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**The Competitive and Welfare Effects of New Product Introduction:
The Case of Crystal Pepsi**

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# The Competitive and Welfare Effects of New Product Introduction: The Case of Crystal Pepsi *

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**Abstract**

The introduction of new products is an important method of competition in many markets. Towards understanding its impact on competition and welfare, this paper estimates the effects of Crystal Pepsi being introduced by PepsiCo.

Estimating a structural model of the soft drink market, the competitive effect is decomposed into two parts: the effect on the prices of existing products from increased competition, and the effect of having additional product variety. I find that firms' profit and consumer welfare both increased in response to the introduction of Crystal Pepsi, with the price effect accounting for nearly 90% of the gain in consumer surplus. The introduction of Crystal Pepsi is also used as an experiment to test the competitiveness of the soft drink market. Evidence of price collusion is found.

In comparing the welfare impact of introducing Crystal Pepsi under price collusion and price competition, I find that social welfare increases more under collusion. Under competition, rivals of PepsiCo increase prices and, consequently, a new product introduction actually harms consumers; at the same time, PepsiCo's profit gain is smaller. This finding suggests that firms have a stronger incentive to invest in $R\&D$ when they collude in price than when they compete in price.

**JEL CLASSIFICATION:** L11, L13, L49, L66, O31

**Keywords:** New Product Introduction, Social Welfare, Market Structure, Random Coefficient Model

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# 1 Introduction

New product introduction is a common phenomenon in many industries; cereal, beer, soft drink and yogurt are a few examples. Consumers benefit from this continuous development of new products. On the one hand, consumer welfare improves as the choice set expands because they have more products with different attributes. This is called the variety effect. On the other hand, the introduction of a new product enhances competition on the supply side and lowers the prices of existing products, allowing consumers to enjoy the same utility through a lower level of expenditure than when the new product does not exist. This is called the price effect. Of course, firms are the driving force behind these developments. They introduce new products or brands to crowd the product space, gain market share from rival firms, and to deter potential entry[1].

Some papers have studied the effects of new product introduction in a discrete choice framework. For example, Trajtenberg (1989) studied the social gains from innovation in computed tomography (CT) scanners. Pakes et al (1993) used the discrete choice system to compute an ideal price index for automobiles that accounts for new good introduction. Nevo (2003) also constructed a price index that takes into account new product introduction and quality changes in the Ready to Eat (RTE) breakfast cereal market. Petrin (2002) estimated consumer welfare and producer surplus from minivan introduction using a random coefficient model complemented with micro moments. Kim (2004) estimated the effects of new brands on incumbents' profits and consumer welfare in the U.S. processed cheese market. These studies all assumed a particular competition model, mostly Bertrand Nash oligopoly, to estimate the effects of new product introduction[2], so they ignored the question of whether the assumed market structure is correct for the target industry. As my findings indicate, different market structures may have different or even opposite implications regarding welfare, so it is important to examine the competition model first, then analyze welfare estimates.

Hausman and Leonard (2002) used retail scanner data from before and after new product introduction to estimate the benefit to consumers from a new brand in U.S. bath tissue market.

[1] See Schmalensee (1978).

[2] This is partly because they normally only have the data for post-introduction period, and not enough for market structure analysis.

They compared the "direct" and "indirect" estimates of price effect to assess the validity of the assumed competition model.[3] However, they employed Gorman's two-stage budgeting approach, which suffers from the two common problems of market-level demand systems: the inability to incorporate micro information on consumers, and the restriction of substitution patterns between products. [4]

In this paper, I follow the discrete choice approach taken in Berry et al. (2004), which allows flexible substitution patterns, and investigate the implicit competition behavior of firms in soft drink industry to analyze the competition effects of the introduction of Crystal Pepsi. I use the introduction of Crystal Pepsi as an experiment to infer the market structure and find that price collusion best describe the competition behavior between firms. Then I quantify the change in consumer welfare from the introduction of Crystal Pepsi in the soft drink market, decomposing it into a variety effect and price effect. I also estimate changes in producer surplus, measuring the extent of profit gains by the introducer and the pricing interaction between firms upon the launch of new product under different competition patterns. I find that the launch of a new product has different impacts on social welfare when firms compete in different ways. In particular, a new product can bring more social welfare in a collusive market than an oligopolistic market. Under oligopoly, non-introducing firms can take a "free ride" to increase their prices upon the entry of new product to gain more profit, which would not happen in a collusive market, and this price effect would eventually hurt consumers.

The rest of the paper is organized as follows. Section 2 describes the U.S. soft drink market and the introduction of Crystal Pepsi. Section 3 introduces the demand and supply model used for the analysis. Section 4 describes the data and outlines the estimation strategy. Section 5 presents the empirical results of the model estimation and the counterfactual simulations, and I conclude in section 6.

[3]Direct price effect is the estimates of price reductions for existing products using pre- and post-introduction data. Indirect price effect is to use only post-introduction data to simulate the prices without new product and estimate the price effect of new product.

[4]Nevo(1997) estimates the multilevel demand system and mixed logit model from one dataset of RTE cereal market. The multilevel demand model yields some "disturbing" cross-price elasticities and strange implications, while mixed logit model produces reasonable results.

## 2 The Soft Drink Industry and Crystal Pepsi Introduction

In 2006, the U.S. market consumed 4.89 billion gallons of soft drinks through retail chains, generating \$16.3 billion in revenue[5]. Simmons National Consumer Survey in 2006 shows that more than 80% of the population drinks carbonated beverages, and among those who drink, the average amount of consumption in the last seven days is more than 5.5 glasses.

The soft drink industry is highly concentrated. The market share of Coca-Cola, the number-one manufacturer, was 38.3% in 2006, followed by PepsiCo with 32.2%. The three-firm concentration (C3) was nearly 90%.

The soft drink industry is one of the most prodigious introducers of new brands or flavors. As is typical of most new products, most new soft drink brands do not succeed[6]. However, by introducing new brands manufacturer can take market share and profits from rivals, and at the same time, the new brands crowd the product space and make the market more competitive, which can lower the prices of existing brands and improve consumer welfare. As an example, I use the introduction of Crystal Pepsi by PepsiCo in the early 90's to examine the competitive effects of new product introduction and its impact on consumer welfare.

Crystal Pepsi is a caffeine-free soft drink; it tastes like original Pepsi but it is colorless. In April 1992, PepsiCo began testing the market in Providence, Denver and Dallas with good feedback, and in December Crystal Pepsi was distributed national-wide with a large marketing campaign. After three months Crystal Pepsi captured a national market share of 2.4%, which is an excellent performance according to industry criterion. But it fell quickly and ended up with the annual share of 1.1% in 1993, and was pulled off the market in early 1994.

Since the data for estimation are prices set by the retailers, while my research question is about manufacturers' behavior, if the interactions between retailer and manufacturers are not taken into account, the implications of the estimation results will be ambiguous.[7] Here I review the marketing chain from manufacturers to consumers in the soft drink industry.[8] The soft drink marketing chain

[5]Mintel Report on Carbonated Soft Drink 2007, and the retail chain exclude Wal-Mart.

[6]Urban et.al(1983) shows that around 80% of new consumers goods introduction failed.

[7]Many empirical studies on merger, new product introduction treat scanner retail prices as set by manufacturers, so whether the implied effects are from retailers or manufacturers is not clear. For example, Dube (2005), Kim (2004) and Nevo (2000).

[8]Most of the contents in this paragraph are from Tollison, Kaplan and Higgins (1991).

comprises three parts: *concentrate or syrup producers*, *bottlers*, and *retailers.* Concentrate or syrup producers are the firms that produce concentrate or syrup, the raw material used to produce the finished soft drink products. Bottlers perform two major roles, the first is to purchase concentrate or syrup, manufacture soft drink by mixing the syrup with carbonated water and other ingredients and pack them into finished products ready to sell, and second is to deliver and market finished soft drink products to the retailers.[9] And retailers are firms such as grocery stores that make soft drinks available to consumers. Historically, Coca-Cola Co. and PepsiCo produced the concentrate or syrup and sold them to independent bottlers. However, from the late 1970s there was a trend of vertical integration of bottlers by concentrate producers, and by 1993, 70.8% of Coca-Cola and 70.6% of PepsiCo's concentrate volume were distributed by their company-owned bottlers.[10] For example, PepsiCo manufactures concentrates and sells them to its own bottlers, as well as independent franchise bottlers, throughout the United States, and the bottlers manufacture, distribute and market finished soft drink products under PepsiCo trademarks.[11]

In a regional market, as the metropolitan area of my sample, bottlers compete with each other for the trademarks they carry, and price discounting has been a major weapon. Among the soft drink products sold in retailers, around 75% of the volume was sold at a discount price[12], and the costs of discounting were mainly borne by bottlers.[13] Bottlers are offering price breaks and feature ads based on numbers of cases sold and they even pay for shelf space.[14]

In this paper, the term *manufacturer* refers to the combination of concentrate producer and bottler, and the results and conclusions should be explained accordingly.

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[9] Generally speaking, distributors lie between bottlers and retailers in the marketing chain, and this second function is performed by the distributor, but in soft drink industry, bottlers take the roles of both parts.

[10] See Saltzman, Levy and Hilke (1999) Table III.5.

[11] PepsiCo bottlers, whether independently owned or company owned, generally manufacture and distribute soft drink from other concentrate or syrup producers as well. This fact may contribute partly, but not much, to the price collusion conclusion I draw later.

[12] From Marketing Fact Book, 1983, 1986 and 1989 editions.

[13] The price coupon and feature ads are normally on weekly basis, and the weekly prices variation mainly come from this.

[14] "The soda wars - a report from the battlefront", *US News and World Report*, July 8, 1985, p58.

# 3 The Model

In this section, I present a structural model of demand and supply to evaluate the competitive effects of the introduction of Crystal Pepsi. In contrast with the existing literature on soft drink industry[15], I tailor the framework of the BLP model[16] to fit the market characteristics and to meet the need for the analysis of Crystal Pepsi.

## 3.1 Demand

The core part of the model is to estimate the consumer's demand, and the estimation of supply and the following analysis of competition effects and welfare change all depend on this step.

Suppose there are $J$ products, indexed by $j$, $M$ consumers, indexed by $i$, $M$ is the market size, and we observe $T$ weeks (indexed by $t$). The conditional indirect utility of consumer $i$ from product $j$ in week $t$ is

$$u_{ijt} \quad = \quad x_j\beta_i^* + \alpha_i^* p_{jt} + \xi_{jt} + \epsilon_{ijt} \equiv V_{ijt} + \epsilon_{ijt} \tag{3.1}$$

where $x_j$ is a $K$-dimensional (row) vector of observable product characteristics, $p_{jt}$ is the price of product $j$ in week $t$, $\xi_{jt}$ is an unobservable (by the econometrician) product characteristic, and $\epsilon_{ijt}$ is a mean-zero stochastic term. Finally, $(\alpha_i^* \ \beta_i^*)$ are $K+1$ individual specific coefficients.

Examples of observed characteristics are calories, carbohydrates, sodium, caffeine and whether the drink is clear. The unobserved characteristic covers all factors not included in the model but affect consumer's utility; we assume consumers observe it and then it can be interpreted as consumer taste on that product. So, as $\xi_{jt}$ can change over time, we can think of it as consumer taste changing.

The specification given by (3.1) assumes that all consumers face the same product characteristics. However, consumers with different demographics may have different preference for those product characteristics; this is the motivation of the random coefficient model. I model the distribution of consumers' taste parameters for the characteristics as multivariate normal (conditional

[15] For example, Gasmi et al.(1992), Cotteril et al. (1996), Dube (2005) and Chan (2006)

[16] To my knowledge, this paper is the first one to apply BLP framework in soft drink industry.

on demographics) with a mean that is a function of demographic variables and parameters to be estimated, and a variance-covariance matrix to be estimated as well. Let

$$\begin{pmatrix} \alpha_i^* \\ \beta_i^* \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma \nu_i, \quad \nu_i \sim N(0, I_{k+1})$$

where $K$ is the dimension of the observed characteristics vector, $D_i$ is a $d \times 1$ vector of demographic variables, $\Pi$ is a $(K+1) \times d$ matrix of coefficients that measure how the taste characteristics vary with demographics, and $\Sigma$ is a scaling matrix. This specification allows individual characteristics to consist of demographics that are "observed" and additional characteristics that are "unobserved", denoted $D_i$ and $\nu_i$ respectively. Substitute this into (3.1), we have:

$$u_{ijt} = \delta_{jt}(x_j, p_{jt}, \xi_{jt}; \alpha, \beta) + \mu_{ijt}^1(x_j, p_{jt}, D_i; \Pi) + \mu_{ijt}^2(x_j, p_{jt}, \nu_i; \Sigma) + \epsilon_{ijt}$$

$$\delta_{jt} = x_j\beta + \alpha p_{jt} + \xi_{jt}, \;\; \mu_{ijt}^1 = [p_{jt}, x_j]' * (\Pi D_i), \;\; \mu_{ijt}^2 = [p_{jt}, x_j]' * (\Sigma \nu_i)$$

The utility is now expressed as the mean utility, represented by $\delta_{jt}$, and a deviation from that mean, $\mu_{ijt} + \epsilon_{ijt}$, which are the effects of the random coefficient.

Specification of the demand system is completed with the introduction of an "outside good"; the consumers may decide not to purchase any of the products. The indirect utility from this outside option is

$$u_{iot} = \xi_0 + \pi_0 D_i + \sigma_0 \nu_{i0} + \epsilon_{i0t}$$

I assume that the consumer purchases one unit of the product that gives her the highest utility and no tie exists.[17] Then the probability that consumer $i$ chooses good $j$ in week $t$ is given by

$$Prob(y_{ijt} = 1 | D_i, \nu_i, \epsilon_{ijt}) = Prob(u_{ijt} > u_{ilt}, \forall\, l \neq j, l = 0, 1, \ldots, J | D_i, \nu_i, \epsilon_{ijt}) \tag{3.2}$$

The market share of product $j$ in week $t$, as a function of the mean utility levels of all $J+1$

[17] Hendel (1999) develops a multiple discreteness model in which consumers are allowed to purchase more than one item. And see Dube (2005) for an application.

goods and the parameters, is given by

$$s_{jt} = \int Prob(y_{ijt} = 1) dF^*(D, \nu, \epsilon) = \int Prob(y_{ijt} = 1) dF^*(\epsilon) dF^*(\nu) dF^*(D) \tag{3.3}$$

where $F(\cdot)$ denotes the population distribution function. The second equality comes from the assumption that the distribution of $D$, $\nu$ and $\epsilon$ are independent.

I further assume that $\epsilon_{ijt}$ are $i.i.d.$ with type I extreme value distribution. Then from (3.2), the probability of consumer choosing product $j$ at week $t$ is

$$Prob(y_{ijt} = 1 | D_i, \nu_i) = \frac{exp(V_{ijt})}{\Sigma_{l=0}^{J_t} exp(V_{ilt})} = \frac{exp(V_{ijt})}{1 + \Sigma_{l=1}^{J_t} exp(V_{ilt})}$$

The second equality come from normalizing the mean utility of the outside good to be zero. In my specification, $\nu_i$ is stochastic unobserved individual characteristics, so the above equation produces a mixed logit model, which generate rich substitution pattern between choices. Or, it can be written as

$$Prob(y_{ijt} = 1 | D_i) = \frac{exp(\delta_{jt} + \mu^1_{ijt} + \mu^2_{ijt})}{1 + \Sigma_{l=1}^{J_t} exp(\delta_{lt} + \mu^1_{ilt} + \mu^2_{ilt})} \tag{3.4}$$

## 3.2 Supply and Equilibrium

Suppose there are $F$ groups, each of them contains a subset, $\digamma_f$, of the $j = 1, 2, \ldots, J$ products. The profit of group $f \in F$ is

$$\Pi_f = \Sigma_{j \in \digamma_f} (p_j - mc_j) M s_j(p) - C_f$$

where $s_j(p)$ is the market share of product $j$, which is a function of prices of all products, $M$ is the market size, $mc_j$ is the constant marginal cost of product $j$, and $C_f$ is the fixed cost of production of group $f$. Then, under the assumption of pure-strategy Nash-Bertrand equilibrium, the first order condition of group's profit maximization problem becomes

$$\frac{\partial \Pi_f}{\partial p_j} = s_j(p) + \sum_{r \in \mathcal{F}_f} (p_r - mc_r) \frac{\partial s_r(p)}{\partial p_j} = 0$$

When a multi-product group sets price for a single product, it maximizes the profit of all products within the group. This effect is captured by the second term, which include the impact of $p_j$ on both product $j$'s own price effect on its revenue and other products' revenue inside the group.

These $J$ equations imply the marginal cost and price-cost margin for each product. For notation convenience, define the matrix

$$\Omega_{jr}(p) = -\frac{\partial s_j(p)}{\partial p_r}, j, r \in J$$

and the market structure matrix

$$\Lambda^w_{jr} = \begin{cases} 1 & \text{if } \exists f : \{r, j\} \subset \mathcal{F}_f \\ 0 & \text{otherwise} \end{cases} \tag{3.5}$$

The market structure matrix $\Lambda^w$ indicates the competition pattern behind firms. If firms maximize the single product's profit, $\Lambda^w$ is an identity matrix; if firms compete oligopolistically, $\mathcal{F}_f$ covers all the products produced by firm $f$; and if firms collude in price, $\Lambda^w$ is a matrix with all elements being one.

The first order conditions can be written as

$$s(p) - \Omega(p). * \Lambda^w (p - mc) = 0$$

where $p$, $mc$, $s(p)$ are, respectively, the price vector for all products, the marginal cost vector for all products, and the vector of market shares. This implies a markup equation and a marginal cost equation

$$p - mc = (\Omega(p). * \Lambda^w)^{-1} s(p) \Rightarrow mc = p - (\Omega(p). * \Lambda^w)^{-1} s(p) \tag{3.6}$$

I use equation (3.6) in two ways. First, I use the estimates of the demand system to compute the marginal costs implied by (3.6). These estimates of marginal costs rely on obtaining the consistent estimates of the demand system and on the assumption of equilibrium market structure. Second, under the assumption that the marginal cost does not change and for the same equilibrium structure, I simulate the counterfactual equilibrium prices that would have occurred were Crystal Pepsi not introduced. That is, I replace the post-introduction market structure $\Lambda^w$ in (3.6) with the structure matrix of assumed market structure in pre introduction period, $\Lambda^{wo}$, and plug in the estimated marginal costs. The predicted equilibrium prices without Crystal Pepsi solve

$$p^* = \hat{mc} + (\Omega(p^*). * \Lambda^{wo})^{-1} s(p^*) \tag{3.7}$$

# 4 Data and Estimation

## 4.1 The Data

The data used for demand estimation is a scanner data set collected by Information Resource Inc.(IRI), containing household-level soft drink purchase data and store-level sales data in 8 store chains in a large metropolitan area. The sample period is 104 weeks from June 1991 to June 1993, and Crystal Pepsi is present in the last 25 weeks. The household level data tracks 1024 household's soft drink shopping history with the information on shopping date, units and prices of products purchased, store locations and household demographics. The store level data contains the weekly prices and units sold for each available product, the promotion activity, and the total brands in each week.

The product's characteristics include calories, carbohydrates, sodium content and whether it is clear. Those data are obtained from CocaCola and PepsiCo's websites or supermarket packages [18].

## 4.2 Retailer and Manufacturer Interaction

This section discusses a few comments and assumptions about the role of retailers. As mentioned before, the data used for estimation are the retail prices in the stores, however, my research question

[18] Assuming the current brand's contents are the same as in early 90's

is about manufacturers' behavior. As a bridge between manufactures and consumers, how does the role of retailers fit into the model?[19]

I focus on the category of soft drink products, so if the retail chains compete with each other in this category by optimizing their soft drink prices across all products, the inferred implications from retail prices about competition models and market structures will be ambiguous on whether the interaction is among manufacturers or retailers. In this case, I would have to incorporate the retailers into the model in which manufacturers maximize their profits from the wholesale prices and retailers choose the optimal retail prices based on the manufacturers' wholesale prices. However, if retailers do not compete with each other on the basis of a single product category (in this case, soft drinks), I can reasonably assume that retail prices are determined non-strategically, retailers take the manufacturers' wholesale prices as given, and the strategic pricing is among manufacturers only.

Slade (1995) interviewed managers of grocery stores who report that the majority of consumers do not engage in across-store price comparisons for a given brand. Instead, the price comparison is usually across different manufacturers or brands within a store. Slade empirically tests this argument in the product category of saltine crackers with positive results. In addition, Walters and Mackenzie (1988) find evidence that there is often no strategic interdependence among retailers with respect to the pricing of brands within a particular product category. Moreover, if the manufacturer is the Stackelberg price leader in the retailer-manufacturer interaction game, and if retailers do not compete with each other on the category, Sudhir (2001) shows that the measure of coordination or the competitiveness among products is equivalent between two models: the retailer coordination model, in which the retailer coordinates the prices of the target product category ignoring manufacturers; and the constant margin retailer model, in which the competition is among manufacturers and retailers play non-strategically with a fixed markup.[20] Therefore, the observed retail prices could be used to analyze manufacturers' behavior.

Given the preceding discussion, I assume that retailers set the prices of soft drink products by

[19] Many studies using supermarket scanner data assume that the observed retail prices are set by the manufactures without rationales, for example, Dube (2005), Kim (2004) and Nevo (2000).

[20] In other words, if the retailer sets the prices to maximize the profit of each single product, from econometric pointview, this is equivalent to the scenario that manufacturers' strategy is to maximize single product profit and the retailer charge a constant margin.

the fixed markup rule. Thus, incorporating the retailer explicitly does not change the model stated previously significantly. To see this, suppose $w_{jt}$ is the wholesale price of product $j$ in week $t$, and $P^r_{jt}$ is the retail price, then

$$P^r_{jt} = w_{jt} + r_{jt}$$

where $r_{jt}$ is the retailer mark-up. When retailer applies a fixed mark-up rule, we have:

$$r_{jt} = m * w_{jt}$$

Hence,

$$P^r_{jt} = (1 + m)w_{jt}$$

When manufacturers choose the wholesale prices $w_{jt}$ to maximize their profit and the retailers set the retail prices by fixed mark-up rule accordingly, the system of demand and supply equations remain the same as that without an explicit retail chain, except the adjustment of marginal costs, which would be divided by a factor $(1+m)$.[21] Note that $m$ cannot be identified in the estimation and its value has to be given exogenously using empirical information on retailer's mark-up. However, the exact retail mark-ups are generally not available and have to be estimated from the observed retail prices, which are not accurate and vary under different assumptions.[22] In addition, the demand parameter estimates, price-cost margin ratios, price elasticities and welfare changes are not affected by the incorporation of retailer price setting behavior.[23] As a result, I do not make a distinction between manufacturer and retailer prices.

[21] This can be seen from (3.6) and (5.1).

[22] Barsky et al. (2001) estimated that the retailer's markup on national's brands in soft drink category is between 14% and 37%.

[23] Except that the price coefficients and the absolute level of welfare changes will be discounted by a factor $(1 + m)$, but the sign and significance will not change.

## 4.3 Model Estimation

In this section I describe the procedure I use to estimate the consumers' demand. The parameters to be estimated are $\alpha$, $\beta$, the coefficient matrix $\Pi$ and the scale matrix $\Sigma$. I employ the generalized method of moments (GMM) with both the market share and micro moments that follows Berry et al. (2004). The essential idea is to form the GMM objective function as an interaction of the instruments and a value of unknown parameters, which is an error term computed from the model.

### 4.3.1 The Micro Moments

The idea for using micro moments originally comes from Imbens and Lancaster (1994), and has been used by Berry et al. (2004) and Petrin (2002). The motivation is that the macro data can be viewed as the aggregate of micro data, and the aggregate data may contain useful information on the average of micro variables, so combining both the macro and the micro moments can improve the accuracy of the estimation.

I have the household level purchase data, so I can search for the parameters that match the average model predictions of households' demographics conditional on purchasing a specific brand to the observed averages from the data set. Formally, the micro moments can be written as

$$G_1(\theta) = \sum_j (n_j/n) x_{kj} \{1/n_j \sum_{i_j=1}^{n_j} D_{i_j} - E[D|y_i = j, \beta, \nu]\} \tag{4.1}$$

where $n_j$ is the number of households who purchased product $j$, $x_{kj}$ is the $k$th characteristic of product $j$, $D_{i_j}$ is the demographics of household $i$ who purchase product $j$, and $\{y_i = j\}$ is an indicator function for household $i$ purchasing product $j$.

Notice that we cannot calculate the conditional expectation $E[D|y_i = j, \beta, \nu]$ directly, so I approximate it by Bayes' rule to write it as

$$E[D|y = j, \beta, \nu] = \int_D DdP(D|y = j, \beta, \nu) = \frac{\int_D DPr(y = j|D, \beta, \nu)dP(D)}{Pr(y = j, \beta, \nu)}$$

and substitute from model's predictions for choice probabilities (3.4) to obtain

$$E[D|y=j,\beta,\nu] = \frac{\int_D \int_\nu DPr(y=j|D,\beta,\nu)dP(v)dP(D)}{Pr(y=j,\beta,\nu)} \tag{4.2}$$

To calculate the probabilities, $Pr(y = j|D,\beta,\nu)$ and $Pr(y = j,\beta,\nu)$, in (4.2), I need the model parameters $\theta$ and the mean utility $\delta$. $\theta$ is the parameters to be estimated from the moment conditions, while I substitute the $\delta$ here with the one estimated from the market share moments by contraction mapping. In doing so, for each value of $\beta$, $Pr(y = j,\beta,\nu)$ will equal the observed market share $s_j$. On the other hand, the integral in the numerator of (4.2) has to be simulated. By taking random draws of $(D_r, v_r)$, I can approximate (4.2) as

$$E[D|y=j,\beta,\nu] \approx \frac{(ns)^{-1}\sum_r D_r Pr(y=j|D_r,v_r,\beta,\delta(\beta))}{s_j} \tag{4.3}$$

The micro moments are formed by substituting (4.3) into (4.1). Since I have two demographic variables (income and family size) and six product characteristics (constant, price, advertisement, caffeine dummy, clear dummy and package dummy), there will be $2 \times 6 = 12$ micro moments in total.

### 4.3.2 Moments from Market Share

Let $Z = (z_1, \ldots, z_M)$ be a set of instruments, and $\omega$ is a function of the model parameters, which will be defined below as an error term. The second set of moments can be written as

$$G_2(\theta) = E[Z^{'} \cdot \omega(\theta^*)]$$

where $\theta^*$ denotes the true value of those parameters.

I define the error term as the unobserved product characteristics, $\xi_{jt}$ . To computer these unobserved characteristics, I first solve the mean utility level $\delta_{\cdot t}$ from the system of equations

$$s_{\cdot t}(x, p, \delta_{\cdot t}; \Sigma) = S_{\cdot t} \tag{4.4}$$

where $s_{\cdot t}$ is the market share function of all products in week $t$ defined by (3.3), and $S_{\cdot t}$ is the observed market share. Once $\delta_{jt}$ is solved, the error term, $\xi_{jt}$, is defined as $\delta_{jt}(x, p, S_{\cdot t}; \Sigma) - (x_j\hat{\beta} + \hat{\alpha}p_{jt})$, here $\hat{\alpha}$ and $\hat{\beta}$ are estimates from the regression of $\delta_{jt}$ on $x_j$ and $p_{jt}$.

To solve this system of equations I need to find the market share function. The market share is defined by (3.3). I assume $\epsilon$ follows the type I extreme value distribution, so the market share becomes

$$s_{jt} = \int \frac{exp(V_{ijt})}{1 + \sum_{l=1}^{J_t} exp(V_{ilt})} dF^*(\nu)dF^*(D) \tag{4.5}$$

If I further assume $\nu \sim N(0, I_{K+1})$, and obtain the empirical distribution of $D$, I can approximate the above integral from direct Monte Carlo simulation by

$$s_{jt}(p_{\cdot t}, x_{\cdot t}, \delta_{\cdot t}; \Sigma) = \frac{1}{ns}\sum_{i=1}^{ns} s_{ijt}$$

$$= \frac{1}{ns}\sum_{i=1}^{ns} \frac{exp[\delta_{jt} + \sum_{k=1}^{K+1} x_{jt}^k(\sum_{h=1}^{d} \pi_{kh}D_{ih}) + \sum_{k=1}^{K+1} x_{jt}^k(\sum_{l=1}^{K+1} \sigma_{kl}v_{il}^k)]}{1 + \sum_{m=1}^{J} exp[\delta_{mt} + \sum_{k=1}^{K+1} x_{mt}^k(\sum_{h=1}^{d} \pi_{kh}D_{ih}) + \sum_{k=1}^{K+1} x_{mt}^k(\sum_{l=1}^{K+1} \sigma_{kl}v_{il}^k)]}$$

where $i = 1, \ldots, ns$ are draws from $P^*(\nu)$ and $P^*(D)$ respectively. $x_{jt}^k, k = 1, \ldots, K+1$, are product characteristics including price that have random slope coefficients.[24]

Clearly, with the computation of market share under current full random coefficient model, the mean utility $\delta_{\cdot t}$ does not have an analytical solution from the equation system (4.4). As suggested by Berry et al (1995), they are solved numerically by using the contraction mapping, which is to computing the series

$$\delta_{\cdot t}^{h+1} = \delta_{\cdot t}^h + lns_{\cdot t} - lns(p_{\cdot t}, x_{\cdot t}, \delta_{\cdot t}^h; \Sigma),\ h = 1, \ldots, H \tag{4.6}$$

where $s(\cdot)$ are the predicted market shares from above simulation, $H$ is the smallest integer such that $\|\delta_{\cdot t}^H - \delta_{\cdot t}^{H-1}\|$ is smaller than some tolerance level, and $\delta_{\cdot t}^H$ is the approximation to $\delta_{\cdot t}$.

For the estimation in this step, I treat each week as a separate market and use the average

[24] Here I abuse the notation to include price into $x$, while in the model $x$ and $p$ are denoted separately. However, the meaning is clear here and the equation is simplified with this abuse.

weekly price as the price set by manufacturer. These are strong assumptions, since my data sample contains only one metropolitan area, and the demographic distribution is the same for every week (or for every market). I make different draws for each week, so the variation in market share comes not only from the prices and other varying characteristics but also from the random draws of the distribution of unobserved demographics, $\nu$, and its coefficient matrix $\Sigma$.[25] The economic meaning of $\nu$ will not be limited to unobserved demographics of individuals, it explains the variation of both observed and unobserved demographics that cause the variation in market share from week to week.

#### 4.3.3 The Objective Function

The two sets of moments that enter the GMM objective function are $G_1(\theta)$,the micro moments associated with household level data, and $G_2(\theta)$, the market share moments associated with store level data. The population moment conditions are assumed to equal zero at the true value of $\theta$, or

$$E[G(\theta)] = E[G_1(\theta); G_2(\theta)] = 0$$

Following Hansen (1982), the efficient GMM estimate is

$$\hat{\theta} = argmin_{\theta} G(\theta)^{'} W^{-1} G(\theta) = argmin_{\theta} G^{*}(\theta)^{'} G^{*}(\theta)$$

where $W$ is the weight matrix that is a consistent estimate of the asymptotic variance-covariance matrix of the moments, and $G^{*}(\cdot)$ is the "square root" of $W$ times $G(\cdot)$. By using the variance-covariance matrix of the moments, we give less weight to those moments that have higher variances.

Let $\Gamma = E[\partial G^{*}(\theta)/\partial\theta]$, the gradient of the moments with respect to the parameters evaluated at the true parameter values, and let $V = E[G^{*}(\theta)G^{*}(\theta)']$. The asymptotic variance of $\sqrt{n}(\hat{\theta} - \theta)$ is then given by

$$(\Gamma'\Gamma)^{-1}\Gamma' V \Gamma(\Gamma'\Gamma)^{-1}$$

[25] I tried one set random draws of $\nu$ for all weeks, here the variation of market share only comes from the changes in varying product characteristics, the estimation results are similar.

Reported standard errors are calculated using the consistent estimates $\Gamma(\hat{\theta})$ and $V(\hat{\theta})$.

#### 4.3.4 Instrument

The consistent and efficient estimation of the mean utility $\delta(\beta)$ from the second set of moments relies on the valid instrument variables that satisfy two requirements. First, they are uncorrelated with the the error term of the model, or the unobserved product characteristics, $\xi_{jt}$. Second, they are correlated with the price, $p_{jt}$.

I use two sets of instrument variables. The first set is the total number of brands available in consumer's choice set, which varies over weeks due to entry and exit of brands and over stores due to the generic products. The number of brands is an indicator of 'crowdedness'of product characteristics space and is a measure of the intensity of the competition a single product faces in that week, so it will be correlated with price since the markup of each product depends on the competition intensity and the distance from the nearest product on characteristic space. On the other hand, the number of brands in each week is purely firm's behavior, and it is likely to be exogenous to unobserved product characteristics.

Since an alternative explanation of the error term is the consumer's taste towards products, one may argue that the decision of a firm to introduce a new brand is to satisfy those tastes. In this case, the number of brands will be correlated with the error term. I would say that it is more sound to argue that the firm's decision of new product launch depends on the overall population taste on soft drink market level, and when it comes to consumer's taste for a single product, this correlation will be weak if it exits at all. Another concern about this instrument is that the variation of number of brands in the store does not come from manufacturers' introducing new products, but from the retailer's decision on shelf space. If so, the number of brands on the shelf does not indicate the competition intensity among manufacturers.[26] To address this concern, imagine that in a single store, the number of brands is what the consumers would choose from, and it is a measure of competition intensity in that store. When the retailer changes the number of brands in the store, it will adjust the prices accordingly. Since I assume retailers employ the fixed mark-up rule to

[26] For an extreme example, if manufacturers' brands remain the same over thewhole sample period, and the number of brand in the data set varies because stores add to or remove brands from the shelf week by week.

set the retail price proportional to manufacturer's wholesale price, the price change is attribute to manufacturers even if it is retailer's decision. Even though this is a simplified assumption on retailer-manufacturer interaction, it makes this instrument valid. In addition, as mentioned in Section 2, bottlers of different trademarks compete with each other in local markets by discounting price and even paying for the shelf space, which is the main source of weekly price variation,[27] so the number of products in stores indicates the competition intensity and is correlated with the prices, while this competition is not correlated with unobserved product characteristics.

The second set of instrument variables comes from exploiting the rich panel data; they are the prices of rival firms' products in the past. For example, for $\xi_{jt}$ of PEPSI BOTTLE 67.6 oz in first week of 1993, the average price of Coca-Cola and Cadbury Schweppes in the first week of June 1991 can be the instrument. This instrument is valid under the assumption that the consumer's taste changes over time. In the soft drink market, this is not unusual, for example, in the early 90's, diet beverages gained popularity and clear products (including Crystal Pepsi) were advertised heavily, affecting consumer's preference. In addition, consumer demand fluctuates in different seasons like winter and summer.[28] Given this, the price of rival firm's products in past different season is exogenous to consumer taste, or the unobserved characteristics. At the same time, the rival firm's past price will be correlated with current product price, since in one city, all firms share some same cost, such as transportation cost and cost to put the products on the same retail chain. For the products' characteristics are constant over time, the prices are also correlated from the direct competition in same area.

Here are some notes on the instruments. First, I use both the number of brands and number of UPC's as instruments in the estimation. The argument for number of UPC's as valid instruments is similar to number of brands. Second, the first set of instruments varies across weeks but not products, while the second set of instruments varies across products but not weeks. Using each single set of instrument would not identify the parameters since they lack variation in one dimension,

[27]In my sample, around 33% of the soft drink UPC's were sold on discount from either feature or display in the post introduction period.

[28]For example, the average weekly market share of regular Pepsi in the sample followed a cyclical pattern over seasons. The market share in the summer are obviously higher than in spring, in the summers from 1991 to 1993, the average weekly market shares are 11.5%, 9.6% and 11.7%, while in the springs of 1992 and 1993 are 7.6% and 8.2% respectively. This indicates that consumers prefer Pepsi more in the summer than in the spring.

but by combining two sets of instrument together, I have the variation across both products and weeks. It is this two-dimensional variation that identifies the demand parameters.

### 4.3.5 Measuring the Welfare and Profit Effects

To measure the effects of Crystal Pepsi's introduction, I implement a counterfactual simulation without Crystal Pepsi and estimate the consumer's surplus and firms' profit in 25 week after Crystal Pepsi was launched. I simulate the counterfactual equilibrium prices from (3.7) with the new structure matrix $\Omega^{wo}(\cdot)$, assuming the marginal costs do not change. And in the new equilibrium, the market shares change accordingly with the new price vector.

Then I estimate the change of profit for each firm by computing the simulated profit without Crystal Pepsi, and comparing with the profit with Crystal Pepsi.

$$\Delta\Pi_f = \sum_{t=1}^{T}[\Pi_f^t(p_1, mc; \theta) - \Pi_f^t(p_0, mc; \theta)]$$

where $\Pi_f^t(p_1, mc; \theta)$ is firm $f$'s profit at the post-introduction equilibrium price $p_1$ and $\Pi_f^t(p_0, mc; \theta)$ is firm $f$'s profit at the counterfactual equilibrium price $p_0$. So, $\Delta\Pi_f$ measures the firm's profit change from the introduction of Crystal Pepsi. The total supplier's surplus change is the sum of those profit changes.

Consumer welfare is measured by the compensating variation (CV), which is the dollar amount a consumer needs to be compensated in the equilibrium without Crystal Pepsi to attain the same utility level as in equilibrium with Crystal Pepsi. If the marginal utility of income is fixed for each consumer, McFadden(1981) and Small and Rosen(1981) show that the compensating variation for individual $i$ can be written as

$$CV_i = \frac{ln[\sum_{j=0}^{J} V_{ij}^{w}(p_1)] - ln[\sum_{j=0}^{J-1} V_{ij}^{wo}(p_0)]}{\alpha_i^*} \tag{4.7}$$

where $V_{ij}^{w}(p_1)$ represents the utility level of individual $i$ from product $j$ at the equilibrium price $p_1$ with Crystal Pepsi as defined by (3.1), and $V_{ij}^{wo}(p_0)$ is the utility at the counterfactual equilibrium price without Crystal Pepsi. $\alpha_i^*$ is defined in (3.1) and is the marginal utility of income.

The compensating variation can be decomposed into two parts for two different effects, the variety effect and the price effect.

$$CV_i = CV_i^{ve} + CV_i^{pe} \tag{4.8}$$

$$= \frac{ln[\sum_{j=0}^{J} V_{ij}^{w}(p_1)] - ln[\sum_{j=0}^{J-1} V_{ij}^{wo}(p_1)]}{\alpha_i^*} + \frac{ln[\sum_{j=0}^{J-1} V_{ij}^{wo}(p_1)] - ln[\sum_{j=0}^{J-1} V_{ij}^{wo}(p_0)]}{\alpha_i^*}$$

The first part is the variety effect of compensating variation, which captures the consumer's welfare change when removing the Crystal Pepsi from the actual equilibrium but keeping the equilibrium prices fixed. The second part measures the price effect: the welfare change in a market without Crystal Pepsi but the prices move from the counterfactual equilibrium level to actual equilibrium level.

The total consumer's compensating variation is given by the integral over the population

$$M \int CV_i(\cdot) dP^*(D) dP^*(\nu)$$

# 5 Results

## 5.1 Descriptive Statistics

In soft drink market, there are many brands and each brand has various package sizes. Every combination of brand and package size is identified as a UPC in the data set, which adds up to more than one thousand UPC's in the market. Obviously, it is unrealistic to include all the UPC's in the model. Instead, I choose the top 45 UPC's with the largest market shares, and define a product by brand and an indicator of large package with 288 OZ, which ends up with 26 products for my model. The characteristics of those products are reported in table 1 [29] . In the sample period, large bottle Pepsi has the biggest market share of 2.37%, Crystal Pepsi has the highest price of 0.90 dollar per 32 fluid ounce, and the most advertised brand is Diet Coke. Before the entry of Crystal Pepsi, the clear brands are 7UP, Canada Dry and Sprite, and small package 7UP

[29] Calories, carbohydrates and sodium are the common ingredient of soft drink, and I tried including them in the estimation but it turns out that they have very little effect on the demand, so I exclude them in the reported results.

has the biggest market share of 2.04%.

Table 2 summarizes the income and family size of households in the sample, the mean annual income is $\$35,700$ and the mean family size is 2.66 . And Table 3 reports the average demographics of purchasers for each product, which shows that the average income of Crystal Pepsi purchasers is $\$37,300$ and the average family size is 3.18, both are higher than the population mean.

### 5.2 Parameter Estimates

Table 4 and 5 present the results from four different demand-side models: ordinary least square (OLS) logit, logit model with instrumental variables, conditional logit with fixed effect, and random coefficient model with micro moments. In Table 4, the size of estimated price coefficient decreases significantly from OLS to instrumental variables, which is similar to Berry et al.(1995) and Petrin (2002)'s findings, indicating that instrumental variables are important in the final specification. The OLS and IV logit models restrict the parameters of interaction terms and random coefficients in Table 4 to be zero. As many interaction terms and random coefficients are significantly different from zero, the Wald test is to reject OLS or IV in favor of the more flexible framework.

Columns 2 and 3 of Table 5 report the demand coefficient estimates and their standard errors from a conditional Logit model with fixed effect. The household data tracks what households purchase in each week from what store, while the store level data contains the prices of available products for each store in every week. I match each household's shopping trip with the available products of the store in that week to form a group.[30] Then I run the fixed effect logit on those groups using maximum likelihood estimation.[31] Most parameters are significant and all the primary parameters of product characteristics are highly significant with expected signs.

Conditional logit model exploits the information of households' demographics and the characteristics of products they directly choose from, however, this model assumes that the error term follows the logistic distribution, and as a consequence, the unobserved consumer taste variation over weeks is assumed away. I use the results from conditional logit as a benchmark to check with

[30]For example, household $x$ purchased product $i$ at store $y$ in week $t$, and store $y$ had $m$ soft drink products on the shelf, so I know that household $x$ chose item $i$ from those $m$ products, this forms a group.

[31]The fixed effects are for groups, and the likelihood is calculated relative to each group, i.e. conditional likelihood is used.

the demand estimates from the final specification. Columns 4 and 5 in Table 5 are estimated from the random coefficient model with micro moments stated in the paper, and compared with columns 2 and 3, the coefficients of product's characteristics and the interaction terms with demographics are significant and of the same sign as conditional logit except two out of eleven. Thus the random coefficient model combining the micro moments from household level data and the moments from market level data provides reasonable and significant estimates of demand for the analysis of social welfare and market structure.

### 5.3 Elasticities and Substitutes

There is no analytical expression for demand elasticities, so I numerically compute the own and cross price elasticities of market share for all the products. From (4.5), the elasticity of product $j$ to product $h$ is

$$\eta_{jht} = \frac{\partial s_{jt} p_{ht}}{\partial p_{ht} s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt}(1 - s_{ijt}) dF^*(D) dF^*(\nu) & \text{if } j = h \\ \frac{p_{ht}}{s_{jt}} \int \alpha_i s_{ijt} s_{iht} dF^*(D) dF^*(\nu) & \text{if } j \neq h \end{cases} \tag{5.1}$$

where $s_{ijt} = P(y_{ijt} = 1) = \frac{exp(V_{ijt})}{1+\sum_{l=1}^{J_t} exp(V_{ilt})}$. The integral is obtained from direct Monte Carlo simulation. And $\frac{\partial s_{jt}}{\partial p_{ht}}$ will be used in (3.5) to estimate the marginal cost.

I compute the elasticities for each market and report the median of own and cross price elasticities for a sample in Table 6.[32] Own price elasticities are between $-3.36$ and $-8.37$, which are reasonable compared to the estimates in other studies of the soft drink industry reported in Table 7. The elasticities demonstrate that for some brands consumers tend more to substitute between products of the same size than to other sizes of the same brand. For example, demand for large Diet 7UP is more sensitive to the price of large Pepsi (0.40) than to the price of small Diet 7UP (0.05). This result is consistent to the findings by Guadagni and Little (1983) and Dube (2005) that households tend to switch among products of the same package size.

[32]The complete set of elasticities is available in a separate appendix.

### 5.4 Examination of Market Structure

One advantage of the model is that I can simulate the prices without Crystal Pepsi under different scenarios of market structure. As I have the data of prices before introduction, the comparison of actual prices with the simulated prices without Crystal Pepsi could shed light on the competition pattern between firms. The actual and simulated prices change due to the introduction of Crystal Pepsi should be approximately equal if the demand system is correctly specified, the firms' marginal costs are constant over the sample period and over the relevant range of output, and the assumed model of competition is correct. The random coefficient model used for demand system is flexible, and the estimates are reasonable and robust comparing to alternative specifications, in addition, the price changes are relatively small, so misspecification of the demand system is unlikely to be substantial if it exists at all. In the same way, for relatively small quantity changes, the marginal cost changes are not likely to be large unless firms are operating at near full capacity. Other reasons that could cause big changes in marginal cost are production efficiency improvements or local labor cost variation, however, given that the sample length is only two years in a single metropolitan area, substantial marginal cost changes are not likely to happen. Thus, neither of the first two potential reasons should lead to a substantial difference between actual and simulated prices without Crystal Pepsi, and consequently, the finding of a substantial divergence between two sets of prices would suggest the failure of the assumed model of competition to accurately describe the true firms' behavior.

I access three alternative models of competition for both pre and post introduction of Crystal Pepsi to examine which simulated price changes match the actual price changes closest. I consider three market structures: oligopoly price competition, in which each firm sets the prices to maximize profit; perfect price collusion, in which the prices of all products are set by a cartel; and single product pricing, in which prices are set to maximize each single product's profit. Since either pre or post introduction period can be one of those three structures, there are nine possible combinations. For example, firms may collude in price before the introduction of Crystal Pepsi, but they become oligopoly competing in price in post introduction period. It is worth noting that the marginal cost estimates depend on the assumed model of post introduction period, thus for each combination, I hold the marginal cost constant from the post introduction estimates, and simulate the prices without Crystal Pepsi from the assumed pre-introduction market structure.

Columns 2 and 3 of table 8 report the mean and standard error of weekly median actual and simulated prices of 26 products, and column 4 presents the paired t-statistics of the null hypothesis that the actual percent price changes of all products from pre to post introduction are the same as simulated one. Of the nine alternative competition models, simulated prices from collusion/collusion model stand out to be reasonably close in magnitude and not statistically significantly different from zero compared to the actual prices without Crystal Pepsi. And oligopoly/oligopoly model rejects the null hypothesis at 6.2% level. All other assumed competition models reject the null hypothesis significantly with absolute value of t-statistics greater than 8[33].

This finding is different from Gasmi et al. (1992) whose evidence does not support collusive pricing in the soft drink industry. However, Gasmi et al. (1992) employs the reduced linear demand equations, limits itself to interactions between two firms (CocaCola and PepsiCo) and aggregates each firm's differentiated brands as one single product. This simplification is questionable because each single brand is priced and advertised separately to meet corporation goal.[34] Compared to the aggregate linear market-level demand system, random coefficient logit model distinguishes different brands, considers more than two manufacturers and exploits the interactions between consumer preferences and product characteristics, which leads to more realistic substitution pattern, and consequently allows richer strategic interaction among firms.

In addition, the aggregation in Gasmi et al (1992) is equivalent to assuming that each firm maximizes its profit over all brands and then testing whether cooperation exists among duopoly, while in this paper, I evaluate all three possible market structures. So I am confident that the finding in this paper about the existence of price collusion is more reliable.[35]

[33] The degrees of freedom is 24.

[34] I do not say the goal is to maximize firm's overall profit, because this is one of the hypotheses I will examine. The possible goals could be maximizing single brand's profit, maximizing the whole market profit (collusion) or maximizing firm's overall profit (oligopoly).

[35] Actually, the adjusted LR statistic in Gasmi et al (1992) does not reject the price collusion significantly.

## 5.5 Changes in Consumer Welfare

As stated in section 4.3.5, I use compensating variation to measure changes in consumer welfare from the introduction of Crystal Pepsi. In the counterfactual scenario, there is no Crystal Pepsi, and other soft drink prices solve the set of equilibrium first order conditions in (3.7). For consumers not purchasing Crystal Pepsi, the compensation is determined entirely by the changes in soft drink prices associated with the entry of Crystal Pepsi. Households benefits more from purchasing products whose prices decrease more. Table 9 summarizes the median current prices and the counterfactual prices without Crystal Pepsi under the collusion model. It shows that Crystal Pepsi products were substitutes to all existing clear brands, in particular, large 7UP and large Diet 7UP experienced the largest percentage price decreases. In addition, large Caffeine Free Diet Pepsi, large Pepsi, large Coke Classic, RC and all Dr Pepper products decreased their price upon the entry of Crystal Pepsi. Specifically, large Pepsi's price was reduced by nearly 12%, this shows the cannibalization effect of new product on introducer's existing brands. As reported in Table 11, the estimated gains to non-Crystal Pepsi purchasers from increased price competition account for almost 89% of total consumer benefits, and if measured in per 32 fluid ounce serving of soft drink, the price effect is 0.55 cents.

For Crystal Pepsi purchasers, welfare change is the dollar amount that a Crystal Pepsi consumer needs to be compensated at the new equilibrium prices to achieve the "Crystal Pepsi standard of living". The variety effect is measured as the first term in (4.8), which is 0.07 cents per 32 fluid ounce serving and accounts for 11% of total consumer surplus.

## 5.6 Profit Dissipation and Total Welfare Change

Before turning to measure the firms' profit change, I compare the markups of all products with and without the entry of Crystal Pepsi. Table 10 reports the estimated marginal costs and the margins. The third column of post-introduction margins indicates that carbonated soft drink is a high profit industry, the average markup is 43%, large Pepsi has the highest markup of 58%, while the new introduced product Crystal Pepsi has the lowest markup of 29%. The fact that Crystal Pepsi has the highest marginal cost and lowest markup shows that introducing a new product is costly for firms.

Upon the entry of Crystal Pepsi, six out of seven clear products decreased their margins, specifically margins of large Diet 7UP and large 7UP decreased by more than 10%, which is the largest decreases of all products. The only exception is small Diet 7UP whose margin increased by 1%. Among seven PepsiCo products (excluding Crystal Pepsi), margins of four increased and three decreased. This illustrates that Crystal Pepsi competed more with other clear brands while the effect on introducer's brands was mixed.

Changes in PepsiCo and all firms' variable profit due to the introduction of Crystal Pepsi are reported in row 2 of Table 11. These estimates are obtained by computing implied profits without Crystal Pepsi and comparing them to the profit with Crystal Pepsi using the median prices over weeks. Results suggest that PepsiCo benefited significantly from introducing Crystal Pepsi, as variable profits increased by $5,052.07 per week in the sample relative to what profits would be without the introduction.[36] Other manufactures benefited as well from PepsiCo's innovation, their weekly profit in sample increased by $1,301, which is an increase of 12% of their total profit[37]. Total profit of firms were increased by $6,353, approximately 38% of the profit were Crystal Pepsi not introduced. However, the introducer, PepsiCo, took most profit benefits (80%) from the innovation.

Social welfare is the sum of consumer surplus and producer welfare, which add up to $7,879 per week in the sample. Around 81% of the social welfare surplus went to producers, however, in particular the introducer of Crystal Pepsi, this shows that firms have incentive to keep introducing new brands to gain more profit. For consumer surplus, purchasers of Crystal Pepsi gained positive utility from the characteristics of the new product, while most benefits went to non Crystal Pepsi consumers due to price reduction.

### 5.7 Market Structure and Welfare

The results reported in preceding sections are under the competition model of collusion that best matches the observed data. However, the oligopoly competition model is not unreasonably far

[36]The profit increase is 87.6% of PepsiCo's profit if not introducing Crystal Pepsi. This number is huge at first glance, but I only include the products of PepsiCo in the model that are most correlated with Crystal Pepsi, so this ratio is over estimated of the actual percentage increase.

[37]For the same reason that only part of the products are included in the model, the number here only illustrate the change in the sample.

in magnitude and not statistically significantly different from zero according to the t-test. Here I simulate the equilibrium prices and the social welfare change under the price competition of oligopoly, and compare them to the results from the collusion model to investigate the effects of new product on social welfare under different market structures. This exercise would illustrate the incentive of firm's innovation and its impact on social welfare under different antitrust policies.

The welfare changes from oligopoly competition are reported in the first row of Table 11. The consumer surplus from the variety effect remains the same and the profit increase for new product introducer PepsiCo is smaller than in collusion case. However, contrary to the collusion model, the price effect of consumer surplus is dropped to $-\$1,405$ from $\$1,352$ and the rival firms' profit improvement rises from $\$1,301$ to $\$2,162$. As a result, total consumer welfare would decrease from the introduction of Crystal Pepsi if firms competed in oligopoly, while total social welfare improvement is reduced to $\$5,090$, which is around 35% decrease from collusion model.

The above comparison shows that when a firm in a cartel introduces a new product, consumers benefit from the innovation, and both the innovator firm and other producers' profit increase. On the other hand, when a firm introduces new product in oligopolistic market, introducer will gain less profit and the rival firms could take a "free ride" on the innovation to raise prices for more revenue, while, surprisingly, consumers would be hurt from the innovation.

# 6 Conclusions

This paper examines the effects of introduction of Crystal Pepsi in the soft drink market on consumer welfare and firms' profits. The effects of new product introduction in carbonated soft drink market has not been analyzed formally before using a random coefficient model combining household level and store level data.

The estimation results of logit models indicate that controlling for price endogeneity is important in this market. The price coefficient estimates increase significantly by using instrumental variables. The results from a random coefficient model show that advertising has significantly positive effects on demand, but this effect decays as household income increases.

Comparing the price effect of Crystal Pepsi introduction from counterfactual equilibrium under various competition models to the actual price effect, the price collusion model best describes the firms' behavior. Under the collusion model, the new product increased consumer's welfare mostly by the price effect due to the price reduction from the entry. The new product helped the introducer PepsiCo to capture the combined market share and increase its profit. And the profit of other firms increases as well from the introduction of the new brand.

Simulated equilibrium from the oligopolistic model demonstrates that non-introducing firms would raise their prices upon the entry of the new product and gain more profit, and at the same time, the introducer would capture less profit than in the collusion model. Surprisingly, consumers would be hurt from the innovation if producers compete in oligopoly. The social welfare improvement is still positive from the innovation but is lower than in a collusive market.

My results suggest that the innovation in a collusion market will bring more social welfare improvement. Firms in an oligopolistic market would have less incentive to invest in $R\&D$ and innovation because they can take "free ride" by increasing prices to gain profit when other firms introduce new products.

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Table 1: Market Share, Price and Product Characteristics

| | Market *Share*[3] | Price ($/32 oz) | *Advertisement*[4] (M$/week) | Caffeine (dummy) | Clear (dummy) |
|---|---|---|---|---|---|
| *7UP(DS)*[12] | 2.04 | 0.47 | 0.53 | 0 | 1 |
| *7UP/L(DS)*[1] | 0.17 | 0.71 | 0.53 | 0 | 1 |
| Caf Free Diet Coke (CC) | 0.57 | 0.69 | 1.86 | 0 | 0 |
| Caf Free Diet Coke/L (CC) | 0.11 | 0.75 | 1.86 | 0 | 0 |
| Caf Free Diet Pepsi (P) | 0.13 | 0.69 | 0.81 | 0 | 0 |
| Caf Free Diet Pepsi/L (P) | 0.35 | 0.68 | 0.81 | 0 | 0 |
| Caf Free Pepsi (P) | 0.36 | 0.68 | 0.19 | 0 | 0 |
| Canada Dry (CS) | 0.39 | 0.55 | 0 | 0 | 1 |
| Coke Classic (CC) | 1.60 | 0.72 | 1.74 | 1 | 0 |
| Coke Classic/L (CC) | 0.45 | 0.76 | 1.74 | 1 | 0 |
| Crystal Pepsi (P) | 0.22 | 0.90 | 0.61 | 0 | 1 |
| Diet 7UP (DS) | 0.83 | 0.47 | 0.19 | 0 | 1 |
| Diet 7UP/L (DS) | 0.05 | 0.66 | 0.19 | 0 | 1 |
| Diet Coke (CC) | 1.50 | 0.72 | 1.86 | 1 | 0 |
| Diet Coke/L (CC) | 0.58 | 0.75 | 1.86 | 1 | 0 |
| Diet Dr Pepper (DS) | 0.40 | 0.48 | 0.51 | 1 | 0 |
| Diet Dr Pepper/L (DS) | 0.11 | 0.71 | 0.51 | 1 | 0 |
| Diet Pepsi (P) | 2.19 | 0.69 | 0.81 | 1 | 0 |
| Dr Pepper (DS) | 0.42 | 0.46 | 0.55 | 1 | 0 |
| Dr Pepper/L (DS) | 0.08 | 0.71 | 0.55 | 1 | 0 |
| Mountain Dew (P) | 0.25 | 0.69 | 0.20 | 1 | 0 |
| Pepsi (P) | 1.06 | 0.70 | 0.19 | 1 | 0 |
| Pepsi/L (P) | 2.37 | 0.68 | 0.19 | 1 | 0 |
| RC (RC) | 1.72 | 0.48 | 0.02 | 1 | 0 |
| Sprite (CC) | 0.15 | 0.76 | 0.02 | 0 | 1 |
| Sprite/L (CC) | 0.08 | 0.67 | 0.02 | 0 | 1 |

**Note**:
(1)*brand* means the brand of small packages, and the *brand/L* refers to the brands with the large package of 288 Ounce.
(2)The letters in parentheses refers to the manufacture. DS refers to Dr Pepper/Seven-Up Corp; CC refers to Coca Cola Co.; P refers to PepsiCo Inc.; CS refers to Cadbury Schweppes Inc; RC refers to Royal Crown Co.
(3) *Market share* is the percent average volume share over the sample period.
(4) *Advertisement* is the average weekly advertising expenditure, measured in Million dollars.

Table 2: Demographic Statistics

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Income | 3.57 | 2.27 | 0.5 | 8 |
| Famsize | 2.66 | 1.39 | 1 | 6 |

Table 3: Average Demographics of Product's Purchasers

| | Income | Famsize |
|---|---|---|
| 7UP (DS) | 3.0199 | 3.1404 |
| 7UP/Large (DS) | 2.953 | 2.4945 |
| CAFF FREE DIET Coke (CC) | 4.8194 | 2.4045 |
| CAFF FREE DIET Coke/Large (CC) | 3.7745 | 2.0288 |
| CAFF FREE DIET Pepsi (P) | 3.7773 | 3.2182 |
| CAFF FREE DIET P/Large (P) | 3.991 | 2.8853 |
| CAFF FREE PEPSI (P) | 3.6712 | 3.2683 |
| CANADA DRY (CS) | 3.7486 | 2.6041 |
| COKE CLASSIC (CC) | 3.6896 | 2.9145 |
| COKE CLASSIC/Large (CC) | 4.0755 | 3.466 |
| CRYSTAL PEPSI (P) | 3.7308 | 3.1821 |
| DIET 7UP (DS) | 3.23 | 2.0668 |
| DIET 7UP/Large (DS) | 2.0074 | 1.0737 |
| DIET COKE (CC) | 4.1615 | 2.2876 |
| DIET COKE/Large (CC) | 3.0073 | 2.1699 |
| DIET DR PEPPER (DS) | 5.3862 | 2.3063 |
| DIET DR PEPPER/Large (DS) | 2.5505 | 2.0101 |
| DIET PEPSI (P) | 4.6549 | 2.9191 |
| DR PEPPER (DS) | 2.3338 | 2.731 |
| DR PEPPER/Large (DS) | 2.0223 | 1.9192 |
| MOUNTAIN DEW (P) | 1.3625 | 1.4615 |
| PEPSI (P) | 3.236 | 3.1209 |
| PEPSI/Large (P) | 3.6926 | 3.5654 |
| RC (RC) | 2.8434 | 3.1161 |
| SPRITE (CC) | 2.584 | 2.5577 |
| SPRITE/Large (CC) | 2.4176 | 2.4628 |

**Note** : The reported average demographics are over weeks after the introduction of Crystal Pepsi.

Table 4: Demand Parameter Estimates: Logit OLS & Logit with IV's

| | OLS | Logit | IV | Logit |
|---|---|---|---|---|
| Variable | Model 1 | Model 2 | Model 1 | Model 2 |
| Constant | -5.15*** | -4.14*** | -3.82*** | -2.38** |
| | (0.43) | (0.30) | (0.70) | (0.76) |
| Price | -2.64*** | -4.07*** | -4.23** | -5.93*** |
| | (0.47) | (0.27) | (0.99) | (0.96) |
| Advertising | 0.62*** | 0.13** | 0.62*** | 0.13** |
| | (0.05) | (0.03) | (0.06) | (0.04) |
| Caffeine | 0.89*** | -0.45* | 0.84*** | -0.88** |
| | (0.13) | (0.30) | (0.13) | (0.30) |
| Clear | 0.55** | -0.18 | 0.48** | -0.72* |
| | (0.15) | (0.30) | (0.16) | (0.46) |
| Package | 0.14* | 0.82** | -0.01 | 0.15 |
| | (0.08) | (0.28) | (0.08) | (0.34) |
| Week Dummies | o | o | o | o |
| Product Dummies | x | o | x | o |
| R-square | 0.31 | 0.80 | 0.24 | 0.75 |
| First Stage R-square | – | – | 0.29 | 0.29 |

**Note** :
(1) Standard errors are in parentheses.
(2) *** $t - value > 5$; ** $t - value > 2$; * $t - value > 1$.

Table 5: Demand Estimates

| | Conditional | Logit | Random | Coefficient |
|---|---|---|---|---|
| Variable | Parameter Estimates | Standard Error | Parameter Estimates | Standard Error |
| Constant | – | – | -1.69*** | 0.12 |
| Price | -2.73*** | 0.35 | -14.88*** | 0.08 |
| Advertising | 0.09* | 0.06 | 3.43*** | 0.10 |
| Caffeine | 0.68** | 0.16 | 0.58*** | 0.07 |
| Clear | 0.44** | 0.19 | 0.70*** | 0.13 |
| Package | -0.43** | 0.13 | -1.44*** | 0.04 |
| Price*Income | 0.34*** | 0.06 | 1.04** | 0.22 |
| Adv*Income | -0.02** | 0.01 | -0.79** | 0.18 |
| Pkg*Income | 0.02* | 0.02 | 0.20*** | 0.03 |
| Price*Famsize | -0.74*** | 0.11 | -0.64* | 0.49 |
| Clear*Famsize | 0.14** | 0.05 | -0.13 | 0.60 |
| Pkg*Famsize | 0.23*** | 0.03 | 0.004 | 0.24 |
| Constant*v | – | – | 1.51* | 0.77 |
| Price*v | – | – | -1.01 | 1.47 |
| Adv*v | – | – | 0.74** | 0.23 |
| Caffeine*v | – | – | -1.49* | 1.30 |
| Clear*v | – | – | 0.76 | 5.55 |
| Pkg*v | – | – | 1.48** | 0.47 |

**Note** : *** $t - value > 5$; ** $t - value > 2$; * $t - value > 1$.

Table 6: Own and Cross-Price Elasticities

| Product | Canada Dry | Coke Classic | Crystal Pepsi | DIET 7UP | Diet Coke | Diet Coke/L | Diet Pepsi | Pepsi | Pepsi/L |
|---|---|---|---|---|---|---|---|---|---|
| 7UP (DS) | 0.07 | 0.17 | 0.17 | 0.10 | 0.13 | 0.07 | 0.42 | 0.16 | 0.17 |
| 7UP/Large (DS) | 0.05 | 0.05 | 0.09 | 0.06 | 0.06 | 0.14 | 0.19 | 0.07 | 0.37 |
| Caff Free Diet Coke (CC) | 0.03 | 0.37 | 0.06 | 0.02 | 0.36 | 0.21 | 0.31 | 0.03 | 0.02 |
| Caff Free Diet Coke/L (CC) | 0.02 | 0.17 | 0.04 | 0.01 | 0.19 | 0.40 | 0.17 | 0.01 | 0.02 |
| Caff Free Diet Pepsi (P) | 0.04 | 0.34 | 0.13 | 0.08 | 0.21 | 0.15 | 0.48 | 0.16 | 0.19 |
| Caff Free Diet Pepsi/L (P) | 0.04 | 0.12 | 0.09 | 0.05 | 0.09 | 0.19 | 0.24 | 0.10 | 0.40 |
| Caff Free Pepsi (P) | 0.03 | 0.16 | 0.08 | 0.08 | 0.04 | 0.01 | 0.31 | 0.29 | 0.34 |
| Canada Dry (CS) | -4.20 | 0.06 | 0.12 | 0.07 | 0.08 | 0.06 | 0.25 | 0.12 | 0.14 |
| Coke Classic (CC) | 0.01 | -8.37 | 0.05 | 0.03 | 0.58 | 0.35 | 0.74 | 0.24 | 0.20 |
| Coke Classic/L (CC) | 0.01 | 0.64 | 0.03 | 0.03 | 0.30 | 0.62 | 0.52 | 0.20 | 0.39 |
| Crystal Pepsi (P) | 0.06 | 0.12 | -7.36 | 0.09 | 0.12 | 0.05 | 0.35 | 0.15 | 0.16 |
| Diet 7UP (DS) | 0.07 | 0.16 | 0.15 | -5.52 | 0.07 | 0.03 | 0.40 | 0.21 | 0.24 |
| Diet 7UP/L (DS) | 0.04 | 0.03 | 0.07 | 0.05 | 0.03 | 0.05 | 0.13 | 0.07 | 0.40 |
| Diet Coke (CC) | 0.02 | 0.66 | 0.05 | 0.02 | -7.71 | 0.40 | 0.43 | 0.05 | 0.04 |
| Diet Coke/L (CC) | 0.01 | 0.34 | 0.02 | 0.01 | 0.40 | -5.80 | 0.33 | 0.02 | 0.06 |
| Diet Dr Pepper (DS) | 0.04 | 0.37 | 0.07 | 0.05 | 0.22 | 0.14 | 0.83 | 0.31 | 0.37 |
| Diet Dr Pepper/L (DS) | 0.03 | 0.10 | 0.05 | 0.03 | 0.09 | 0.18 | 0.33 | 0.15 | 0.78 |
| Diet Pepsi (P) | 0.03 | 0.46 | 0.07 | 0.05 | 0.33 | 0.22 | -7.11 | 0.28 | 0.33 |
| Dr Pepper (DS) | 0.03 | 0.41 | 0.07 | 0.05 | 0.24 | 0.16 | 0.86 | 0.31 | 0.36 |
| Dr Pepper/L (DS) | 0.03 | 0.11 | 0.05 | 0.03 | 0.09 | 0.20 | 0.35 | 0.16 | 0.77 |
| Mountain Dew (P) | 0.05 | 0.12 | 0.07 | 0.04 | 0.14 | 0.08 | 0.57 | 0.25 | 0.39 |
| Pepsi (P) | 0.02 | 0.24 | 0.04 | 0.04 | 0.06 | 0.02 | 0.51 | -5.98 | 0.55 |
| Pepsi/Large (P) | 0.01 | 0.07 | 0.03 | 0.03 | 0.01 | 0.03 | 0.23 | 0.24 | -3.36 |
| RC (RC) | 0.06 | 0.10 | 0.07 | 0.04 | 0.15 | 0.10 | 0.54 | 0.18 | 0.20 |
| Sprite (CC) | 0.06 | 0.10 | 0.13 | 0.11 | 0.05 | 0.02 | 0.30 | 0.22 | 0.25 |
| Sprite/L (CC) | 0.04 | 0.01 | 0.07 | 0.04 | 0.01 | 0.02 | 0.07 | 0.05 | 0.39 |

**Note** :
(1) The entry $i, j$, where $i$ indexes row and $j$ column, gives the percent change in market share of product $i$ with a 1% change in price of $j$.
(2) Each entry is the mean of the elasticities across 26 weeks.

Table 7: Comparison of Own Elasticity Estimates in Literature

| | Range | Model | Unit |
|---|---|---|---|
| Chan (2005) | [-5.49, -11.09] | Continuous Hedonic Choice Model | Attributes Group |
| Dube (2005) | [-3.06, -6.03] | Multiple-Discrete Choice Model | UPC |
| Cotterill, et. al (1996) | [-2.68, -5.08] | Almost Ideal Demand System | Brand |
| Xiao (2008) | [-3.36, -8.37] | Random Coefficient Model | Brand/Large |

Table 8: Comparison of Actual and Simulated Price Effects from Different Market Structures

| Market *Structure*[1] | Mean Price %*Change*[2] | Standard Error | $t - statistics$[3] |
|---|---|---|---|
| *Actual*[4] | -1.39 | 0.63 | N/A |
| Oligopoly/Oligopoly | 3.53 | 2.57 | -1.96 |
| *Collusion/Collusion*$^\star$ | -2.57 | 1.71 | 0.75 |
| Single/Single | 15.47 | 1.24 | -10.91 |
| Oligopoly/Collusion | -10.50 | 1.34 | 11.71 |
| Oligopoly/Single | 22.06 | 1.74 | -12.50 |
| Collusion/Oligopoly | 53.97 | 4.27 | -13.10 |
| Collusion/Single | 61.56 | 4.43 | -13.41 |
| Single/Oligopoly | 11.24 | 1.42 | -8.98 |
| Single/Collusion | -8.22 | 0.85 | 8.57 |

**Note** :
(1) The assumed market structure refers to Pre-Introduction/Post-Introduction.
(2) *Mean price % change* is the mean of the percent price change of all products, i.e. $100 * (P_w - P_{wo})/P_{wo}$.
(3) *t-statistics* is for the null hypothesis that the simulated percent change of price equals the actual price change.
(4) *Actual* refers to the direct price change from data due to the introduction of Crystal Pepsi, see text for details.

Table 9: New Equilibrium Price Without Crystal Pepsi

| | Current Price (P) | Price w/o CP ($P_{wo}$)[1] | $\Delta P$ ($P - P_{wo}$) | Change (%) $100 * (\Delta P/P_{wo})$ |
|---|---|---|---|---|
| 7UP (DS) | 0.56 | 0.58 | -0.01 | -2.52 |
| 7UP/Large (DS) | 0.59 | 0.73 | -0.14 | -19.08 |
| Caff Free Diet Coke (CC) | 0.69 | 0.61 | 0.08 | 13.23 |
| Caff Free Diet Coke/L (CC) | 0.65 | 0.65 | 0.01 | 1.01 |
| Caff Free Diet Pepsi (P) | 0.62 | 0.62 | 0.00 | 0.13 |
| Caff Free Diet Pepsi/L (P) | 0.65 | 0.66 | -0.01 | -1.97 |
| Caff Free Pepsi (P) | 0.58 | 0.54 | 0.03 | 6.32 |
| Canada Dry (CS) | 0.47 | 0.49 | -0.03 | -5.20 |
| Coke Classic (CC) | 0.63 | 0.60 | 0.02 | 4.12 |
| Coke Classic/L (CC) | 0.67 | 0.67 | 0.00 | -0.61 |
| Diet 7UP (DS) | 0.53 | 0.52 | 0.01 | 1.77 |
| Diet 7UP/L (DS) | 0.60 | 0.74 | -0.14 | -19.13 |
| Diet Coke (CC) | 0.69 | 0.62 | 0.07 | 11.39 |
| Diet Coke/L (CC) | 0.68 | 0.59 | 0.08 | 13.57 |
| Diet Dr Pepper (DS) | 0.55 | 0.58 | -0.04 | -6.33 |
| Diet Dr Pepper/L (DS) | 0.66 | 0.74 | -0.07 | -10.03 |
| Diet Pepsi (P) | 0.59 | 0.64 | -0.04 | -6.78 |
| Dr Pepper (DS) | 0.52 | 0.56 | -0.04 | -7.11 |
| Dr Pepper/L (DS) | 0.67 | 0.71 | -0.04 | -5.99 |
| Mountain Dew (P) | 0.67 | 0.66 | 0.01 | 1.53 |
| Pepsi (P) | 0.62 | 0.61 | 0.01 | 1.10 |
| Pepsi/Large (P) | 0.64 | 0.72 | -0.08 | -10.93 |
| RC (RC) | 0.47 | 0.53 | -0.06 | -11.89 |
| Sprite (CC) | 0.60 | 0.63 | -0.04 | -5.75 |
| Sprite/L (CC) | 0.65 | 0.68 | -0.03 | -5.11 |

**Note** :
(1) The counterfactual price without Crystal Pepsi is assuming price collusion both pre and post introduction and is based on the estimates in Table 2.
(2) The reported *Current Price* and *Price w/o CP* are the median of each product over weeks.

Table 10: Marginal Cost and Margins

| | Marginal Cost (MC) | Current Margins $100*(P-MC)/P$ | Margins w/o CP $100*(P_{wo}-MC)/P_{wo}$ | $\Delta Margin$ |
|---|---|---|---|---|
| 7UP (DS) | 0.36 | 35.41 | 37.04 | -1.63 |
| 7UP/Large (DS) | 0.32 | 45.48 | 55.88 | -10.40 |
| Caff Free Diet Coke (CC) | 0.42 | 38.43 | 30.28 | 8.14 |
| Caff Free Diet Coke/L (CC) | 0.36 | 44.62 | 44.07 | 0.56 |
| Caff Free Diet Pepsi (P) | 0.42 | 32.61 | 32.53 | 0.09 |
| Caff Free Diet Pepsi/L (P) | 0.42 | 35.41 | 36.68 | -1.27 |
| Caff Free Pepsi (P) | 0.33 | 42.29 | 38.64 | 3.65 |
| Canada Dry (CS) | 0.22 | 53.84 | 56.25 | -2.40 |
| Coke Classic (CC) | 0.39 | 37.53 | 34.95 | 2.57 |
| Coke Classic/L (CC) | 0.45 | 33.13 | 33.54 | -0.41 |
| Crystal Pepsi (P) | 0.52 | 28.69 | N/A | N/A |
| Diet 7UP (DS) | 0.30 | 43.25 | 42.24 | 1.01 |
| Diet 7UP/L (DS) | 0.34 | 43.11 | 54.00 | -10.88 |
| Diet Coke (CC) | 0.38 | 44.31 | 37.96 | 6.35 |
| Diet Coke/L (CC) | 0.35 | 48.68 | 41.72 | 6.96 |
| Diet Dr Pepper (DS) | 0.32 | 41.05 | 44.78 | -3.73 |
| Diet Dr Pepper/L (DS) | 0.37 | 43.95 | 49.57 | -5.62 |
| Diet Pepsi (P) | 0.39 | 34.74 | 39.16 | -4.43 |
| Dr Pepper (DS) | 0.29 | 43.02 | 47.07 | -4.05 |
| Dr Pepper/L (DS) | 0.38 | 42.66 | 46.10 | -3.43 |
| Mountain Dew (P) | 0.34 | 49.23 | 48.45 | 0.78 |
| Pepsi (P) | 0.33 | 45.99 | 45.40 | 0.59 |
| Pepsi/Large (P) | 0.27 | 57.62 | 62.25 | -4.63 |
| RC (RC) | 0.20 | 57.34 | 62.41 | -5.07 |
| Sprite (CC) | 0.32 | 46.25 | 49.34 | -3.09 |
| Sprite/L (CC) | 0.35 | 45.35 | 48.14 | -2.79 |

**Note** : Marginal cost is estimated under price collusion model and they are the median over weeks.

Table 11: Social Welfare Decomposition

| | | Consumer | Surplus | | |
|---|---|---|---|---|---|
| | Total Welfare | Variety Effect | Price Effect | Total Profit | PepsiCo Profit |
| Oligopoly | 5090.36 | 174.52 | -1404.79 | 6320.63 | 4158.45 |
| Collusion | 7879.33 | 174.52 | 1351.83 | 6352.98 | 5052.07 |

**Note** : Oligopoly here means firms compete in oligopoly both in pre and post introduction period, and it is the same for collusion.

Table 12: Price and Market Share Change in Different Models

| | Collusion | Model | Oligopoly | Model |
|---|---|---|---|---|
| | Price Percent *Change*[1] | Market Share *Change*[2] | Price Percent *Change*[1] | Market Share *Change*[2] |
| 7UP (DS) | -2.51 | 0.50 | 1.15 | 0.42 |
| 7UP/Large (DS) | -19.08 | 0.05 | 6.63 | -0.47 |
| Caff Free Diet Coke (CC) | 13.24 | 0.25 | 16.53 | 0.22 |
| Caff Free Diet Coke/L (CC) | 1.01 | 0.44 | 7.43 | 0.43 |
| Caff Free Diet Pepsi (P) | 0.13 | 0.06 | -8.29 | 0.15 |
| Caff Free Diet Pepsi/L (P) | -1.98 | 0.16 | -14.64 | 0.32 |
| Caff Free Pepsi (P) | 6.31 | 0.12 | -16.70 | 0.54 |
| Canada Dry (CS) | -5.21 | 0.02 | 4.88 | -0.03 |
| Coke Classic (CC) | 4.11 | -0.92 | 9.02 | -1.17 |
| Coke Classic/L (CC) | -0.62 | 0.74 | 14.46 | -1.93 |
| Diet 7UP (DS) | 1.77 | 0.13 | 11.47 | 0.00 |
| Diet 7UP/L (DS) | -19.14 | -0.26 | 8.69 | -0.53 |
| Diet Coke (CC) | 11.39 | 0.38 | 19.40 | -0.08 |
| Diet Coke/L (CC) | 13.58 | 1.14 | 8.41 | 1.39 |
| Diet Dr Pepper (DS) | -6.34 | 0.00 | 8.10 | -0.17 |
| Diet Dr Pepper/L (DS) | -10.03 | 0.16 | 16.35 | -0.09 |
| Diet Pepsi (P) | -6.78 | 0.25 | -18.03 | 2.68 |
| Dr Pepper (DS) | -7.12 | -0.07 | 3.37 | -0.22 |
| Dr Pepper/L (DS) | -5.99 | 0.16 | 15.75 | -0.10 |
| Mountain Dew (P) | 1.54 | 0.02 | -14.00 | 0.24 |
| Pepsi (P) | 1.10 | 0.54 | -16.30 | 1.61 |
| Pepsi/Large (P) | -10.93 | 4.78 | -18.83 | 4.91 |
| RC (RC) | -11.89 | -0.41 | 12.25 | -3.64 |
| Sprite (CC) | -5.75 | 0.14 | 14.47 | 0.03 |
| Sprite/L (CC) | -5.11 | 0.08 | 16.73 | 0.01 |

**Note** :
(1) *Price Percent Change* is the percent change of price from pre-introduction to post-introduction period, i.e. $100 * (p_w - p_{wo})/p_{wo}$.
(2) *Market Share Change* is the difference of percent market share between post-introduction and pre-introduction, i.e. $s_w - s_{wo}$.

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