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The Effect of Advertising and In-Store Promotion on the Demand for Chocolate

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The Effect of Advertising and In-Store Promotion on the Demand for Chocolate

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Abstract

This paper analyzes the effect of TV advertising and in-store displays on the sales of chocolates. I examine which method is more effective in gaining customers and in increasing total sales. Also, I look at the evidence to see whether the lack of advertising by a firm will hurt the industry as a whole. In this essay, I use a nested logit model on scanner data obtained by the Zwick Center for Food and Resource Policy at the University of Connecticuts Department of Agricultural and Resource Economics to examine the effect of TV advertising on chocolate sales. The results show that in-store displays and advertising both help increase the demand for chocolate.

Keywords: nested logit, scanner data, advertising, in-store promotions

JEL Classification Numbers: D12, L25, L66, M37

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1. Introduction

The candy industry is the third largest consumer food industry in terms of total sales in the United States behind soft drinks and milk. Advertising plays an important role in the marketing strategies of companies (See Appendix A). General Motors spent $3.65 billion in 2002 to advertise automobiles and trucks, and Procter and Gamble spent $3.32 billion in 2003 to advertise detergents and cosmetics (Carlton and Perloff, 2005; Bagwell, 2005). Among chocolate companies, Hershey spent $414 million in 2011 and Mars $630 million in 2011 to advertise their products. The success of firms can sometimes depend on the marketing strategy that they implement. Scott and Walker (2010) illustrate that promotional activities proved key to the success of British department stores in fending off competition from chain stores during the interwar years. I estimate the demand for chocolate using the product space characteristic approach. This essay utilizes a nested logit model to look into the role that advertising and in-store displays play in the demand for chocolate. This paper looks into the effectiveness of in-store displays and television ads on the demand for chocolate. I use scanner and advertising data that cover 16 metropolitan areas in the U.S. over a three-year period. I try out two specifications of my model: one where Hershey and Mars form the two nests and one where chocolate brands with nuts and without nuts form the two nests. I also calculate the elasticities for each brand as well as their price cost margins and marginal costs.

Before I review the literature on advertising and the chocolate industry I provide some background data on the chocolate industry. Table 2.1 shows the market value of the chocolate industry as well as the volume consumed of chocolate from 2007 to 2011. The compound annual growth rate (CAGR) of market value over those years is 2% which is less than that of the European (2.8%) and Asian (3.6%) markets (MarketLine, 2013). Consumption value had a CAGR of 0.9% between 2007 and

2011.

Figure 2.1 shows the market shares of the major players in the chocolate market. We see that Hershey and Mars combine for more than 70% of the markets value with Hershey being the top chocolate maker in the country with a 40.6% share. If we add the other big players (Nestle and Russell Stover) the big four chocolate firms would control about 86% of the market thus it is a very concentrated industry.

Figure 2.2 shows the distribution channel of the chocolate market. Supermarkets/hypermarkets and independent retailers combined account for about 57% of the markets value. Table 2.2 shows the demographics of chocolate consumers in the U.S. We see that majority of chocolate consumers are white or married or employed. Almost half have children under the age of 18 and most reside in either the South or the Midwest.

The next section discusses the literature relevant to this study. I then discuss the various discrete choice models followed by an explanation of my model, data, and estimation strategy, a discussion of the estimation results, elasticities and price cost margins and the conclusion.

2. Review of Related Literature

The history of promoting chocolate is almost as old as the industry itself. Rossfeld (2008) examined the history of the Swiss chocolate company Suchard and the *Verband Reisender Kaufleute der Schweiz* (Association of Swiss Commercial Travelers) and described the economic significance, social image, and everyday life of traveling salesmen between 1860 and 1920. By 1900, commercial travelers formed a critical link between the enterprise and the market, helping to drive the vertical integration of production and distribution. Many of them were promoted to executive levels and they were largely responsible for obtaining information and expanding product sales in an era that preceded specialized market research and the domination of advertising companies.

Fitzgerald (2005) examined the development of marketing in Cadbury from 1900 to 1939. He stated that by 1939, Cadburys marketing knowhow was a main factor in its commercial expansion and it exerted its influence on the nature of the confectionery industry.

There has been significant debate in the literature about the effect of advertising on sales. Eagle and Ambler (2002) found no association between the weight of advertising and market growth in the chocolate industry among five Western European countries (Belgium, France, Germany, the Netherlands and the United Kingdom). They also found that the Western European market is mature and shows signs of slow growth.

Allenby and Ginter (1995) examined the influence of merchandising variables on household consideration sets using a scanner-panel dataset of tuna purchases. They showed that consideration sets do exist and that in-store displays and feature advertisements influence inter-brand competition through these household consideration sets. Households more actively consider the price of brands within their consideration set compared to brands outside of it.

Woodside and Waddle (1975) found that consumers bought more goods when there is a point-of-sale promotion compared to a price reduction. Bemmaor and Mouchoux (1991) found a strong positive interaction between price reduction and advertising is evidenced, and that this interaction effect is smaller for the leading brands.

Kumar and Leone (1988) used store-level scanner data to investigate the effect of retail store price promotion, featuring, and displays on sales of brands of disposable diapers within a city. They found that within a store, price promotion produced the largest amount of substitution followed by featuring and displays. These activities also produced store substitution in some cases.

Volle (2001) examined the short-term effects of store level promotions (weekly flyers, radio and outdoor advertising) on grocery store choices. He estimated household-level multinomial logit models of store choice on panel data. His results showed that the short-term effect of store-level promotions on store choice was weak and that store choice is mostly driven by loyalty.

Allenby and Lenk (1995) used a random-effects, autocorrelated, logistic regression model to anlayze brand choice decisions. Their estimates on the influence on in-store displays and feature advertisement on switching is shown to be about two to three times more effective than estimates of previous studies.

Walters and MacKenzie (1988) developed a series of hypotheses about the effects of loss leaders, in-store price specials, and double coupon promotions on overall sales, profit and traffic. They found out that most loss leader promotions had no impact on store profit. They also discovered that double coupon promotions affected profit by increasing sales of products purchased with a coupon rather than by increasing store traffic. Finally, they found that in-store price specials have no effect on store profit, sales or traffic.

Blattberg et al. (1995) synthesized findings across the sales promotion literature in order to gain a better understanding of how promotions work. They emphasized the need of a standard measure to compare results and also the importance of generalizations.

Shaffer and Zettelmeyer (2009) have stated that the manufacturer will want and the retailer will allow an in-store advertisement of the manufacturer, whether or not compliance can be monitored, if and only if the display would increase the overall joint profit between the retailer and the manufacturer. In their model, if the retailer accepts offers from manufacturer X and manufacturer Y to use in-store displays in its store then its payoff will be $\widetilde{\Pi}_{xy} - \pi_x - \pi_y$ where $\widetilde{\Pi}_{xy}$ represents overall joint profit, π_x represents manufacturer X's profit and π_y represents manufacturer Y's profit. If the retailer accepts Y's offer but not X's then its payoff will be $\Pi_y - \pi_y$. Thus based on the two earlier equations, manufacturer X's payoff must be equal to $\widetilde{\Pi}_{xy} - \Pi_y$ if the retailer is to accept X's offer. They also point out that it is optimal for the retailer and the manufacturer to display the manufacturers ads in store if $s_x \geq 1 - e(x^*)$ where s_x is the market share of manufacturer X and $e(x^*)$ is defined as the emphasis of a given advertising message. This means that the probability of the retailer showing an in-store ad is higher if the manufacturers market share is bigger. Porter (1974) suggests that consumers are more responsive to advertising by manufacturers of convenience goods than non-convenience goods. Manufacturers of convenience goods have a better bargaining position with retailers.*

Cotterill and Haller (1997) found that own advertising and couponing increase sales for the firm while competitor activities reduce sales. Bagwell (2005) distinguished the empirical studies done under the structure-conduct-performance (SCP) approach from those the used the New Empirical Industrial Organization (NEIO) approach. He stated that the SCP approach assumes that there is a stable causal relationship across industries that flows from structure to conduct to performance and that market power can be estimated from available data. The NEIO approach meanwhile does not assume symmetry across industries, does not assume that market power is observable, and it does not treat firm and industry conduct as implications of market structure variables. Bagwell (2005) states the three main ingredients of the NEIO approach: (1) specified demand functions, (2) specified marginal cost functions, and (3) specified supply relationships. One criticism of the SCP approach is that it used inter industry data to measure the effect of structure on performance (e.g. effect of concentration and advertising on profits), but they never addressed that advertising could be endogenous. Inter industry studies may hide the varying effect of advertising on sales by industry. For example, the effect of advertising on

*Convenience goods are low-priced, frequently purchased consumer goods such as soft drinks and toothpaste. Non-convenience goods are high-priced, infrequently purchased consumer goods such as furniture and television (Porter, 1974).

sales in furniture industry may be insignificant, but the effect of advertising on sales in cigarette industry might be significantly positive and thus the overall positive effect of advertising on sales in inter industry studies does not reveal the varying effect of advertising by industry.

Ackerberg (2001) used a binary logit model to examine the purchase decisions of households when a new yogurt brand, Yoplait 150, was introduced. He found out that while advertising has a positive and significant effect for inexperienced consumers, it had a small and insignificant effect on experienced ones. Erdem and Keane (1996) used scanner and advertising data for laundry detergent and found that experience gives consumers, who are risk averse, more information than advertising. Because consumers are risk averse, they stay loyal to brands which have given them a positive experience.

Bagwell (2005) stated that there are three main views on advertising: persuasive, informative and complementary. The persuasive view emphasizes the fact that advertising creates brand loyalty and serves as a deterrent for new entrants in an industry. Shum's (2004) study of the cereal industry showed that advertising encourages brand switching by households. Cereal advertising is able to overcome the brand loyalty of consumers by persuading them to try out brands they have never tried before. The informative view stresses the fact that advertising can convey new information to consumers. Finally, the complementary view emphasizes that consumers have stable preferences and advertising serves as a tool to reinforce those preferences. Bagwell (2005) also reviewed several studies on the effects of advertising on sales and found three main conclusions. First, he found that advertising results in a short-lived increase in sales for the firm. Second, advertising is combative. When a firm increases its advertising it may reduce the sales of its competitors and the competitors strike back with their own increase in advertising. Third, the studies have shown that the effect of advertising on demand varies across industries.

3. Discrete Choice Models

There are many cases in which individuals have to choose among a discrete set of alternatives. In discrete choice models individual i assigns utility u_{ij} to choice j and then chooses the option that provides him with the highest level of utility. In the logit model, consumer heterogeneity only enters through idiosyncratic errors.

Discrete choice models are used to examine a relationship between a dependent variable Y and one or more independent variables X. Y is a discrete variable that represents a choice from a set of mutually exclusive choices. The independent variables are assumed to affect the choice of the decision maker and these represent a priori beliefs about the causal or associative elements important in the choice process.

Each choice set must display the following characteristics:

- Alternatives must be exhaustive
- Alternatives must be mutually exclusive
- There must be a finite number of alternatives

The basic assumptions of discrete choice models are:

- The observations on Y are assumed to have been randomly sampled.
- Y is caused by or associated with the *X's* and the *X's* are determined by factors independent of the model.
- There is uncertainty in the relation between Y and the *X's*
- The error term distribution must be examined in order to determine the appropriateness of the model used.

Discrete choice models are used to create models that analyze behavioral choice or event classification. Choice models reflect the a priori assumptions of its creator as to what factors will affect the decision making process. Some uses of discrete choice models include examining the choice of purchasing goods like vehicles or appliances, as well as choice of transportation mode or voting decisions.

3.1. Logit

The simple logit states that the market share of good j is equal to the probability that consumer i will purchase it. The formula is:

$$s_j = \frac{e^{\delta_j}}{(\Sigma_{k=0}^{N} e^{\delta_k})} \tag{1}$$

for k, j = 0, 1, ...N. And

$$\delta_j = x_j \beta_i + \alpha P_j + \xi_j + \epsilon_{ij}. \tag{2}$$

where p_j is the price of product j, x_j is a vector of observable product characteristics, ξ_j is the unobservable utility shocks, α and β are parameters and ϵ_{ij} is the error term that measures the distribution of consumer preferences.

The outside good share is:

$$s_o = \frac{e^{\delta_o}}{(\Sigma_{k=0}^{N} e^{\delta_k})} \tag{3}$$

The ratio between the share of good j and the outside good is:

$$e^{\delta_j} = \frac{s_j}{s_o} \tag{4}$$

We can then get the linear form of this equation when we take the natural log of both sides:

$$ln(s_j) - ln(s_o) = \delta_j = x_j \beta_i - \alpha P_j + \xi_j + \epsilon_{ij}. \tag{5}$$

The own and cross price elasticities can be derived using the following equations:

$$\eta_{jk} = \alpha p_k s_j if j \neq k \tag{6}$$

$$\eta_{jk} = -\alpha p_j (1 - s_j) if j = k \tag{7}$$

Thus under the simple logit model the elasticities only depend on market share and price. This leads to substitution patterns that are unreasonable and restricted.

In the simple logit model consumer heterogeneity only enters through idiosyncratic errors ϵ_{ij} which is assumed to be identically and independently distributed across choices and consumers (Berry, 1994). Therefore $v_{ij} = \epsilon_{ij}$. McFadden (1974) pioneered the use of discrete choice characteristic space demand models. He stated that simple logit models suffer from the independence of irrelevant alternatives (IIA) problem. IIA states that for a specific individual the ratio of the choice probabilities of any two alternatives is not affected by the utilities of any other alternatives. In other words the relative odds of two categories do not change when a new category is added. This implies that the introduction of a new product does not affect the ranking of existing products. Another drawback of this model is that it has restricted substitution patterns, which means that cross-price elasticities would only depend on market shares. This means that only the mean utility level would differentiate the products. This implies that only the mean utility levels will determine all properties of market demand such as elasticities and market shares.

In order to mitigate the effects of IIA careful categorization must be made in order to provide more structure to the model. This can be done through the use of decision trees or multistage budgeting. Also, product characteristics must be allowed to enter the relative odds of choosing one alternative over the other. Another way of relaxing IIA is to allow for consumer heterogeneity to enter the relative odds of choosing alternatives.

There have been several papers that have dealt with solving the IIA problem. Goldberg (1995) estimated a model of the U.S. automobile industry using consumer expenditure survey data. She used a nested logit model on the demand side and an oligopolistic differentiated model for the supply side. In her nested logit model, IIA holds for alternatives within each nest or stage but not for the whole choice set. She then allowed for the interaction of consumer and vehicle specific attributes to relax IIA within each nest. Berry (1994) and Berry et al. (1995) used a mixed logit model to get rid of IIA. In these papers they were able to introduce consumer heterogeneity by interacting observed consumer demographics with product characteristics and by interacting unobserved consumer demographics with product characteristics. Chintagunta, Jain and Vilcassim (1991) estimated a model that utilizes the demographic characteristics of consumers.

3.2. Multinomial Logit

The multinomial logit (MNL) model is an extension of the simple logit model to include more than two alternatives. MNL shows that the probability that a specific choice is chosen is the exponent of the utility of the chosen alternative divided by the exponent of the sum of all alternatives whether they are chosen or not. These probabilities range from zero to one. MNL models have two properties: (1) they have linear parameter restrictions and (2) it exhibits the IIA property.

3.3. Nested Logit

Nested logit models have relaxed substitution patterns. These models require the grouping of products into separate nests. Because of this, a good knowledge of the market is required in order to determine which product characteristics are significant enough to sow unique substitution patterns. The nested logit model allows for partial relaxation of the IIA property. What this means is that the IIA property holds for two products within the same nest but it does not hold for two products which belong in separate nests.

Berry (1994) states that nested logit model allows for correlation to be modeled between groups of similar products in a simple manner. This model allows correlation patterns to depend only on groupings of products that are made prior to estimation and not on continuous variable values. The model also allows for more reasonable substitution patterns compared to the simple logit case. The model is able to be estimated on the demand side using linear techniques. Berry (1994) also stated that nested logit models are preferred if there is a heavy penalty placed on computational complexity or when someone wants to model substitution effects as depending only on predetermined groups of goods. Also as we shall see later, the nested logit model can be estimated in linear form similar to the simple logit.

3.4. Mixed Logit

Mixed logit models allow for flexible substitution patterns by letting consumer heterogeneity enter the mean utility. This is made possible because of interaction with observed/unobserved consumer characteristics and product characteristics. Berry, et al. (1995) solved the endogeneity problem by using instruments. These instruments were able to ferret out the unobservables from the nonlinear share equation. These unobservables are then taken care of by instrumental regression. In very simple terms the model for utility is shown below

$$U_{in} = \beta_n X_{in} + \epsilon_{in} \tag{8}$$

$$\beta_n \sim g(\beta | b, W) \tag{9}$$

where b is the mean of the ns and W is the covariance of the ns. The mixed logit model is thus shown below

$$L_{in}(\beta_n) = \frac{e^{\beta_n X_{in}}}{\sum_j e^{\beta_n X_{jn}}} \tag{10}$$

However, since we do not have an idea of each persons β_n we integrate β_n over all its possible values

$$P_{in} = \int L_{in} \cdot g(\beta|b, W) d\beta \tag{11}$$

where P_{in} is the mixed logit probability. Berry (1994) stated that mixed logit would be the preferred model when the researcher places a premium on richer demand patterns.

3.5. Multinomial Probit

Multinomial probit (MNP) models allow for more than two alternatives. However these models are difficult to estimate because the model becomes more mathematically complex as the number of alternatives increases. Mutinomial probit models relax the IIA property without using a nesting structure. This is possible because the model assumes that the errors are normally distributed. Because of this there is no closed form for the MNP model. Maximum simulated likelihood is used in this model.

The advantage of MNP is that there are no restrictions on which choices are close substitutes. The problem with this approach is that a large number of parameters are generated with just a reasonable amount of choices. Estimating all the covariance parameters based on first choice data is difficult. Aside from that, the model requires specifying correlations with all other goods in order to predict for new goods.

4. Model

I adopt a nested logit model to estimate the effects of traditional (i.e. television) and in-store advertising on chocolate sales. I assume in this model that consumers choose Hershey, Mars or an outside good and then choose a brand of chocolate within that particular company. I let G denote the set of product groups where $g \in G$ From Berry (1994) the utility of consumer i from choosing a unit of product $j \in G$ is:

$$u_{ij} = x_j\beta - \alpha p_j + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij} \tag{12}$$

where p_j is the price of product j, x_j is a vector of observable product characteristics, ξ_j is the unobservable utility shocks, α and β are parameters and ζ_{ig} is a common feature of all products in group g. The parameter σ is between zero and one and it represents the within group correlation of utility levels which also represents a measure of the value of the degree of substitution within the group. Berry (1994) explains that as approaches one, the within group correlation of utility levels will go to one and as approaches zero then the within group correlation will go to zero. If $\sigma = 1$, the products within the group are perfect substitutes. If $\sigma = 0$ then the elasticities of the simple logit and the nested logit would be the same. In a nested logit model the elasticities of demand are weighted by σ. ϵ_{ij} is an identically and independently distributed extreme value.

The market share of brand j within group g is shown as:

$$s_{j/g} = \frac{exp(\frac{\delta_j}{1-\sigma})}{\sum_{j\in g} exp(\frac{\delta_j}{1-\sigma})} \tag{13}$$

where $\delta_j = x_j\beta + \xi_j - \alpha p_j$ is the mean utility. The market share of choosing a product within group g is:

$$s_g = \frac{(\sum_{j\in g} exp\{\frac{\delta_j}{1-\sigma}\})^{1-\sigma}}{\sum_{g\in G}(\sum_{j\in g} exp\{\frac{\delta_j}{1-\sigma}\})^{1-\sigma}}. \tag{14}$$

Therefore the market share of barand j can be represented as $s_j = s_{j/g}s_g$.

When we normalize to zero the mean utility of the outside good (Berry, 1994), the nested logit then becomes:

$$ln(s_j) - ln(s_o) = x_j\beta - \alpha p_j + \sigma ln(s_{j/g}) + \xi_j \tag{15}$$

where s_j is the market share of product j for the whole market, s_o is the outside good market share and $s_{j/g}$ is the conditional market share of product j in group g.

The own price elasticity of brand j is:

$$\eta_{jj} = \frac{\alpha}{1-\sigma} p_j (1 - \sigma s_{j/g} - (1-\sigma)s_j) \tag{16}$$

The cross-price elasticity of brand j is:

$$\eta_{jk} = -\alpha s_k p_k \tag{17}$$

if brands j and k belong to the same nest. This shows that the cross-price elasticity of two brands in the same group depends on price sensitivity, market share and the price of the good. The cross price elasticity of brands j and k if they do not belong to he same nest is:

$$\eta_{jk} = \frac{\alpha}{1-\sigma} p_k (-\sigma s_{j/g} - (1-\sigma)s_j) \tag{18}$$

5. Data and Estimation

5.1. Data

The data from this study comes from two datasets from A.C. Nielsen. It is weekly HomeScan data for the period of February 2006 to December 2008, for sixteen Designated Market Areas (DMAs). I also use A.C. Nielsen television advertising data. These datasets were purchased by the Zwick Center for Food and Resource Policy (formerly the Food Marketing Policy Center) at the Department of Agricultural and

Resource Economics at the University of Connecticut. A DMA is a region (usually a group of counties) where the population can receive the same television broadcast. The dataset contains a panel which tracks the chocolate purchases of thousands of households. These purchases were made in places such as grocery stores, drug stores, vending machines, and on-line shopping sites. The dataset classifies the data by category, company, subsidiary and brand. Each purchase by a household contains product characteristics (brand Universal Pricing Code, flavor, package and size); marketing information (unit price, price paid, coupon use, in-store display use and features); as well as the location and time of each transaction. The data also contains demographic information such as the age, race and gender of the shoppers, number of children in each household and income. The 16 DMAs are: Atlanta, Baltimore, Boston, Chicago, Detroit, Hartford-New Haven, Houston, Kansas City, Los Angeles, Miami-Ft. Lauderdale, New York, Philadelphia, San Francisco-Oakland-San Jose, Seattle-Tacoma, Springfield-Holyoke, and Washington, D.C.

The advertising data consists of weekly Gross Ratings Points (GRP) at the brand level for each DMA. There are GRPs on both the national (cable, network, and syndicated) and local (spot) level. The dataset also includes advertising expenditures at each level. The market size for each DMA was defined as the per capita consumption of chocolate per month (in ounces) multiplied by the population of the DMA. DMA population data also was provided by A.C. Nielsen. Market shares for each brand were obtained by dividing total sales in ounces per month per DMA by the market size. The data is aggregated to the monthly level resulting in 7,236 observations denoting 13 brands over 35 months and 16 DMAs.

5.2. Estimation Strategy

In the model the independent variables are price, nutritional characteristics, advertising, the natural logarithm of within-group market shares, household income, use of in-store displays as well as DMA dummy variables. Nutritional characteristics used in this model include calories, sodium, protein, and sugar. Nutritional data was sourced from the websites of Hershey and Mars. Table 2.3 provides us with the nutritional characteristics of the brands. Table 2.3 also shows how each brand is grouped in each specification. The column labeled Group 1 shows which brands belong to the two nests in specification 1 (Hersheys or Mars). The column labeled Group 2 shows which brands belong to which nest in specification 2 (nuts or no nuts). Table 2.4 gives us the means of price, market share and within group market share for each brand over 35 months from February 2006 to December 2008. Table 2.5 provides some descriptive statistics (mean, standard deviation, minimum and maximum) on selected explanatory variables. Within group share 1 represents the within group share for specification 1 while within group share 2 represents the within group share for specification 2.

As Berry (1994) suggests, price and within group market share are endogenous. Price is correlated with the error term because it is a function of marginal cost. It is also a markup that is an indicator of some change in the market (Nevo, 2001). Within group market shares are endogenous because they might be affected by the brands market share s_j (Kusuda, 2011). Advertising is also endogenous because it has an effect on market shares and firms adjust the amount of advertising they put out based on their market share. Using ordinary least squares (OLS) would lead to misleading results. To control for endogeneity and eliminate any potential biases, I used a set of instrumental variables (IVs) in the regression. Instrumental variables have to be correlated with the explanatory variable and they have to be uncorrelated with the unobservables. Berry (1994) suggests the use of input prices as an instrument for price. I use the per ounce world price of cocoa, a vital ingredient in chocolate manufacturing, as an instrument for price. The data for cocoa prices comes from the International Cocoa Organization. I also use the per ounce price of milk as another instrument for price. Milk price data comes from the website of the University of Wisconsin Department of Agricultural and Applied Economics. Berry (1994) suggests using the characteristics of other firms within the group as an instrument for within group shares. I use the average of within group market share over all other cities during all periods as my instrument for within group shares. Average advertising expenditures over all other cities during all periods serve as an instrument for advertising. The model was estimated in STATA using Two-stage least squares (2SLS). OLS results are also provided.

I use two specificatons for this paper. The first uses Hersheys and Mars as the two nests in the nested logit model. This nest is thus based on whichever firm supplies the brand. The second specification divides the brands into those that have nuts (Hersheys with Almonds, Peanut M&M, etc.) with those that do nut have nuts (Hersheys Special Dark, Dove, etc.). I chose this nest because consumers may have strong preferences for buying chocolate with or without nuts. Some people may like the taste or texture of nuts while others may not like it or may have an allergic reaction to it.

6. Results

Table 2.6 presents the estimation results and almost all coefficients are significant and have the expected signs. The price coefficient is negative as was expected meaning that an increase in price reduces consumers utility. The within group share coefficient for specifications 1 and 2 are 0.680 and 0.643 respectively meaning that there is a high level of correlation between consumers utility within a firm. As I described earlier, this variable is a measure of the degree of correlation between the nests. As the within group share coefficient approached one it shows a higher degree of substitution. The coefficients for the two specifications are both relatively high indicating that the correlation between nests in both specifications is relatively high and that consumers value the products within the nests similarly. Therefore consumers consider Hershey chocolates as a subsitute for Mars chocolates. They also consider nutty chocolates as a substitute for smooth chocolates. Table 2.6 also shows that both advertising and in-store displays have a positive and significant effect on demand. The coefficient for in-store displays is slightly larger than that of advertising in specification 1 while the coefficient for advertising is much larger than that of in-store displays in specification 2. Both in-store displays and advertising thus steepen and expand the demand for chocolate. It is interesting to note that in the OLS regressions, advertising is not significant and is negative. However seeing that in-store displays have a higher impact than advertising in specification 2 could lend credence to Hersheys strategy to emphasize in-store displays. As we know in-store displays do tend to promote impulse purchases. The coefficients for all product characteristics except sugar are significant as well. The results show that consumers prefer chocolates with higher contents of calories and sodium and lower content of protein. The coefficient for sugar however is positive in specification 1 and negative in specification 2. The coefficient for household income is positive and significant for both specifications meaning that chocolate demand increases as income goes up.

I use the 2SLS results of specification 2 (nuts or no nuts) to come up with the elasticity table (Table 2.7). The coefficients for price and within group market shares allow us to estimate the own and cross-price elasticities which are shown in Table 2.7. I use average price and average within group market share in each group to estimate the elasticities. Cross-price elasticites are higher between brands within the same group as compared to those between brands in different groups. This means that the substitution patterns are stronger within the nest. Therefore if the price of brand j_1 in nest g_1 increases, the consumer will prefer to shift his consumption to brand j_2 in nest g_1 instead of any other brand j in nest g_2. The cross-price elasticities are positive signifying that they serve as substitutes instead of complements.

7. Price Cost Margins and Marginal Costs

Table 2.8 shows aggregate estimates on the costs of production calculated from North American Industry Classification System (NAICS) codes 311320 (chocolate and confectioery manufacturing from cacao beans) and 311330 (confectionery manufacturing from chocolate) combined. I use these two NAICS codes to represent the chocolate industry. The third and fourth columns of the table show equivalent figures for the entire food industry (NAICS 311). The gross margins are about the same, 29 percent for the chocolate industry and 27.9 percent for the food industry as a whole. The data for this table comes from the 2011 Annual Survey of Manufactures which is available from the website of the U.S. Census Bureau.

Hausman, Leonard, and Zona (1994) takes a direct approach to analyzing the effects of a merger. They found that it is possible to estimate a change in price once demand elasticities have been estimated. The elasticities from Table 2.7, which were derived from the price and within group market shares 2SLS coefficients of specification 2 (nuts or no nuts), enable us to calculate the price cost margins and marginal costs for each brand in our analysis. From Nevo's (2001) model, let us assume that there are F firms each of which produces a subset χ_f of products $j =$ *1,.,*J in the market. Each firms profit can be wrtitten as:

$$\Pi_f = \sum_{j \in \chi_f} (p_j - mc_j) M s_j(p) - C_f \tag{19}$$

where $s_j(p)$ represent market shares of brand j, M is the size of the market and C_f is the fixed cost of production. If we assume that a pure-strategy Bertrand-Nash equilibrium exists and that prices are strictly positive, the price p_j satisfies the first order condition

$$s_j(p) + \sum_{r \in \chi_f} (p_r - mc_r) \frac{\partial s_r(p)}{\partial p_j} = 0 \tag{20}$$

We can then define $S_{jr} = -\frac{\partial s_r(p)}{\partial p_j}, j, r = 1....J$ and

$$\Omega^*_{jr} = \begin{cases} 1, \text{if } \exists f : \{r, j\} \supset \chi_f, \\ 0, \text{otherwise} \end{cases} \tag{21}$$

where Ω is a JxJ matrix and $\Omega_{jr} = \Omega^*_{jr} * S_{jr}$. The first order conditions can then be written as

$$s(p) - \Omega(p - mc) = 0 \tag{22}$$

where *p*, *mc,* and *s(p)* are *Jx1* vectors of prices, marginal costs and market shares respectively. The markup can then be solved as

$$p - mc = \Omega^{-1} s(p) \tag{23}$$

We can now build different ownership matrices Ω^*_{jr} to examine three different causes for the markups: the effect due to the differentiation of products, the portfolio effect, and the price collusion effect (Nevo, 2001). When we look at the effect due to product differentiation, a profit maximizing agent sets the price of a brand considering only that brands price. In the portfolio effect, multi-product corporations set the prices of all their brands jointly. In the price collusion effect there is joint maximization of profits by all brands which correlates to perfect price collusion or a monopoly.

Tables 2.9, 2.10 and 2.11 show the price cost margins and marginal costs under the three ownership structures. For most brands the price cost margins (PCM) for the price collusion effect is higher than that of the product differentiation or portfolio effects. PCMs for the protfolio effect are generally higher than those of the product differentiation effect. Looking at Table 2.9, M&M Peanut has the highest PCM meaning that it has the highest market power among all the brands. However looking at Tables 2.10 and 2.11 Hershey Kisses has the highest PCM when it comes to the portfolio and price collusion effects.

8. Conclusion

This paper used a nested logit model to estimate the effect of in-store displays and advertising on the demand for chocolate using scanner data that tracked the purchase of chocolate by thousands of households in sixteen American cities over a span of 35 months. The results show that in-store displays and advertising both help increase the demand for chocolate. In the first specification both advertising and in-store displays have roughly the same impact on sales while in the second specification advertising has a bigger impact compared to in-store displays. It is therefore imperative that advertising is included in demand estimation models for chocolate or other differentiated products so that price impact biases could be avoided.

References

[1] Ackerberg, D. A. (2001). Empirically distinguishing informative and prestige eects of advertising. *Rand Journal of Economics, 32*(2), 316-333.

[2] Allenby, G. M., & Ginter, J. L. (1995). The effects of in-store displays and feature advertising on consideration sets. *International Journal of Research in Marketing, 12*(1), 67-80.

[3] Allenby, G. M. & Lenk, P. J. (1995). Reassessing brand loyalty, price sensitivity, and merchandising effects on consumer brand choice. Journal of Business & *Economic Statistics, 13*(3), 281-289.

[4] Bagwell, K. (2005). *The economic analysis of advertising.* Columbia University Department of Economics Discussion Paper No. 0506-01.

[5] Bemmaor, A. C. & Mouchoux, D. (1991). Measuring the short-term effect of in-store promotion and retail advertising on brand sales: A factorial experiment. *Journal of Marketing Research 28*(2), 202-214.

[6] Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The Rand Journal of Economics, 25*(2), 242-262.

[7] Berry, S. T., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841-890.

[8] Blattberg, R. C., Briesch, R., & Fox, E. J. (1995). How promotions work. *Marketing Science, 14*(3), G122-G132.

[9] Bruno, H. A., & Vilcassim, N. J. (2008). Structural demand estimation with varying product availability. *Marketing Science, 27*(6), 1126-1131.

[10] Carlton, D. & Perloff, J. (2005). *Modern industrial economics* (4th ed.). Boston: Pearson.

[11] Chintagunta, P. K., Jain, D. C., & Vilcassim, N. J. (1991). Investigating heterogeneity in brand preferences in logit models for panel data. *Journal of Marketing Research, 28*(4), 417-428.

[12] Cotterill, R. W. & Haller, L. E. (1997). *An econometric analysis of the demand for RTE cereal: Product market definition and unilateral market power effects.* Food Marketing Policy Center Research Report No. 35, University of Connecticut, Storrs, CT.

[13] Eagle, B. & Ambler, T. (2002). The influence of advertising on the demand for chocolate confectionery. *International Journal of Advertising, 21*(4), 437-454.

[14] Erdem, T. & Keane, M. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science, 15*(1), 1-20.

[15] Fitzgerald, R. (2005). Products, firms and consumption: Cadbury and the development of marketing, 1900-1939. *Business History, 47*(4), 511-531.

[16] Goldberg, P. K. (1995). Product differentiation and oligopoly in international markets: The case of the U.S. automobile industry. *Econometrica 63*(4), 891-951.

[17] Hausman, J., Leonard, G. & Zona, J. D. (1994). Competitive analysis with differentiated products. *Annals of Economics and Statistics, (34),* 159-180.

[18] Kumar, V. & Leone, R. P. (1988). Measuring the effect of retail store promotions on brand and store substitution. *Journal of Marketing Research 25*(2), 178-185.

[19] Kusuda, Y. (2011). *Nested logit demand estimation in Japanese beer-like beverage markets.* Paper presented at the 10th International Conference of the Japan Economic Policy Association.

[20] McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105-142). New York: Academic Press.

[21] MarketLine. (2013, January). *Industry profile: Chocolate confectionery in the United States.* Retrieved from EBSCOhost database.

[22] Michman, R. D. & Mazze, E. M. (1998). *The food industry wars: Marketing triumphs and blunders.* Westport, CT: Quorum Books.

[23] Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica, 69*(2), 307-342.

[24] Porter, M. E. (1974). Consumer behavior, retailer power and market performance in consumer goods industries. *The Review of Economics and Statistics, 56*(4), 419-436.

[25] Rossfeld, R. (2008). Suchard and the emergence of traveling salesmen in Switzerland, 1860-1920. *Business History Review, 82*(4), 735-759.

[26] Scott, P. & Walker, J. (2010). Advertising, promotion and the competitive advantage of interwar British department stores. *Economic History Review, 63*(4), 1105-1128.

[27] Shaffer, G., & Zettelmeyer, F. (2009). Comparative advertising and in-store displays. *Marketing Science, 28*(6), 1144-1156.

[28] Shum, M. (2004). Does advertising overcome brand loyalty? Evidence from the breakfast cereals markets. *Journal of Economics and Management Strategy, 13*(2), 241-272.

[29] Snell, A., & Tonks, I. (1988). The sweet taste of information: A study of the demand for new brands in the UK confectionery industry. *Applied Economics, 20*(8), 1041-1055.

[30] Volle, P. (2001). The short-term effect of store-level promotions on store choice, and the moderating role of individual variables. *Journal of Business Research, 53*(2), 63-73.

[31] Walters, R. G., & MacKenzie, S. B. (1988). A structural equations analysis of the impact of price promotions on store performance. *Journal of Marketing Research, 25*(1), 51-63.

[32] Woodside, A. G., & Waddle, G. L. (1975). Sales effects of in-store advertising. *Journal of Advertising Research, 15*(3), 29-33.

[33] Zhang, J. (2006). An integrated choice model incorporating alternative mechanisms for consumers' reactions to in-store display and feature advertising. *Marketing Science, 25*(3), 278-290.

Table 1: US Chocolate Industry Market Value and Market Volume 2007-2011

Year	**Market Value ($ million)**	**% Growth**	**Market Volume (million kg.)**	**% Growth**
2007	16,321.2		1,599.5	
2008	16,668.1	2.1	1,620.7	1.3
2009	16,994.2	2.0	1,635.2	0.9
2010	17,327.7	2.0	1,648.0	0.8
2011	17,664.1	1.9	1,660.0	0.7

Source: MarketLine, (2013)

Table 2: Chocolate Consumer Demographics

Demographic	
Location	40% South, 24% Midwest, 22% West, 18% Northeast
Race	70% Non-Hispanic White
Marital Status	53% Married
Family Status	43% Have Children Under 18
Employment Status	53% Employed
Education	28% College Degree or More
Income	24% Household Income > $100,000

Source: National Confectioners Association

Table 3: Nutritional Characteristics (in grams)

Brand	Group 1	Group 2	Calories	Sodium	Protein	Sugar
H. Kisses	Hershey	No nuts	138.29	24.20	2.07	15.90
H. Milk Chocolate with Almonds	Hershey	Nuts	145.20	17.29	2.77	13.14
H. Milk Chocolate	Hershey	No nuts	138.45	23.08	1.98	15.82
Reese's Peanut Butter Cups	Hershey	Nuts	141.75	101.25	3.37	14.17
H. Special Dark	Hershey	No nuts	131.38	10.37	1.38	14.52
H. Kissables	Hershey	No nuts	140.00	20.00	2.00	16.67
M&M Peanut	Mars	Nuts	143.68	14.37	2.87	14.37
Milky Way	Mars	No nuts	126.83	46.34	0.98	17.07
Snickers	Mars	Nuts	135.23	67.61	1.93	14.49
3 Musketeers	Mars	No nuts	122.03	51.63	0.94	18.77
Twix Caramel	Mars	No nuts	139.79	55.92	1.12	13.42
M&M Plain	Mars	No nuts	142.01	17.75	1.18	18.34
Dove	Mars	No nuts	152.12	17.29	1.38	15.21

Table 4: Mean Statistics for Price and Market Share

Brand	Price ($/oz.)	Market Share	Within Group Share 1	Within Group Share 2
H. Kisses	0.2085	0.0227	0.3028	0.229
H. Milk Chocolate with Almonds	0.3738	0.0045	0.0690	0.0757
H. Milk Chocolate	0.3025	0.0118	0.1807	0.1338
Reese's Peanut Butter Cups	0.2692	0.0227	0.3162	0.3366
H. Special Dark	0.3488	0.0050	0.0790	0.0584
H. Kissables	0.2756	0.0042	0.0556	0.0416
M&M Peanut	0.1943	0.0225	0.2628	0.3620
Milky Way	0.3031	0.0060	0.0639	0.0629
Snickers	0.2784	0.0155	0.1668	0.2258
3 Musketeers	0.3360	0.0072	0.0771	0.0761
Twix Caramel	0.3232	0.0044	0.0483	0.0471
M&M Plain	0.2045	0.0283	0.3196	0.2996
Dove	0.3908	0.0053	0.0632	0.0554

Table 5: Descriptive Statistics of Select Explanatory Variables

Variable	Mean	SD	Min	Max
Price ($/oz.)	0.2928	0.1499	0.0220	3.6239
Within Group Share 1	0.1548	0.1320	0.0001	0.9101
Within Group Share 2	0.1547	0.1369	0.0001	0.9146
Advertising	1,483.881	1,445.079	0	7,652.612

Table 6: Estimation Results

	Specification 1		***Specification 2***	
Variables	**OLS**	**2SLS**	**OLS**	**2SLS**
Price	-0.3764** (0.0591)	-3.2324** (0.6760)	-0.4288** (0.0596)	-3.5908** (0.6814)
Within group share	0.9422** (0.0173)	0.6797** (0.0724)	0.8957** (0.0168)	0.6433** (0.0727)
Advertising	-0.0845 (0.0843)	0.3684* (0.1453)	-0.0039 (0.0085)	0.6413** (0.1605)
In-store Display	0.3694** (0.0270)	0.3979** (0.0388)	0.3797** (0.0273)	0.3934** (0.0413)
Calories	0.0230** (0.0024)	0.0325** (0.0044)	0.0142** (0.0025)	0.0252** (0.0053)
Sodium	0.0066** (0.0006)	0.0062** (0.0008)	0.0009 (0.0006)	0.0019* (0.0010)
Protein	-0.4474** (0.0306)	-0.3273** (0.0508)	-0.2333** (0.0299)	-0.1700** (0.0440)
Sugar	-0.0317** (0.0103)	-0.0036 (0.0179)	0.0235* (0.0101)	0.0284 (0.0166)
Household Income	0.1400* (0.0591)	0.2097** (0.0796)	0.1570** (0.0597)	0.2184** (0.0839)
R-squared	0.6843	0.958	0.6775	0.9531
Constant	-4.8729** (0.4225)	-6.3996** (0.8110)	-4.7404** (0.4296)	-5.9621** (0.8985)
Hansen J statistic		3.387 (p=0.0657)		3.641 (p=0.0564)
DMA dummies	Yes	Yes	Yes	Yes

Sample errors are enclosed in parentheses.
* denotes significance at the 5% level.
** denotes significance at the 1% level

Table 7: Own and Cross-Price Elasticities

	H. Kisses	H. Milk Choco w/ Almonds	H. Milk Chocolate	Reese's PB Cups	H. Special Dark	Hershey's Kissables	M&M Peanut	Milky Way	Snickers	3 Musk.	Twix Caramel	M&M Plain	Dove
H. Kisses	-1.7727	0.5848	0.4733	0.4212	0.5457	0.4312	0.0158	0.0247	0.0227	0.0274	0.0263	0.0167	0.0319
H. Milk Choco w/ Almonds	0.1056	-3.5737	0.1532	0.1363	0.1766	0.1396	0.0031	0.0049	0.0045	0.0054	0.0052	0.0033	0.0063
H. Milk Chocolate	0.1895	0.3397	-2.7703	0.2447	0.3170	0.2505	0.0082	0.0128	0.0118	0.0142	0.0137	0.0087	0.0166
Reeses PB Cups	0.4715	0.8453	0.6840	-2.1012	0.7887	0.6232	0.0158	0.0247	0.0227	0.0274	0.0263	0.0167	0.0319
H. Special Dark	0.0826	0.1481	0.1198	0.1066	-3.3731	0.1092	0.0035	0.0054	0.0050	0.0060	0.0058	0.0037	0.0070
H. Kissables	0.0593	0.1063	0.0861	0.0766	0.0992	-2.6960	0.0029	0.0046	0.0042	0.0051	0.0049	0.0031	0.0059
M&M Peanut	0.2710	0.4859	0.3932	0.3499	0.4534	0.3582	-1.6751	0.4382	0.4024	0.4857	0.4672	0.2956	0.5649
Milky Way	0.0471	0.0844	0.0683	0.0608	0.0788	0.0622	0.0514	-2.9710	0.0737	0.0889	0.0856	0.0541	0.1035
Snickers	0.1691	0.3031	0.2453	0.2183	0.2828	0.2235	0.177	0.2762	-2.5489	0.3062	0.2945	0.1863	0.3561
3 Musk.	0.0570	0.1021	0.0827	0.0736	0.0953	0.0753	0.0622	0.097	0.0891	-3.2749	0.1034	0.0654	0.1250
Twix Caramel	0.0353	0.0632	0.0512	0.0455	0.0590	0.0466	0.0384	0.0599	0.0550	0.0664	-3.1897	0.0404	0.0772
M&M Plain	0.2243	0.4021	0.3254	0.2896	0.3752	0.2965	0.2446	0.3816	0.3505	0.423	0.4069	-1.8012	0.492
Dove	0.0415	0.0744	0.0602	0.0536	0.0694	0.0548	0.0453	0.0707	0.0649	0.0784	0.0754	0.0477	-3.8429

Table 8: Aggregate Estimates of Production Costs

	Chocolate Industry (NAICS 311320 and 311330)		***Food Manufacturing (NAICS 311)***	
Item	**Value (in millions of $)**	**% of value of shipments**	**Value (in millions of $)**	**% of value of shipments**
Value of Shipments	13,510	100.0	710,366	100.0
Materials	7,149	52.9	415,532	58.5
Labor	2,262	16.7	85,180	12.0
Energy	184	1.4	11,132	1.6
Gross Margin		29.0		27.9

Source: Annual Survey of Manufacturers (2011)

Table 9: Price Cost Margins and Marginal Costs Due to Product Differentiation

Brand	Price Cost Margin	Marginal Cost
Hersheys Kisses	0.5641	0.0909
Hersheys Milk Chocolate with Almonds	0.2798	0.2692
Hersheys Milk Chocolate	0.3610	0.1933
Reeses Peanut Butter Cups	0.4759	0.1411
Hersheys Special Dark	0.2965	0.2454
Hersheys Kissables	0.3709	0.1734
M&M Peanut	0.5970	0.0783
Milky Way	0.3366	0.2011
Snickers	0.3923	0.1692
3 Musketeers	0.3053	0.2334
Twix Caramel	0.3135	0.2219
M&M Plain	0.5552	0.0910
Dove	0.2602	0.2891

Table 10: Price Cost Margins and Marginal Costs Due to Portfolio Pricing

Brand	**Price Cost Margin**	**Marginal Cost**
Hersheys Kisses	0.6563	0.0717
Hersheys Milk Chocolate with Almonds	0.2982	0.2623
Hersheys Milk Chocolate	0.4004	0.1814
Reeses Peanut Butter Cups	0.5703	0.1157
Hersheys Special Dark	0.3120	0.2400
Hersheys Kissables	0.3852	0.1694
M&M Peanut	0.6472	0.0685
Milky Way	0.3437	0.1989
Snickers	0.4166	0.1624
3 Musketeers	0.3130	0.2308
Twix Caramel	0.3185	0.2203
M&M Plain	0.5983	0.0822
Dove	0.2651	0.2872

Table 11: Price Cost Margins and Marginal Costs Due to Collusion

Brand	**Price Cost Margin**	**Marginal Cost**
Hersheys Kisses	0.6722	0.0683
Hersheys Milk Chocolate with Almonds	0.3006	0.2614
Hersheys Milk Chocolate	0.4065	0.1795
Reeses Peanut Butter Cups	0.5857	0.1115
Hersheys Special Dark	0.3143	0.2392
Hersheys Kissables	0.3874	0.1688
M&M Peanut	0.6616	0.0657
Milky Way	0.3453	0.1984
Snickers	0.4229	0.1607
3 Musketeers	0.3148	0.2302
Twix Caramel	0.3197	0.2199
M&M Plain	0.6099	0.0798
Dove	0.2662	0.2868

Figure 1: U.S. Chocolate Industry Market Share (% Share, by Value 2011)
Source: MarketLine, (2013)

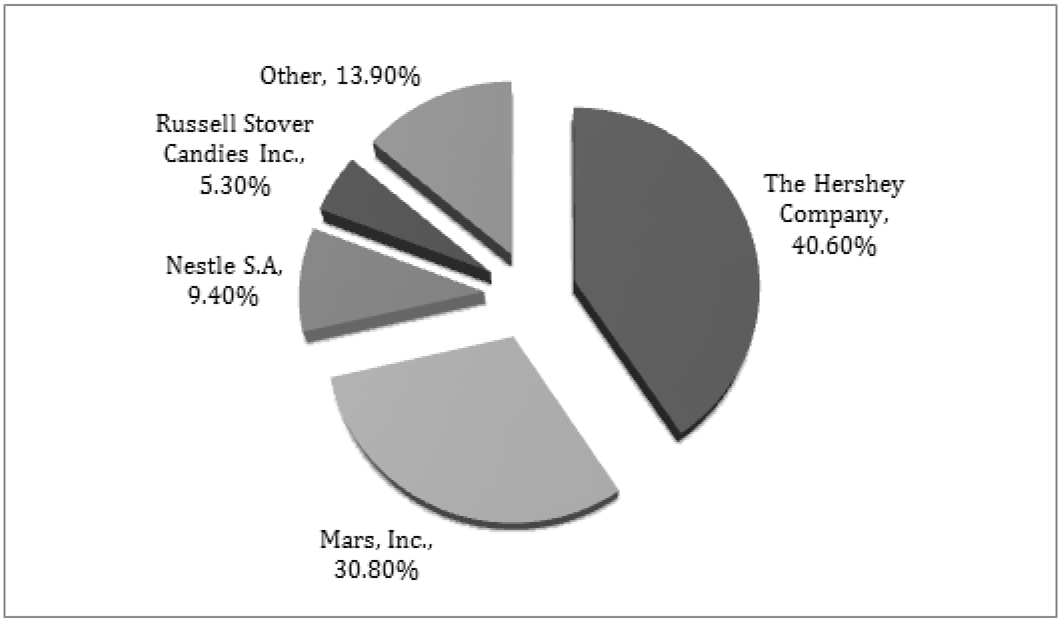
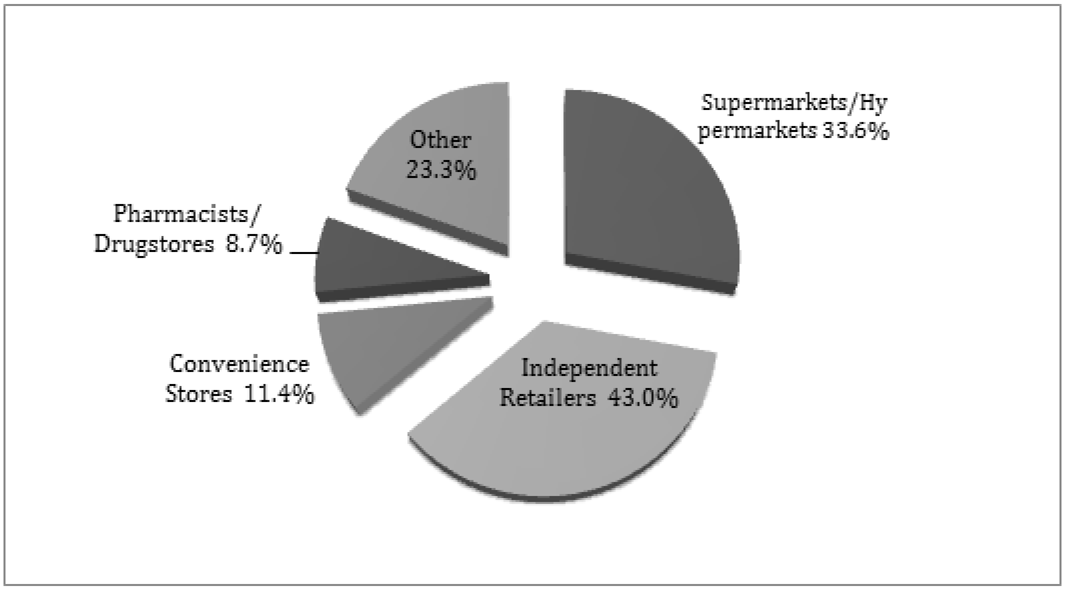


Figure 2: U.S. Chocolate Market Distribution (% Share, by Value 2011)
Source: MarketLine, (2013)



Appendix A: Twenty-Five Leading Advertisers in the U.S.

	Rank	U.S. Advertising in 2002 ($ millions)	Advertising as a Percentage of U.S. Revenue (%)
Automotive			
Daimler Chrysler	6	2,032	2.8
Ford Motor	5	2,252	2.1
General Motors	1	3,652	2.6
Honda	18	1,193	3.1
Toyota	13	1,553	3.0
Electronic and Office Equipment			
Sony	11	1,621	8.2
Entertainment and Media			
AOL Time Warner	2	2,923	9.0
Viacom	16	1,260	6.1
Walt Disney	7	1,803	8.7
Food, Restaurants, Soft Drinks			
Altria	17	1,206	2.7
McDonalds	15	1,336	24.6
Nestle	25	1,073	5.8
PepsiCo	21	1,114	6.7
Government			
U.S. government	24	1,083	n.a.
Personal Care			
LOreal	20	1,118	26.3
Procter & Gamble	3	2,673	12.6
Unilever	10	1,640	14.2
Pharmaceutical			
GlaxoSmithKline	12	1,554	9.7
Johnson & Johnson	8	1,799	8.0
Merck	19	1,158	2.4
Pfizer	4	2,566	12.4
Retail			
J. C. Penney	22	1,108	3.4
Sears Roebuck	9	1,661	4.5
Telephone			
SBC Communications	23	1,092	2.5
Verizon	14	1,528	2.4

Source: Carlton and Perloff, (2005)