned}
&\left(\frac{1}{ns}\sum_{i=1}^{ns} s_{ijt}(p_t^{CF}+\psi)\right)+(p_{jt}^{CF}-mc_{jt}) \\
&*\left(\frac{1}{ns}\sum_{i=1}^{ns}\left\{[\alpha+(\Pi D_i+\Sigma v_i)_p]_j * s_{ijt}(p_t^{CF}+\psi)*(1-s_{ijt}(p_t^{CF}+\psi))\right\}\right) \\
&+\sum_{k\in F_{ft},k\neq j}\Bigg((p_{kt}^{CF}-mc_{kt}) \\
&*\left\{\frac{1}{ns}*\sum_{i=1}^{ns}\left\{(-1)[\alpha+(\Pi D_i+\Sigma v_i)_p]_j * s_{ijt}(p_t^{CF}+\psi)*s_{ikt}(p_t^{CF}+\psi)\right\}\right\}\Bigg) \\
&=0 \qquad \text{(A.25)}
\end{aligned}
$$

In the equationA.25, only p_{jt}^{CF} is unknown. In the market t, there are J prices. Therefore there are J unknowns and J equations.