ESSAYS ON DEMAND ENHANCEMENT BY FOOD INDUSTRY PARTICIPANTS

by

LEE LESLIE SCHULZ

B.S., University of Wisconsin-River Falls, 2006
M.S., Michigan State University, 2008

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

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Manhattan, Kansas

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Abstract

This dissertation empirically examines how demand-enhancing activities conducted by food industry participants affect retail beef steak pricing, consumer demand for ground beef, and industry concentration. It follows the journal article style and includes three self-contained chapters.

Chapter 1 uses a two step hedonic model with retail scanner data of consumer beef steak purchases to determine if there are incentives to identify certain attributes and to determine what types of attributes entertain price premiums and at what levels these premiums exists. Results indicate that most branded beef steak products garnered premiums along with organic claim, religious processing claim, and premium steak cuts. Factors influencing brand equity are new brands targeting emerging consumer trends, brands with regional prominence, and those positioned as special-labels, program/breed specific, and store brands.

Chapter 2 reports tests of aggregation over elementary ground beef products and estimates composite demand elasticities. Results suggest consumers differentiate ground beef according to lean percentage (70-77%, 78-84%, 85-89%, 90-95%, and 96-100%) and brand type (local/regional, national, store, and unbranded). The range in composite elasticity estimates shows the value of analyzing demand elasticity based on differentiation and not simply considering ground beef as being homogeneous. Composite elasticity estimates provide improved understanding of how consumers make decisions concerning ground beef purchases.

Chapter 3 examines industry concentration for the U.S. food manufacturing sector. This study is the first to examine whether particular subsectors within the food manufacturing industry, which operate in the presence of industry-funded check-off programs such as marketing orders, are more or less concentrated than industries without such research and marketing

programs. Results provide evidence to support the hypothesis that industries with demand-enhancing check-off programs have lower concentration relative to industries without these programs.

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Table of Contents

List of Figures

List of Tables

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Dedication

This dissertation is dedicated to my family, Cliff, Carol, Megan, and Kelly, for their unending support and encouragement.

Introduction

The marketing of foods to consumers is a dynamic activity. Food industry participants engage a portfolio of demand-enhancing activities which include offering food products having characteristics desired by consumers, package labeling, product promotion and information, and providing assurances about product attributes that consumers can trust. This dissertation empirically examines how demand-enhancing activities conducted by food industry participants affect retail beef steak pricing, consumer demand for ground beef, and industry concentration. The first chapter examines implicit values of retail beef steak product characteristics and branding. The second chapter tests whether consumers differentiate elementary ground beef products and models consumer demand for composite ground beef products. The third and final chapter examines how the presence of an industry-funded check-off program affects concentration in industries where market power exists.

Chapter 1, "Value of Beef Steak Branding: Hedonic Analysis of Retail Scanner Data," explores the incentives to identify credence attributes and brand retail beef steak products. Patterns in consumer purchasing behavior have shown that consumers are concerned with, not only, price and taste, but recently emerging is their demand for certain attributes that are not considered experience attributes. These credence factors can include attributes that pertain to breed claim, organic claim, religious practices, and branding. Branding beef has created niche markets that attract consumers for a variety of reasons. Branding is advantageous for buyers because it i) helps identify the product they like or dislike, ii) identifies the marketer, iii) helps reduce the time needed for purchase, iv) helps evaluate quality of products especially if unable to judge a products characteristics, and v) helps reduce buyers perceived risk of purchase. As producers and retailers discover more about branding beef, questions arise regarding the incentives to brand. For example does branding: i) differentiate product offering from competitors, ii) identify the firms' products making repeat purchases easier for customers, iii) facilitate promotional efforts, iv) foster brand loyalty helping to stabilize market share, and v) enable charging a premium for the brand. The last action is the emphasis of this essay as we aim to determine what types of brands entertain price premiums and at what levels these premiums exist, after adjusting for a myriad of product characteristics.

This essay relies on retail scanner data which permit consumer behavior and preferences to be better quantified than previous work that has used much more aggregate data; thereby, improving our understanding of a range of consumer demand drivers. The retail-level scanner data offer a larger market share and enable evaluation of pricing by individual brand which has not previously been examined in great detail in the literature. A two step hedonic model is used to first estimate implicit values of retail beef steak characteristics and in the second stage estimate factors affecting estimated brand value.

Results provide important implications for industry strategies to enhance beef demand. For example, results identify which types of brand initiatives, product assurances, and product characteristics are most likely to enhance demand. Furthermore, different types of branding initiatives have been able to gain different levels of market penetration and associated price premiums. This information is essential as the industry continues to determine the optimal role of producers, packers, processors, and retailers in vertically coordinating production and marketing efforts to produce and position branded beef products that enhance consumer demand which ultimately will increase beef industry profitability.

Chapter 2, "Composite Ground Beef Demand," tests whether information on product differentiation is important to consumer demand for ground beef and reports demand estimates of differentiated ground beef products. Ground beef is differentiated in the retail counter by brand and percentage lean; however, limited information exists on the equity of ground beef brands and consumer demand for leanness. Because differentiating ground beef is not costless, retailers need more information to determine whether the benefits of differentiation exceed the costs.

Retail scanner data of weekly ground beef purchases are used. Ground beef brands are classified into four brand types: local/regional, national, store, and other; and five lean percentage categories: 70-77%, 78-84%, 85-89%, 90-95%, and 96-100% lean. Lewbel's Generalized Composite Commodity Theorem is used to test whether consumers differentiate ground beef according to brand type, whether they differentiate ground beef according to lean percentage, or whether they behave as if all ground beef is the same. The absolute price version of the Rotterdam model is used to estimate demand elasticities for composite ground beef products.

Generalized Composite Commodity Theorem tests validate estimating a demand system having five lean percentages with brand types aggregated, a demand system having four brand types with lean percentages aggregated, or estimating ground beef as a single commodity aggregated across brand type and lean percentage. The range in elasticity estimates shows the value of analyzing demand elasticity based on product differentiation and not simply considering ground beef as being homogeneous. This information is important for determining the benefits and sensitivity of consumers to ground beef product differentiation.

Chapter 3, "Presence of Check-off Programs and Industry Concentration in the Food Manufacturing Sector," examines how the presence of an industry-funded check-off program affects concentration in industries where market power exists. Firms throughout the food supply chain are carving out their own successful brands and differentiating their products through quality improvements and advertising in markets previously considered homogeneous. Furthermore, many food industry firms operate under the support of a check-off program. "Got Milk", "Pork. The Other White Meat", and "Beef. It's What's for Dinner" are examples of messages from various commodity boards who are attempting to impact the demand for their food products. The provision of product promotion and information as a demand-enhancing activity is growing dramatically, although little is known about how these industry-funded programs affect market structure. Theoretical arguments indicate that check-offs can have a pro-competitive effect as agricultural industries become increasingly concentrated. However, empirical findings for the correlation between industry concentration and the presence of check-offs are absent from the literature.

Analysis of the effect of check-offs on industry concentration in the food manufacturing industry is conducted using U.S. Economic Census data. Applying an econometric model we estimate the impact of various industry structural characteristics and market factors on the Herfindahl-Hirschman Index (HHI) and the concentration ratio of the top four firms in each industry (CR4). Results suggest the presence of a check-off is correlated with a less concentrated industry as predicated by theory. Results are of importance for the food industry and for agricultural policy as government-sanctioned check-off programs for such things as generic advertising have never been promoted on their procompetitive impact.

Chapter 1 - Value of Beef Steak Branding: Hedonic Analysis of Retail Scanner Data

Introduction

Branding of beef retail products has gained momentum in recent years. In 2004, 42% of beef retail products were branded and this increased to 63% in 2010 according to the National Meat Case Studies conducted jointly by The Beef Checkoff, National Pork Board, and Cryovac®. As potential value of differentiating and branding retail beef have become apparent, a proliferation of branding strategies has emerged. A review of Freshlook retail data reveals more than 100 beef brands are now present in U.S. retail markets.

Product differentiation and branding are especially prevalent in beef steaks. The steak market is intriguing because numerous physical attributes and marketing characteristics are being used to differentiate the product. However, limited information exists on implicit values of various steak product attributes and brand labels. Revealed preference is used in this study to determine implicit prices for retail steak product characteristics and brands. This study determines implicit premiums and discounts associated with descriptive package label characteristics and product brands of retail beef steaks.

This study employs a two step analysis. A hedonic model is used to reveal implicit prices of retail steak characteristics that include both physical (e.g., retail steak cut and bone presence) and credence (e.g., brand name, breed claim, organic labeling, religious processing claim) attributes. Understanding factors affecting implicit values is also of importance. For example, a brand can be thought of as a mix of hedonic, instrumental, and price preferences that represent value to the consumer and that are reasonably consistent over time (Zeithaml 1988). To that end, estimated brand coefficients from the hedonic price model are utilized as a dependent variable to determine factors associated with brand premiums or discounts. Knowing how branding initiatives affect brand value help to identify brand strategies for targeting consumers. The benefit to consumers of employing a brand strategy is that a brand provides the consumer with a set of known product attributes, at a known quality level, and generally within a known price range relative to similar products (Owen, Wright, and Griffith 2000). As such, product brands reduce search costs and uncertainty about product performance for consumers.

Previous Research

Previous studies have elicited attribute values for retail beef products: eating quality (Hahn and Mathews 2007), fat content (Brester et al. 1993; Unnevehr and Bard 1993; Shongwe et al. 2007), tenderness (Feldkamp, Schroeder, and Lusk 2005; Feuz et al. 2004; Lusk et al. 2001; Platter et al. 2005), packaging (Menkhaus et al. 1992; Harrison, Harstad, and Rutstrom 2004), labeling (Loureiro and McClusky 2000; Lusk and Fox 2002; Loureiro and Umberger 2003), organic (Boland and Schroeder 2002), and multiple other attributes and attribute bundles (Alfnes and Rickertsen 2003; Lusk, Roosen, and Fox 2003; Tonsor et al. 2005; Loureiro and Umberger 2007; Parcell and Schroeder 2007; Ward, Lusk, and Dutton 2008; Martinez 2008; Froehlich, Carlberg, and Ward 2009; Hanagriff, Rhoades, and Wilmeth 2009; Abidoye et al. 2011). Several of these studies have paid special attention to the issue of retail beef product branding, recognizing its importance for product differentiation and in providing purchase cues to consumers.

Feldkamp, Schroeder, and Lusk (2005) evaluated consumers' preferences for generic, guaranteed tender, natural, USDA choice, and Certified Angus Beef® steaks. Consumers were willing to pay an economically important premium, greater than $2.00/steak, for Certified Angus Beef® relative to generic steak, suggesting brand name recognition of the Certified Angus Beef® brand.

Parcell and Schroeder (2007) analyzed panel diary retail beef product purchase prices to determine how pricing varied among products, geographic location, store type, sale items, composition (fresh, frozen, or cooked), and package size. Supermarket/grocery store branding was compared to Angus beef branding. Angus branded medium quality and high quality steak cuts commanded premiums of $1.26/lb. and $1.22/lb., respectively, relative to supermarket/grocery store branded products. In contrast, low quality steak cuts appeared to be targeting price-sensitive consumers by selling lower-priced products where the Angus brand premium was $0.76/lb.[1]

Ward, Lusk, and Dutton (2008) identified the value consumers place on observable characteristics of fresh beef sold at retail. Premiums for branded steaks/roasts ranged from $0.00/lb. to $6.20/lb. relative to generic or unbranded product. In general, special and other brands were priced higher than generic or unbranded beef.

Martinez (2008) found wide variation in brand premiums and discounts across branded beef steaks, ranging from -$0.44/lb. to $4.15/lb., relative to unbranded steaks. Products receiving the largest premiums included branded beef alliances with specific production requirements, including natural, organic, source verified, grass-fed, and breed specific.

Froehlich, Carlberg, and Ward (2009) analyzed consumer willingness to pay for fresh branded beef in an experimental auction framework. Survey participants preferred branded products relative to generic with hypothetical premiums that ranged from $1.12/12-oz. steak to $1.32/12-oz. steak.

Past research has assessed the valuation of branding in the national beef retail sector as well as other attributes that affect price. This study differs from and builds upon information from previous research in several important ways. First, it relies on retail scanner data rather than hypothetical surveys or experiments to determine implicit market values of individual product characteristics. The scanner data provide a complete sample of sales of all steak products in the participating retail outlets over a five-year period. Second, rather than aggregating brands into arbitrary groupings, each individual brand premium or discount is estimated, after adjusting for other product characteristics. This allows the implicit price of the brand itself to be determined separately from the values of other product attributes bundled with the particular brand. Third, factors associated with implicit brand value are estimated. As such, this study gains insight into factors contributing to brand equity, and thus, why consumers respond more favorably to certain brands.

Hedonic Model

An underlying assumption of the hedonic model is that goods can be distinguished by various product characteristics. As a result, marginal or implicit values can be estimated for each characteristic at the observed purchase price which is linked with the presence of the particular characteristic.

Rosen (1974) hypothesized that the marginal implicit pricing schedule for a characteristic is a series of equilibriums between supply of and demand for the characteristic over time or between markets. According to Rosen, some may inappropriately interpret the equilibrium points representing the marginal implicit values estimated from the standard hedonic pricing equation, as the demand function for that characteristic. Rosen argued that those points are just a sequence of supply and demand equilibriums that shift due to changes in exogenous supply and demand factors. He showed that standard hedonic pricing modeling overlooks changing marginal implicit values for different levels of characteristics because only consumer behavior is considered, while producer behavior is overlooked. "Estimated hedonic price-characteristics functions typically identify neither supply nor demand. In fact, those observations are described by a joint-envelope function and cannot by themselves identify the structure of consumer preferences and producer technologies that generate them" (Rosen 1974, p. 54). Accordingly, implicit premiums or discounts for specific product attributes are driven by a combination of consumer demand and product supply.

Following Rosen (1974) suppose a market good is composed of *n* characteristics,

$$z = (z_1, z_2, \dots, z_n). \tag{1.1}$$

Prices can be related to the characteristics as:

$$p(z) = p(z_1, z_2, \dots, z_n), \tag{1.2}$$

where it is assumed that each product has a market price, *p*, and the summation of product attributes can be expressed by *z*.

A vector of implicit marginal values is obtained by differentiating *p(z)* with respect to its *i*th argument, z_i.

$$p_i(z) = \frac{\partial p(z)}{\partial z_i}, \tag{1.3}$$

where p_i are the characteristics' marginal values.

We apply a two step model to first estimate implicit values of retail beef steak characteristics in the hedonic model and in the second stage estimate factors affecting estimated brand value. Estimated brand coefficients from the standard hedonic price model were used as a dependent variable.

Hedonic Retail Steak Model Using Price and Characteristics

A hedonic pricing model is applied to a panel of retail steak sales to estimate the impact various physical attributes, product claims, and brands have on retail steak pricing. A fixed effects estimator is hypothesized to control for the time invariant unobserved brand factors that may impact retail steak price.[2] Consider the model:

$$P_{ijt} = (\alpha + c_j) + x_{ijt}\beta + u_{ijt} \quad i = 1, \ldots, I, j = 1, \ldots, J, \text{ and } t = 1, \ldots, T, \tag{1.4}$$

where P_{ijt} denotes the price of the ith steak package with the jth brand for the tth time period, α is the overall model intercept, c_j is the time invariant individual brand effect considered part of the intercept, x_{ijt} is a $1 \times K$ row vector of observable variables associated with product characteristics, β is a $K \times 1$ parameter vector of marginal effects of product attributes, and u_{ijt} are the idiosyncratic errors which change across i, j, and t (Wooldridge 2002 and Baltagi 2008). The c_j component consists of a dummy variable for each individual brand. The regression is a least squares dummy variable (LSDV) or a fixed effects model with constant slopes but intercepts that differ according to the cross-sectional unit, in this case, brand.

The data utilized in this study have repeated observations per cross-section and over time. As a result, the errors are potentially serially correlated (i.e., correlation over t for a given i and j) and/or heteroskedastic. Inclusion of fixed individual-specific effects can reduce serial correlation in the errors (Cameron and Trivedi 2005).[3] A Breusch-Pagan/Cook-Weisberg test rejected the null hypothesis that the error variances are constant. White's heteroskedasticity consistent covariance matrix is used to estimate standard errors.[4]

Following Greene (2003), an F test, resembling the structure of the F test for R^2 change, is used to test the hypothesis that the brand-specific constants are all equal; thereby, testing the significance of the individual brand fixed effects. The F ratio used for this test is:

$$F\left(n-1, \sum_{i=1}^{n} T_i - n - K\right) = \frac{(R^2_{LSDV} - R^2_{Pooled})/(n-1)}{(1 - R^2_{LSDV})/(\sum_{i=1}^{n} T_i - n - K)}, \tag{1.5}$$

where *LSDV* and *Pooled* indicate a LSDV model and a pooled model with only a single intercept for *n* brands and *T* time periods. Under the null hypothesis that the brand-specific constants are the same, this statistic is an *F* random variable with *n*-1 numerator and *nT*-*n*-*K* denominator degrees of freedom. The value of the *F* random variable is *F*(61, 198349) = 1108.35 (*p*-value = 0.000). This shows that the brand-specific constants differ and a pooled model with one intercept is not appropriate. Overall, we conclude that the alternative pooled model omits important time-invariant brand effects, and hence we use a fixed effects model.

The retail steak price is modeled as:

$$Price_{ijt} = \alpha + \sum_{j=1}^{62} \beta_{1j} Brand_j + \beta_2 Breed_{it} + \beta_3 Organic_{it} \tag{1.6}$$

$$+ \beta_4 Religious_{it} + \beta_5 Bone_{it} + \sum_{c=1}^{33} \beta_{6c} Cut_{ict} + \sum_{t=1}^{273} \beta_{7t} Week_{it} + u_{ijt},$$

where *i* refers to steak package (package is used here to refer to weekly sales of the specific product), *j* refers to brand, and *t* refers to time period. All other variables are defined in table 1.1.

Brand Value Model

Brand value is the value beyond the physical and credence characteristics associated with the product's production or processing. Numerous steak brands are present appealing to different consumer preferences. As such, it is difficult to distinguish characteristics driving individual brand premiums and discounts from just the hedonic model parameter estimates on binary brand variables. For example, brands may differ across many dimensions, such as longevity or breadth of national distribution. Implicit values needed to determine brand value differences are obtained from estimating equation (1.6). The implicit values (β_{1j} estimates from equation 1.6) are used to determine factors contributing to brand value. The brand value determination model takes the form:

$$BrandValue_j = \alpha + \sum_{a=1}^{4} \beta_{1a} BrandAge_{aj} + \sum_{l=1}^{3} \beta_{2l} Location_{lj} \tag{1.7}$$

$$+ \sum_{p=1}^{4} \beta_{3\mathrm{p}} Positioning_{pj} + \beta_4 ChoicePlus_j + \beta_5 MultiMeat_j + \varepsilon_j,$$

where j refers to brand and all other variables are defined in table 1.2.

Using coefficient estimates as dependent variables in subsequent regression analysis is common (e.g., Bowman and Ethridge 1992; Chiou, Chen, and Capps 1993; Jusko and Shively 2005). Achen (2005) reviews several alternative estimation techniques for two-step regression modeling. He concludes that the method we employ of estimating each equation separately by OLS is acceptable and even preferable under certain conditions to other potential estimation methods. Achen notes that the second stage model estimated using OLS for each separate equation can be delicate if the first stage is not well specified. Specification errors at the first stage will cause biases and inconsistencies at the second stage, even if the second stage has no problems of its own. He further suggests that the first stage sample size be orders of magnitude larger than the second stage and that there are not large influential points in second stage parameters. Our models and associated estimates pass all of these conditions as discussed in the results.

Data

Scanner data of steak purchases in U.S. retail outlets over the period 2004 through March 2009 were obtained from Freshlook Marketing Group. Freshlook Marketing Group collects meat department info-scan random weight sales data from more than 14,000 retail food stores nationwide. Data recorded for each sale included: sales value, pounds sold, brand name, breed claim, organic labeling, religious processing claim, bone presence, and individual steak cut. The data set contains 198,719 weekly aggregated steak sales observations. Weekly aggregations are pounds sold each week by brand name, steak cut, breed, organic, and religious processing claims, and presence of bone.

Due to confidentiality, specific brand names cannot be identified. As such, we name the brands *Brand 1* through *Brand 62*. Likewise, we simply note whether a specific breed claim was present or not. Organic claims are certified by an accredited certifying agent as utilizing a system of organic production and handling as described by the Organic Foods Production Act (OFPA) of 1990. Organic products must be produced and handled without the use of synthetic chemicals and in compliance with an organic plan agreed to by the producer and handler of the product and the certifying agent (USDA 2010). The religious processing claims consist of Kosher, Kosher-Glatt, Halal, and No Religious Claim. All religious claims were combined into a single binary variable equal to one if the product had a religious processing claim, and zero otherwise.

Previous studies (e.g., Parcell and Schroeder 2007; Ward, Lusk, and Dutton 2008) included USDA quality grades Prime, Choice, Select, and not graded to categorize meat quality. There is considerable collinearity present in our data set between individual brands and quality grades. As such, we estimate a model excluding quality grade variables as they are embedded in the brand effects.

Thirty-three different steak cuts were present in the data (figure 1.1). Steak cuts that are considered premium cuts are expected to have positive coefficients on the cut-specific binary variables included in the hedonic model and everyday steaks are expected to have negative coefficient estimates. In addition, cuts with the presence of a bone (*Bone*=1) are expected to have a lower retail price per pound than boneless cuts. To adjust for changing aggregate steak prices over time, we included weekly binary variables.

In addition to details of aggregate weekly sales, information describing each individual brand were collected that was hypothesized to affect brand value. Variables defined in table 1.2 are used in stage two of the analysis where the estimated product brand premiums and discounts from the hedonic model are regressed against factors associated with each brand name. Brand longevity is the continued presence of a brand in the relevant market (Banbury and Mitchell 1995; Li 1995). The longevity of brands is essential for a firm's survival as it is linked to performance measures such as profitability and market share (Kanter and Brinkerhoff 1981; Suarez and Utterback 1995). Brand longevity was categorized into five segments of 1) three years and less (7%), 2) four to six years (18%), 3) seven to ten years (5%), and 4) eleven years and greater (70%). Brands having a longer presence in the industry are expected to have greater consumer recognition and thus higher brand value.

The data set consisted of 60 steak brands that were classified into three geographic distribution categories for use in the brand value model.[5] A *local* brand is a brand that is only distributed within a local geographic area and is privately owned and controlled by a small company. A *regional* brand is a brand distributed regionally to retail outlets and is owned and controlled by a private company. Distribution is to one or more regions but not nationwide. A *national* brand is a brand that is distributed to retail locations nationwide and is controlled by the company or the supplier(s) who own the brand. Of the 60 brands, 8, 27, and 25 brands were classified as *local*, *regional*, or *national*, respectively.

Brand prominence could have either positive or negative relationship with implicit price. Previous research supports this assertion that there are mixed expectations regarding the geographic scope of a brand and its affect on brand value. Jekanowski et al. (2000) surveyed consumers in Indiana and concluded that consumers were willing to pay a premium for locally produced meats. This is consistent with similar results obtained for consumers from California (McGarry-Wolf and Thulin 2000), Colorado (Thilmany, Grannis, and Sparling 2003), and Chicago and Denver (Umberger et al. 2003). National brands have much larger overall volume, greater advertising expenditures, and as such garner broader general consumer awareness which might enable them to secure greater brand value and secure a higher price (Parcell and Schroeder 2007). Previous studies (Darby et al. 2006; Hu 2007) have shown that taste is the single most important attribute in repeated purchases of a food, and consumers are more likely to have had experience with a nationally branded food product than with a small distribution, local or regional brand. In the early days of branded beef in the United States some of the major beef brands were spearheaded by producer groups (e.g., American Angus Association developed Certified Angus Beef®). The early emergence of nationally branded beef products in the United States encouraged retailers and packers to establish their brands.

Because different branded products are positioned to appeal to different consumers, brand positioning was included to determine how brand value differs between different types of brands. Brand types include: *special* (33%), *program* (7%), *store* (23%), and *other* (37%) which are consistent with the categories of Ward, Lusk, and Dutton (2008). *Special* brands are those that carried special labels related to production practices such as “natural.” Special-label products have higher production costs than products without special labeling or production methods (Yanik et al. 1999). Therefore, for special brands to exist in the marketplace they are expected to have a high brand value. *Program* brands are breed-specific products. Generally we would expect a breed name on the package would help to promote consumer confidence and loyalty, due to the accountability and product assurance that come with the breed name. S*tore* brands are specific to a certain retail store or chain of stores. *Other* brands were those that could not be classified readily into one of the previous three brand types. *Other* brands tend to be owned by a processor or meat market.

Quality grade variables were excluded from the retail price estimation because they are embedded with the brand effects. Because Prime and Choice quality grades signal high quality they are hypothesized to increase brand value. As such, the proportion of pounds sold by a particular brand grading Choice or Prime (*ChoicePlus*) was included in the brand value determination model.

Brand recognition can be strengthened by branding multiple food products. For example, certain brands offer combinations of beef, poultry, and/or pork products carrying the same brand name. Multiple-product brands might enjoy greater brand equity because of broader consumer recognition of, and loyalty to, the brand name across food products. Sixty-three percent of the brands in this sample represent products from companies having multiple meat species brands.

Implicit Prices of Retail Beef Steak Characteristics

In empirical estimation, the theoretical foundation for hedonic models provides little guidance on appropriate functional form. Here, steak is assumed to be separable and additive in the various characteristics (e.g., breed claim, organic claim, religious processing claim, cut) suggesting a linear relationship.[6] This implies steak characteristics can be unbundled, repackaged, and purchased in any combination. Empirical results for the hedonic pricing model are presented in table 1.3.[7] Coefficient estimates refer to a change in retail steak price in $/lb. from a one-unit change in the independent variable, *ceteris paribus*. A positive coefficient represents a premium for the particular steak characteristic; while a negative coefficient indicates a discount.

Brand coefficients (figure 1.2), range from -$1.24/lb. to $5.77/lb. compared to unbranded steak products. Ward, Lusk, and Dutton (2008) found premiums of $0.00/lb. to $6.20/lb. relative to generic or unbranded roast/steak. While the range found by Ward, Lusk, and Dutton (2008) is similar to our results, notable differences exist in measurement across the studies. Our study estimates individual brand coefficients as opposed to brands grouped into special, program/breed, store, other, and none/generic categories. Furthermore, our study employs nationwide retail scanner data; while Ward, Lusk, and Dutton (2008) used data from a sample of retail stores in Oklahoma City and Tulsa, Oklahoma, and Denver, Colorado. Martinez (2008) found steak brand premiums from -$0.44/lb. to $4.15/lb. in analysis of Nielson Homescan Panel data.

The breed claim coefficient indicates steaks having a breed claim, *ceteris paribus,* had a $1.27/lb. lower price on average than a product without a breed claim. We expected breed claim to have a positive coefficient because one would anticipate that a breed claim is made in order to appeal to consumers that have a breed preference. Furthermore, the breed claim can always be omitted from the product label if it reduces product value. Perhaps breed claims have proliferated to the point where they do not, by themselves, garner steak product value enhancement. In further analysis that we cannot report due to confidentiality, we determined that certain brands with a breed claim garner a premium while other brands with a breed claim are discounted. Thus, to predict the price of a steak that has a breed claim, one needs to take into consideration the brand parameter estimate together with the breed claim estimate.

Organic steak product garners a premium of $2.98/lb. compared to a steak product that has no organic designation. Results are consistent with expectations because organic products tend to exhibit a higher price because they represent a particular niche market that is costly to supply relative to conventionally produced products. Moreover, the organic price premium may indicate growing consumer demand for organic products. The intuition follows similarly for religious processing claims which exhibit a premium of $1.18/lb.

As expected, retail cuts with the presence of bone have a lower retail price of $0.77/lb. relative to boneless product. Shongwe et al. (2007) found the presence of bone discounted T-bone and rump steaks by 23 percent. Unnevehr and Bard (2003) found the presence of bone in the cut reduced value sharply; $1.11/lb. (rib steaks), $0.91/lb. (loin steaks), and $0.30/lb. (sirloin steaks).

Tenderloin, porterhouse, T-bone, ribeye, top loin, and lip on ribeye garner premiums relative to sirloin steaks (figure 1.3). Premium steak cut coefficients reveal an average premium of $3.43/lb. The tenderloin cut garners the highest premium of $7.60/lb. relative to sirloin steaks. Steaks categorized as "everyday" steaks received discounts of $0.05/lb. to $4.67/lb. Everyday steaks are likely discounted because consumers perceive these cuts as being less flavorful and less tender. Often additional processing and preparation is necessary when cooking everyday steaks. The steak cut coefficients coincide with The Beef Checkoff (2008) classification of premium and everyday steaks.

Retail Beef Steak Brand Value

The previous discussion highlights the value consumers place on descriptive characteristics of steak and identifies individual brand values. But what factors influence brand value? The second step of the analysis was used to provide insight into this question. According to Achen

(2005), two step estimation is viable when: 1) first stage models are well specified, 2) first stage samples (of size n_j) are much larger than second stage sample sizes (of size m), and 3) influential points at the second stage are thoroughly assessed. We assert that our first stage specification is appropriate. There should be an order of magnitude more retail steak prices than there are brands. Achen finds that simple examples indicate that consistency requires $m/n \rightarrow 0$ asymptotically. Clearly, we adhere to the sample size principle as 60/198179=0.0003. Finally, to determine if results of the second step regression analysis are significantly influenced by outlier observations, we computed influential diagnostics; namely, DFBETAS. According to Belsley, Kuh, and Welsch (1980, p.263), "DFBETAS point to characteristics of the data to which the coefficient estimates or their estimated standard errors are particularly sensitive and are especially useful for examining the suitability of the data for structural estimation." Our discussion of results follows the base model in which we did not eliminate any potential outlier observations (model 1). However, we highlight specific results that may be impacted by outlier data by comparing and contrasting the base model to model 2 in which we delete influential outlier observations as determined by the DFBETAS.

Results of estimating equation (1.7) are presented in table 1.4.[8] New brands, brands that have existed in the industry for three years or less, have $1.69/lb. premium relative to brands that have been in the industry for greater than ten years. When consumers have many brands to choose from, there is an emphasis on the development of new and different product attributes, rather than emphasizing the value found in a traditional product (Outlaw et al. 1997). The estimate found here indicates that new brands are introduced with premium prices. Perhaps newly launched brands are targeting specific emerging consumer trends. How many of these brands will be successful in sustaining premium value over time is unknown, but likely some will fail. Estimates for medium-age brands are not statistically significant.

Regional brands garnered \$0.76/lb. premium relative to national brands. The alternative model estimated after deleting influential outliers indicate the regional brand premium could be as large as \$1.02/lb. relative to national brands. This is a surprising result since regional brands have smaller market share and presumably less general consumer recognition. In contrast, *local* brands do not have statistically different brand equity relative to *national* brands.

Results support recent changes in firms' attempts to differentiate products through brand positioning. Estimates of this positioning show that *Special* brands have \$2.32/lb. higher prices relative to *Other* brands; while *Program* and *Store* brands have \$1.54/lb. and \$1.31/lb. greater brand value, respectively. The alternative model adjusted for influential observations show premiums could be as large as \$2.54/lb. (*Special*), \$2.91/lb. (*Program*), and \$2.34/lb. (*Store*) relative to *Other* brands.

Both models fail to show a statistically significant affect for proportion of pounds sold by a particular brand grading Choice or Prime (*ChoicePlus*) or whether the company that owns the brand also has meat from other species carrying the same brand name (*MultiMeat*).

Conclusions and Implications

The objective of this study was to determine how retail beef steak product attributes affect prices. We were particularly interested in determining implicit price premiums and discounts for beef steak brands. Certain brands garner premiums while others receive discounts relative to unbranded products. We found 55 of 61 retail steak brands received premiums while the remaining brands were discounted relative to unbranded products. Additional steak product attributes were identified that exhibit premiums or discounts. Characteristics other than brand that garner a premium include organic claim, religious claim, and boneless products. Premium steaks, such as Tenderloin, Porterhouse, T-bone, Ribeye, Top Loin, and Lip On Ribeye exhibit premiums when compared to Sirloin steaks. Steak cuts perceived to be lower quality were discounted. Consumers exhibit complex purchasing behavior which different beef industry sectors are taking into consideration in order to provide desired products. Results should help every sector of the beef industry understand implicit prices of product attributes and provide information as to how to improve branding strategies.

Product characteristics that are not necessarily unique to a brand, such as organic and religious claim receive premiums that are economically important relative to the brand premium. In addition, different steak cuts, related to quality differences, have price differentials that exceed price differentials across brands. The bottom line is that a lower-quality steak cut will command a lower price and a higher quality cut will receive a higher price, regardless of the brand.

Newly introduced brands tend to have higher prices than existing brands. New brands may be targeting specific consumer trends and, as such, incurring added costs to provide specific product assurances. Products aligned well with emerging consumer preferences may be able to capture premium prices. Our study did not have data to determine new brand failure rate, but that must be kept in mind relative to pricing strategy.

A target market for branded beef is consumers who prefer specific product characteristics that are best suited for a particular product brand type. For example, brands that target production practices such as certified breed programs attract consumers who are specifically drawn to such claims. Also, branding tied to a particular retailer or store can help to promote and/or ensure confidence and loyalty. Tonsor, Schroeder, and Pennings (2009) concluded that store reputation influences consumer perceptions about food product quality and safety and store branding is an additional way to leverage value from store reputation. We expect store brands to continue to play a substantial and growing role in branded beef products in the future.

Brand value is not strongly associated with beef quality grade. Most branded beef products do not use quality grade as a substantial part of their product labeling scheme, even though quality grade is often part of the brand's specifications. This may be because consumers tend not to understand or be well informed about formal beef grades (Cox, McMullen, and Garrod 1990).

For a branded steak product to be successful there must be a strong link between consumers' attitudes and the attributes that the brand offers. Marketers must realize that consumer perceptions change over time as a result of added information, increased competition in a product category, and changing expectations. The dynamic nature suggests that marketers must track perceptions over time and align product and branding strategies with changing views.

An important limitation of this analysis is that we are not able to determine whether implicit premiums and discounts for specific product attributes are driven more by consumer demand or by product supply. That is, a certain product attribute such as an organic claim has a statistically significant premium of $2.98/lb. However, organic product represents only 4% of the steak market and, as such, determining whether to target product to this market requires both an understanding of added costs to meet this product standard as well as the elasticity of demand for organic steak. Similarly, a particular steak brand may be enjoying a premium price in the market, but the premium is associated with both demand and supply of that brand. As such, in design of strategies for expanding or contracting a brand's presence, elasticity of demand for the specific branded product must be known. Determining demand elasticities for specific steak product attributes is a logical step for future research.

Endnotes

[1] The steak quality categories employed by Parcell and Schroeder represented aggregated primal cuts: high quality (rib, ribeye, tenderloin, and filet mignon), medium quality (T-bone, sirloin, NY strip, top loin, top sirloin, tip, porterhouse, and round), and low quality (chuck, blade, arm, shoulder, flank, London broil, cube, and other).

[2] The Durbin-Wu-Hausman test was used to determine if the time invariant unobservable factors should be treated as a fixed effect or random effect (Wu 1973). The test was performed by obtaining the group means of the time invariant variables and adding them to the estimated random effects model. Then the joint hypothesis that the coefficients on the group means are all zero was tested. The hypothesis that the individual effects are uncorrelated with the other regressors was rejected. This suggests that these effects are correlated with other variables in the model, thus the fixed effects model is appropriate.

[3] In order to test for serial correlation, a time variable must be specified. However, for this data there was not a consistent time variable because we have more than one observation per time period per cross section. Thus, to detect the presence of first-order serial correlation, the mean of the errors from equation (1.4) was computed for each unique date. These mean errors were utilized in a Cochrane-Orcutt procedure which showed a (Rho) first-order autocorrelation estimate that was not statistically significant.

[4] White's robust standard error estimation was used instead of feasible generalized least squares (FGLS) because given the large sample size the loss of efficiency in parameter estimates is rather small. Results using the FGLS estimator were quantitatively similar.

[5] Unbranded products and products that were included in a conglomerate store grouping were not included in the data set used for stage two of the analysis. Thus, 62 brand categories were reduced to 60 brands.

[6] We also considered a log-linear model. Box-Cox regressions suggest a log-linear functional form is more appropriate. However, the difference in "fit" is slight. In this case, the linear functional form is preferred as the price per pound interpretation is more straightforward for step one and step two modeling. General conclusions from each model specification are qualitatively the same.

[7] Influence diagnostics were performed to determine if results were significantly influenced by outlier observations (Belsley, Kuh, and Welsch 1980). Overall, the parameter estimates are not significantly influenced by a specific subset of outlier data.

[8] Additional diagnostic tests were conducted for the brand value model. The presence of heteroskedasticity was tested using the Breusch-Pagan test with the test failing to reject the null hypothesis of constant variances. Variance inflation factor statistics indicated no problems with multicollinearity. Box-Cox regressions were used to compare goodness of fit of models in which the dependent variable is in levels or logs; results suggest a linear functional form is more appropriate.

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Tables

Table 1.1 Description of Variables and Summary Statistics of Sale Observations

Variable	Description	Mean	Standard Deviation
	Dependent variable		
$Price_{ijt}$	Retail price for package *i* of brand *j* during week *t* ($/lb.)	7.85	4.27
	Independent variables		
$Brand_j$	Binary variables for brand (*j*)[a]	n/a	n/a
$Breed_{it}$	Binary variable =1 if a breed claim is present, =0 otherwise	0.48	0.50
$Organic_{it}$	Binary variable =1 if an organic claim is present, =0 otherwise	0.04	0.19
$Religious_{it}$	Binary variable =1 if a religious processing claim is present, =0 otherwise	0.06	0.24
$Bone_{it}$	Binary variable =1 if bone is present, =0 otherwise	0.20	0.40
Cut_{ict}	Binary variables for retail cut (*c*) for package *i*[b]	n/a	n/a
$Week_{it}$	Binary variable for week of package sale *i* (1/11/2004=1,…,3/29/2009=273)	n/a	n/a

Note: [a] Proportion of sales associated with each brand are not presented due to confidentiality. [b] Proportion of sales for each retail cut are presented in figure 1.1.

Table 1.2 Description of Variables and Summary Statistics of Brands

Variable	Description	Model 1		Model 2 (DFBETAS)	
		Mean	Standard Deviation	Mean	Standard Deviation
	Dependent Variable				
$BrandValue_j$	Implicit value of brand (\$/lb.)	2.40	1.74	2.36	1.47
	Independent Variables				
$BrandAge_{aj}$	Binary variables for age of brand *j*				
$a =$	1 - 3 years	0.07	0.25	0.02	0.15
	4 - 6 years	0.18	0.39	0.19	0.39
	7 - 10 years	0.05	0.22	0.07	0.26
	> 10 years	0.70	0.46	0.72	0.45
$Location_{lj}$	Binary variables for geographic scope of brand *j*				
$l =$	Local	0.13	0.34	0.12	0.32
	Regional	0.45	0.50	0.42	0.50
	National	0.42	0.50	0.47	0.50
$Positioning_{pj}$	Binary variables for positioning of brand *j*				
$p =$	Special	0.33	0.48	0.33	0.47
	Program	0.07	0.25	0.07	0.26
	Store	0.23	0.43	0.21	0.41
	Other	0.37	0.49	0.40	0.49
$ChoicePlus_j$	Proportion of brand *j's* total sale pounds labeled as grading Choice plus Prime over entire data set	0.18	0.38	0.20	0.40
$MultiMeat_j$	Binary variable =1 if multiple meat species brand, =0 otherwise	0.63	0.49	0.56	0.50

Note: Observations that were deemed to be influential and removed from model 2 data were $|DFBETAS| > 2\sqrt{n}$ where n is the number of observations used (Belsley, Kuh, and Welsch 1980).

Table 1.3 Determinants of Steak Price per Pound, 2004 - March 2009

Variable	Coefficient Estimate	Standard Error
Intercept	6.39***	0.08
$Brand_j$ (*default*: unbranded)	figure 1.2	
Breed	-1.27***	0.03
Organic	2.98***	0.05
Religious	1.18***	0.04
Bone	-0.77***	0.02
Cut_c (*default*: Sirloin)	figure 1.3	
Observations	198,179	
R^2	0.73	

Note: Coefficient estimates refer to a change in retail steak price in $/lb. from a one-unit change in the independent variable, *ceteris paribus*. Three (***) asterisks denote coefficients significantly different from zero at the 0.01 level.

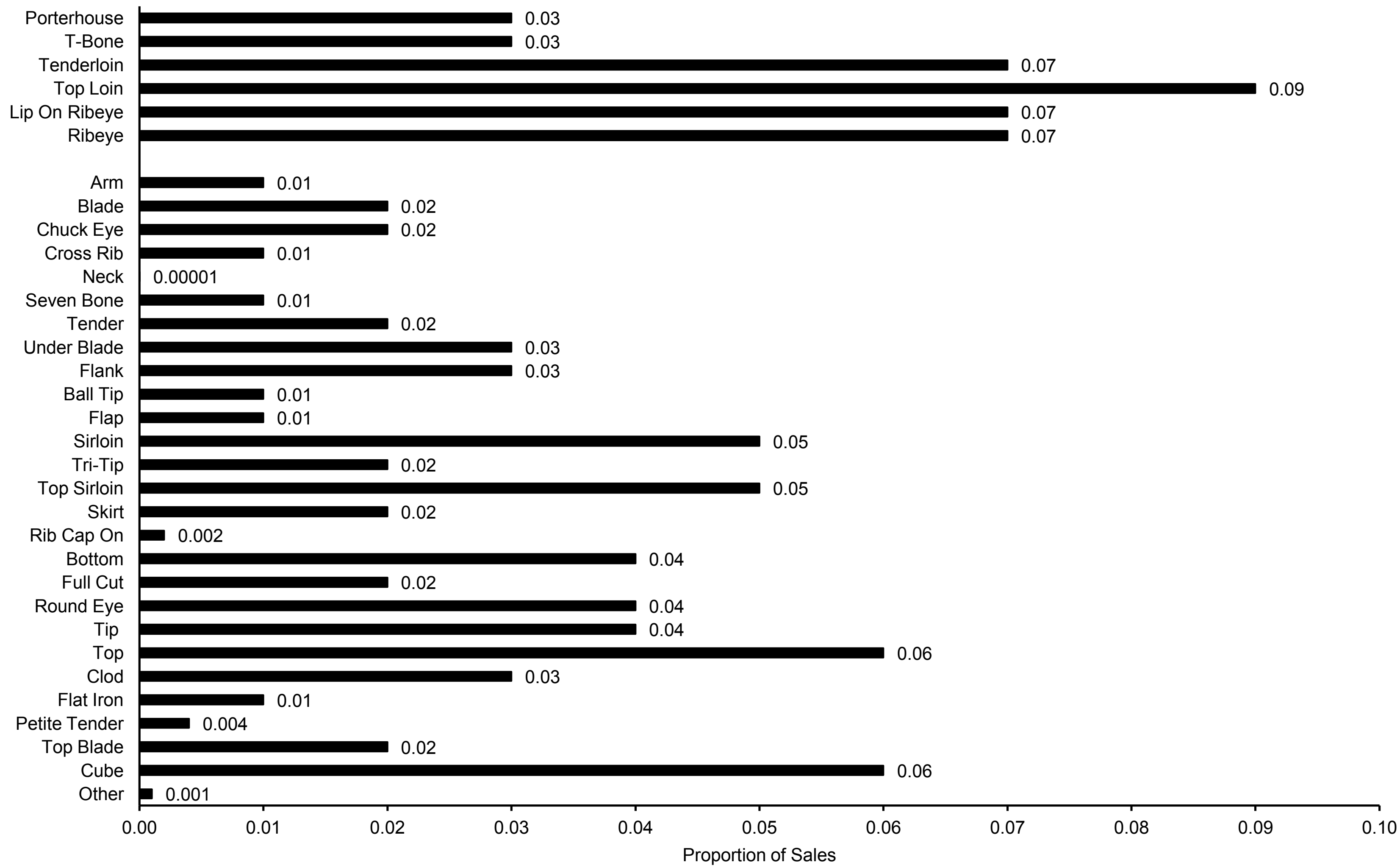
Table 1.4 Determinants of Brand Value per Pound

Variable	Model 1 Coefficient Estimate	Model 1 Standard Error	Model 2 (DFBETAS) Coefficient Estimate	Model 2 (DFBETAS) Standard Error
Intercept	0.41	0.63	0.09	0.50
$BrandAge_a$ (*default*: > 10 years)				
1 - 3 years	1.69**	0.82	1.94*	1.00
4 - 6 years	-0.71	0.59	-0.60	0.46
7 - 10 years	-0.28	1.02	-0.76	0.71
$Location_l$ (*default*: National)				
Local	0.09	0.62	0.85	0.52
Regional	0.76*	0.43	1.02***	0.32
$Positioning_p$ (*default*: Other)				
Special	2.32***	0.48	2.54***	0.41
Program	1.54*	0.90	2.91***	0.76
Store	1.31**	0.64	2.34***	0.55
ChoicePlus	0.73	0.61	0.32	0.52
MultiMeat	0.56	0.48	0.51	0.40
Observations	60		43	
R^2	0.43		0.70	

Note: Coefficient estimates refer to a change in brand value in $/lb. from a one-unit change in the independent variable, *ceteris paribus*. One (*), two (**), and three (***) asterisks denote coefficients significantly different from zero at the 0.10, 0.05, and 0.01 level, respectively. Observations that were deemed to be influential and removed from model 2 estimation were $|\text{DFBETAS}| > 2\sqrt{n}$ where n is the number of observations used (Belsley, Kuh, and Welsch 1980).

Figures

Figure 1.1 Retail Steak Cut Proportion of Sales



Note: Following The Beef Checkoff (2008), retail steak cuts are classified as premium (porterhouse, T-bone, tenderloin, top loin, lip on ribeye, and ribeye) and everyday (arm, blade, chuck eye, cross rib, neck, seven bone, tender, under blade, flank, ball tip, flap, sirloin, tri-tip, top sirloin, skirt, rib cap on, bottom, full cut, round eye, tip, top, clod, flat iron, petite tender, top blade, cube, and other).

Figure 1.2 Estimated Steak Brand Premium or Discount Compared to Unbranded Product, 2004 - March 2009

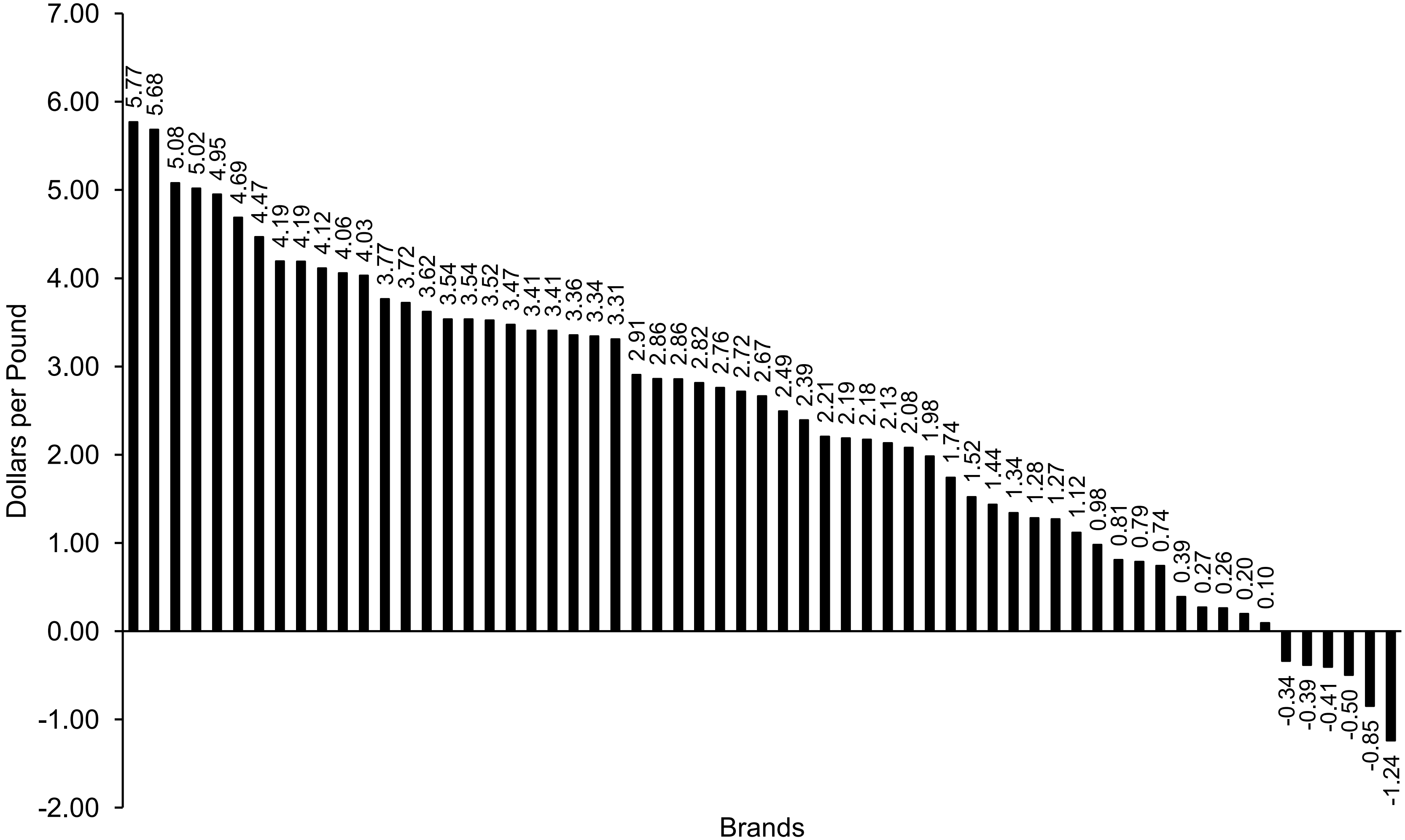
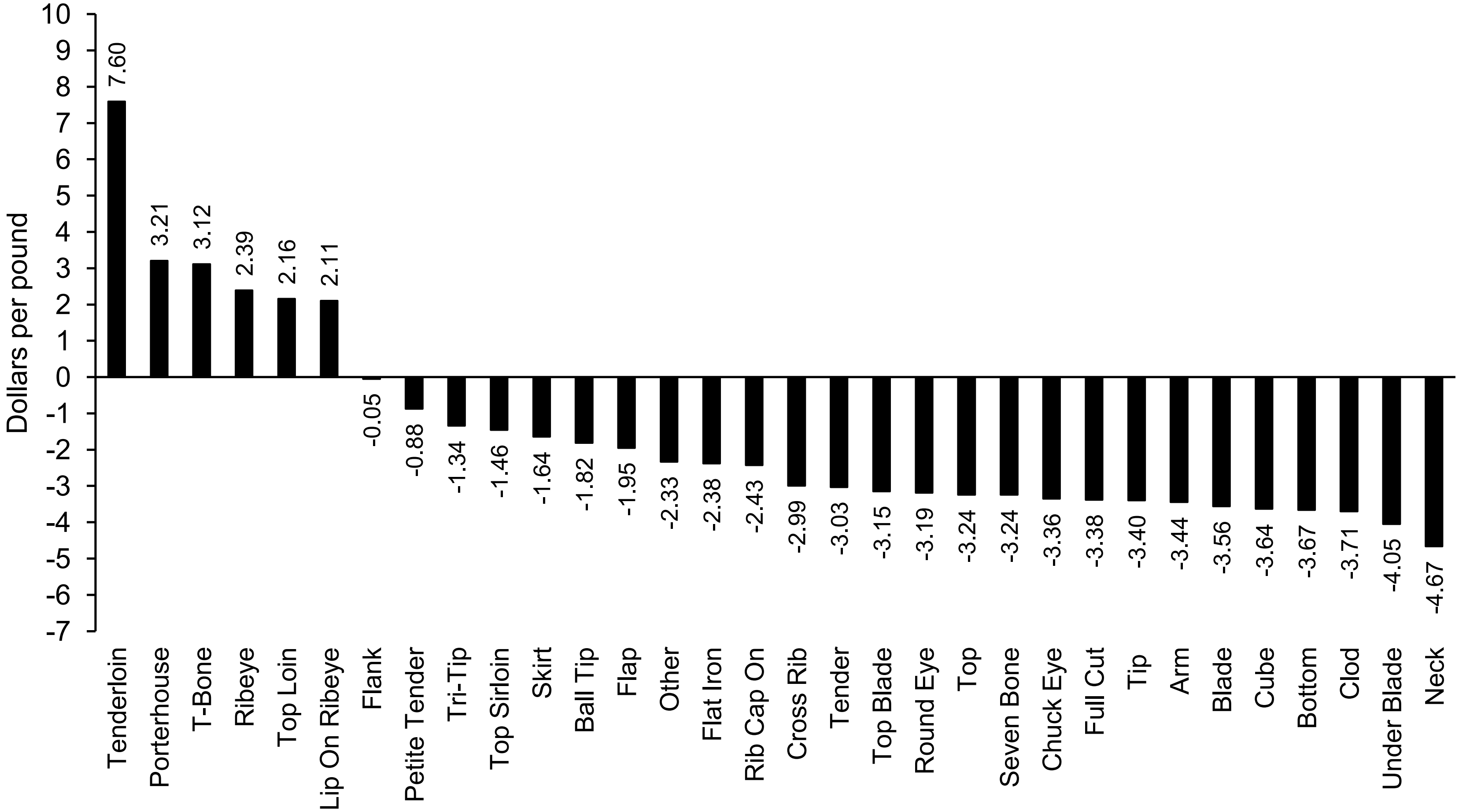


Figure 1.3 Estimated Steak Cut Premium or Discount Compared to Sirloin Steak, 2004 - March 2009



Note: Following The Beef Checkoff (2008), retail steak cuts are classified as premium (porterhouse, T-bone, tenderloin, top loin, lip on ribeye, and ribeye) and everyday (arm, blade, chuck eye, cross rib, neck, seven bone, tender, under blade, flank, ball tip, flap, sirloin, tri-tip, top sirloin, skirt, rib cap on, bottom, full cut, round eye, tip, top, clod, flat iron, petite tender, top blade, cube, and other).

Chapter 2 - Composite Ground Beef Demand

Introduction

Beef demand has fallen in recent years (Tonsor 2012), motivating the beef industry to search for ways to reverse this trend. At retail, consumers have increased their share of ground beef purchases. Retail scanner data reveals an increase in quantity of ground beef sold relative to total fresh beef sales from 44% in 2004 to 48% in 2009. Furthermore, ground beef sales revenue share increased from 33% in 2004 to 37% in 2008.[1] To improve our understanding of this growing market, detailed quantitative analysis of ground beef demand is needed.

Ground beef is differentiated in the retail counter by brand and percentage lean. Store branding of ground beef increased from 7% in 2004, to 21% in 2007, to 37% in 2010 (National Meat Case 2010). Increased consumer preferences for low-fat ground beef (Brester et al. 1993; Lusk and Parker 2009) has lead retailers to differentiate the product by lean percentage varying from 70% to 100% lean. While retailers have increasingly differentiated ground beef, there are no published estimates of demand elasticities for elementary ground beef products. Because differentiating ground beef is not costless, retailers need more information to determine whether the benefits of differentiation exceed the costs.

Retail scanner data of ground beef purchases provide accurate volume-weighted pricing data revealing what consumers are purchasing and how much they are spending on elementary ground beef products. However, a number of modeling issues arise from scanner data use in demand models. Estimating demand models for ground beef at the most elementary-level would require estimating excessively large systems of equations fraught with multicollinearity, degrees of freedom issues, and computational limitations. These issues necessitate aggregation at some level. Further, aggregation allows specific research questions to be addressed; in this case, whether consumers differentiate ground beef according to brand type, whether they differentiate ground beef according to lean percentage, or whether they behave as if all ground beef is the same. Inappropriate data aggregation can mask important details about individual product demand and can result in biased and unreliable elasticity estimates. Thus, it is prudent to test for valid aggregates as opposed to aggregating by convenience.

In this study we limit our analysis to ground beef with various brand types and lean percentages. In doing so, we implicitly assume that consumer preferences for ground beef are separable from all other goods. In this framework we use the Generalized Composite Commodity Theorem (Lewbel 1996) to test whether consumers differentiate ground beef. Elasticity estimates show how the nature of product differentiation is important to consumer demand for ground beef.

Demand and Aggregation

In their survey of agricultural economics literature, Shumway and Davis (2001) identified twenty-two empirical studies that tested for consistent aggregation of food and/or agricultural commodities. The theory of commodity aggregation provides the conditions under which consumer demand for a vast number of elementary goods is accurately described by consumers whom act as if they are optimizing over a considerably smaller number of aggregate goods.

Until recently there have been two ways to justify commodity aggregation. The first is based on separable preferences. If the preference ordering for a group of goods is unaffected by the preference ordering for goods outside the group, consumer preferences are said to be weakly separable and the arguments of the consumer's utility function consist of one or more sub-utility functions with arguments consisting of the elementary goods in a group. If in addition preferences are homothetic, then demand for the groups of goods will depend on group price indices. The second method of justifying commodity aggregation has been based on the Composite Commodity Theorem (CCT) (Hicks 1939 and Leontief 1936) which requires constant relative prices of all elementary goods in a group. Tests of separability are difficult to implement, have low power, and are often rejected empirically, while the CCT requires the prices of all elementary goods in a group to move absolutely synchronously, a requirement that will always be rejected empirically.

The Generalized Composite Commodity Theorem (GCCT) (Lewbel 1996) relaxes the restriction of constant relative prices by requiring only that relative prices be statistically independent of group prices. This restriction generally concurs with the widely observed multicollinearity of prices over time, and more specifically requires that changes in relative prices of goods within a group be unrelated to the general rate of inflation of the group (Lewbel 1996).

Previous studies on commodity aggregation use the GCCT in both consumer (Lewbel 1996; Davis 1998; Eales, Hyde, and Schrader 1998; Asche, Bremnes, and Wessells 1999; Asche, Guttormsen, and Tveteras 2001; Capps and Love 2002; Reed, Levedahl, and Clark 2003; Karagiannis and Mergos 2002; Reed, Levedahl, and Hallahan 2005) and production data (Davis, Lin, and Shumway 2000; Williams and Shumway 2000). However, few studies have used the GCCT to address how differentiated elementary consumer goods can be aggregated. This study applies the GCCT to retail data to better understand consumer demand for ground beef.

Generalized Composite Commodity Theorem

This study applies the GCCT (Lewbel 1996) to retail data on ground beef because this theorem relaxes the restrictive requirements for aggregation implied by separable preferences and constant relative prices. This section briefly reviews the GCCT and restrictions required for commodity aggregation. The reader is referred to Lewbel (1996) for further details.

Following Lewbel (1996) let p_i and w_i denote respectively the price and budget shares for $i = 1, 2, ..., n$, elementary goods and $\mathbf{p}$ and $\mathbf{w}$ be the corresponding vectors. Likewise, let $\mathbf{P}$ and $\mathbf{W}$ represent vectors of group price indices P_I and group budget shares $W_I = \sum_{i \in I} w_i$, where I indexes groups of goods $\{I = 1, 2, \ldots, N\}$ and $n > N$. Each elementary good i is an element of a group I. Furthermore, define $r_i = \ln p_i$, $R_I = \ln P_I$, and let $\mathbf{r}$ and $\mathbf{R}$ represent the corresponding vectors. Relative prices are defined as the difference between the natural log of the elementary good price and the natural log of the group price index for which the elementary good is an element: $\rho_i = r_i - R_I$ for $i \in I$. The vector of relative prices is denoted by $\boldsymbol{\rho}$, and z denotes the natural log of a consumer's total consumption expenditure.

An elementary good's budget share w_i is defined to be composed of a systematic Marshallian demand function $g_i(\mathbf{r}, z)$ plus an error term e_i with a conditional mean zero such that:

$$w_i = g_i(\mathbf{r}, z) + e_i \tag{2.1}$$

where $E(e_i \mid \mathbf{r}, z) = 0$ and $g_i(\mathbf{r}, z) = E(w_i \mid \mathbf{r}, z)$. Because g_i form a valid elementary demand system, they satisfy adding-up ($\sum_{i=1} g_i(\mathbf{r}, z) = 1$), homogeneity ($g_i(\mathbf{r} - k, z - k) = g_i(\mathbf{r}, z)$ for all i), and Slutsky symmetry $((\partial g_k / \partial r_j) + (\partial g_k / \partial z)g_j = (\partial g_j / \partial r_k) + (\partial g_j / \partial z)g_k)$. The compensated demands also satisfy negative semi-definiteness. Aggregate, or composite, share equations are similarly defined as:

$$W_I = G_I(\mathbf{R}, z) + \varepsilon_I \tag{2.2}$$

where $E(\varepsilon_I \mid \mathbf{R}, z) = 0$ and $G_I(\mathbf{R}, z) = E(W_I \mid \mathbf{R}, z)$. The orthogonality of the model errors, e_i and ε_I, ensure that $g_i(\mathbf{r}, z)$ and $G_I(\mathbf{R}, z)$ are optimal predictors of elementary and aggregate shares, respectively. By definition there is also a function $G_I^*(\mathbf{r}, z)$ such that $G_I^*(\mathbf{r}, z) = \sum_{i \in I} g_i(\mathbf{r}, z)$

which expresses the group I demands in terms of the natural log of a consumer's total consumption expenditure (z) and the natural log of prices of elementary goods ($\mathbf{r}$).

Lewbel (1996) demonstrates a clear relationship between $G_I^*(\mathbf{r}, z)$ and $G_I(\mathbf{R}, z)$ and unambiguous justification for aggregation of the vector $\mathbf{r}$ into the aggregate vector $\mathbf{R}$ if two assumptions hold. One, the elementary demand functions $g_i(\mathbf{r}, z)$ for $i = 1, 2, ..., n$ are rational. That is, the elementary budget share functions satisfy all the properties of budget share equations arising from utility maximization. Two, the distribution of the vector of relative prices $\boldsymbol{\rho}$ is statistically independent of $\mathbf{R}$ and z. This states that movements in group prices cannot help predict movements in relative prices. This is the key assumption and in order to justify aggregation under the GGCT, this assumption must be empirically tested.

Based on these two assumptions, the intuition of Lewbel's GCCT approach is to redefine each elementary price as being a deviation from its group price. This redefined price is then substituted into $G_I^*(\mathbf{r}, z)$ and the deviations are integrated out. More formally, because $\rho_i = r_i - R_I$ by definition, then $\boldsymbol{\rho} = \mathbf{r} - \mathbf{R}^*$ where $\mathbf{R}^*$ denotes the n-vector of group prices with R_I in row i and in every row $i \in I$. Substitute this equation into $G_I^*(\mathbf{r}, z)$ and let the distribution function of $\boldsymbol{\rho}$ be denoted by $F(\boldsymbol{\rho})$. Integrating over this distribution function yields:

$$\begin{aligned} \int G_I^*(\mathbf{R}^* + \boldsymbol{\rho}, z)dF(\boldsymbol{\rho}) &= \mathrm{E}[G_I^*(\mathbf{R}^* + \boldsymbol{\rho}, z) \mid \mathbf{R}, z] \\ &= G_I(\mathbf{R}, z) \end{aligned} \tag{2.3}$$

This equation states that the aggregate budget share equation written in terms of the group price indices $G_I(\mathbf{R}, z)$ is equal to the conditional expected value of the sum over the elementary budget share equations $G_I^*(\mathbf{r}, z)$ when the elementary prices are written as deviations from the group price indices, $\mathbf{R}^* + \boldsymbol{\rho} = \mathbf{r}$.

Lewbel (1996) shows that if the two assumptions hold, then all standard properties of the elementary demand share functions are retained by the group share equations. This relates directly to demand system estimation. First, $G_I(\mathbf{R}, z)$ for $I = 1, \ldots, N$ is a valid system of aggregate demand equations because this system inherits the adding-up, homogeneity, and Slutsky symmetry from the elementary demands. Second, the demand elasticities of $G_I(\mathbf{R}, z)$ are best, unbiased estimates of within-group sums of elementary demand elasticities.

Empirical Strategy

The empirical section proceeds as follows. First, elementary ground beef data is tested for valid demand aggregates based on the GCCT. Second, if valid aggregation is found, implied by the GCCT, composite demands are estimated with a Rotterdam model. Tests for different types of aggregation and the resulting composite demand estimates reveal information about the value consumers place on ground beef brand type and lean percentage.

Testing Overview

As stated above, empirical testing requires determining whether relative elementary prices (ρ_i) are statistically independent of an aggregate price index for that group (R_I). First, an aggregate group price index must be computed for each group I. Second, the relative prices are defined as: $\rho_i = r_i - R_I$, where $r_i = \ln p_i$ and $R_I = \ln P_I$.

Following Lewbel (1996), tests depend on time series properties of the data. Unit root tests are used to determine the stationarity of ρ_i and R_I. Specifically, 1) if ρ_i and R_I are both stationary then a test for independence such as a correlation test is done, 2) if ρ_i and R_I are both nonstationary then a test for independence such as a cointegration test is done, 3) if ρ_i is stationary and R_I is nonstationary then aggregation is valid, and 4) if ρ_i is nonstationary and R_I is stationary then aggregation is valid. A result of no correlation or cointegration suggests the series are independent and can be aggregated. In cases 3) and 4), where one series is stationary (either ρ_i or R_I) and the other is nonstationary, no test for independence is required because two series cannot be cointegrated if one is stationary and the other is nonstationary (Granger and Hallman 1989).

Rotterdam Model

The absolute price version of the Rotterdam model is used to estimate composite demand systems implied by the GCCT tests. See Theil (1980) for a detailed development of the Rotterdam model. This specification is chosen because it allows imposition of restrictions derived from consumer demand theory (symmetry and homogeneity) and is sufficiently flexible to capture variations in consumer behavior, especially demand elasticities (Brester and Wohlgenant 1991; Capps and Love 2002). Although the Rotterdam model is not derived from an underlying utility or expenditure function, it satisfies the integrability conditions when homogeneity and symmetry are imposed (Deaton and MuellBauer 1980). The Rotterdam model handles nonstationary data easily as price and quantity variables are expressed in natural logarithmic differences, which is an advantage over other demand systems such as the Almost Ideal Demand System (Capps and Love 2002; Capps, Church, and Love 2003). Rotterdam model use is common in demand system estimation using scanner data (Nayga and Capps 1994; Seo and Capps 1997; Capps, Seo, and Nichols 1997; Capps and Love 2002).

The ith equation of the estimated model is given by:

$$w_i\Delta\ln(q_i) = \theta_i\Delta\ln(Q) + \sum_{j=1}\pi_{ij}\Delta\ln(p_j) + v_i, \tag{2.4}$$

where w_i is the budget share of the ith product (time subscripts [t] on each variable are omitted for convenience); Δ is the standard first-difference operator [e.g., $\Delta\ln Y_t = \ln(Y_t) - \ln(Y_{t-1})$]; q_i is consumption of the ith product; p_j is the price of the jth product; $\Delta\ln(Q)$ is the Divisia volume index $[\sum_{i=1} w_i \Delta\ln(q_i)]$; v_i is a random error term; and θ_i and π_{ij} are parameters to be estimated.

Adding-up, homogeneity, and symmetry restrictions are imposed as maintained assumptions to ensure the demand model is consistent with theory. The adding-up restrictions are $\sum_{i=1}\theta_i = 1$ and $\sum_{i=1}\pi_{ij} = 0$. The homogeneity and symmetry restrictions are imposed, respectively, by $\sum_{j=1}\pi_{ij} = 0$ and $\pi_{ij} = \pi_{ji}$.[2] If $\pi_{ij} > 0$, then products i and j are substitutes; if $\pi_{ij} < 0$, the respective products are complements, and if $\pi_{ij} = 0$, the products are independent. The own- and cross-price compensated demand elasticities are $\varepsilon_{ij} = \pi_{ij} / w_i$. The expenditure elasticity is $\eta_i = \theta_i / w_i$.[3]

Data

Retail scanner data offers accurate volume-weighted pricing data revealing what consumers are purchasing and how much they are spending on elementary retail products. Scanner data allow significant advances in understanding food product marketing because they enable estimation of firm-, brand-, and commodity-level demand models (Cotterill 1994; Capps and Love 2002). Lensing and Purcell (2006) find that the prices collected by the Bureau of Labor Statistics (BLS) have been higher than the prices that consumers use to make their buying decisions. Volume weighted prices, provided by scanner data, more accurately reflect what consumers actually pay for fresh meat in contrast to BLS summaries of posted prices (Lensing and Purcell 2006). Furthermore, use of simple average monthly prices biases own-price elasticities upward compared to weekly and volume-weighted price estimations because price change measures in BLS data are smaller for simple average monthly prices than for weekly prices or for volume-weighted prices (Lensing and Purcell 2006).

Weekly retail scanner data were collected from the Freshlook Marketing Group from 2004 through March 2009. Freshlook Marketing Group collects meat department info-scan random weight sales data from more than 14,000 retail food stores nationwide. In all, there are approximately 175 retail market areas covered and approximately 68% of all U.S. grocery stores captured. Data recorded for each sale included: revenue (dollars), quantity (pounds), price, brand name, and lean percentage.

The data consisted of 64 different ground beef brands that were classified into the following categories: 1) local/regional - distributed within a local or regional geographic area and is owned and controlled by a private company, 2) national - distributed to retail locations nationwide and controlled by the company or the supplier(s) who owns the brand, 3) store - specific to a certain retail store or chain of stores and owned and controlled by the retail grocery store or chain of stores, or 4) unbranded - a product without a brand name on the label.

Ground beef is grouped by Freshlook into five lean percentage categories: 1) 70-77%, 2) 78-84%, 3) 85-89%, 4) 90-95%, or 5) 96-100% lean. Data on store brands of 96-100% lean was not available. This is because within the ground beef market there are few transactions of this lean category. Table 2.1 provides the share of packages, revenue, and quantity of each elementary ground beef product.

There are 19 ground beef products (4 brand types * 5 lean percentages less the store brand 96-100% lean). The GCCT tests conducted involved three possible subsets of these products. Table 2.2 identifies the three groups of products we tested for consistency with the GCCT. Common letters in each aggregation column indicate which products were hypothesized to be valid aggregates in a particular group. Groups A-E were aggregated based on lean percentage and groups F-I were aggregated based on brand type. Group J aggregates all ground beef products into a single product.

Empirical Results

This section presents tests for valid aggregation of 19 elementary ground beef products and estimates of composite ground beef demand elasticities.

Tables 2.3, 2.4, and 2.5 summarize the GCCT tests for the relative and group prices under the proposed aggregation schemes. Following Lewbel (1996), two stationary tests were conducted: the Augmented Dickey-Fuller (ADF) test with a null of nonstationarity and the Kwaitkowski, Phillips, Schmidt, and Shin (KPSS) test with a null of stationarity. Having two tests introduces the possibility of conflicting results. Therefore, inferences based on the joint confirmation hypothesis (JCH) of a unit root were used when the ADF and KPSS tests conflicted (Carrion-i-Silvestre, Sanso-i-Rossello, and Ortuno 2001). In all three test groups, the group price indices were nonstationary and 14 (test group 1), 13 (test group 2), and 14 (test group 3) of the 19 relative prices were nonstationary; consequently, where relative prices were nonstationary aggregation rested on cointegration tests alone and where relative prices were stationary aggregation was deemed valid. Engle Granger tests were used to test for cointegration. Since the Engle Granger tests failed to reject the null of a spurious regression for all of the individual price comparisons, there was no need to perform family-wise tests (see Davis, Lin, and Shumway 2000). The individual test results support the notion that each of the three ground beef aggregation schemes proposed in this study can be described by a valid composite consumer demand system. That is, we justify estimating a demand system having five different lean percentages with brand types aggregated, a demand system having four different brand types with lean percentages aggregated, or estimating ground beef as a single commodity aggregated across brand type and lean percentage. Previous research has suggested that the stochastic nature of the GCCT may support numerous aggregation schemes (Reed, Levedahl, and Hallahan 2005).

Table 2.6 presents estimates of the compensated own-, cross-price, and expenditure elasticities of the percent-lean-based ground beef demand system. The own-price elasticities are all negative and statistically significant at the 1% level. We are unaware of any other study that has estimated price elasticities for differentiated ground beef. Previous estimates are available for aggregate ground beef elasticities. For example, compensated own-price elasticity estimates for ground beef include Brester and Wohlgenant (1991) with an estimate of -1.02; Nayga and Capps (1994) with an estimate of -1.22; and Coffey, Schroeder, and Marsh (2011) with an estimate of -1.08. Our elasticity estimates range from -0.44 to -1.29, being inelastic for 70-77%, 78-84%, and 85-89% lean and elastic for 90-95% and 96-100% lean.

The more inelastic demand for the lower lean percentage ground beef relative to leaner products suggests that consumer purchases of the cheaper, less lean, ground beef products are less responsive to own-price changes. Based on hedonic modeling, White (2010) found that 90% and higher lean ground beef had a retail price premium of a $1.00/lb or more relative to less than 85% lean products. We hypothesize that less lean ground beef is purchased by relatively lower-income consumers compared to the more expensive high lean product. Thus, less lean ground beef products may be more of a necessity for consumers that regularly purchase the product, compared to those who buy the leaner product.

All of the statistically significant cross-price elasticities are positive, as is expected for substitute products. The two lean percentages with the largest market shares are 70-77% (40% of revenue and 48% of quantity) and 90-95% (23% of revenue and 17% of quantity). These two products tend to be the strongest substitutes for the others. Expenditure elasticities range from

1.22 for 70-77% to 0.48 for 96-100% lean. The 96-100% lean product is a niche market having only 3% revenue and 2% quantity market share among the five products. The fact that the lowest lean product has the largest expenditure elasticity again suggests that lower-income, budget-constrained consumers, may represent a large share of the consumers purchasing the product.

Table 2.7 presents elasticity estimates of the brand-type-based ground beef demand system. The own-price elasticities for brands are negative as expected. The elasticity estimates range from -0.13 to -4.55, being inelastic for unbranded products and elastic for local/regional, national, and store brand types. An implied ranking of consumer's price sensitivity to own-price is (from most to least sensitive): (1) local/regional, (2) store, (3) national, and (4) unbranded. Consumers are more sensitive to price increases for less commonly known brands and less sensitive to price increases for well-known national brands and unbranded products. There are no published demand elasticities for branded ground beef to compare to our estimates. Richards and Padilla (2009) estimated elasticities that included fast food restaurants that specialize in hamburgers including McDonalds, Burger King, and Wendy's. They found elasticities for brand choice ranged from -2.9 to -3.8 for these three firms and for purchase quantity once in the establishment ranged from -1.6 to -1.9.

As expected, all the brand type expenditure elasticities are positive and consistent with economic intuition. The local/regional brand expenditure elasticity was not statistically significant at the 1-, 5-, or 10% level. All the cross-price elasticities are positive indicating the brands are all substitutes as is expected with such closely related products. Unbranded ground beef (93% of revenue and 94% of quantity) is relatively cheap compared to the branded products. As such, generic ground beef may represent a staple or necessity for budget-constrained households. In contrast, branded ground beef products have strong substitutes of other brands or the cheaper generic product.

Conclusions and Implications

Beef producers and producer groups have invested significant resources in retail beef case projects to further understand consumers' purchasing decisions. Ground beef is an increasingly important component of overall beef demand. In addition, both branding and labeling of lean percentage in ground beef have become commonplace. Lewbel's (1996) aggregation procedure was used to test whether consumers differentiate ground beef. Results suggest consumers differentiate ground beef by lean percentage (70-77%, 78-84%, 85-89%, 90-95%, and 96-100%) and by brand type (local/regional, national, store, and unbranded).

Composite demands, implied by Lewbel's (1996) aggregation procedure, were estimated to reveal information about the value consumers place on ground beef brand type and lean percentage. Compensated own-price elasticities for 70-77%, 78-84%, 85-89%, 90-95%, and 96-100% lean were -0.44, -0.51, -0.87, -1.29, and -1.20, respectively. The least lean ground beef had the highest expenditure elasticity; suggesting that lower-income, budget-constrained consumers may represent a large share of the consumers purchasing the product. Compensated own-price elasticities for local/regional, national, store, and unbranded were -4.55, -2.20, -2.42, and -0.13, respectively. This suggests consumers are more sensitive to price increases for less commonly known brands and less sensitive to price increases for well-known national brands and unbranded products. Furthermore, branded ground beef products have strong substitutes of other brands or the cheaper unbranded product. The range in elasticity estimates shows the value of analyzing demand elasticity based on product differentiation and not simply considering ground beef as being homogeneous. This information is important for determining the benefits and sensitivity of consumers to ground beef product differentiation.

Elementary product data can be expected to further advance the understanding of retail demand for differentiated products. Scanner data provides data for detailed demand analysis. However, assessing appropriateness and impacts of aggregation will be an on-going challenge in such analysis.

Endnotes

[1] Quantity (pounds) and revenue (dollars) of ground beef sales were calculated from Freshlook Marketing Group data used in this analysis.

[2] Demand models were estimated using the PROC MODEL procedure in SAS 9.2. Each system was estimated using iterated seemingly unrelated regression, with an allowance for common serial correlation across all equations. Starting values of 0.0001 were used.

[3] The variance of each elasticity estimate was obtained by the delta method. The delta method estimates the variance of a nonlinear function of two or more random variables by taking a first-order Taylor series expansion around the mean value of the variable and calculating the variance on that newly created random variable (Greene 2003). The delta estimates of the variances of the compensated price and expenditure elasticities are $\text{var}(\varepsilon_{ij}) = (1/\overline{w}_i^2) \times \text{var}(\hat{\pi}_{ij})$ and $\text{var}(\eta_i) = (1/\overline{w}_i^2) \times \text{var}(\hat{\theta}_{ij})$, respectively. Using the variance of the elasticity estimates, *t*-values were computed and used to test for statistical significance for each estimate.

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Tables

Table 2.1 Share of Packages, Revenue, and Quantity of Elementary Ground Beef Products, 2004 - March 2009

Number	Brand Type	Lean Percentage	Packages (%)	Revenue (%)	Quantity (%)
1	Local/Regional	70-77%	4.39	0.45	0.52
2	National	70-77%	6.86	0.28	0.27
3	Store	70-77%	7.39	0.60	0.64
4	Unbranded	70-77%	5.64	38.40	46.17
5	Local/Regional	78-84%	1.61	0.13	0.11
6	National	78-84%	6.01	0.38	0.36
7	Store	78-84%	6.52	0.41	0.36
8	Unbranded	78-84%	2.35	20.68	21.23
9	Local/Regional	85-89%	2.79	0.04	0.02
10	National	85-89%	7.54	0.59	0.41
11	Store	85-89%	11.87	1.29	1.05
12	Unbranded	85-89%	3.52	11.32	10.27
13	Local/Regional	90-95%	3.19	0.06	0.04
14	National	90-95%	7.84	1.25	0.80
15	Store	90-95%	10.83	0.95	0.59
16	Unbranded	90-95%	3.28	20.36	15.48
17	Local/Regional	96-100%	1.84	0.16	0.11
18	National	96-100%	4.12	0.88	0.48
19	Unbranded	96-100%	2.39	1.78	1.09

Notes: Share of packages, revenue (dollars), and quantity (pounds) of each elementary ground beef product was calculated directly from Freshlook Marketing Group data.

Table 2.2 GCCT Test Groups

	Commodity		Aggregation Test Groups[a]		
Number	Brand Type	Lean Percentage	1	2	3
1	Local/Regional	70-77%	A	F	J
2	National	70-77%	A	G	J
3	Store	70-77%	A	H	J
4	Unbranded	70-77%	A	I	J
5	Local/Regional	78-84%	B	F	J
6	National	78-84%	B	G	J
7	Store	78-84%	B	H	J
8	Unbranded	78-84%	B	I	J
9	Local/Regional	85-89%	C	F	J
10	National	85-89%	C	G	J
11	Store	85-89%	C	H	J
12	Unbranded	85-89%	C	I	J
13	Local/Regional	90-95%	D	F	J
14	National	90-95%	D	G	J
15	Store	90-95%	D	H	J
16	Unbranded	90-95%	D	I	J
17	Local/Regional	96-100%	E	F	J
18	National	96-100%	E	G	J
19	Unbranded	96-100%	E	I	J

Notes: [a] Brand type and lean percentage rows sharing the same letter in each aggregation test group column are hypothesized to be in the valid aggregates in a particular product grouping. Groups A-E (test group 1) were aggregated based on lean percentage, groups F-I (test group 2) were aggregated based on brand type, and group J (test group 3) aggregated all ground beef products into a single product.

Table 2.3 GCCT Test Results for Test Group 1 (Lean Percentage Composites)

Group and Relative Prices	Aggregate Share (%)	ADF Test H$_0$: *I(1)*[a]	KPSS Test H$_0$: *I(0)*[b]	*I(0)* or *I(1)*?[c]	Engle-Granger Test H$_0$: Not Cointegrated (*NC*)[d]
		τ_t	η_t		T_k
R(70-77%)		-2.306 (7)	0.326 (5)*	*I(1)*	
ρ(Local/Regional)	1.22	-2.491 (8)	0.570 (5)*	*I(1)*	-2.982 (4)
ρ(National)	0.72	-3.411 (9)*	0.254 (5)*	*I(0)* (JCH)	*NC*
ρ(Store)	1.78	-3.420 (6)*	0.252 (5)*	*I(0)* (JCH)	*NC*
ρ(Unbranded)	96.28	-2.826 (4)	0.331 (5)*	*I(1)*	-2.809 (4)
R(78-84%)		-2.945 (5)	0.191 (5)*	*I(1)*	
ρ(Local/Regional)	0.65	-2.570 (6)	0.281 (5)*	*I(1)*	-2.153 (6)
ρ(National)	1.80	-1.683 (6)	0.708 (5)*	*I(1)*	-1.734 (6)
ρ(Store)	1.98	-2.965 (11)	0.582 (5)*	*I(1)*	-3.265 (10)
ρ(Unbranded)	95.56	-0.718 (6)	0.831 (5)*	*I(1)*	-0.437 (6)
R(85-89%)		-2.759 (6)	0.277 (5)*	*I(1)*	
ρ(Local/Regional)	0.32	-4.634 (3)*	0.399 (5)*	*I(0)* (JCH)	*NC*
ρ(National)	4.44	-3.320 (10)*	0.134 (5)*	*I(1)* (JCH)	-2.686 (10)
ρ(Store)	9.81	-1.519 (7)	0.557 (5)*	*I(1)*	-1.975 (7)
ρ(Unbranded)	85.44	-1.702 (7)	0.505 (5)*	*I(1)*	-1.934 (7)
R(90-95%)		-2.618 (11)	0.433 (5)*	*I(1)*	
ρ(Local/Regional)	0.29	-1.370 (4)	0.441 (5)*	*I(1)*	-1.422 (4)
ρ(National)	5.53	-2.650 (11)	0.469 (5)*	*I(1)*	-2.263 (11)
ρ(Store)	4.23	-3.128 (4)	0.360 (5)*	*I(1)*	-2.933 (8)
ρ(Unbranded)	89.96	-2.698 (10)	0.604 (5)*	*I(1)*	-2.427 (9)
R(96-100%)		-2.558 (10)	0.663 (5)*	*I(1)*	
ρ(Local/Regional)	6.49	-10.898 (1)*	0.122 (5)*	*I(0)* (JCH)	*NC*
ρ(National)	31.25	-3.750 (8)*	0.087 (5)*	*I(0)*	*NC*
ρ(Unbranded)	62.26	-2.974 (9)	0.185 (5)*	*I(1)*	-3.235 (7)
10% critical values		-3.130	0.119	(-3.391, 0.114)	-5.727

Notes: Asterisk (*) denotes rejection of the null at the 0.10 significance level.
[a] The test statistics (τ_t) of the null hypothesis of *I(1)* are the augmented Dickey-Fuller (1979) (ADF) *t*-statistics of the coefficient on the lagged level variable in the regression of the first-differences on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by *R 2.10.1*.
[b] The test statistics (η_t) of the null hypothesis of *I(0)* are the Kwaitkowski, Phillips, Schmidt, and Shin (1992) (KPSS) *t*-statistics. The *t*-statistics are sums of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend. For the correction of the error term a Bartlett window with five lags was used to ensure the variance matrix was well behaved.
[c] Inferences based on the joint confirmation hypothesis (JCH) of a Unit Root are used when the ADF and KPSS tests conflict (Carrion-i-Silvestre, Sanso-i-Rossello, and Ortuno 2001). The joint critical values of (-3.391, 0.114) represent the critical values for 300 observations for the ADF and the KPSS with trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than -3.391 and the value of the KPSS statistic is less (greater) than 0.114 then the series is considered (at the 0.90 level) stationary (nonstationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary.
[d] The test statistics (T_k) of the null hypothesis that the *k*th relative price and the vector of composite group prices are not cointegrated are augmented Dickey Fuller tests of *I(1)* residuals from regressing the *k*th relative price on each of the integrated group price indices. The number of lagged first difference residuals included (in the residual regression) is reported in parenthesis, and is determined by *R* 2.10.1. The 0.10 critical values reported for the individual tests are based on 273 observations and eleven integrated explanatory variables, so that *k*=12 in MacKinnon (1996).

Table 2.4 GCCT Test Results for Test Group 2 (Brand Type Composites)

Group and Relative Prices	Aggregate Share (%)	ADF Test H_0: *I(1)*[a]	KPSS Test H_0: *I(0)*[b]	*I(0)* or *I(1)*?[c]	Engle-Granger Test H_0: Not Cointegrated (*NC*)[d]
		τ_t	η_t		T_k
R(Local/Regional)		-2.367 (9)	0.617 (5)*	*I(1)*	
ρ(70-77%)	52.90	-2.650 (7)	0.423 (5)*	*I(1)*	-2.413 (7)
ρ(78-84%)	15.32	-2.993 (6)	0.278 (5)*	*I(1)*	-2.081 (6)
ρ(85-89%)	4.58	-3.691 (4)*	0.595 (5)*	*I(0)* (JCH)	*NC*
ρ(90-95%)	7.06	-1.178 (7)	0.558 (5)*	*I(1)*	-1.307 (11)
ρ(96-100%)	20.15	-2.807 (9)	0.563 (5)*	*I(1)*	-2.575 (10)
R(National)		-2.264 (9)	0.387 (5)*	*I(1)*	
ρ(70-77%)	8.35	-3.577 (4)*	0.261 (5)*	*I(1)*	*NC*
ρ(78-84%)	11.44	-1.427 (10)	0.736 (5)*	*I(0)* (JCH)	-2.068 (10)
ρ(85-89%)	17.27	-3.158 (5)*	0.210 (5)*	*I(1)*	-3.021 (8)
ρ(90-95%)	36.85	-1.586 (11)	0.419 (5)*	*I(1)* (JCH)	-1.706 (11)
ρ(96-100%)	26.09	-1.685 (10)	0.529 (5)*	*I(1)*	-1.813 (8)
R(Store)		-1.662 (11)	0.652 (5)*	*I(1)*	
ρ(70-77%)	20.88	-2.537 (5)	0.227 (5)*	*I(1)*	-1.927 (4)
ρ(78-84%)	12.63	-3.441 (10)*	0.107 (5)	*I(0)*	*NC*
ρ(85-89%)	38.25	-3.834 (4)*	0.189 (5)*	*I(0)* (JCH)	*NC*
ρ(90-95%)	28.23	-1.882 (11)	0.663 (5)*	*I(1)*	-2.915 (8)
R(Unbranded)		-2.347 (7)	0.464 (5)*	*I(1)*	
ρ(70-77%)	41.43	-2.015 (8)	0.335 (5)*	*I(1)*	-2.150 (11)
ρ(78-84%)	22.35	-3.097 (11)	0.615 (5)*	*I(1)*	-3.465 (7)
ρ(85-89%)	12.24	-4.328 (7)*	0.165 (5)*	*I(0)* (JCH)	*NC*
ρ(90-95%)	22.07	-3.908 (11)*	0.064 (5)	*I(0)*	*NC*
ρ(96-100%)	1.91	-1.830 (8)	0.662 (5)*	*I(1)*	-2.618 (11)
10% Critical Value		-3.130	0.119	(-3.391, 0.114)	-5.727

Notes: Asterisk (*) denotes rejection of the null at the 0.10 significance level.

[a] The test statistics (τ_t) of the null hypothesis of *I(1)* are the augmented Dickey-Fuller (1979) (ADF) *t*-statistics of the coefficient on the lagged level variable in the regression of the first-differences on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by *R 2.10.1*.

[b] The test statistics (η_t) of the null hypothesis of *I(0)* are the Kwaitkowski, Phillips, Schmidt, and Shin (1992) (KPSS) *t*-statistics. The *t*-statistics are sums of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend. For the correction of the error term a Bartlett window with five lags was used to ensure the variance matrix was well behaved.

[c] Inferences based on the joint confirmation hypothesis (JCH) of a Unit Root are used when the ADF and KPSS tests conflict (Carrion-i-Silvestre, Sanso-i-Rossello, and Ortuno 2001). The joint critical values of (-3.391, 0.114) represent the critical values for 300 observations for the ADF and the KPSS with trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than -3.391 and the value of the KPSS statistic is less (greater) than 0.114 then the series is considered (at the 0.90 level) stationary (nonstationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary.

[d] The test statistics (T_k) of the null hypothesis that the *k*th relative price and the vector of composite group prices are not cointegrated are augmented Dickey Fuller tests of *I(1)* residuals from regressing the *k*th relative price on each of the integrated group price indices. The number of lagged first difference residuals included (in the residual regression) is reported in parenthesis, and is determined by *R* 2.10.1. The 0.10 critical values reported for the individual tests are based on 273 observations and eleven integrated explanatory variables, so that *k*=12 in MacKinnon (1996).

Table 2.5 GCCT Test Results for Test Group 3 (Ground Beef Composite)

Group and Relative Prices	Aggregate Share (%)	ADF Test H_0: *I(1)*[a]	KPSS Test H_0: *I(0)*[b]	*I(0)* or *I(1)*?[c]	Engle-Granger Test H_0: Not Cointegrated (*NC*)[d]
		τ_t	η_t		T_k
R(All Products)		-2.332 (7)	0.475 (5)*	*I(1)*	
ρ(Local/Regional 70-77%)	0.48	-3.116 (4)	0.541 (5)*	*I(1)*	-3.201 (4)
ρ(Local/Regional 78-84%)	0.14	-2.202 (6)	0.217 (5)*	*I(1)*	-2.143 (6)
ρ(Local/Regional 85-89%)	0.04	-4.767 (3)*	0.420 (5)*	*I(0)* (JCH)	*NC*
ρ(Local/Regional 90-95%)	0.06	-1.526 (4)	0.454 (5)*	*I(1)*	-1.486 (4)
ρ(Local/Regional 96-100%)	0.18	-5.652 (5)*	0.224 (5)*	*I(0)* (JCH)	*NC*
ρ(National 70-77%)	0.28	-3.161 (9)*	0.269 (5)*	*I(1)* (JCH)	-3.647 (8)
ρ(National 78-84%)	0.39	-1.693 (6)	0.621 (5)*	*I(1)*	-1.781 (6)
ρ(National 85-89%)	0.59	-3.292 (8)*	0.127 (5)*	*I(1)* (JCH)	-3.141 (8)
ρ(National 90-95%)	1.25	-2.989 (11)	0.493 (5)*	*I(1)*	-2.455 (11)
ρ(National 96-100%)	0.89	-2.592 (8)	0.550 (5)*	*I(1)*	-2.182 (8)
ρ(Store 70-77%)	0.71	-3.416 (4)*	0.300 (5)*	*I(0)* (JCH)	*NC*
ρ(Store 78-84%)	0.43	-3.099 (11)	0.728 (5)*	*I(1)*	-3.414 (10)
ρ(Store 85-89%)	1.30	-1.481 (11)	0.536 (5)*	*I(1)*	-2.058 (11)
ρ(Store 90-95%)	0.96	-3.073 (7)	0.382 (5)*	*I(1)*	-2.954 (8)
ρ(Unbranded 70-77%)	38.25	-2.085 (8)	0.322 (5)*	*I(1)*	-2.120 (8)
ρ(Unbranded 78-84%)	20.62	-3.076 (11)	0.609 (5)*	*I(1)*	-3.456 (7)
ρ(Unbranded 85-89%)	11.30	-4.202 (7)*	0.174 (5)*	*I(0)* (JCH)	*NC*
ρ(Unbranded 90-95%)	20.36	-3.917 (11)*	0.0623 (5)	*I(0)*	*NC*
ρ(Unbranded 96-100%)	1.76	-1.747 (8)	0.667 (5)*	*I(1)*	-2.605 (11)
10 percent critical values		-3.130	0.119	(-3.391, 0.114)	-5.727

Notes: Asterisk (*) denotes rejection of the null at the 0.10 significance level.

[a] The test statistics (τ_t) of the null hypothesis of *I(1)* are the augmented Dickey-Fuller (1979) (ADF) *t*-statistics of the coefficient on the lagged level variable in the regression of the first-differences on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by *R 2.10.1*.

[b] The test statistics (η_t) of the null hypothesis of *I(0)* are the Kwaitkowski, Phillips, Schmidt, and Shin (1992) (KPSS) *t*-statistics. The *t*-statistics are sums of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend. For the correction of the error term a Bartlett window with five lags was used to ensure the variance matrix was well behaved.

[c] Inferences based on the joint confirmation hypothesis (JCH) of a Unit Root are used when the ADF and KPSS tests conflict (Carrion-i-Silvestre, Sanso-i-Rossello, and Ortuno 2001). The joint critical values of (-3.391, 0.114) represent the critical values for 300 observations for the ADF and the KPSS with trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than -3.391 and the value of the KPSS statistic is less (greater) than 0.114 then the series is considered (at the 0.90 level) stationary (nonstationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary.

[d] The test statistics (T_k) of the null hypothesis that the *k*th relative price and the vector of composite group prices are not cointegrated are augmented Dickey Fuller tests of *I(1)* residuals from regressing the *k*th relative price on each of the integrated group price indices. The number of lagged first difference residuals included (in the residual regression) is reported in parenthesis, and is determined by *R* 2.10.1. The 0.10 critical values reported for the individual tests are based on 273 observations and eleven integrated explanatory variables, so that *k*=12 in MacKinnon (1996).

Table 2.6 Lean Percentage Level Compensated Price and Expenditure Elasticities

Elasticity of the quantity of	With respect to the price of					With respect to
	70-77%	78-84%	85-89%	90-95%	96-100%	Expenditure
70-77%	-0.439***	0.044	0.105***	0.287***	0.004	1.223***
78-84%	0.082	-0.509***	-0.010	0.424***	0.013*	0.759***
85-89%	0.304***	-0.016	-0.869***	0.548***	0.033***	0.791***
90-95%	0.505***	0.395***	0.332***	-1.290***	0.059***	1.001***
96-100%	0.077	0.153*	0.245***	0.726***	-1.201***	0.484***

Notes: Asterisks (*, **, ***) indicate statistical significance at the 10-, 5-, and 1-% levels.

Table 2.7 Brand Type Compensated Price and Expenditure Elasticities

Elasticity of the quantity of	With respect to the price of				With respect to
	Local/Regional	National	Store	Unbranded	Expenditure
Local/Regional	-4.550***	0.077	0.931*	3.542***	0.291
National	0.028	-2.199***	0.306***	1.865***	0.743***
Store	0.400*	0.363***	-2.420***	1.656***	0.752***
Unbranded	0.038***	0.055***	0.041***	-0.133***	1.021***

Notes: Asterisks (*, **, ***) indicate statistical significance at the 10-, 5-, and 1-% levels.

Chapter 3 - Presence of Check-off Programs and Industry Concentration in the Food Manufacturing Sector

Introduction

The food manufacturing industry in the United States consists of approximately 22,000 companies. Profitability of these individual companies depends on both efficient production and processing as well as demand stimulation. These latter activities include expenditures on advertising and non-advertising promotion, differentiated product positioning, value-added attributes, and new product development. Because of agricultural policies extending back to the 1930s, the food sector is somewhat unique in the United States in that the roles of product creation, advertising, and publicity are not everywhere and entirely private decisions of an individual firm. As part of U.S. farm policy, these decisions are made by industry representatives seeking to enhance demand for all firms in an industry. Because of the governmental backing of these industry programs, whether such industry decisions affect industry structure is an intriguing question. In a purely theoretical paper, Crespi and Marette (2009) show that “industry-funded, demand-enhancing activities, like the research and development of new, better, and healthier commodities or generic commodity promotion, matter not only for the quality of goods in the marketplace and firm profitability, but also for influencing industry market structure” (p. 399).

In referring to demand-enhancing activities, Crespi and Marette (2009) present a case for check-off programs having such a role. The Federal check-off programs known as marketing orders were authorized by the Agricultural Marketing Agreement Act of 1937. The so-called stand-alone check-off programs for specific commodities (beef, pork, and cotton for example) were authorized by various statutes in subsequent years (often the terms marketing orders and check-offs are used interchangeably though there is a legal distinction).[1] All the statutes are similar generally providing specific purposes for check-offs which have included (Neff and Platto 1995, p. 2): (a) creating orderly marketing conditions to achieve parity prices to farmers, (b) protecting consumer interest by gradually moving prices toward parity and disallowing actions intended to maintain prices above parity, (c) promoting an orderly flow of the supply of each commodity to market throughout its normal marketing season to avoid unreasonable fluctuations in supplies and prices, and/or (d) conducting production research, marketing research, and development projects; set container and pack requirements; establish minimum standards of quality and maturity; and maintain grading and inspection requirements. The last activity is the emphasis of this current study.

Crespi and Marette (2009) employ an analytical model with subsequent simulation exercises to show that the existence of check-off programs can dampen a dominant firm's ability to exclude a rival through setting a high sunk cost. Furthermore, they contend that this procompetitive effect is predicated on both the size of the program and how the check-off actually affects perceived demand. In all, their theoretical arguments indicate that check-offs can have a procompetitive effect as agricultural industries increasingly become concentrated.

The purpose of this study is to examine whether particular subsectors within the food manufacturing industry, which operate in the presence of check-offs, are less concentrated than industries without such research and marketing programs. Individual industry characteristics such as sunk and variable costs and advertising expenditures are known to be correlated with concentration (the interested reader is referred to the discussion of the empirical studies and the theory for this relationship in Sutton 1996). Thus, controlling for the myriad of factors influencing industry concentration will be necessary for examining the relative impacts of check-offs on an industry's structure, in doing so, even with the aggregated nature of the data used, the first test of the hypothesis put forward in the 2009 study, is provided.

Background and Previous Research

Check-offs may regulate commodity quantity and quality, container and pack standards, and the conduct of research and market programs (Neff and Platto 1995). The U.S. Department of Agriculture's (USDA) stance on governing check-offs has been one of developing and maintaining markets rather than controlling markets. Limited regulatory burdens have allowed check-offs to be established and in many cases flourish. Check-offs have aided food product producers by providing an environment for producers to jointly solve marketing problems that cannot be solved individually. These agreements are legal instruments, enforced by the USDA, which ensures an appropriate balance between the interests of producers looking for fair prices and consumers who expect an adequate quality supplied at reasonable prices.

There exists an extensive body of empirical literature with respect to check-offs. These include Ippolito and Masson (1978), Dardis and Bedore (1990), Zheng and Kaiser (2009), and Chouinard et al. (2010) on milk, French (1982) on fruits and vegetables, Thompson and Lyon (1989) and Powers (1992) on oranges, Williams, Capps, and Palma (2007) on grapefruit and oranges, French and Nuckton (1991) on raisins, Williams (1999) on soybeans, Murray et al. (2001) on cotton, Crespi and Chacon-Cascante (2004) on almonds, and Ward and Lambert (1993), Ward (1999), and Davis (2005) on beef. A few of these studies evaluated the extent of the effects of check-offs on market power accruing to program participants. Findings suggest that that the market power exerted by these legal cartels is significantly less than would be expected from a profit-maximizing cartel. Extensions of this literature evaluated the distribution and redistribution of check-off programs' generated surpluses in the presence of market power along the supply chain. Specific studies include: Richards et al. (1996) on lemons, and Kawaguchi, Suzuki, and Kaiser (1997) on milk.

Another line of literature examined the benefits and costs of check-off programs, especially advertising and promotion. An assumption implicitly underlying much of this work is a competitive market structure; however, a few researchers have examined how marketing by one program affects firms in a competing program (Kinnucan, Xiao, and Hsia 1996; Alston, Freebairn, and James 2001; Crespi and James 2007). What is thus far missing is an empirical study examining whether particular subsectors within the manufacturing industry, which operate in the presence of check-offs, are more or less concentrated than industries without such industry-sponsored market enhancement programs.

A few conceptual issues must be addressed initially. The structure of check-offs for industries within the food manufacturing sector is similar but does differ in check-off fee, minimum participation rate, and the allocation of funds across advertising, research, and other activities. All check-off fees are on a per unit sold basis and the assessments are gathered at the first handler level and remitted to the appropriate marketing board. Given that the structure is similar across industries and only the standardized characteristics within the check-off vary, we are able to compare general check-off program effects across industries.

The analytical model by Crespi and Marette (2009) finds that once market power reaches the point where economic profits, garnered in part by check-off stimulated demand, allow the strategic use of sunk costs to exclude a rival, the strategic interplay among firms in an industry becomes complicated. Furthermore, the existence of a regulatory body that can elicit funds from industry players to fund these check-off programs can importantly influence these programs. In all, industry-funded demand enhancing activities are not only expected to affect the quality of goods in the marketplace and firm profitability, but also to influence industry market structure.

For the basis of this study market concentration will be measured using the Herfindahl-Hirschman Index (HHI). The HHI measures market concentration as a function of the individual firms' market shares and is calculated as follows:

$$\text{HHI} = \sum_{i=1}^{N} s_i^2 \tag{3.1}$$

where s_i is the market share of the *i*th firm and *N* is the total number of firms. In practice, the shares are measured in percentage terms as opposed to decimal terms. Of the various measures employed to measure market concentration, the HHI reflects more fully the information in the concentration, that is, reflects the combined influence of both unequal firm sizes and the concentration of activity in a few large firms (Pepall, Richards, and Norman 2008).

Data

The analysis of the effect of check-offs on industry concentration in the food manufacturing industries is conducted using U.S. Economic Census data for 1997, 2002, and 2007. The specific series used are the Detailed Statistics by Industry and the Share of Value of Shipments Accounted for by the 4, 8, 20, and 50 Largest Companies. The food manufacturing industries subject to the analysis are taken to the sixth digit [e.g., food manufacturing (311), grain and oilseed milling (3112), starch and vegetable fats and oils manufacturing (31122), soybean processing (311222)].

In order to determine which industry is likely to be (directly) impacted by an industry-sponsored marketing program, we developed the following guidelines while examining both the nature of the individual check-off programs and the definitions of the North American Industry

Classification System (NAICS) industry classifications in the *Census of Manufactures* ("*Census"*). First, the check-off had to be active in all three years of the *Census*. Second, the check-off had to be national in scale. Third, the check-off had to be active in marketing products directly to consumers (that is we did not consider an order if it was marketing a product specifically as an input to the processing sector but not to consumers, e.g., whey protein). Fourth, the order had to market product in one of the food industries in the *Census* categories. If one combines the eleven dairy orders into one order, then at the time of this writing there are currently 51 U.S. federal check-offs and stand-alone check-off programs that can partake in generic advertising, promotion and/or development of new consumer products.

We examined all 51 of these programs and narrowed the list to 15 programs as impacting directly the manufacturing sectors in the analysis. The main reason for excluding an order was that many of the 51 orders that use promotion, advertising or research and development cover only fresh-food (e.g. cherries, citrus, avocados, apricots, grapes, onions, peaches, potatoes, nectarines, tomatoes just to name a few). Fresh-products such as these are not classified as manufacturing under the *Census* and so are excluded from this study based on our fourth rule, though it would be interesting and worthwhile to re-examine these industries if one could find the requisite industry data like that provided by the *Census*. Dried fruits and processed nuts, on the other hand, are marketed by their industry boards in both their fresh product and processed product forms and are included because the *Census of Manufactures* includes categories for these industries. We also excluded other commodity promotion programs that have only state authorization and operate exclusively within the boundaries of the authorizing state because we wanted our analysis to coincide with the national statistics gathered by the *Census*, although doing so may under-represent the impacted industries. The orders and programs that met our requirements are Marketing Order 981: California Almonds; Marketing Order 929: Cranberries; Marketing Order 987: California Dates; Marketing Order 982: Oregon and Washington Hazelnuts; Marketing Order 983: California Pistachios; Marketing Order 993: California Dried Prunes; Marketing Order 924: Washington-Oregon Prunes; Marketing Order 989: California Raisins; Marketing Order 984 California Walnuts; Dairy Federal Milk Marketing Orders (currently there are 11 federal marketing orders); Beef Promotion and Research Program; Dairy Producer Check-off Program; Fluid Milk Processor Promotion Program; Peanut Promotion Research and Information Order, and the Pork Promotion and Research Program.

It is worth noting that check-offs are initiated at the farm (producer) level as a means for enhancing producer profits although the marketing is at the consumer level. While tying some of the check-offs to the food manufacturing sector can easily be argued (i.e., fluid milk, soybean) others might be more *ad hoc* since there is obviously aggregation issues (i.e., meat processed from carcasses) in the food manufacturing data collected by the U.S. Census Bureau. However, this point can be easily reasoned away. Recall, that demand enhancements (i.e., advertising; value added activities) affect consumer demand and, hence, affect all the intermediate derived demands back to the producer. As such, it is appropriate to look at what happens at the manufacturing level unless one thinks that, for example, the "Beef, it's what's for dinner" demand shift is somehow appropriated entirely by the cow-calf producer without helping packers. Given the availability of the data, looking at the food manufacturing sector to see if the demand enhancement makes the food manufacturing sectors more or less concentrated addresses the merits of the testable hypothesis laid out in the theory although future research should also undertake this examination at the intermediate levels. In Table 3.1, the manufacturing industries used in the analysis are listed; and the use of asterisks indicates which industries are impacted directly by check-offs.

Crespi and Marette (2009) posited that costs were important factors in determining the impact of the demand-enhancing programs on concentration and empirical tests should control for such factors. Following Sutton (1996) we use proxies for three common industry variables that have been found to be related to the HHI in previous industry studies: sunk cost, variable cost, and advertising. Sunk costs (*Sunk*) are calculated by dividing industry-level, gross book value of depreciable assets by the total value of shipments by industry. Variable costs (*Variable*) are calculated in a similar fashion by dividing annual payroll by the total value of shipments by industry. Advertising expenditures (*Advertise*) are calculated by dividing advertising and promotional services by the total value of shipments by industry. Advertising and promotional services account for payments made to other companies for these services which were paid directly by the establishment. Although many of the check-offs under consideration in this analysis also engage in industry-wide, generic advertising, these expenditures are paid as assessments to the various marketing boards by the first handlers of the commodity and are, thus, not collected as part of the *Census of Manufactures* survey on advertising expenditures by manufacturing firms. In other words, the variable *Advertise* is not inclusive of generic marketing programs but do include payments by the manufacturing firms for printing, media coverage, and other services and materials and are, as such, likely to be rough proxies for true advertising expenditures. To capture the effect of any demand-enhancing marketing program on an industry's HHI, we include a binary variable for the presence of a check-off (*Checkoff*) in the industry. While it would be beneficial to have these data in terms of total expenditures by each marketing program in each industry, these data are considered proprietary by the marketing boards and are not readily available for each of the check-offs examined though attempts were made to obtain these.

We were able to create an unbalanced panel of 44 industries, totaling 129 observations, for our analysis from the *Census of Manufactures* survey.[2] In Table 3.2, the statistics for the variables used in the study are provided.

Econometric Model

A simple econometric model is applied to estimate the impact of various industry structural characteristics and market factors on the HHI. The underlying assumption in the development of this model is that the HHI can be distinguished by various characteristics. The fundamentals of such models have been used on numerous occasions; in our case we follow the review of the literature and the analysis of markets as laid out in Sutton (1996). The specification can be written as:

$$HHI_i = \alpha_0 + \sum_{j=1}^{J} \beta_j IC_{ij} + \varepsilon_i \tag{3.2}$$

where HHI_i is the HHI for the i^{th} industry (time subscripts [t] on each variable are omitted for convenience), the intercept is represented as α_0 with ε_i as white noise error term, IC is the j^{th} industry structure characteristic of the i^{th} industry and β_j is the parameter associated with the jth industry structure characteristic. Although equation (3.2) represents the general specification of the model, we estimated several variants based on equation (3.2). In particular, we report estimations using both the level and natural logarithms of continuous variables. In addition to the HHI, we also used an additional measure of concentration as a dependent variable, CR4 (measuring the percent value of shipments of the top four firms in each industry).

Because of the potential for capturing panel effects, i.e., time effects, fixed effects and random effects estimation was considered. Fixed effects were tested by the (incremental) *F* test. Random effects were examined by the Lagrange Multiplier test (Breusch and Pagan 1980). The *F* test failed to reject the null hypothesis that the time effects are zero. Similarly, the Lagrange Multiplier test failed to reject the null hypothesis that the time series error variances are zero. Failure to reject the null hypothesis in both cases, suggests a pooled ordinary least squares (OLS) regression is favored. Poolability was tested by estimating time-by-time OLS regressions. We failed to reject the null hypothesis of poolability across time. Therefore, the HHI (or CR4) was estimated with pooled OLS as:

$$HHI_{it} = \alpha + \beta_1 SunkCost_{it} + \beta_2 VariableCost_{it} + \beta_3 Advertising\ Expenditures_{it} \quad (3.3)$$
$$+ \beta_4 checkoff_{it} + \varepsilon_{it}$$

where *i* refers to an individual industry and *t* is one of the three years reported in the *Census of Manufactures*.

The data utilized in this study have observations from each industry over time. As a result, the errors in the econometric model are potentially heteroskedastic and/or serially correlated. A likelihood-ratio test failed to confirm the presence of panel-level heteroskedasticity. Furthermore, using Wooldridge's (2002) test for serial correlation in panel-data models, we failed to reject the null hypothesis of no first-order autocorrelation. The test results for panel-level heteroskedasticity and serial correlation further provide evidence that equation (3.3) is the appropriate specification.

Results

Regression results are presented in table 3.3. Theory provides little guidance on the correct functional form for the equations to be estimated. Therefore, two models are presented for each concentration measure (HHI and CR4), one estimated with continuous variables in levels (referred to as the levels model) and one with log transformations of the continuous variables (referred to as the logs model). Overall, both models fit the data well and presentation of both models provides readers an indication of robustness across functional forms.[3] Results were relatively insensitive to specification of the variables in levels or logs. Coefficients represent marginal effects, i.e., differences in the levels model, and percentage differences in the logs model.

Given that the collected data encompass widely disparate industries, it is important to note that the models estimated do explain a notable percentage of the variation in average industry concentration with adjusted R^2 values ranging from 0.24 to 0.38 in the four models estimated. This is not necessarily surprising, on reflection, given that three of the variables (*Sunk*, *Variable*, and *Advertise*) were specifically chosen as they have been found to correlate well with concentration in previous studies. The patterns are consistent with sunk costs and advertising showing positive correlation with both HHI and CR4 and variable cost showing negative correlation. *Sunk* and *Variable* show statistically significant effects on the concentration measures across all specifications while the variable *Advertise* shows only significant correlation in the HHI-dependent model where all variables are measured in levels. The specification does not have any appreciable effect on the pattern of the correlations across models. Overall, we would conclude that these four specifications are revealing the same correlations.

The specific hypothesis of interest in this paper, however, is whether the addition of the dummy variable indicating the presence of an agricultural check-off significantly impacts the concentration in a food industry. Looking at models 2 and 4, the presence of a check-off is correlated with an average decline in the HHI by 52% and an average decline in the CR4 by 27%. Models 1 and 3 show nearly the same percent change on the average HHI and CR4 from the presence of a check-off. Indeed, in all four models, the coefficient on *Checkoff* is negative and statistically significant at the 1% hypothesis level indicating the presence of a check-off is correlated with a less concentrated industry as predicated by theory.[4]

Conclusion

The purpose of this analysis is to test the hypothesis put forward by Crespi and Marette (2009) that the presence of an industry-sponsored, demand enhancing program such as a marketing order or other check-off program for promotion and advertising or other related demand marketing can have a procompetitive impact on an industry. The question is of importance as markets in food and agriculture become more and more concentrated. Under the present leadership, the United States Departments of Justice and Agriculture, for example, have chosen to make the regulation of anticompetitive behavior of firms in agriculture a focus of both departments (see, for example, U.S. Department of Justice 2010). Government-sanctioned check-off programs for such things as generic advertising have never been promoted on their procompetitive impacts, so testing for the presence or absence of such impacts is of importance for agricultural policy. While there is debate as to the link between competition and concentration, the results show that when market concentration is examined, the presence of such a marketing program is correlated with significantly lower levels of industry concentration, which is consistent with theory. Future analyses should consider alternative theories, such as whether less concentrated industries are more likely to have check-off programs, and the impacts of check-offs on concentration at the farm and other levels of the marketing chain as well as use various measures of check-off variables, such as the actual dollar amount of expenditure.

Nonetheless, as a test of one particular hypothesis with implications for agricultural policy, our empirical model provides fodder for the discussion of the benefits of check-offs that extend beyond the rate-of-return measures typically examined in the literature.

Endnotes

[1] See Crespi (2003) for the legal distinction. In this paper we use the term check-off to refer to all mandatory, industry-funded marketing programs.

[2] The Census of Manufactures survey contained 51, 47, and 47 food manufacturing industries in 1997, 2002, and 2007, respectively. Confectionery Manufacturing from Purchased Chocolate - Retail Chocolate (3113301), Confectionery Manufacturing from Purchased Chocolate - Commercial Chocolate (3113302), Nonchocolate Confectionery Manufacturing - Retail Nonchocolate (3113401), and Nonchocolate Confectionery Manufacturing - Commercial Nonchocolate (3113402) were eliminated from the 1997 data because these industries were not reported in the 2002 or 2007 survey. Herfindahl-Hirschman indices for Cane Sugar Refining (311312), Other Snack Food Manufacturing (311919), and Flavoring Syrup and Concentrate Manufacturing (311930) were withheld from the survey data to avoid disclosing data for individual companies, and therefore, these industries were removed from the data used for analysis. Three industries were missing advertising expenditures. In 1997, Retail Bakeries (311811) advertising expenditures were withheld because the estimate did not meet publication standards. In 2002, Specialty Canning (311422) and Ice Cream and Frozen Desert Manufacturing (311520) advertising expenditures were withheld to avoid disclosing data for individual companies. Thus, we have an unbalanced panel of 44 food manufacturing industries (less three industries removed due to withheld advertising expenditures) and three time periods (i.e., 44 * 3 = 132 – 3 = 129).

[3] Box-Cox regressions suggest a logs functional form is more appropriate for the HHI model, but the levels functional form is more appropriate for the CR4 model. However, the difference in "fit" is slight. Both models are presented given the small advantage in statistical sense for picking one model over the other. Some readers may prefer interpreting results in terms of differences and some in terms of percentage differences. See Appendix A for models and test statistics.

[4] A reviewer correctly points out that failing to refute a null hypothesis (here, Crespi and Marette's hypothesis that generic advertising can cause lower industry concentration) is not the same as proving it nor does it mean that competing hypotheses have been refuted. We agree. The reviewer posits that the existence of free ridership due to the presence of branded advertising would also be consistent with both low concentration and the existence of a check-off program. The correlation of the private advertising and check-off variables in our data revealed almost no correlation ($r = 0.007$), however. Further, though intriguing, as far as we know, no such alternative theory currently exists. Consider, for example, that a hypothesis that positive firm-level advertising externalities is a necessary condition for generic advertising would arise under a Bertrand framework with only two firms producing a homogeneous good just as it would arise under a Cournot framework with many firms producing a homogeneous product. As such, free-ridership, on its own, is not a necessary condition for low concentration. Future research should, of course, consider alternative theories and future empirical tests must distinguish among them to be useful, and we thank the reviewer for asking us to make this point clear.

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Tables

Table 3.1 Food Manufacturing Industries and the Presence of Check-offs

NAICS	Food Manufacturing Industry	NAICS	Food Manufacturing Industry
311111	Dog and cat food manufacturing	311513	Cheese manufacturing*
311119	Other animal food manufacturing	311514	Dry, condensed, and evaporated dairy product manufacturing*
311211	Flour milling	311520	Ice cream and frozen dessert manufacturing*
311212	Rice milling	311611	Animal (except poultry) slaughtering
311213	Malt manufacturing	311612	Meat processed from carcasses*
311221	Wet corn milling	311613	Rendering and meat byproduct processing
311222	Soybean processing*	311615	Poultry processing
311223	Other oilseed processing	311711	Seafood canning
311225	Fats and oils refining and blending	311712	Fresh and frozen seafood processing
311230	Breakfast cereal manufacturing	311811	Retail bakeries
311311	Sugarcane mills	311812	Commercial bakeries
311313	Beet sugar manufacturing	311813	Frozen cakes, pies, and other pastries manufacturing
311320	Chocolate and confectionery manufacturing from cacao beans	311821	Cookie and cracker manufacturing
311330	Confectionery manufacturing from purchased chocolate	311822	Flour mixes and dough manufacturing from purchased flour
311340	Nonchocolate confectionery manufacturing	311823	Dry pasta manufacturing
311411	Frozen fruit, juice, and vegetable manufacturing	311830	Tortilla manufacturing
311412	Frozen specialty food manufacturing	311911	Roasted nuts and peanut butter manufacturing*
311421	Fruit and vegetable canning*	311920	Coffee and tea manufacturing
311422	Specialty canning	311941	Mayonnaise, dressing, and other prepared sauce manufacturing
311423	Dried and dehydrated food manufacturing*	311942	Spice and extract manufacturing
311511	Fluid milk manufacturing*	311991	Perishable prepared food manufacturing
311512	Creamery butter manufacturing*	311999	All other miscellaneous food manufacturing

Notes: NAICS = North American Industry Classification system. Marketing orders and check-off programs that directly impact the food manufacturing industries were: Marketing Order 981: California Almonds; Marketing Order 929: Cranberries; Marketing Order 987: California Dates; Marketing Order 982: Oregon and Washington Hazelnuts; Marketing Order 983: California Pistachios; Marketing Order 993: California Dried Prunes; Marketing Order 924: Washington-Oregon Prunes; Marketing Order 989: California Raisins; Marketing Order 984 California Walnuts; Dairy Federal Milk Marketing Orders (currently there are 11 federal marketing orders); Beef Promotion and Research Program; Dairy Producer Check-off Program; Fluid Milk Processor Promotion Program; Peanut Promotion Research and Information Order; and the Pork Promotion and Research Program. Asterisk (*) indicates a food manufacturing industry directly impacted by a check-off program.

Table 3.2 Variable Statistics

Variable	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
		1997			2002			2007	
Dependent Variable									
HHI	956.670	699.600	669.528	942.881	792.800	629.851	1048.123	769.750	780.816
CR4	46.800	43.700	18.455	47.600	46.800	18.634	49.298	45.650	20.051
Independent Variables									
Sunk	0.329	0.312	0.156	0.405	0.361	0.195	0.384	0.342	0.200
Variable	0.095	0.099	0.043	0.106	0.096	0.054	0.092	0.090	0.047
Advertise	0.003	0.002	0.004	0.003	0.003	0.003	0.005	0.002	0.009
Checkoff	0.233	0.000	0.427	0.214	0.000	0.415	0.227	0.000	0.424

Notes: HHI = Herfindahl-Hirschman Index. CR4 = measure of the percent value of shipments of the top four firms in each industry. *Sunk* = industry-level gross book value of depreciable assets divided by the total value of shipments by industry. *Variable* = annual payroll divided by the total value of shipments by industry. *Advertise* = advertising and promotional services divided by the total value of shipments by industry. *Checkoff* = binary variable equal to one for the presence of a check-off in an industry, zero otherwise.

Table 3.3 Econometric Results

Variable	Model 1 - HHI Levels	Model 2 - HHI Logs	Model 3 - CR4 Levels	Model 4 - CR4 Logs
Intercept	1308.126	4.635	58.334	2.632
	(0.000)	(0.000)	(0.000)	(0.000)
Sunk	837.992	0.491	31.516	0.296
	(0.007)	(0.006)	(0.000)	(0.001)
Variable	-6354.490	-1.116	-216.724	-0.618
	(0.000)	(0.000)	(0.000)	(0.000)
Advertise	17658.140	0.021	313.198	-0.001
	(0.057)	(0.711)	(0.170)	(0.965)
Checkoff	-390.078	-0.520	-10.142	-0.269
	(0.007)	(0.007)	(0.005)	(0.007)
Adj-R^2	0.238	0.304	0.380	0.359

Note: *P* values are reported in parentheses. Models in levels show differences and models in logs show percentage differences. HHI = Herfindahl-Hirschman Index. CR4 = measure of the percent value of shipments of the top four firms in each industry. *Sunk* = industry-level gross book value of depreciable assets divided by the total value of shipments by industry. *Variable* = annual payroll divided by the total value of shipments by industry. *Advertise* = advertising and promotional services divided by the total value of shipments by industry. *Checkoff* = binary variable equal to one for the presence of a check-off in an industry, zero otherwise.

Appendix A - Chapter 3 Models and Test Statistics

Fixed Effects vs. Pooled OLS

A fixed time effect model investigates how time affects the intercept. The model might have autocorrelation owing to time-lagged temporal effects; as such, the residuals may have autocorrelation in the process. The fixed time effect model is formulated as:

$$y_{it} = \alpha + \tau_t + X'_{it}\beta + \varepsilon_{it} \qquad (A.1)$$

where α is the overall model intercept, τ_t time effect considered part of the intercept, X'_{it} is a $1 \times K$ row vector of observable variables that change across *t* but not *i*, variables that change across *i* but not *t*, and variables that change across *i* and *t*, β is a $K \times 1$ parameter vector of marginal effects of these variables, and ε_{it} are the idiosyncratic error which change across *t* as well as across *i*. The null hypothesis is that all the time effect parameters except one for the dropped variable are zero:

$$H_0: \tau_t = \cdots = \tau_{T-1} = 0. \qquad (A.2)$$

The pooled regression model is used as the baseline for the comparison. The *F* ratio used for this test is:

$$\frac{(e'e_{POOLED} - e'e_{WITHIN})/(T-1)}{(e'e_{WITHIN})/(\sum_{i=1}^{n} T_i - T - k)} \sim F\left(T-1, \sum_{i=1}^{n} T_i - T - k\right) \qquad (A.3)$$

where *POOLED* and *WITHIN* indicate a pooled model and a fixed effects model with only a single intercept and *T* time periods. Under the null hypothesis that the time effect constants are the same, this statistic is an *F* random variable with *T*-1 numerator and $\sum_{i=1}^{n} T_i - T - k$ denominator degrees of freedom.

HHI Model: $\frac{(45481127.51-45469548.85)/(3-1)}{(45469548.85)/(129-3-4)} \sim F(3-1, 129-3-4)$. The value of the *F* random variable is *F*(2, 122) = 0.016 (*p*-value = 0.9846). We fail to reject the null hypothesis and conclude that the pooled OLS model is favored.

CR4 Model: $\frac{(27621.26-27586.69)/(3-1)}{(27586.69)/(129-3-4)} \sim F(3-1, 129-3-4)$. The value of the *F* random variable is *F*(2, 122) = 0.076 (*p*-value = 0.9265). We fail to reject the null hypothesis and conclude that the pooled OLS model is favored.

Random Effects vs. Pooled OLS

A random effects model estimates variance components for times and error, assuming the same intercept and slopes. The random time effect model is formulated as:

$$y_{it} = \alpha + X_{it}'\beta + \tau_t + v_{it},\ w_{it} = \tau_t + v_{it} \text{ where } \tau_t \sim IID(0, \sigma_\tau^2) \text{ and } v_{it} \sim IID(0, \sigma_v^2) \quad (A.4)$$

where α is the overall model intercept, τ_t time effect considered part of the error, X_{it}' is a $1 \times K$ row vector of observable variables that change across *t* but not *i*, variables that change across *i* but not *t*, and variables that change across *i* and *t*, β is a $K \times 1$ parameter vector of marginal effects of these variables, and v_{it} are the idiosyncratic errors which change across *t* as well as across *i*. The τ_t are assumed independent of v_{it} and X_{it}', which are also independent of each other for all *t* and *i*. The difference among time periods lies in their variance of the error term, not in their intercepts. The null hypothesis is that the time series variance components are zero:

$$H_0: \sigma_\tau^2 = 0. \quad (A.5)$$

The Breusch and Pagan Lagrange multiplier (LM) test is designed to test random effects. The *LM* test statistic is:

$$LM_\tau = \frac{\sum_{i=1}^{n} T_i}{2(n-1)} \left[\frac{\sum (n\bar{e}_{.t})^2}{\sum \sum e_{it}^2} - 1 \right]^2 \sim \chi^2(1). \quad (A.6)$$

where $\bar{e}_{.t}$ are the time specific means of pooled regression residuals and e_{it}^2 is the SSE of the pooled OLS regression.

HHI Model: $LM_\tau = \frac{129}{2(44-1)}\left[\frac{372701.20}{45481127.51} - 1\right]^2 \sim \chi^2(1)$. The value of the LM_τ statistic is $\chi^2(1)$ = 1.476 (*p*-value = 0.2202). We fail to reject the null hypothesis and conclude that the pooled OLS model is favored.

CR4 Model: $LM_\tau = \frac{129}{2(47-1)}\left[\frac{222.75}{27621.26} - 1\right]^2 \sim \chi^2(1)$. The value of the LM_τ statistic is $\chi^2(1)$ = 1.380 (*p*-value = 0.2399). We fail to reject the null hypothesis and conclude that the pooled OLS model is favored.

Poolability

Poolability tests whether or not slopes are the same over time. The null hypothesis of the poolability test is:

$$H_0: \beta_{ik} = \beta_k. \tag{A.7}$$

The poolability test is undertaken under the assumption of $\mu \sim N(0, s^2 I_{NT})$. The test uses the *F* statistic:

$$F_{obs} = \frac{(e'e - \sum e_t' e_t)/(T-1)k}{(\sum e_t' e_t)/(\sum_{i=1}^n T_i - Tk)} \sim F\left[(T-1)k, \sum_{i=1}^n T_i - Tk\right] \tag{A.8}$$

where $e_t'e_t$ is the SSE of the OLS regression at time *t*.

HHI Model: $F_{obs} = \frac{(45481127.51-42134432.00)/(3-1)4}{(42134432.00)/(129-3*4)} \sim F[(3-1)4, 129-3*4]$. The value of the F_{obs} statistic is $F[8, 117]$ = 1.162 ($F[critical_{0.05}] = 2.02$). We fail to reject the null hypothesis and conclude that the panel data are poolable.

CR4 Model: $F_{obs} = \frac{(27621.26-25832.53)/(3-1)4}{(25832.53)/(129-3*4)} \sim F[(3-1)4, 129-3*4]$. The value of the F_{obs} statistic is $F[8, 117]$ = 1.013 ($F[critical_{0.05}] = 2.02$). We fail to reject the null hypothesis and conclude that the panel data are poolable.

Panel-Level Heteroskedasticity

A likelihood ratio test iss used to test for panel-level heteroskedasticity. The likelihood ratio is:

$$LR = 2[L(Null) - L(Alternative)]. \qquad \text{(A.9)}$$

HHI model: $LR = 2[L(-1006.001) - L(-1006.901)]$. The value of the LR statistic is $\chi^2(2)$ = 1.80 (p-value = 0.4066). We fail to reject the null hypothesis and conclude that the model does not have panel-level heteroskedasticity.

HHI model: $LR = 2[L(-528.9665) - L(-529.1842)]$. The value of the LR statistic is $\chi^2(2)$ = 0.44 (p-value = 0.8044). We fail to reject the null hypothesis and conclude that the model does not have panel-level heteroskedasticity.

Panel-Level Serial Correlation

The Lagrange-Multiplier test was used to test for serial correlation.

HHI model: The F statistic is $F(1, 40)$ = 0.114 (p-value = 0.7369). We fail to reject the null hypothesis of no first-order autocorrelation.

CR4 model: The F statistic is $F(1, 40)$ = 2.414 (p-value = 0.1281). We fail to reject the null hypothesis of no first-order autocorrelation.

Linear vs. Log-Log Model

Box-Cox regressions were used to compare the goodness-of-fit of models in which the continuous variables are in levels or logs. The Box-Cox statistic is:

$$BoxCox = \left(\frac{N}{2}\right) * Log\left(\frac{RSS_{largest}}{RSS_{smallest}}\right) \sim \chi^2(1). \qquad (A.10)$$

HHI model: $BoxCox = \left(\frac{129}{2}\right) * Log\left(\frac{93.0621339}{76.7633024}\right)$. The *BoxCox* statistic is $\chi^2(1) =$ 12.419 $\left(\chi^2\left[critical_{1,0.05}\right] = 3.84\right)$. We reject the null hypothesis that the models are the same; concluding that the models are significantly different in terms of goodness-of-fit. The log functional form is a better fit.

CR4 model: $BoxCox = \left(\frac{129}{2}\right) * Log\left(\frac{20.2276345}{715.1990422}\right)$. The *BoxCox* statistic is $\chi^2(1) =$ 18.435 $\left(\chi^2\left[critical_{1,0.05}\right] = 3.84\right)$. We reject the null hypothesis that the models are the same; concluding that the models are significantly different in terms of goodness-of-fit. The linear functional form is a better fit.