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Three Essays on Consumer Demand in Online and Offline Markets

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Abstract

Consumers face various costs when investigating and purchasing products in either online or offline markets: the travel cost to visit a store and the search cost to examine the product attributes once they are at a store. The relative magnitude of the costs may lead to different store pricing and consumer search behavior. This dissertation builds game-theoretic search models and examines the interaction between store pricing and consumer search behavior under different travel and search costs in online and offline markets, and positive stockout probabilities in Chapter 1. To quantify the difference in consumer demand under different costs, a structural demand model has been developed to empirically examine consumer demand regarding prices and stockouts between online and offline markets in Chapter 2. This dissertation extends the empirical structural demand model and estimates the consumer demand for products across different categories. The contribution of the dissertation is that it advances the knowledge and understanding of consumer demand by: (1) separating the travel and search costs and incorporating possible product stockouts associated with consumer demand during a shopping trip in online and offline markets; (2) providing empirical evidence that supports the relevant theories between online and offline markets; and, by (3) shedding light on consumer demand across product categories.

1. Let Them Stay or Let Them Go? Price Competition in Online and Offline Markets with Consumer Search and Product Stockouts

1.1 Introduction

Both online and offline consumers incur various costs during their shopping process. For the offline consumers, they travel to visit a retailer, they may spend time to investigate product attributes and evaluate the suitableness of the product, and occasionally, they may have to go to other retailers due to product unavailability, all of which incur costs. For the online consumers, they take time to set up their computers or other digital devices to connect to the Internet and browse online websites, they may also spend time to investigate product attributes and evaluate the suitableness of the product, and occasionally, they may switch to other retailers due to product unavailability, all of which also incur costs.

Consumer search behavior depends on the costs of switching stores and switching products (Corstjens and Corstjens 1995). The difference in the costs associated with a shopping trip may affect consumer search behavior differently (Lynch and Ariely 2000), thus resulting in different consumer responses to prices and product availabilities. Despite a number of studies on consumer search behavior (e.g., Diamond 1971, Lal and Sarvary 1999), few have decomposed the costs that consumers incur during a shopping trip (Bakos 1997, Lynch and Ariely 2000), and none of them consider the scenario in which a product may be out of stock. In this chapter, we seek to narrow the literature gaps by developing a game-theoretic model in which consumers in purchasing a product incur travel costs to a retailer. Then, if an intended product is out of stock at a favorite retailer, consumers incur additional costs of investigating product attributes of unfamiliar products or incurring additional costs of traveling to a backup retailer in search of the intended product. Note that with offline shopping, travel costs are literal; and with online shopping, travel costs are the opportunity cost of time involved in shopping and could also be the disutility associated with navigating backup websites.

In our analysis, we characterize the Nash equilibrium of a price-setting game in which the equilibrium is a function of the parameter values, representing travel costs, product attribute search costs, possible consumer value of products, and product stockout probabilities. The Nash equilibrium, depending on the parameter values, is one of two types: “let them stay” in which the retailer retains consumers when the retailer runs out-of-stock of their intended product; and “let them go” in which the retailer releases consumers following a stockout. That is, in some circumstances it is best for retailers to set prices so that customers are willing to investigate unfamiliar products at the same store when the retailers run out-of-stock of customers’ familiar ones; and in other cases retailers set prices knowing that customers will go to competitors following stockouts.

Comparing online and offline travel and search costs, in most scenarios travel costs for online shopping are low compared to those of offline shopping. However, for certain unfamiliar products the costs of investigating the attributes of unfamiliar products can be higher online than offline as offline consumers can easily see and feel the products while online consumers can only learn product attributes by reading descriptions. If so, our model indicates that consumers when shopping online, compared to shopping offline, are more likely to switch retailers following a product stockout. In terms of our model, for parameter values that correspond to online shopping, we are more likely to observe a "release-customer equilibrium" (let them go) and for parameter values that match offline shopping (in which retailers are geographically separated), we are more likely to observe a "retain-customer equilibrium" (let them stay).

In each type of equilibrium, prices are decreasing in travel and search costs as well as the stockout probability. This is because consumers are less likely to visit a store when the travel and search costs and stockout probability are high.

Section 1.2 reviews the related literature. Section 1.3 develops the model where consumers face separated travel and search costs and possible product stockouts and purchase one product by searching multiproduct stores. Section 1.4 analyzes store pricing decisions given the separated travel and search cost and product stockout probabilities. Section 1.5 discusses the results and the limitation of the model.

1.2 Literature Review

Since the seminal paper by Stigler (1961), many researchers have built game-theoretic models on consumer search behavior in single-product stores. For example, Diamond (1971) constructs a search model where consumers pay a search cost to visit a store and learn the price charged by the store. He finds that stores charge monopoly price with the existence of search cost no matter how small the search cost is, which is known as Diamond paradox. Despite that this result heavily relies on the model assumptions, he argues that competitive equilibrium will not be converged with a positive search cost.

Researchers have further studied effects of different types of search costs. Bakos (1997) partitions search costs into three types – the cost of traveling to a store, the cost of acquiring price information, and the cost of acquiring information about product attributes – and examines consumer search behavior among multiple single-product stores. He finds that a nonzero search cost for price can result in monopoly prices just as that argued by Diamond (1971), while zero search cost for price can result in Bertrand-type competition even with a positive search cost for product attributes.

Lal and Sarvary (1999) study consumer search behavior between substitute products where consumers search for one product in two single-product stores. They separate the costs associated with a shopping trip to the travel cost from home to a store, the switch cost from a store to another, and the (dis)utility of the unfamiliar product if the product is (un)fit. They examine how the reduced travel and switch cost affect store pricing and consumer search behavior and find that stores are able to set monopoly prices when consumers only purchase from their favorite store. The monopoly pricing maintains if reducing the travel and search cost does not induce consumers to search their backup store. Lal and Sarvary (1999)'s model fits the price-directed search model setting, where consumers observe price information before search (Armstrong and Zhou 2011, Choi et al. 2016, Haan et al., 2015, Shen 2015). For the price-directed search model, Armstrong and Zhou (2011) find equilibrium prices decrease with search costs and Haan et al. (2015) show that higher search costs intensify price competition.

Though most of the search models (e.g., Armstrong and Zhou 2011, Bakos 1997, Haan et al. 2015, Lal and Sarvary 1999) have been concentrated on single-product stores, where stores only sell one product, multiproduct stores make the model more complex and have interesting implications of its own. Zhou (2014) studies consumer search behavior between two multiproduct stores. He assumes consumers can buy multiple products carried by both stores. His model shows a joint-search effect where consumers can obtain information for products once they visit a store. The economies of scale in search make consumers more likely to stop searching and buy multiple products at a store if the store reduces the price of one product.

Despite search costs, consumer search behavior is also related to product stockouts (Corstjens and Corstjens 1995). Campo et al. (2000) construct a consumer utility model regarding stockout. They separate the components of consumers' stockout cost: the costs of travel to stores and the costs to search for product attributes, and examine how each component contributes to a store's stockout losses. However, they only focus on consumers' response to stockout without studying the interaction between store strategy and consumer search behavior.

In this paper, we construct price-directed game-theoretic search models and examine the interaction between retailer pricing and consumer search behavior. Specifically, we refine the previous search models by separating the travel and search costs associated with a shopping trip. We focus on consumer search behavior between substitute products where consumers only purchase one product from one multiproduct retailer. We incorporate stockout probabilities, which, to the best of our knowledge, have not been discussed in the previous game-theoretic search models.

1.3 Model Setup

There are two retailers A and B, each with one store, selling products 1 and 2 (e.g., a Colgate toothbrush and an Oral B toothbrush) at constant marginal costs, which are normalized to zero. In our symmetric model, both retailers are online or both are offline. Each consumer intends to purchase one product (e.g., a toothbrush) from either retailer A or retailer B.

Each consumer has a favorite retailer. Additionally, each consumer is familiar with only one of the two products, for example by having experience with the product in the past or by having taken time to read its product label, but no knowledge about the other. With a unit mass of consumers, they are uniformly distributed across favorite retailers and familiar products. For example, for one-quarter of them retailer A is their favorite retailer and they are familiar with product 1.

Consumers have a positive, certain valuation v of their familiar product. At the onset of shopping, consumers are uncertain about their valuations of the unfamiliar product and only can be certain once they have investigated its product attributes. Their valuation of the unfamiliar product is either v with probability r, or 0 with probability $(1 - r)$. Consumers have a positive product attribute search cost k_0 to learn the unfamiliar product's attributes, which they could bear at a physical or online retailer.

In the offline markets, consumers need to pay a transportation cost to travel to a brick-and-mortar retail store. In the online markets, consumers need to set up their devices (computers, tablets, and/or smartphones) to browse online retailers. The cost to each consumer to travel to her favorite retailer from her home is k_1. Consumers spend time and effort to switch from one retailer to another, where k_s represents a base cost of switching retailers. Consumers incur an additional cost k_a to visit their backup retailer. Hence, the cost of switching from a backup to a favorite retailer is k_s and the cost of switching from a favorite to a backup retailer is $k_s + k_a$. Offline consumers need to follow the navigation system to travel to their backup retailer, while online consumers have to get used to the website setting of their backup retailers, which can be interpreted as a disutility of k_a.

We assume the prices of both products at both retailers are public information. In reality, firms market their price via online ads, TV commercials, telemarketing, and etc. Consumers can obtain price information even before their shopping trips.

The probability of a product is in stock at a retailer is $q, q < 1$, for each consumer who visits a retailer. Hence, the stockout probability is $1 - q$. We assume the probability that a retailer runs out of stock of a product is positive, exogenous to the retailer's control, and independent of the stockout probabilities of other products. This assumption corresponds to a situation where a retailer cannot control its vendor's order fulfillment performance. Another case is that an unusually high demand caused by exogenous demand shocks (e.g., weather, natural disaster) leads to retailer stockouts that a retailer cannot predict. We assume stockout probabilities are public information and the status of product availability in a retailer is learned by consumers after their visit to the retailer.

Consumers are time-sensitive such that they are only able to do at most two things: purchase their familiar product at the first retailer, purchase their unfamiliar product at the first retailer, or purchase their familiar product after switching from the first retailer to the second. This assumption is extreme but not unrealistic. For example, it is common for the consumers with larger incomes or young children to restrict their shopping time. This assumption follows Stigler (1961).

The timing of the events is as follows: The retailers set prices simultaneously. Given the advertised product prices, consumers decide which retailer to visit. Once the consumers arrive at a retailer, they learn about the availability of both products at the retailer. Consumers select a product and, if it is in stock, purchase it. If out is out of stock, they either switch to the other product (which involves investigation if it is the unfamiliar product) or switch retailers. If they switch retailers, they would purchase only their familiar products.

Figure 1 summarizes consumers' shopping strategies and the corresponding payoffs for visiting retailer *A*. The process and payoffs of visiting retailer *B* are analogous to those of visiting retailer *A*. In the figure, branches (1)-(4) indicate product availability statuses: (1) product 1 is in stock with probability

q; (2) product 1 is out-of-stock with probability $1-q$; (3) product 2 is in stock with probability q; (4) product 2 is out-of-stock with probability $1-q$. We start with the consumer segment who is familiar with product 1 and favors retailer A. The other segments follow the same analyses. Consumers have five strategies: buy the familiar product at the favorite retailer; buy the unfamiliar product at the favorite retailer; buy the familiar product at the backup retailer; buy the unfamiliar product at the backup retailer; do not enter the market.

In our model, a consumer's utility is

$$U = \begin{cases} v - price - travel\&search\ costs & if\ the\ consumer\ purchases\ a\ product\ with\ value\ v, \\ -price - travel\&search\ costs & if\ the\ consumer\ purchases\ a\ product\ with\ value\ 0, \\ 0 & if\ the\ consumer\ does\ not\ enter\ the\ market. \end{cases}$$

Retailer A's expected profit is

$$\pi_A(p) = p_{A1}D_{A1}(p) + p_{A2}D_{A2}(p),$$

where D_{A1} and D_{A2} are expected demand at prices $p = (p_{A1}, p_{A2}, p_{B1}, p_{B2})$. Retailer B's profit is analogous.

1.4 Equilibrium Analysis

In the equilibrium of our model, which is symmetric in the sense that the retailers set the same prices of the two products, because the travel cost to visit the favorite retailer k_1 is lower than the cost ($k_1 + k_a$) to visit their backup retailer, consumers always visit their favorite retailer first, whenever the prices set by their favorite retailer are no more than the prices set by their backup retailer. Given the same prices at both retailers, switching retailers happens only when consumers run across a stockout/stockouts of their familiar product/both products at their favorite retailer. Consumers search the other retailer only if their expected utility of purchasing from the other retailer is higher than that by purchasing from the current retailer. Consumers are aware that they may incur a stockout of one or both products after they switch to the other retailer.

Once consumers are at a retailer, they will search for only their unfamiliar product under two scenarios: (1) their familiar product is in stock and the price of their unfamiliar product is sufficiently low to compensate their uncertainty of the valuation of the unfamiliar product; or (2) their familiar product is out-of-stock. In the case that retailers only sell to their consumer segments (i.e., the consumers who favor the retailer), the first scenario will never happen as the retailer earns lower profits by setting a lower price on one product than the other and attracting both consumer segments by the lower-priced product than by setting the same prices and attracting each consumer segment by the individual product. We therefore focus on the second scenario when consumers may search for the unfamiliar product only if their familiar product is out-of-stock. With the strategy of not entering the market, the consumers earn a payoff of zero. In the case (1) product 1 is in stock at retailer A, the consumer earn a payoff of $v - k_1 - p_{A1}$ by purchasing product 1. In case (2) product 1 is out-of-stock and in case (3) product 2 is in stock at the same time. If so, with the purchase strategy, the consumer payoff is $r \cdot (v - p_{A2}) - k_1 - \mathrm{k}_0$ by purchasing from the same retailer, retailer A. This is because the consumers will not buy the unfamiliar product if they have a zero valuation of their unfamiliar product. Now consider the case in which (2) and (3) occur simultaneously. If the consumers choose not to buy, they have paid the travel cost k_1 to check the availability of product 1 at retailer A. If the consumers choose to switch to their backup retailer, they buy product 1 and have a payoff of $v - p_{B1} - k_1 - k_s - k_a$ whenever product 1 is available as long as $v \geq p_{B1}$. Since the consumers are time-sensitive, they give up the purchase if their familiar product is not available in the second retailer and make a payoff of $-k_1 - k_s - k_a$.

We turn to case (2) and (4) in which neither product is in stock at retailer A. Recall that the consumers have already paid the travel cost k_1 to visit their favorite retailer, they make a negative payoff of $-k_1$ by giving up their purchase. If they switch retailers and purchase product 1 whenever it's in stock, their payoff is $v - p_{B1} - k_1 - k_s - k_a$. If they find the familiar product is not available or neither product is available and choose not to purchase, they make a payoff of $-k_1 - k_s - k_a$ by giving up the purchase.

Having outlined consumers' options, we move on to characterize the two potential pure-strategy equilibria: (a) consumers always purchase from their favorite retailer and give up their purchase if neither product is in stock, (b) consumers always purchase their familiar product and give up their purchase if their familiar product is not available. In equilibrium (a), the retailer retains its consumers when it runs out of stock of a product, we thus call it retain-customer equilibrium. In equilibrium (b), the retailer releases its consumers when it runs out of stock of a product, we thus call it release-customer equilibrium.

1.4.1 Retain-Customer Equilibrium

Proposition 1. *There is a unique pure strategy symmetric Nash equilibrium in which consumers only purchase from their favorite retailers if and only if*

$$k_s + k_a - \frac{k_0 \cdot (-q^3 + q^2 + q) + k_1 \cdot (q - r)}{q \cdot [1 + r \cdot (1 - q)]} \geq 0, \tag{1.1}$$

$$k_1 \cdot r - k_0 \cdot q \geq 0, \tag{1.2}$$

$$\begin{aligned} -v \cdot q \cdot (1 - q) + k_0 \cdot q^2 - k_0 \cdot \frac{2 + r - q^2 \cdot r}{1 + r \cdot (1 - q)} + (k_s + k_a) \\ \cdot (2 + r - q \cdot r - q) + k_1 \cdot \frac{r - q}{q} + \frac{k_1 \cdot r \cdot (1 - q)}{q \cdot [1 + r \cdot (1 - q)]} \\ \geq 0, \end{aligned} \tag{1.3}$$

$$-v \cdot q + k_s \cdot (2 + r - q \cdot r) + \frac{k_0 \cdot q \cdot (1 - q) + k_1}{1 + r \cdot (1 - q)} \geq 0. \tag{1.4}$$

In this equilibrium, prices are positive $p^r = p_{A1} = p_{B1} = p_{A2} = p_{B2} = v - \frac{k_0 \cdot q(1-q) + k_1}{q \cdot [1 + r \cdot (1-q)]}$. *In case of a bad search that consumers obtain zero utility on their unfamiliar product, consumers give up the purchase. Retailers' profits are* $\frac{-(r \cdot v - k_0) \cdot q^2 + [(r+1) \cdot v - k_0] \cdot q - k_1}{2}$, *and consumer surplus is 0.*

Proof of Proposition 1

In proposed retain-customer equilibrium, because all prices are the same, if a consumer's familiar product is available at her favorite retailer, she purchases it. Otherwise, following a stockout of this product, also in equilibrium, the consumer would stay in the same retailer and investigate her unfamiliar product. She would do so because her expected utility in the retain-customer equilibrium, U^r, is no less than her expected utility of first visiting her favorite retailer, then following a stockout of her familiar product, switching retailers, U^S. Specifically,

$$U^r - U^s = r \cdot (v - p_r) - k_0 - k_1 - [q \cdot (v - p_r) - k_1 - k_s - k_a]$$

$$= k_s + k_a - \frac{k_0 \cdot (-q^3 + q^2 + q) + k_1 \cdot (q - r)}{q \cdot [1 + r \cdot (1 - q)]} \geq 0.$$

Additionally, her expected utility of the retain-customer equilibrium is no less than her outside option utility, 0:

$$U^r - (-k_1) = r \cdot (v - p_r) - k_0 - k_1 - (-k_1) = \frac{k_1 \cdot r - k_0 \cdot q}{q \cdot [1 + (1 - q) \cdot r]} \geq 0.$$

The first inequality is equivalent to condition (1.1), and the second inequality is equivalent to condition (1.2).

Next, we identify conditions under which deviations by the retailers from the proposed equilibrium prices are unprofitable. There are two possible deviations by a retailer to consider: (i) decrease the price of one of its products just enough to induce the other retailer's consumers who are familiar with the product to switch retailers following a stockout of the product, and (ii) decrease price even further, but also just enough, to attract these same consumers to visit the deviating retailer first.

Consider deviation (i). The expected utility a consumer can get by switching given her familiar product is not available at her favorite retailer, $U^{s\prime}$, must be no less than the utility of purchasing from the current retailer, $U^{r\prime}$:

$$U^{s\prime} = q \cdot (v - p_1) - k_1 - k_s - k_a \geq U^{r\prime} = r \cdot (v - p_r) - k_0 - k_1.$$

The retailer's optimal price to induce this deviation, p^{so}, is:

$$p^{so} \equiv v - \frac{k_s + k_a}{q} + \frac{k_0 \cdot q - k_1 \cdot r}{q^2 \cdot [1 + r \cdot (1 - q)]}.$$

The equilibrium profit, π_1^r, less the profit from this deviation, π_1^{so}, which is condition (1.3), is:

$$\pi^r - \pi^{so} = \frac{1}{4} \cdot \left\{ -v \cdot q \cdot (1 - q) + k_0 \cdot q^2 - k_0 \cdot \frac{2 + r - q^2 \cdot r}{[1 + r \cdot (1 - q)]} + (k_s + k_a) \right.$$
$$\left. \cdot (2 + r - q \cdot r - q) + k_1 \cdot \frac{r - q}{q} + \frac{k_1 \cdot r \cdot (1 - q)}{q \cdot [1 + r \cdot (1 - q)]} \right\} \geq 0.$$

Therefore, a retailer does not set p^{so}.

Consider deviation (ii). A consumer's expected utility of initially visiting her backup retailer, and remaining there following a stockout of her familiar product, U^b, must be no less than her expected utility of the retain-customer equilibrium, U^r. That is:

$$U^b = q \cdot (v - p_2) + (1 - q) \cdot q \cdot [r \cdot (v - p_r) - k_0] - k_1 - k_a \geq U^r$$
$$= q \cdot (v - p_r) + (1 - q) \cdot q \cdot [r \cdot (v - p_r) - k_0] - k_1.$$

The retailer's optimal price that induces this deviation, p^b, is:

$$p^b \equiv v - \frac{k_0 \cdot q \cdot (1 - q) + k_1}{q \cdot [1 + r \cdot (1 - q)]} - \frac{k_a}{q} = p_r - \frac{k_a}{q}.$$

The equilibrium profit, π^r, less the profit from this deviation, π^b, which is condition (1.4), is:

$$\pi^r - \pi^b = \frac{1}{4} \cdot \left[-v \cdot q + k_s \cdot (2 + r - q \cdot r) + \frac{k_0 \cdot q \cdot (1 - q) + k_1}{1 + r \cdot (1 - q)} \right] \geq 0.$$

With conditions (1.1) through (1.4) satisfied, a retain-customer equilibrium exists.

Q.E.D.

Proposition 1 states the conditions under which consumers only purchase from their favorite retailer and never switch to the backup retailer. Lemma 1 suggests that retailers are able to set monopoly prices even when consumers have zero cost to obtain price information. The positive probabilities that consumers incur product stockouts make it possible for retailers to increase prices without altering consumer search behavior. The result is consistent with Lal and Sarvary (1999) that the monopoly pricing maintains when no consumers switch retailers and consumer surplus remains zero.

1.4.2 Release-Customer Equilibrium

Proposition 2. *There is a unique pure strategy symmetric Nash equilibrium where consumers only purchase their familiar products if and only if*

$$k_0 - \frac{(k_s + k_a) \cdot [q + (1-q) \cdot r] + k_1 \cdot (r - q)}{q \cdot (2-q)} \geq 0, \tag{1.13}$$

$$k_1 - k_s - k_a \geq 0, \tag{1.14}$$

$$\begin{aligned} &-r \cdot q \cdot (1-q) \cdot v + k_0 \cdot q \cdot \frac{[r \cdot (1-q) - q + 2]}{r} + k_1 \cdot q \cdot \frac{r+1}{r} \\ &\qquad + 2 \cdot \frac{k1}{q-2} - (m+x) \cdot \frac{q + 2 \cdot r}{r} - 2 \cdot \frac{m+x}{q-2} \geq 0, \end{aligned} \tag{1.15}$$

$$\begin{aligned} &v \cdot (q^2 \cdot r - q^2 - q \cdot r) + k_s \cdot (q - q \cdot r) + k_a \cdot (3 \cdot q - q^2 \cdot r) \\ &\qquad - \frac{(k_s + k_a) \cdot (q - r) - k_1 \cdot [q + (1 - \square) \cdot r]}{2-q} \geq 0 \end{aligned} \tag{1.16}$$

In this equilibrium, prices are positive $p^s = p_{A1} = p_{B1} = p_{A2} = p_{B2} = v - \frac{k_1 + (k_s + k_a) \cdot (1-q)}{q \cdot (2-q)}$*, retailers' profits are* $\frac{-q^2 \cdot v + (2 \cdot v + k_s + k_a) \cdot q - k_1 - k_s - k_a}{2}$ *and consumer surplus is 0.*

Proof of Proposition 2

In the proposed release-customer equilibrium, because all prices are the same, if a consumer's familiar product is available at her favorite retailer, she purchases it. Otherwise, following a stockout of this product, also in equilibrium, the consumer would switch to the other retailer and purchase her familiar product if it is available. She would do so because her expected utility of the release-customer equilibrium, U^s, is no less than her expected utility of first visiting her favorite retailer, then following a stockout of her familiar product, searching for her unfamiliar product, U^r. Specifically,

$$U^s - U^r = q \cdot (v - p_s) - k_1 - k_s - k_a - [r \cdot (v - p^s) - k_0 - k_1]$$

$$= k_0 - \frac{(k_s + k_a) \cdot [q + (1 - q) \cdot r] + k_1 \cdot (r - q)}{q \cdot (2 - q)} \geq 0.$$

Additionally, her expected utility of the release-customer equilibrium is no less than her outside option utility, 0:

$$U^s - (-k_1) = q \cdot (v - p^s) - k_1 - k_s - k_a - (-k_1) = \frac{k_1 - k_s - k_a}{2 - q} \geq 0.$$

The first inequality is equivalent to condition (1.13), and the second inequality is equivalent to condition (1.14).

Next, we identify conditions under which all possible deviations from the proposed equilibrium are unprofitable. There are two possible deviations: (i) decrease the price of one of its products just enough to prevent its own consumers who are familiar with the product to switch retailers following a stockout of the product, and (ii) decrease price even further, but also just enough, to induce the other retailer's consumers who are familiar with the product to visit the retailer first.

Consider deviation (i). The expected utility a consumer can get by searching for her unfamiliar product at her favorite retailer given her familiar product is not available, U^r, must be no less than the utility of purchasing from the other retailer, $U^{s\prime}$:

$$U^{r\prime} = r \cdot (v - p^{ro}) - k_0 - k_1 \geq U^{s'} = q \cdot (v - p^s) - k_1 - k_s - k_a.$$

The retailer's optimal price to induce this deviation, p^{ro} is:

$$p^{ro} \equiv v - \frac{k_0}{r} - \frac{k_1 - k_s - k_a}{(2-q) \cdot r}.$$

The equilibrium profit, π^s, less the profit from this deviation, π^{ro}, which is condition (1.15), is:

$$\pi^s - \pi^{ro} = \frac{1}{4} \cdot \left\{ -r \cdot q \cdot (1-q) \cdot v + k_0 \cdot q \cdot \frac{[r \cdot (1-q) - q + 2]}{r} + k_1 \cdot q \right.$$
$$\left. \cdot \frac{r+1}{r} + 2 \cdot \frac{k1}{q-2} - (m+x) \cdot \frac{q + 2 \cdot r}{r} - 2 \cdot \frac{m+x}{q-2} \right\} \geq 0.$$

Therefore, a retailer does not set p^{ro}.

Consider deviation (ii). A consumer's expected utility of initially visiting her backup retailer, and switching to her favorite retailer following a stockout of her familiar product, U^b, must be no less than her expected utility of the release-customer equilibrium, U^s. That is:

$$U^b = q \cdot (v - p_4) + (1-q) \cdot [q \cdot (v - p_s) - k_s] - k_1 - x \geq U^s$$
$$= q \cdot (v - p_s) + (1-q) \cdot [q \cdot (v - p_s) - k_s - k_a] - k_1.$$

The retailer's optimal price that induces this deviation, p^b, is:

$$p^b \equiv v - x - \frac{k_1 + (k_s + k_a) \cdot (1-q)}{(2-q) \cdot q}.$$

The equilibrium profit, π^s, less the profit from this deviation, π^b, which is condition (1.16), is:

$$\pi^s - \pi^b = \frac{1}{4} \cdot \left\{ v \cdot (q^2 \cdot r - q^2 - q \cdot r) + k_s \cdot (q - q \cdot r) + k_a \cdot (3 \cdot q - q^2 \cdot r) \right.$$
$$\left. - \frac{(k_s + k_a) \cdot (q - r) - k_1 \cdot [q + (1 - q) \cdot r]}{2 - q} \right\}.$$

With conditions (1.13) through (1.16) satisfied, a retain-customer equilibrium exists.

Q.E.D.

Proposition 2 states the conditions under which consumers only purchase their familiar product and never purchase their unfamiliar product. In other words, the retailer releases its consumers after a product stockout. Release-customer equilibrium requires that the travel cost from home is relatively higher than the summation of the additional cost to the backup retailer and the base switch cost from one retailer to another (see condition (1.14)), while retain-customer equilibrium requires that the product attribute search cost is low and the travel cost is high (see condition (1.2)). There is no overlap of their parameter spaces except when consumers are indifferent between purchasing from their favorite retailer or purchasing their familiar product. In this case, the retain-customer equilibrium prices are equal to the release-customer equilibrium prices.

Our model can be easily applied to online and offline retailing given the difference in travel and search costs between online and offline markets. Online markets are considered to reduce the travel cost while offline markets are advantageous in providing the information of product attributes (Lal and Sarvary

1999). Therefore, retain-customer equilibrium is suitable to describe the offline markets where the travel cost is more significant than the product attribute search cost. Consistent with retain-customer equilibrium, offline consumers are more likely to search for substitute products carried by the same retailer. To retain consumers, offline retailers implement substitution strategies to substitute a product for the one that is not in stock. Release-customer equilibrium is applicable to the online markets where the additional cost to the backup retailer and the base switch cost from one retailer to another are marginal. Consistent with release-customer equilibrium, online consumers are willing to search for their familiar product across various retailers.

1.4.3 Effects of Travel and Search Costs and Stockout Probability

Having outlined the two mutually exclusive equilibria, it is important to examine the effects of travel and search costs and stockouts on the equilibrium price. Hence, we calculate the comparative statics of the equilibrium price regarding the travel cost to the favorite retailer k_1, the additional cost to the backup retailer k_a, the base switch cost from one retailer to the other k_s, the product attribute search cost to learn the attributes of the unfamiliar product k_0, and the probability a product is in stock q.

Proposition 3: *The price is decreasing in: (1) the travel cost to the favorite retailer k_1 in both retain-customer and release-customer equilibria, (2) the product attribute search cost k_0 in retain-customer equilibrium, and (3) the additional cost to the backup retailer k_a or the base switch cost from one retailer to the other k_s in release-customer equilibrium.*

Proof of Proposition 3

The first-order derivative of retain-customer equilibrium price regarding k_1 is

$$\frac{-1}{[1+(1-q)\cdot r]\cdot q},$$

and that of release-customer equilibrium price regarding k_1 is

$$\frac{-1}{(2-q)\cdot q},$$

both of which are negative. Both equilibrium prices are decreasing in the travel cost k_1.

The first-order derivative of retain-customer equilibrium price regarding k_0 is

$$\frac{-1+q}{1+(1-q)\cdot r},$$

which is negative. The equilibrium price is decreasing in the product attribute search cost k_0. As consumers only purchase from their favorite retailer, the additional cost/disutility to visit their backup retailer k_a and the cost to switch retailers k_s are irrelevant to consumers' purchase decisions. The first-order derivative of retain-customer equilibrium price regarding either k_a or k_s is 0.

The first-order derivative of release-customer equilibrium price regarding either additional cost/disutility to the backup retailer k_a or the cost of switch cost k_s is the same

$$-\frac{1-q}{q\cdot(2-q)},$$

which is negative. In the release-customer equilibrium, consumers only purchase their familiar products, thus making the product attribute search cost k_0 irrelevant to consumers' purchase decision. The first-order derivative of release-customer equilibrium price regarding k_0 is 0. **Q.E.D.**

The proposition indicates that both equilibrium prices are decreasing in the travel cost k_1, since a higher travel cost makes it more difficult for consumers to make a purchase in the first place. As a result, a retailer reduces prices to compensate for the reduction of consumers' expected utility due to the high travel cost. The product attribute search cost k_0 is irrelevant to release-customer equilibrium as consumers never examine the product attributes of their unfamiliar product in release-customer equilibrium. The additional cost to the backup retailer k_a or the base switch cost from one retailer to the other k_s are irrelevant to retain-customer equilibrium as consumers only purchase from their favorite retailer.

The retain-customer equilibrium price is decreasing in the product attribute search cost k_0, since a higher search cost makes it more difficult for consumers to stay at the retailer and purchase their unfamiliar product. As a result, the retailer reduces prices to retain consumers following the stockout of a product. The release-customer equilibrium price is decreasing in the additional cost to the backup retailer k_a or the switch cost from one retailer to the other k_s, since a higher cost to get to the backup retailer or a higher base switch cost makes it more difficult for consumers to go to the unfamiliar or second retailer. The retailer reduces prices to attract the other retailer's consumers when the other retailer runs out-of-stock.

Since the equilibrium price is decreasing in travel and search costs, retailers have the incentive to reduce the costs associated with a shopping trip. The Internet reduces the travel cost from home and switch costs to another retailer by allowing consumers to visit online retailers without physically traveling to the brick-and-mortar retail stores. Online retailers adopt similar webpage settings to reduce consumer disutility to get used to their websites and various strategies to reduce the product attribute search cost. Amazon.com uses customer review systems to rate products. Besides customer review systems, tirerack.com measures the relevant tires' (relevant to consumer specified vehicle) performance on a set of metrics and presents an easy-to-read comparison table to further reduce the product attribute search cost. In the offline markets, shopping malls are located near a highway to reduce consumer travel time. Brick-and-mortar retail stores tend to cluster to reduce the switch cost from one retailer to another and the additional disutility that consumers need to navigate to another retailer. The retailers optimize their layout so that consumers can easily search for products and may hire advisors to help consumers get familiar with product attributes.

Proposition 4: *Price is decreasing in the stockout probability* $1-q$ *in both retain-customer and release-customer equilibria*.

Proof of Proposition 4

The first-order derivative of retain-customer equilibrium price regarding q is

$$\frac{k_0 \cdot q^2 - 2 \cdot k_1 \cdot q \cdot r + k_1 \cdot r + k_1}{q^2 \cdot (1 + r - q \cdot r)^2},$$

and that of release-customer equilibrium price regarding q is

$$\frac{(k_s + k_a) \cdot q^2 - 2 \cdot (k_1 + k_s + k_a) \cdot q + 2 \cdot k_1 + 2 \cdot k_s + 2 \cdot k_a}{q^2 \cdot (2 - q)^2},$$

both of which are positive. This implies both equilibrium prices are decreasing in the stockout probability $1-q$. **Q.E.D.**

The proposition shows that the effect of stockouts is two-fold in both equilibria. On one hand, consumers are less likely to visit a retailer when they face a higher probability to incur a stockout. The retailer needs to reduce prices to attract consumers in the first place. On the other hand, consumers are more likely to stay in the current retailer with a lower stockout probability, which reduces the competition between retailers. Therefore, the retailers are able to increase price and still get the same market share.

Besides the effect of travel and search costs and stockouts on consumer search and price competition, it is important to point out that the equilibrium profit is the highest profit that a retailer can earn given the best response of the other retailer. In other words

Proposition 5: *A retailer is better off and makes a higher profit by giving up its consumers to the other retailer when it runs out-of-stock of a product in release-customer equilibrium. When the travel and search costs as well as the stockout probability satisfy conditions in retain-customer equilibrium, it is worth setting prices to retain consumers following a product stockout.*

Proof of Proposition 5

Following the proofs of both equilibria, a retailer earns less profit when deviating from the equilibrium prices. Specifically, when a retailer runs out of stock of a product, it is unprofitable for the retailer to lower its price and attracts the other's consumers under the retain-customer equilibrium; and it is also unprofitable for the retailer to lower its price to prevent its own consumers from switching retailers under the release-customer equilibrium. **Q.E.D.**

Given the relatively low switch cost from one retailer to another, online consumers can easily search for their familiar product across online retailers. As a result, online retailers are better off by giving up consumers when they run out-of-stock. Offline consumers are likely to search for their unfamiliar product in the same retailer given the relatively low product attribute search cost, thus offline retailers should set prices to retain consumers following a product stockout.

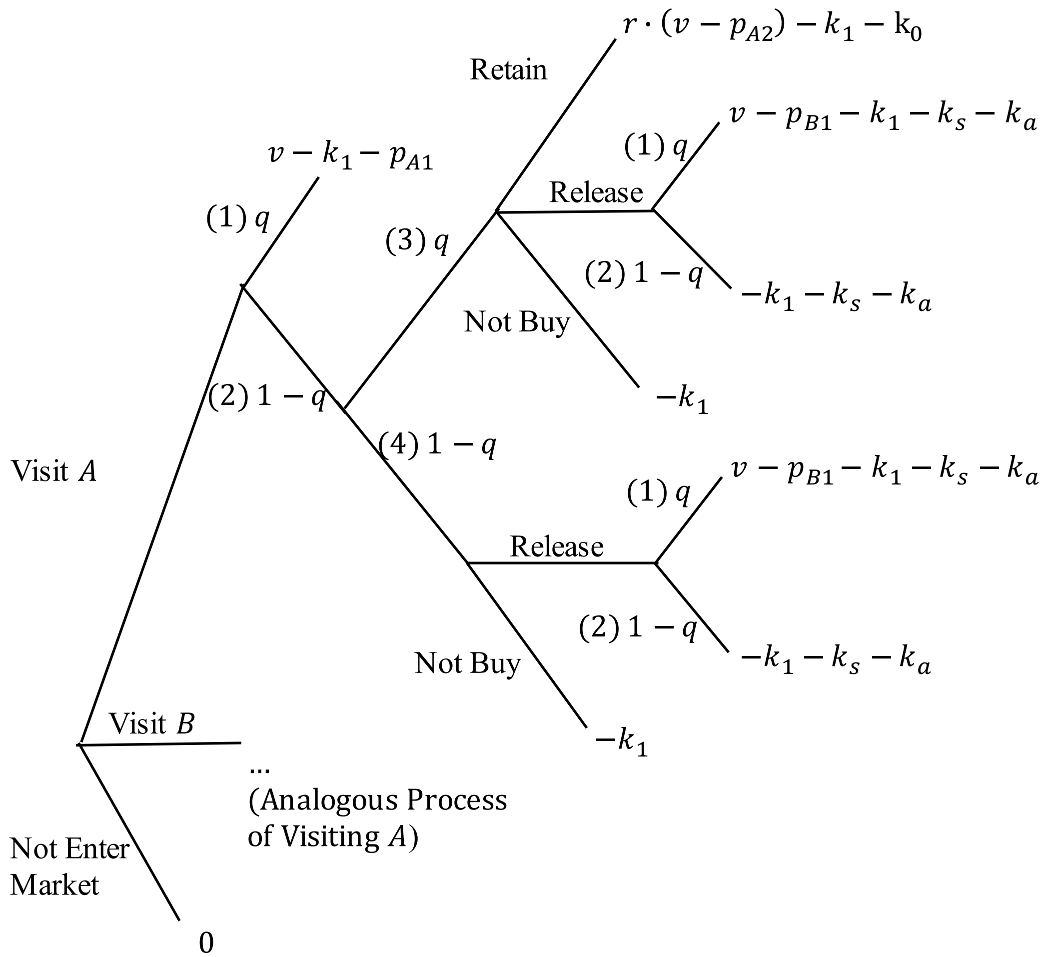
1.5 Concluding Remarks

In this paper, we seek to understand retailer pricing and consumer search behavior with separated travel and search costs associated with a shopping trip. We consider four possible costs: the travel cost from home to visit a retailer, the switch cost from one retailer to another, the additional cost to visit the backup retailer, and the product attribute search cost. We examine the interaction between retailer pricing and consumer search behavior with the existence of separated travel and search costs, as well as positive probabilities that a consumer incurs product stockouts.

We identify two types of equilibria with distinct consumer search behavior. Consumers visit their favorite retailer for their familiar product and purchase the other product from the same retailer when their familiar product is out-of-stock in retain-customer equilibrium, whereas consumers search various retailers for their familiar product in release-customer equilibrium. In retain-customer equilibrium, retailers are able to set monopoly prices when consumers are loyal to purchase from their favorite retailer because of the existence of positive stockout probabilities. In both retain-customer and release-customer equilibria, we find that equilibrium prices are decreasing in the travel and search costs as well as the stockout probabilities because consumers are less likely to visit a retailer when the costs and/or stockout probabilities are high. The retailers thus have the incentive to reduce the costs associated with a shopping trip and implement various inventory policies to reduce stockout probabilities. However, retailers are better off by giving up consumers to the rival retailer when consumers only purchase their familiar product.

Our model can be applied to online and offline retailing given the difference in the travel and search costs between online and offline markets. Retain-customer equilibrium is suitable to describe offline markets, where the travel cost is more significant than the product attribute search cost. Offline consumers have a high travel cost to go to another brick-and-mortar retail store, thus offline retailers implement substitution strategies to retain consumers when they run out-of-stock. Release-customer equilibrium is applicable to the online markets where the additional cost to the backup retailer and the base switch cost from one retailer to another are marginal. Online consumers are willing to search for their familiar product across various retailers and online retailers are better off by giving up consumers following product stockouts. Finally, we discuss a few possible future research directions. First, future studies can relax the assumption that consumers face the same costs to/at either retailer and make the costs asymmetric. For example, consumers may shop in the online and offline markets at the same time. They may have a low travel cost to an online retailer but find it is easier to examine product attributes in the brick-and-mortar retail stores. Second, one can allow endogenous stockouts. In the real world, high-tech companies conduct hunger marketing which restricts product supply to stimulate consumers' purchasing desire. The endogenous stockout probability can be incorporated in a two-stage game where retailers set inventory levels first and then prices.

Figure 1.1: Consumers' Strategies and Corresponding Payoffs



2. Between Online and Offline Markets: A Structural Estimation of Consumer Demand

2.1 Introduction

The online markets enabled by the Internet are more efficient than the offline markets (Brynjolfsson and Smith 2000) due to the reduced consumers' search costs (Bakos 1997). In the online markets, with the help of search engines such as Google Shopping, consumers can search stores and products without having to physically travel to offline stores. The classic model of Bertrand competition predicts perfectly elastic demand since consumers can freely switch between competitive offerings, and it leads firms to set a uniform price.

Over the past decades, along with the development of the online markets, a large body of literature has studied the supply-side effect of the online markets and debated on whether the online markets are truly efficient. On the one hand, some studies compare prices between online and offline markets and find empirical support of both lower prices (e.g., Brown and Goolsbee 2002, Brynjolfsson and Smith 2000, Degeratu et al. 2000) and lower price dispersions (e.g., Brynjolfsson and Smith 2000, Ghose and Yao 2011) in the online markets. On the other hand, other studies show that prices may be higher in the online markets than those in the offline markets (e.g., Bailey 1998, Lal and Sarvary 1999) or insignificantly different between online and offline markets (Cavallo 2017), and price dispersions are still sizable in the online markets (e.g., Baye et al. 2003, 2004, 2006a, and 2006b, Clay et al. 2001 and 2002, Clemons et al. 2002).

The research of the demand-side is limited (Granados et al. 2012). Several studies have made attempts to evaluate the price elasticity in the online and offline markets and found mixed evidence (e.g., Chu et al. 2008, Ghose and Yao 2011, Granados et al. 2012). For example, using the federal government data and travel agency data, respectively, Ghose and Yao (2011) and Granados et al. (2012) find a higher own-price elasticity online than offline, whereas Chu et al. (2008) show a lower own-price elasticity online than offline in a grocery chain.

The mixed findings suggest two departures from the classic Bertrand model is important in determining the price elasticity of demand, product heterogeneity and search cost. During a shopping trip, the search costs affect consumer decision on which products to buy. For example, a consumer going to a grocery store planning to buy the *Colgate 360 Adult Full Head Soft Toothbrush 4 Pack* toothbrushes ends up buying a *Crest Proplus Soft/Medium Toothbrush 2 Pack* since the two products lay side-by-side on the shelf and the consumer finds the latter more attractive in both price and attributes.

Hence, empirically estimating the price elasticity of demand and product substitutability online and offline sheds light on search costs in these two channels. Given the difference in search costs between online offline markets, is there any difference in consumer demand? We are particularly interested in two demand-triggering variables, price changes and product stockouts (e.g., Duan et al. 2015, Mas-Colell et al. 1995, Smith and Agrawal 2000). We are trying to answer the research question: given the difference in search costs, do offline consumers do differently than online consumers regarding price change and product stockouts?

In this chapter, we use a large-scale dataset on consumer packaged goods collected from a large supermarket chain and estimated a random coefficients discrete choice demand model within stores. We compute the own- and cross-price within stores elasticities which gives us implications on search costs comparisons online and offline. We then conduct counterfactuals on how price changes and product stockouts affect market shares, brand, and store revenue. We find that the own-price elasticity is higher in magnitude offline (i.e., -1.74 on average) than that online (i.e., -0.87 on average), suggesting that the offline consumer demand is more price-elastic than the online consumer demand, and that the cross-price elasticity is also higher offline (i.e., 0.18 on average) than that online (i.e., 0.05 on average), suggesting that the offline consumers are more likely to buy substitute products than the online consumers. When a product is out-of-stock, in the offline markets, 6.55% of the loss of the market share goes to the common products carried by both online and offline stores on average, while in the online markets, 6.05% of the loss of the market share goes to the common products on average. Our findings suggest that, when considering substitute products, the impact of price increases can be surprising. The retailer may not be worse off because the gains in the revenue from the substitute products can make up more than the losses. While the retailers may not be worse off when increasing the prices, through consumer welfare analysis, we find that consumers are hurt more in the offline markets than in the online markets because the offline market is more concentrated on the common products carried by both online and offline markets.

Our study makes a number of important contributions. First, while there is extensive literature comparing prices and price dispersions between online and offline markets on the supply-side, researches of the demand-side are still limited, and the findings are mixed at best. As put by Granados et al. (2012), "there is still much research to be done on the demand-side effects." Although our study is unlikely to close the debate, it provides empirical evidence that lends support to the view that the online own-price elasticity is lower than the offline own-price elasticity in certain settings. Furthermore, there have been very few studies on estimating and comparing cross-price elasticity between online and offline markets. Estimating the cross-price elasticity in the online and offline markets helps us better understand the changes in customer demand under different levels of search costs. Second, our study extends the theoretical model to a more realistic setting where customers can search for substitute products, induced by price changes and product stockouts. We focus on the search costs to learn product attributes at a store and develop theoretical arguments on why both own- and cross-price elasticities are higher offline than online. The theoretical arguments are confirmed by our empirical findings that, when price increases or product is out-of-stock, offline customers are more likely to purchase substitute products from the same store, and online customers are less responsive to buy substitute products. Third, our study estimate and compare the gains or losses in consumer welfare from price increases or product stockouts between online and offline markets. Our results complement prior studies on estimating the gains in consumer welfare from the Internet (Bapna et al. 2008, Brynjolfsson et al. 2003, Ghose and Yao 2011, Ghose et al. 2006) by showing that online consumers' welfare is reduced in the offline markets when price increases or product stocks out.

The rest of the chapter is organized as follows. Section 2.2 provides a summary of the relevant literature and the theoretical background. Section 2.3 details our empirical context and data. Section 2.4 presents the econometric model and describes our estimation method. Section 2.5 presents the estimation results and analyses. Section 2.6 presents the analysis of consumer welfare estimation. Finally, Section 2.7 discusses the results, theoretical and managerial implications, research limitations, and future research.

2.2 Literature and Theory

2.2.1 Price Elasticity

As discussed above, there are two approaches to study the difference between online and offline markets, the supply-side perspective and the demand-side perspective. From the supply-side perspective, an extensive body of literature has examined and compared prices and price dispersions between online and offline markets (e.g., Baye et al. 2004, Brynjolfsson and Smith 2000, Ghose and Yao 2011, Li et al. 2013, Overby and Forman 2014, Zhao et al. 2015) However, from the demand-side perspective, the literature has been scarce on the comparison of consumer demand between online and offline markets.

To compare consumer demand between online and offline markets, studies examine the own-price elasticity and the cross-price elasticity between online and offline markets and the findings are not in consensus. Granados et al. (2012) use airline ticket booking data in both online and offline markets and find the own-price elasticity at offline phone-based or face-to-face travel agencies is -0.73, lower than -1.11 at online consumer direct-booking platforms such as Expedia and Travelocity and -1.64 at opaque online travel agencies such as Hotwire and Priceline.com. Using transaction data from the U.S. government, Ghose and Yao (2011) report a higher own-price elasticity in the online market than that in the offline markets: -1.47 in the online market and -0.84 in the offline markets. Ellison and Ellison (2009) empirically study the loss-leader strategy that obfuscates consumers by posting low prices of damaged goods at an online price search engine and find extremely high own-price elasticities (more than -3.6) for the products at two online computer parts sellers. Degeratu et al. (2000) study a grocery chain and find a higher price sensitivity in the online market than that in its offline markets. By contrast, Chu et al. (2008), who also study a grocery chain, use households who shop groceries both online and offline and show a lower own-price elasticity in the online market than that in the offline markets. They attribute the lower online own-price elasticity to consumers' time sensitivity and convenience of shopping online, both of which may reduce price elasticity online. Lynch and Ariely (2000) conduct experiments at two online wine retailers and examine consumers' price sensitivity on wine, and find that a lower price search cost and a lower search cost to compare stores result in a higher own-price elasticity while a lower product attribute search cost reduces consumer price sensitivity.

While some studies examine the cross-price elasticity between product categories (Gentzkow 2007, Kim et al. 2010), few papers have studied the cross-price elasticity between online and offline markets. Among the few, Ellison and

Ellison (2009) find negative cross-price elasticities for computer memory modules at two online computer parts sellers, implying the price increases of the focal product reduce the demand for substitute products; Danaher et al. (2014) examine market-level demand data for songs and albums sold by a label company at an online retailer and demonstrate a negative cross-price elasticity that may be due to consumers' switching behavior from songs to albums when price increases. The paucity of the research on estimating and comparing the cross-price elasticity between online and offline markets points to an important contribution of our study.

2.2.2 Search Cost under Product Substitution

Consumers' search cost can be decomposed into several components: the travel cost to visit a store, the search cost to acquire price information, and the search cost to learn product attributes (Bakos 1997, Lynch and Ariely 2000). When prior literature considers the search cost, they mostly consider the search cost associated with searching for a single product (e.g., Bakos 1997, Diamond 1971). For example, Diamond (1971) assumes stores carry a homogenous good and consumers pay search costs to learn the price charged by each store. He does not consider the search cost for substitute products. Our setting is different in that we study the consumers' switching behavior regarding price increases or product stockout. When these scenarios happen, a consumer may search for and purchase substitute products. Hence, in our setting, we consider the search costs associated with searching for the substitute products; that is, the search cost to acquire substitute products' price information and the search cost to learn substitute products' attributes.

The components of the search cost are different between online and offline markets, thereby resulting in different levels of search costs online and offline. For the search cost to acquire price information, we fold this component within search cost to learn substitute products' attributes, online or offline, the consumer should easily acquire price information as the price information is posted on the shelf or along with the product on the webpage.

For the search cost to learn substitute products' attributes, it is determined by how products are demonstrated between online and offline markets. In the offline markets (i.e., a retail store), all the substitute products are displayed next to each other in a shelf section. Consumers can easily pick up substitute products and study the information on the package, and even look into, touch and feel the products in the package. For the online markets, consumers need to start from scratch to search for substitute products. (Note that online recommender systems normally recommend complementary products instead of substitute products.) Once consumers find a substitute product, they need to read the webpage that contains the product information. To illustrate it as an example, we produced this process in Amazon.com. Assume our focal product is Crest 1 Pack toothbrush. We went to Amazon.com and search for the Crest 1 Pack toothbrush. From the Crest 1 Pack toothbrush search result page, we clicked into the product page. Now, at this moment, assume that we wanted to check out a substitute product Colgate 1 Pack toothbrush. We did a search again and a long list of Colgate toothbrushes showed up (14 webpages with each page showing 20 products), and spent much time to compare and choose an appropriate one. Once we landed on the Colgate 1 Pack toothbrush product page, it took us roughly 1.5 minutes to read through the product information on the page.

Figure 2.1 shows an example of the shelf display of toothbrushes in one of the offline stores which provided data to us and a screenshot of the webpage during the search process in Amazon.com. As it can be seen from the figure, there are a large number of substitute products for toothbrushes on the shelf in the offline store. However, they are concentrated in a narrow section in the shelf and it is easy for the consumers to search and compare. In the online markets, repeating the search process for each of the substitute products can be a long and costly process. Thus, we posited that the online consumers have a higher search cost for substitute products' attributes.

2.2.3 Consumer Demand under Product Substitution

We considered two common scenarios that trigger consumers to consider substitute products: the price increase of a product and a product stockout (e.g., Duan et al. 2015, Mas-Colell et al. 1995, Smith and Agrawal 2000). We measured consumer demand resulting from the price changes by using the own-price elasticity and the cross-price elasticity, and we measured consumer demand resulting from the product stockouts by using the changes in market share of the substitute products when a product is out-of-stock[1].

Consider a price increase, the consumer may still buy the focal product that increases its price or buy a substitute product. Each option incurs different levels of

[1] The own-price elasticity, the cross-price elasticity and the changes in market share of the substitute products are measured for the focal store only as we do not observe the consumer demand at the competing stores.

search costs for the online and offline consumers, which has theoretical implications for the consumer demand evidenced by the own-price elasticity. The consumer's response to the price increase depends on the search costs. Price increases will lead to lost demand for the focal product at the focal store when the consumer purchases a substitute product, resulting in a higher own-price elasticity and a higher cross-price elasticity. Hence, if a consumer can more easily choose a substitute product, the own-price elasticity will be higher. As discussed above, between online and offline markets, the search cost for substitute products' attributes is higher online than offline. For the online consumers, given that search cost for substitute products' attributes is high, typical consumers should choose to still buy the focal product. For the offline consumers, given that search cost for substitute products' attributes is low, typical consumers should choose to buy a substitute product. Therefore, the price increase may result in a higher own-price elasticity and a higher cross-price elasticity in the offline market. Hence, we expect that both the own price-elasticity and the cross-price elasticity are higher offline than that online.

When stockouts happen, a consumer cannot buy the unavailable product. As discussed above, the online consumers are less likely to purchase the substitute product since their search cost for substitute products' attributes is higher, and the offline consumers are more likely to purchase the substitute product their search cost for substitute products' attributes is lower. We expect that the changes in market share of the substitute products are greater in the offline markets than those in the online markets.

Table 2.1 summarizes the comparison of search cost components, our expected own- and cross-price elasticity, and the changes in market share of the substitute products under stockouts between online and offline markets.

2.3 Empirical Context and Data

We collect data from one of the largest supermarket chains in China from August 8, 2011, to December 31, 2014. The supermarket chain had annual sales of $4.37[2] Billion in 2011 and manages a network of supermarket stores across the country and an online store. We select the 34 offline stores and the online store that serve the Shanghai metropolitan area for our data collection. (Note that the online store only serves the Shanghai metropolitan area.) Both the online store and 34 offline stores are supplied by the same distribution center located in the rural area in Shanghai. Although the online retail markets were developing rapidly in China from 2011 to 2014, they were still much smaller than the offline retail markets. By the end of 2014, the online retail markets in China accounted for less than 10% of the total transactions of the whole retail industry in China[3].

We select the toothbrush category for our analysis because toothbrush products are common consumer packaged goods that are in supply over a long-term and year-round (not products in the market for a few months and then discontinued, or in the market only for a few months a year). For the offline stores, we collected the Point-of-Sales (POS) data that consist of product information, sales price, sales

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[2] Converted from figures in Chinese currency RMB. $1=RMB6.3 in July 2011 when the data were collected. This applies to all dollar calculations throughout the paper.
[3] National Bureau of Statistics of People's Republic of China. http://www.stats.gov.cn/tjsj/zxfb/201501/t20150120_671071.html (Accessed on August 27, 2017).

unit, and transaction time for each transaction. We also collect daily inventory data and wholesale price data for each stock keeping unit (SKU) in each store. There are 98 toothbrush SKUs for the offline stores, but not every store carries every SKU. Due to the volume of our offline data[4], we used a one-month period from August 8th to September 8th, 2011 for our analysis. During the one-month period, 41,043 consumers made 41,335 transactions on toothbrush products. For the online store, we also collected the POS data that include product information, transaction time, sales price, and sales unit for each transaction. The supermarket chain's online store was at its early stage of development in 2011 and was only used as a complementary source of sales to the offline stores. Hence, the online data is much less than the offline data, including 1,418 consumers who made 1,998 transactions on 226 toothbrush products.

The supermarket chain sells toothbrush products of 5 brands in the offline stores and toothbrush products of 22 brands in the online store. We select the toothbrush brands with more than 10% of the market sale in the category and treated the remaining brands as the outside good. As a result, three toothbrush brands, Crest, Colgate, and 5A, were selected. These brands account for 90 SKUs and 97.56% of total sales in the category in the offline stores. Four brands, Colgate, Crest, Darlie,

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[4] Note that we use discrete choice models to estimate consumer demand for all available products. Thus, the number of observations in our dataset is the number of transactions times the number of all available products for each transaction, which becomes far more than the number of transactions. For example, a customer purchased a product. Our data shows an observation for the transaction. We need to create additional observations for other products in the consideration set for which the customer did not buy. If the consideration set contains 9 products, the one observations becomes 9 observations. The raw data for the month have 41,355 transactions. After creating the data for other products in the consideration set, the number of observations becomes 366,883.

and Lion, were selected. These brands account for 135 SKUs and 80.88 % of total sales in the online store. Toothbrush products are sold in various packaging sizes, and different packaging sizes use nonlinear pricing scheme (e.g., Crest 1 Pack is $1.37, Crest 2 Packs is $2.50). To compare products with different packaging sizes, we calculated the price as the weighted (by average monthly unit sales across the whole data period) average unit price. Table 2.2A presents the market share and the average unit price for each toothbrush product and brand in both the online and offline markets. We further collected the transaction history by the consumer including if the consumer has purchased the same product before, the total dollar amount the consumer has spent, and the number of purchases the consumer has made during the data collection period. Tables 2.2B and 2.2C present the consumer purchase history.

Following Zipkin (2000), for the offline stores, we defined that a product stocks out when the product's inventory is zero during a day. Using this definition, the average stockout rate is 0.07% (on average, products stockout in 7 out of 10,000 days) for our data, much lower than the industry average stockout rate of 8% (Musalem et al. 2010). This is likely because of the potential discrepancy between system-recorded inventory and the actual inventory in the store (Musalem et al. 2010). For example, the system shows 3 units in inventory, but the store is already out-of-stock. As a result, we treated a product as out-of-stock when its inventory hits its minimum inventory level during the year, and its sales are zero at the same time. For the online store, since we do not observe its inventory status, we assumed that a product is out-of-stock if it has no sales for a week.

To help better understand our data, Figure 2.2 presents the average unit prices, daily sales and stockouts of a sample product (Crest 2 Pack) in an offline sample store and the online store, respectively. It is interesting to note that the prices vary much more frequently in the online stores than those in the offline store, and the sales are negatively associated with prices.

2.4 Model and Estimation

2.4.1 The Econometric Model

We derived consumers' utility maximization behavior and specify a random coefficients multinomial logit (MNL) model to capture the discrete consumer choice over products. Discrete choice models have been used widely in the literature to analyze product substitution pattern with respect to price (e.g., McFadden 1973, Berry et al. 1995, Nevo 2001), brand equity (e.g., Degeratu et al. 2000, Smith and Brynjolfsson 2001, Sriram et al. 2007), ranking (Ghose et al. 2012, Yang and Ghose 2010), and product availability (Musalem 2010, Bruno, et al. 2008). We assume consumer i's indirect utility to purchase product j in store s at time t is given by:

$$V_{ijst} = \alpha_j + \beta_i PRICE_{jst} + \rho PAST_{ij} + \varepsilon_{ijst}, \tag{2.1}$$

where α_j is consumer i's intrinsic preference of product j. $PRICE_{jst}$ is the unit price of product j. $PAST_{ij}$ is a dummy variable with 1 indicating the consumer has purchased product j before, otherwise not. ε_{ijst} is the unobserved utility. We captured consumers' heterogeneous tastes for price by allowing β_i to vary by the consumer's total dollar amount of purchase $AMOUNT_i$ and her number of purchases NUM_i from August 8th, 2011, to December 31st, 2014, as follows:

$$\beta_i = \bar{\beta} + \beta_1 AMOUNT_i + \beta_2 NUMBER_i + v_i, \tag{2.2}$$

$$v_i \sim N(0, \sigma). \tag{2.3}$$

$\bar{\beta}$ is the mean price coefficient and σ is the standard deviation of σ_i.

There is potential endogeneity if $PRICE_{jst}$ is correlated with the unobserved utility ε_{ijst}. The unobserved utility can arise from the product attributes that are observed by consumers but not observed by researchers, for example, the attractiveness of the package design and/or the quality of a product. Following Song and Chintagunta (2006), we used the wholesale price as an instrumental variable (IV) to deal with the endogeneity in the offline markets. The wholesale price reflects supply-side shocks, such as production cost, which is unlikely correlated with consumer demand. For the online store, since we do not have the information on the wholesale price, we constructed the average unit price for the products in the same brand but in different packaging sizes as an IV. The average unit price for the products in the same brand but in different packaging sizes is correlated with the unit price of the focal product as the manufacturer may use the same facilities for production and transportation. However, manufacturers may use different packaging sizes to price discriminate and segment consumers, and conduct independent pricing strategies for different packaging sizes, such that manufacturers do not consider the consumer demand for the other packaging sizes when setting the price for the focal product. In other words, the consumer demand for the products in different packaging sizes does not affect the pricing of the focal product. To purge out the correlation between the price and the unobserved utility, we used the control function approach (Petrin and Train 2010) as the nonlinearity of the structural model makes it invalid to use traditional linear Two-Stage Least Squares (2SLS). In detail, we decompose the unobserved utility to an unobserved error η_{jst}, which is correlated with $PRICE_{jst}$ and an error $\bar{\varepsilon}_{ijst}$ that is uncorrelated with $PRICE_{jst}$ and has *i.i.d* Type I extreme value distribution as follows:

$$\varepsilon_{ijst} = \eta_{jst} + \bar{\varepsilon}_{ijst}. \tag{2.4}$$

We specified the following projection of $PRICE_{jst}$ on the IV:

$$PRICE_{jst} = \Upsilon_0 + \Upsilon_1 Z_{jst} + \mu_{jst}, \tag{2.5}$$

where Υ_0 is the intercept and Z_{jst} is the IV for $PRICE_{jst}$. The IV is weighted (by average monthly shipment quantity) average unit wholesale price for the offline stores and is the average unit price of other products in the same brand for the online store. μ_{jst} is the residual correlated with the unobserved error η_{jst}. The control function is specified by projecting η_{jst} on μ_{jst}:

$$\eta_{jst} = \lambda\mu_{jst} + u_{jst}, \tag{2.6}$$

where u_{jst} has i.i.d standard normal distribution and is not correlated with $PRICE_{jst}$. Plugging (2.6) into (1), consumer *i*'s utility on product *j* becomes:

$$V_{ijst} = \alpha_j + \beta_i PRICE_{jst} + \lambda\mu_{jst} + u_{jst} + \bar{\varepsilon}_{ijst}. \tag{2.7}$$

Hence, conditional on μ_{jst}, $PRICE_{jst}$ is uncorrelated with the unobserved error $\bar{\varepsilon}_{ijst}$.

2.4.2 Estimation Procedure

To estimate our model, we followed the control function approach by Petrin and Train (2010)[5]:

Step 1: Run a linear regression of price on the IV and predict the residuals.

Step 2: Plug in the predicted residuals into Equation (2.6) and use maximum simulated likelihood (MSL) to estimate the parameters.

Our multinomial logit model specifies the following probability to purchase each product:

$$p_{ijst} = \left[\exp\left(\alpha_j + \beta_i PRICE_{jst} + \lambda\mu_{jst} + u_{jst} + \bar{\varepsilon}_{ijst}\right)\right] \cdot \left[\sum_j \exp\left(\alpha_j + \beta_i PRICE_{jst} + \lambda\mu_{jst} + u_{jst} + \bar{\varepsilon}_{ijst}\right)\right]^{-1}. \tag{2.7}$$

Since maximum-likelihood (ML) yields no closed form, we estimated our model by using maximum simulated likelihood (MSL) (Train 2003). We maximized the following simulated likelihood:

$$L(\theta) = \sum_i ln \sum \frac{1}{S} \hat{p}_{ijst}, \tag{2.8}$$

where $\hat{p}_{ijst}$ is the simulated probability of p_{ijst} and S is the number of simulation draws. We estimate both the online and offline demand separately and use 100 Halton draws for each estimation (Cameron and Trivedi 2005, Train 2003).

[5] Alternatively, we can specify moment functions and use the method of simulated moments (MSM) to estimate parameters, but MSM would take a longer time to estimate than MSL (Gentzkow 2007).

2.5 Results and Analyses

2.5.1 Estimation Results

Table 2.3 presents the estimation results from the model. The coefficients for the intrinsic preference for each product, the consumer's purchase history, and the mean price coefficient $\bar{\beta}$ are of the expected signs. The intrinsic preference measures a consumer's utility from purchasing a product: a higher intrinsic preference means the consumer receives more utility when she purchases the product compared to when she purchases the outside good. For the intrinsic preference estimates, most of them are positive and significant. For example, in the offline demand estimation, the largest coefficient for the intrinsic preference is on Colgate 1 Pack (α =4.57, p<0.001), and the smallest coefficient is on Crest 4 Pack (α = -0.67 but insignificant), suggesting that consumers are most likely to purchase Colgate 1 Pack as compared to the outside good and indifferent between purchasing Crest 4 Pack and the outside good. In the online demand estimation, the largest coefficient for the intrinsic preference is on Lion 2 Pack (α = 2.47, p < 0.001) and the smallest coefficient is on Darlie 3 Pack (α = -0.47 but insignificant), suggesting that consumers are most likely to purchase Lion 2 Pack as compared to the outside good and indifferent between purchasing Darlie 3 Pack and the outside good. The estimates of intrinsic preference parameters are in line with the relative market shares between products (e.g., 23.91% for Colgate 1 Pack and 0.01% for Crest 4 Pack in the offline stores, and 17.55% for Lion 2 Pack and 3.52% for Darlie 3 Pack in the online store).

In the offline stores, whether the consumer has purchased the same product before does not have a statistically significant effect on the consumer's utility on a product (e.g., the coefficient of $PAST_{ij}$ in the offline stores is 23.94, but insignificant). In the online store, however, the consumers' utility on a product is positively related to their past purchase of the product (e.g., the coefficient of $PAST_{ij}$ in the online stores is 8.02, p<0.001). Online consumers get a higher utility if they have purchased the product before, which is expected.

The offline consumers' tastes on prices depend on their total dollar amount of purchase and the number of purchases they have made during the data collection period. The coefficient of the total dollar amount of purchase in the offline stores is positive and significant ($\beta = 0.05$, p<0.001), implying the higher dollar amount the consumer has spent, the less price sensitive she is. The coefficient of the number of purchase in the offline stores is negative and significant ($\beta =$-0.08, p<0.001), implying the more purchases the consumer has made, the more price sensitive she is. The coefficients of the total dollar amount of purchase and the number of purchases are not statistically significant for the online consumers. The mean price coefficients in both online and offline estimations are negative and significant ($\bar{\beta}$ = -0.45, p < 0.001 for the offline demand estimation and $\bar{\beta}$ = -0.24, p < 0.05 for the online demand estimation), indicating that consumers' utility decreases with the increase of the price. The standard deviations of price coefficients are also significant in both estimations (σ = 0.27, p < 0.001 for the offline demand estimation and σ = 0.27, p < 0.001 for the online demand estimation), implying consumers have heterogeneous tastes on price.

2.5.2 Price Effect

Because the estimation results of the structural model are not immediately interpretable (Cameron and Trivedi 2005), we compute the own- and cross-price elasticities using the estimates in Table 2.3 and the associated standard errors are estimated by taking the asymptotic distribution of the estimated parameter $\widehat{\beta_i}$, computing the statistic in question at each draw, and calculating the sample standard deviation (Berry et al. 1999, Nevo 2000). To separate the impact of consumer's purchase history on the price elasticities, we forced the value of $AMOUNT_i$ and $NUMBER_i$ to be zero. Tables 4A and 4B present the results for the offline and online estimation, respectively. The diagonal numbers are the own-price elasticities, and the off-diagonal numbers are the cross-price elasticities. The results show that the demands for products in the offline stores are price-elastic (i.e., smaller than -1). The demands for almost half of the products in the online store is price-elastic (i.e., Colgate 1 Pack, Colgate 3 Pack, Crest 1 Pack, Crest 3 Pack, Darlie 3 Pack, and Lion 3 Pack) and the other half (i.e., Colgate 1 Pack, Colgate 3 Pack, Crest 1 Pack, Crest 3 Pack, Darlie 3 Pack, and Lion 3 Pack) are price-inelastic (i.e., Colgate 2 Pack, Colgate 4 Pack, Crest 2 Pack, Darlie 1 Pack, Darlie 2 Pack, Lion 1 Pack, and Lion 2 Pack). For example, the own-price elasticity for Colgate 1 Pack in the offline stores is -1.73 offline and is -1.10 online, indicating that a 1% increase in the price for Colgate 1 Pack results in 1.73% decrease in the demand offline and 1.10% decrease in the demand online. The results are in the similar ranges to the findings in the literature that the price elasticities are typically between -4 and 0 (e.g., Bijmolt et al. 2005, Ghose and Yao 2011, Granados et al. 2012). All of the offline own-price elasticities are significant at the 5% significance level except Crest 2 Pack (-2.34 and insignificant), while a number of own-price elasticities (i.e., Colgate 2 Pack, Crest 2 Pack, Darlie 1 Pack, Darlie 2 Pack, Lion 1 Pack, and Lion 2 Pack) are not significant at the 5% significance level in the online store.

All cross-price elasticities are positive and significant in the offline stores (Table 2.4A), while a number of cross-price elasticities are not significant in the online store (Table 2.4B). All of the cross-price elasticities are smaller than 1 in both the online and offline stores. For example, in Table 2.4A, the offline cross-price elasticity for Colgate 3 (row) on Crest 3 (column) is 0.38 and significant at the 5% significance level, suggesting that a 1% increase in the price for Colgate 3 Pack results in 0.38% increase in the demand for Crest 3 Pack. Take the same example in the online store, the online cross-price elasticity for Colgate 3 (row) on Crest 3 (column) is 0.06 and significant at the 5% significance level, suggesting that a 1% increase in the price for Colgate 3 Pack results in 0.06% increase in the demand for Crest 3 Pack. The results show that the average own-price elasticity is larger in absolute value in the offline stores than that in the online store (i.e., -1.74 offline vs. -0.87 online), and the average cross-price elasticity is larger offline than online (i.e., 0.17 offline vs. 0.04 online). These statistics demonstrate that the own-price elasticity offline is, on average, 2 times as much as that online and that the cross-price elasticity offline is, and that the cross-price elasticity offline is, on average, 4.25 times as much as that online. We further conduct t-tests to statistically compare the own- and cross-price elasticity between online and offline estimations, and obtain statistically significant results. The t-test results are statistically significant at the 5% significance level, indicating higher own-price elasticities and cross-price elasticities offline than online.

2.5.3 Stockout Effect

To estimate the changes in consumer demand due to stockouts, we conduct counterfactual analyses using the estimates in Table 2.3. We simulate the stockouts by using the scenarios when a product is not available in the consumers' consideration set. Table 2.5A and 2.5B present the absolute change in markets shares of substitute products following a stockout of the focal product. The diagonal cells are omitted as the focal out-of-stock products do not have any market share. The last column shows the original market share of the focal out-of-stock products. The off-diagonal cells are the stockout effects of the product in the row on the product in the column. In both online and offline stores, stockouts induce statically significant substitution to substitute products. For example, when Colgate 1 Pack is out-of-stock, Colgate 3 Pack increases its market share by 0.14% in the offline store, while by 0.05% in the online store.

To compare the stockout effects between online and offline markets, we calculate the market shares recovered in substitute products and the market share recovered in common products carried by both online and offline store (Colgate 1 Pack, Colgate 2 Pack, Colgate 3 Pack, Colgate 4 Pack, Crest 1 Pack, Crest 2 Pack, and Crest 3 Pack) following a product stockout. Table 2.6A and Table 2.6B present the results for the offline and online estimation, respectively. Offline market shares are recovered more in the common products than those online. For example, when

Colgate 1 Pack stocks out, 6.84% of the loss of the market share is recovered in the common products in the offline stores (summation of the market share recovered in Colgate 2 Pack, Colgate 3 Pack, Colgate 4 Pack, Crest 1 Pack, Crest 2 Pack, and Crest 3 Pack), while 5.86% is recovered in the common products in the online store. On average, 6.55% of the loss of the market share goes to the common products offline while 6.05% of the loss of the market share goes to the common products online. Table 2.7 summarizes our findings on the difference in consumer demand between online and offline markets.

2.5.4 Economic Impact

While the results are statistically significant, it is important to show that the results are also economically significant. We calculate the effects on revenue in dollars due to price increases in both offline and online stores. Because of the differences between online and offline sales, to be comparable, we assume that the total demand for all products is 10,000 units in either the offline stores or the online store and computed the dollar amount of revenue changes by using the statistics in Table 2.2 and price elasticities in Table 2.4. Table 2.8A and 2.8B presents the changes in revenue in dollars due to a 10% price increase[6] in the offline stores and the online store, respectively. The last column shows the change in the net revenue change in the common products at the store. According to Table 2.8A, in the offline stores,

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[6] $0.14 increase for Colgate 1 Pack, $0.13 increase for Colgate 2 Pack, $0.07 increase for Colgate 3 Pack, $0.04 increase for Colgate 4 Pack, $0.11 increase for Crest 1 Pack, $0.17 increase for Crest 2 Pack, $0.06 increase for Crest 3 Pack, $0.07 increase for Crest 4 Pack, and $0.06 increase for 5A 1 Pack in the offline stores. $0.14 increase for Colgate 1 Pack, $0.12 increase for Colgate 2 Pack, $0.08 increase for Colgate 3 Pack, $0.07 increase for Colgate 4 Pack, $0.15 increase for Crest 1 Pack, $0.14 increase for Crest 2 Pack, $0.07 increase for Crest 3 Pack, $0.11 increase for Darlie 1 Pack, $0.10 increase for Darlie 2 Pack, $0.05 increase for Darlie 3 Pack, $0.16 increase for Lion 1 Pack, $0.12 increase for Lion 2 Pack, $0.10 increase for Lion 3 Pack in the online store.

when Colgate 1 Pack toothbrush's price increases by 10%, the revenue for the Colgate 1 Pack and the common products decreases by $295.69 and $125.93, respectively, while the revenue increases by $47.48 for Crest 1 Pack, $8.73 for Crest 2 Pack, and $34.80 for Crest 3 Pack. There are two interesting observations from the results. First, price increases may have detrimental impacts on the focal product's revenue but the manufacturer may earn a higher revenue from other products in either online or offline stores. For example, Table 2.8B indicates when the price for Colgate 4 Pack increase by 10% in the online store, the Colgate brand increases revenue of $19.47 (summation of $8.17 increase for Colgate 1 Pack, $4.01 increase for Colgate 2 Pack, $6.12 increase for Colgate 3 Pack, and $1.17 increase for Colgate 4 Pack). Second, the revenue loss from the price increases in a brand may be more than fully recovered by the revenue gain of the other brand in either online or offline markets, especially when the less popular product increases its price. For example, Table 2.8A indicates when the price for Crest 3 Pack increase by 10% in the offline store, the Crest brand loses revenue of $26.45 (summation of $24.97 increase for Crest 1 Pack, $4.85 increase for Crest 2 Pack, and $56.29 decrease for Crest 3 Pack) but the revenues for the Colgate brand increases by $96.27, and the net revenue change in the common products at the offline stores is $69.81 increase.

We further calculate the effects on revenue in dollars due to stockouts in both offline and online stores. Table 2.9A and 2.9B show the results for the offline stores and the online store respectively. The last column shows the net revenue change in the common products at the store. Both the manufacturers and the stores are worse off by a product stockout. For example, when Colgate 3 Pack is out-of-stock at the offline store, the Colgate brand loses revenue of $1070.54 (summation of $18.86 increase for Colgate 1 Pack, $7.51 increase for Colgate 2 Pack, $1109.88 decrease for Colgate 3 Pack, and $12.97 increase for Colgate 4 Pack) but the revenues increase by $12.38, $2.13, and $ $21.57 for Crest 1 Pack, Crest 2 Pack, and Crest 3 Pack respectively. In this case, the net revenue change in the common products decreases by $1034.46. In the online store, when Colgate 3 Pack is out-of-stock, the Colgate brand loses revenue of $308.23 (summation of $7.32 increase for Colgate 1 Pack, $3.48 increase for Colgate 2 Pack, $325.44 decrease for Colgate 3 Pack, and $6.42 increase for Colgate 4 Pack) but the revenues increase by $4.60, $0.99, and $ $2.75 for Crest 1 Pack, Crest 2 Pack, and Crest 3 Pack respectively. In this case, the net revenue change in the common products decreases by $299.89.

2.6 Consumer Welfare Analyses

We estimate the changes in consumer welfare with respect to the price changes and stockouts and compare them between the online and offline stores. Previous literature has analyzed consumer welfare gains from the increased product variety on the Internet (Brynjolfsson et al. 2003), the introduction of online markets (Ghose et al. 2006; Ghose and Yao 2011), and the online auctions (Bapna et al. 2008). We use the compensation variation (CV), a standard welfare analysis approach, to calculate the changes in consumer welfare when the characteristics of a product (e.g., price) are changed, or a product is removed from the consumers' consideration set (Cameron and Trivedi 2005). The compensating variation is the amount that the budgetary allotment would have to increase or decrease to yield the same level of utility as that attained prior to any change in consumers' consideration set (e.g., the introduction of a new product, the removal of the existing product or the price change of a product):

$$CV = E_{\varepsilon_{ijst},\beta_i}\left[\max_R\left(V_{ijst}\right)\right] - E_{\varepsilon_{ijst},\beta_i}\left[\max_{R'}\left(V_{ijst}\right)\right],$$

where $E_{\varepsilon_{ijst},\beta_i}[\cdot]$ is the expected value over random error ε_{ijst} and random coefficient β_i ; R is consumers' original consideration set and R' is the consideration set after the change. With TIEV error ε_{ijst}, an analytical solution for the above equation can be written as (Gentzkow 2007):

$$E_{\varepsilon_{ijst},\beta_i}\left[\max_R\left(V_{ijst}\right)\right] = E_{\beta_i}\left[ln\sum_R e^{V_{ijst}}\right] \approx \frac{1}{S}\sum_S\left(ln\sum_R e^{V_{ijst}}\right).$$

We convert CV to dollars by dividing by price coefficient β_i, and computed standard errors for welfare estimates by taking 100 draws from the asymptotic distribution of the estimated price parameter $\widehat{\beta_\iota}$ (Gentzkow 2007).

Table 2.10 presents the changes in consumer welfare due to a 10% price increases or stockouts of a product. In the offline stores, all the price increases except the price increase of Colgate 4 Pack and Crest 4 Pack have a negative and significant effect on the consumer welfare. In the online store, price increases of most products have significant effects on decreasing consumer welfare. We further conduct the t-tests and the results show that the decreases in consumer welfare for the offline consumers are greater than those for the online consumers at the 5% significance level. For example, when Colgate 1 Pack increases its price by 10%, an offline consumer loses \$0.03 on average, whereas an online consumer loses \$0.01 on average, more than the offline consumer does. The results suggest that the offline consumers are hurt more than the online consumers because the offline market is more concentrated on the common products carried by both online and offline markets. Stockouts do not have a significant effect in reducing consumer welfare in either online and offline markets.

2.7 Concluding Remarks

In this chapter, we examine and compare consumer demand under product substitution when price changes or product stocks out between online and offline markets using a large-scale dataset on consumer packaged goods and a random coefficients discrete choice model.

We find consumer demand differs under different search cost between online and offline markets. Specifically, the average own-price elasticity is -1.74 offline vs. -0.87 online, implying price changes have a larger effect on the consumer demand in the offline market than that in the online markets. As we discussed earlier, the own-price elasticity is determined by the search cost for substitute products' attributes. Because the search cost for substitute products' attributes is lower in the offline markets, offline consumers are more likely to give up the product with higher prices and purchase substitute products and the own--price elasticity is higher in the offline market. This result provides empirical support to the study in the literature that also find that online markets have a higher own-price elasticity offline than online (Chu et al. 2008).

In addition to the own-price elasticity, we find that the online cross-price elasticity is lower than the offline cross-price elasticity. The average online cross-price elasticity is 0.04, and the average offline cross-price elasticity is 0.17; that is, the offline cross-price elasticity is 4.25 times higher than the online cross-price elasticity. The statistics suggest that the offline consumers are 4.25 times more likely to buy substitute products than online consumers in a store. This is because the search cost for substitute products' attributes is lower in the offline markets than that in the online markets. When the price of a product increases, consumers in the offline markets can easily search for substitute products, study and buy the substitute products. There have been very few studies in the literature that examine the cross-price elasticity online (e.g., Danaher et al. 2014, Ellison and Ellison 2009) and no studies, to our best knowledge, that compare the cross-price elasticity between online and offline markets. The paucity of the literature highlights the important contributions of our study.

The other trigger for consumers to search for substitute products is product stockouts. From our analyses, we find that the average market share recovered in the common products is 6.55% offline when the focal product is out-of-stock, while the average market share recovered in the common products is 6.05% online; that is, offline consumers are more likely to purchase substitute products than online consumers when stockouts occur. For the online consumers, because their search cost for substitute products' attributes in the same store is high, they are less likely to purchase substitute products. For the offline consumers, because their search cost for substitute products' attributes in the same store is low, they are more likely to search for and buy substitute products from the same store. The intuition on consumer demand behind stockouts is similar to that for the cross-price elasticity. Our findings on the cross-price elasticity and product substitution under stockouts in offline markets are consistent with Shocker et al. (2004) that the demand of the focal product depends on the other products' attributes and availability. Our study extends the research on the product substitution regarding price, ranking, brand equity and product availability to both online and offline markets (e.g., Berry et al. 1995, Smith and Brynjolfsson 2001, Ghose et al. 2012, Musalem 2010). More importantly, similar to the cross-price elasticity, as the first attempts at comparing the effect of product stockouts on consumer demand between online and offline markets, our study makes important contributions.

Our results are not only statistically significant but also economically significant. Price increases may have a detrimental effect on the focal brand's revenue but may have a positive effect to increase the focal brand's revenue. Because of product substitutions, the price increase of the focal product increases the rival brand's revenue. Interestingly, our analyses show that the losses from the price increases may be more than fully recovered from the increases in the rival's revenue. For every 10,000 units in sales in the offline stores, when the price increases by 10% for a product, the average change in revenue for substitute product is \$14.24, and the average revenue change in the common products is \$0.61 (calculated as the average of the numbers in the last column using the results in Table 2.8A). For every 10,000 units in sales in the online store, when the price increases by 10% for a product, the average change in revenue for substitute product is \$2.48, and the average revenue change in the common products is \$11.15 (calculated as the average of the numbers in the last column using the results in Table 2.8B).

Similar to the effect of the price increase, product stockouts have a positive effect to increase substitute products' revenue. For every 10,000 units in sales in the offline stores, when a product is out-of-stock, the average increase in revenue for substitute products' is \$6.04, and the average revenue change in the common products is -\$901.45 (calculated as the average of the numbers in the last column using the results in Table 2.9A). For every 10,000 units in sales in the online store, when a product is out-of-stock, the average increase in revenue for substitute products' is \$4.59, and the average revenue in the common products change is -\$543.02 (calculated as the average of the numbers in the last column using the results in Table 2.9B).

While the stores may not be worse off when increasing the prices, through consumer welfare analysis, we find that consumers are hurt by price increases in the offline markets. In fact, the offline consumers are hurt more than the online consumers[7] because the offline market is more concentrated on the common products. A larger portion of offline consumers is hurt by price increases, even though they are more likely to switch away from the product which increases its price.

Our findings have a number of managerial implications. First, for online retailers, they should realize that the online markets are not responsive to purchase the substitute products. Online retailers are not able to satisfy consumer demand by substitute products when the focal product increases it price or goes out-of-stock,

[7] Stockouts do not have significant effects on the consumer welfare. Through t-test, we showed that consumer welfare decreases more offline than online following a price increase.

therefore they may want to devise online pricing strategies and manage their inventory carefully in order to attract online consumers in the first place. Second, offline retailers need to consider not only the focal product but also substitute products when devising their pricing strategies. Third, from a manufacturer's perspective, a price increase in one product may increase revenues in its other product. And the increase of the revenue may be more than the revenue loss in the product of a higher price. However, the manufacturers lose revenues and customers to rival brands following a product stockout, especially in the offline markets. One possible strategy to mitigate such a situation is that the manufactures should provide incentives for the retailers to keep their products in stock (Yao et al. 2010).

Finally, our research has several limitations that may be considered in future research. First, we examine consumer demand for substitute products but do not study consumer demand for complementary products when price changes or a product is out-of-stock. Studies on consumers' complementary choices are also important to expand our understanding of how consumer demand changes in different scenarios. Second, due to the limitation of our data, we could not examine the consumer demand in response to other demand-triggering variables such as advertising. Given that the online markets have different capacities in advertising from the offline markets (e.g., personalized advertising), it would be interesting to extend our model to research the effect of other demand-triggering events on consumer demand between online and offline markets. Finally, our study used the data collected from a supermarket chain for consumer packaged goods. Our findings should be generalized to other industry settings and other product categories with caution. Future studies may collect additional data from other industries and from other product categories to empirically study consumer demand in different markets.

Figure 2.1: Product Display for Toothbrush Products

Offline Store

Online Store

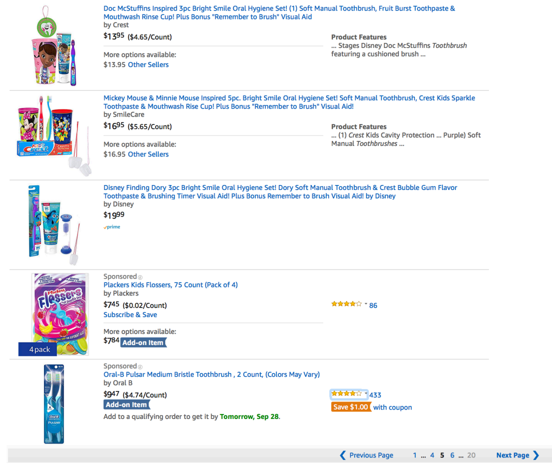
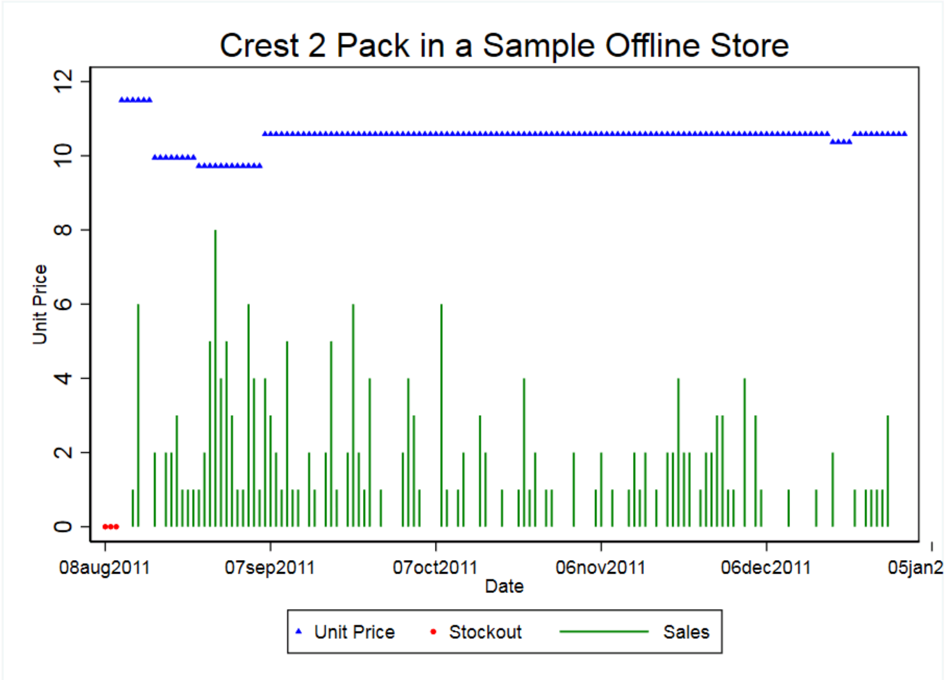


Figure 2.2: Prices, Sales and Stockouts of a Sample Product



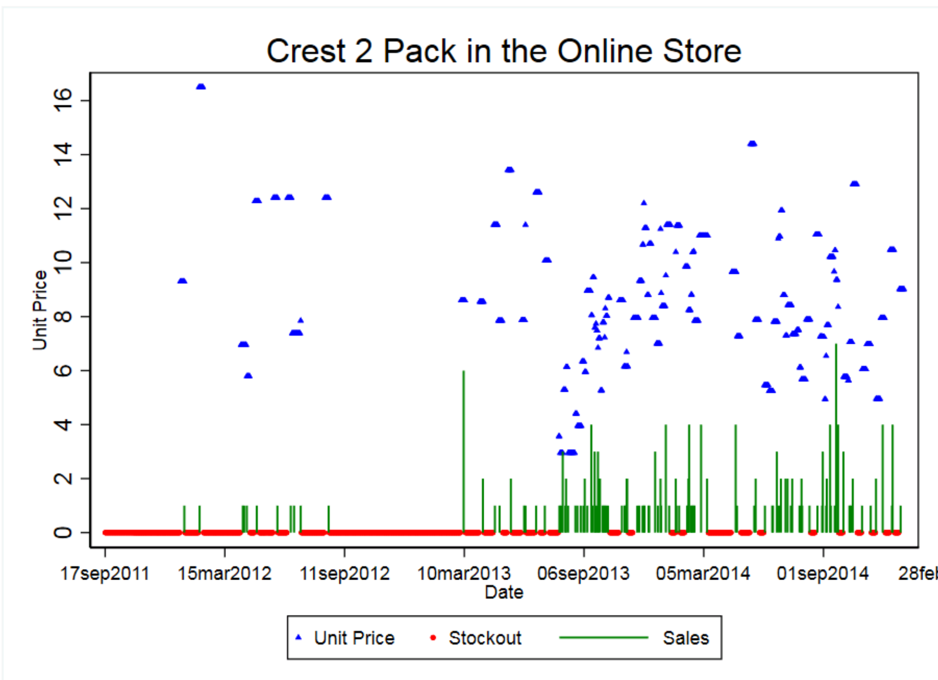


Table 2.1: Search Costs, Price Elasticities and Stockouts

Markets	**Search Cost for Substitute Products' Attributes**	**Own-Price Elasticity**	**Cross-Price Elasticity**	**Changes in Market Share of Substitute Products under Stockout**
Online	High	Low	Low	Low
Offline	Low	High	High	High

Table 2.2A: Unit Prices and Market Shares

	Offline Stores		Online Store	
	Average Unit Price ($)	Market Share	Average Unit Price ($)	Market Share
Colgate 1 Pack	1.37	23.91%	1.41	6.98%
Colgate 2 Pack	1.25	6.91%	1.19	5.98%
Colgate 3 Pack	0.65	15.76%	0.78	8.60%
Colgate 4 Pack	0.43	7.60%	0.69	2.40%
Colgate	**0.95**	**54.18%**	**1.09**	**23.96%**
Crest 1 Pack	1.06	11.84%	1.48	2.35%
Crest 2 Pack	1.66	2.74%	1.36	2.33%
Crest 3 Pack	0.56	17.04%	0.67	10.93%
Crest 4 Pack	0.72	0.01%	-	-
Crest	**1.04**	**31.63%**	**1.06**	**15.61%**
5A 1 Pack	0.63	11.75%	-	-
Darlie 1 Pack	-	-	1.13	4.82%
Darlie 2 Pack	-	-	0.95	9.80%
Darlie 3 Pack	-	-	0.52	3.52%
Lion 1 Pack	-	-	1.62	5.40%
Lion 2 Pack	-	-	1.20	17.55%
Lion 3 Pack	-	-	1.04	0.20%
Other Brand(s)	**0.63**	**11.75%**	**1.10**	**41.31%**

Table 2.2B: Past Purchase by Product

	Offline Stores		Online Store	
	Mean	Standard Deviation	Mean	Standard Deviation
Colgate 1 Pack	0.0007	0.03	0.009	0.09
Colgate 2 Pack	0.0001	0.01	0.004	0.07
Colgate 3 Pack	0.0005	0.02	0.009	0.09
Colgate 4 Pack	0.0002	0.01	0.004	0.06
Colgate	**0.0004**	**0.02**	**0.007**	**0.08**
Crest 1 Pack	0.0002	0.01	0.0009	0.03
Crest 2 Pack	0.00005	0.007	0.0009	0.03
Crest 3 Pack	0.0007	0.03	0.01	0.12
Crest 4 Pack	0	0	-	-
Crest	**0.0003**	**0.02**	**0.007**	**0.08**
5A 1 Pack	0.0004	0.02	-	-
Darlie 1 Pack	-	-	0.006	0.08
Darlie 2 Pack	-	-	0.02	0.15
Darlie 3 Pack	-	-	0.003	0.05
Lion 1 Pack	-	-	0.005	0.07
Lion 2 Pack	-	-	0.06	0.23
Lion 3 Pack	-	-	0.01	0.11
Other Brand(s)	**0.0004**	**0.02**	**0.02**	**0.14**

Note: Past purchase is a dummy variable with 1 indicating the consumer has purchase the product before, otherwise not.

Table 2.2C: Consumer Purchase History

	Offline Stores			Online Store		
	N	Mean	Standard Deviation	N	Mean	Standard Deviation
Total Amount of Purchase	41043	26.21	63.48	1418	5500.94	143152
Number of Purchases	41043	6.89	12.52	1418	22.89	133.30

Table 2.3: Estimation Results

(Robust Standard Errors in Parentheses)

	Offline Stores	Online Store
Intrinsic Preference α		
Colgate 1 Pack	4.57***	1.21
	(0.19)	(0.84)
Colgate 2 Pack	3.19***	1.24
	(0.19)	(0.70)
Colgate 3 Pack	2.82***	0.45
	(0.15)	(0.49)
Colgate 4 Pack	1.65***	0.55
	(0.11)	(0.40)
Crest 1 Pack	3.23***	0.32
	(0.18)	(0.89)
Crest 2 Pack	2.55***	-0.15
	(0.18)	(0.82)
Crest 3 Pack	2.42***	0.37
	(0.12)	(0.41)
Crest 4 Pack	-0.67	
	(0.60)	
5A 1 Pack	2.51***	
	(0.14)	
Darlie 1 Pack		0.51
		(0.69)
Darlie 2 Pack		1.00
		(0.57)
Darlie 3 Pack		-0.47
		(0.34)
Lion 1 Pack		0.77
		(0.97)
Lion 2 Pack		2.47***
		(0.72)
Lion 3 Pack		1.38
		(0.73)
Past Purchase	23.94	8.02***
	(4308.60)	(1.06)
Price Coefficients		
Total Amount of Purchase	0.05***	-0.01
	(0.004)	(0.02)
Number of Purchases	-0.08***	0.02
	(0.005)	(0.02)
	-0.45***	-0.24*

Mean Price Coefficient $\bar{\beta}$	(0.02)	(0.12)
Standard Deviation σ	0.27*** (0.02)	0.27*** (0.03)
Model Statistics		
N	366,883	20,373
Log Likelihood	-84140	-3458
χ2	66***	97***

* *p < 0.05; ** p < 0.01; ***p<0.001*

Table 2.4A: Offline Price Elasticities

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Crest4	5A1
Colgate1	***-1.73***	***0.34***	***0.38***	***0.35***	***0.38***	***0.19***	***0.37***	***0.39***	***0.38***
Colgate2	***0.10***	***-2.08***	***0.14***	***0.13***	***0.13***	***0.08***	***0.13***	***0.14***	***0.14***
Colgate3	***0.17***	***0.21***	***-1.55***	***0.40***	***0.26***	***0.14***	***0.38***	***0.33***	***0.36***
Colgate4	***0.07***	***0.09***	***0.17***	***-1.28***	***0.11***	***0.05***	***0.18***	***0.15***	***0.17***
Crest1	***0.14***	***0.16***	***0.21***	***0.21***	***-2.09***	***0.12***	***0.21***	***0.21***	***0.21***
Crest2	***0.02***	***0.03***	***0.04***	***0.04***	***0.04***	***-1.75***	***0.04***	***0.04***	***0.04***
Crest3	***0.13***	***0.16***	***0.29***	***0.33***	***0.20***	***0.11***	***-1.45***	***0.26***	***0.29***
Crest4	***0.00***	***0.01***	***0.01***	***0.01***	***0.01***	***0.00***	***0.01***	***-2.09***	***0.01***
5A1	***0.12***	***0.15***	***0.26***	***0.29***	***0.19***	***0.10***	***0.27***	***0.24***	***-1.66***

Note: The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 2.4B: Online Price Elasticities

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Darlie1	Darlie2	Darlie3	Lion1	Lion2	Lion3
Colgate1	***-1.10***	***0.07***	***0.10***	***0.14***	***0.11***	***0.07***	***0.12***	0.02	***0.07***	***0.09***	0.02	0.06	***0.08***
Colgate2	***0.06***	-0.88	***0.07***	***0.09***	***0.08***	0.03	***0.08***	-0.02	0.04	***0.06***	-0.03	0.03	0.05
Colgate3	***0.05***	***0.03***	***-1.16***	***0.07***	***0.06***	***0.03***	***0.06***	0.02	***0.04***	***0.05***	0.01	***0.03***	***0.04***
Colgate4	***0.08***	***0.06***	***0.09***	***-0.84***	***0.10***	***0.06***	***0.11***	0.03	***0.06***	***0.08***	0.03	***0.05***	***0.07***
Crest1	***0.05***	***0.03***	***0.05***	***0.07***	***-1.16***	***0.03***	***0.06***	0.02	***0.04***	***0.05***	0.01	***0.03***	***0.04***
Crest2	***0.02***	0.01	***0.02***	***0.02***	***0.02***	-0.90	***0.02***	-0.01	0.01	***0.01***	-0.01	0.01	0.01
Crest3	***0.06***	***0.04***	***0.06***	***0.09***	***0.07***	***0.04***	***-1.12***	0.02	***0.04***	***0.05***	0.02	***0.04***	***0.05***
Darlie1	0.01	-0.02	0.01	***0.02***	0.02	-0.02	***0.02***	-0.19	-0.01	0.00	-0.08	-0.02	0.00
Darlie2	***0.06***	0.03	***0.06***	***0.08***	***0.07***	0.03	***0.07***	0.00	-0.98	***0.05***	-0.01	0.03	***0.05***
Darlie3	***0.02***	0.01	***0.02***	***0.02***	***0.02***	0.01	***0.02***	0.00	***0.01***	***-1.15***	0.00	0.01	***0.01***
Lion1	0.00	-0.03	0.01	***0.03***	0.02	-0.03	0.02	-0.11	-0.02	0.00	-0.07	-0.04	-0.01
Lion2	***0.20***	0.09	***0.22***	***0.30***	***0.24***	0.09	***0.26***	-0.09	0.13	***0.19***	-0.13	-0.78	0.16
Lion3	***0.10***	0.06	***0.10***	***0.14***	***0.11***	0.06	***0.12***	0.01	***0.07***	***0.09***	0.00	0.06	***-1.03***

Note: The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 2.5A: Offline Absolute Changes in Market Share due to Stockouts

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Crest4	5A1	Original Market Share
Colgate1	-	***0.04%***	***0.14%***	***0.08%***	***0.06%***	***0.01%***	***0.12%***	***0.00%***	***0.10%***	23.91%
Colgate2	***0.04%***	-	***0.06%***	***0.04%***	***0.02%***	***0.00%***	***0.05%***	***0.00%***	***0.04%***	6.91%
Colgate3	***0.14%***	***0.06%***	-	***0.30%***	***0.12%***	***0.01%***	***0.39%***	***0.01%***	***0.29%***	15.76%
Colgate4	***0.08%***	***0.04%***	***0.30%***	-	***0.08%***	***0.01%***	***0.30%***	***0.01%***	***0.22%***	7.60%
Crest1	***0.06%***	***0.02%***	***0.11%***	***0.08%***	-	***0.01%***	***0.10%***	***0.00%***	***0.08%***	11.84%
Crest2	***0.01%***	***0.00%***	***0.01%***	***0.01%***	***0.01%***	-	***0.01%***	***0.00%***	***0.01%***	2.74%
Crest3	***0.12%***	***0.05%***	***0.39%***	***0.30%***	***0.11%***	***0.01%***	-	***0.01%***	***0.28%***	17.04%
Crest4	***0.00%***	***0.00%***	***0.01%***	***0.01%***	***0.00%***	***0.00%***	***0.01%***	-	***0.01%***	0.01%
5A1	***0.10%***	***0.04%***	***0.29%***	***0.22%***	***0.08%***	***0.01%***	***0.27%***	***0.01%***	-	11.75%

Note: The last column shows the original market shares of the out-of-stock product. The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 2.5B: Online Absolute Changes in Demand due to Stockouts

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Darlie1	Darlie2	Darlie3	Lion1	Lion2	Lion3	Original Market Share
Colgate1	-	***0.05%***	***0.05%***	***0.16%***	***0.06%***	***0.01%***	***0.07%***	***0.01%***	***0.05%***	***0.02%***	***0.02%***	***0.17%***	***0.09%***	6.98%
Colgate2	***0.05%***	-	***0.03%***	***0.08%***	***0.03%***	***0.01%***	***0.04%***	***0.01%***	***0.03%***	***0.01%***	***0.01%***	***0.11%***	***0.05%***	5.98%
Colgate3	***0.05%***	***0.03%***	-	***0.09%***	***0.03%***	***0.01%***	***0.04%***	***0.01%***	***0.03%***	***0.01%***	***0.01%***	***0.09%***	***0.05%***	8.60%
Colgate4	***0.17%***	***0.08%***	***0.10%***	-	***0.11%***	***0.02%***	***0.15%***	***0.02%***	***0.08%***	***0.03%***	***0.02%***	***0.26%***	***0.14%***	2.40%
Crest1	***0.05%***	***0.03%***	***0.03%***	***0.10%***	-	***0.01%***	***0.04%***	***0.01%***	***0.03%***	***0.01%***	***0.01%***	***0.10%***	***0.05%***	2.35%
Crest2	***0.01%***	***0.01%***	***0.01%***	***0.02%***	***0.01%***	-	***0.01%***	***0.00%***	***0.01%***	***0.00%***	***0.00%***	***0.03%***	***0.01%***	2.33%
Crest3	***0.07%***	***0.04%***	***0.04%***	***0.14%***	***0.04%***	***0.01%***	-	***0.01%***	***0.04%***	***0.01%***	***0.01%***	***0.12%***	***0.06%***	10.93%
Darlie1	***0.01%***	***0.01%***	***0.01%***	***0.02%***	***0.01%***	***0.00%***	***0.01%***	-	***0.01%***	***0.00%***	***0.00%***	***0.03%***	***0.01%***	4.82%
Darlie2	***0.05%***	***0.03%***	***0.03%***	***0.08%***	***0.03%***	***0.01%***	***0.04%***	***0.01%***	-	***0.01%***	***0.01%***	***0.10%***	***0.05%***	9.80%
Darlie3	***0.02%***	***0.01%***	***0.01%***	***0.03%***	***0.01%***	***0.00%***	***0.01%***	***0.00%***	***0.01%***	-	***0.00%***	***0.03%***	***0.01%***	3.52%
Lion1	***0.02%***	***0.01%***	***0.01%***	***0.02%***	***0.01%***	***0.00%***	***0.01%***	***0.00%***	***0.01%***	***0.00%***	-	***0.04%***	***0.02%***	5.40%
Lion2	***0.18%***	***0.11%***	***0.10%***	***0.26%***	***0.10%***	***0.03%***	***0.13%***	***0.03%***	***0.10%***	***0.03%***	***0.04%***	-	***0.17%***	17.55%
Lion3	***0.08%***	***0.05%***	***0.05%***	***0.14%***	***0.05%***	***0.01%***	***0.06%***	***0.01%***	***0.05%***	***0.01%***	***0.02%***	***0.17%***	-	0.20%

Note: The last column shows the original market share of the out-of-stock product. The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 2.6A: Offline Market Share Recovered from Stockouts

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Crest4	5A1
Colgate1	-	***0.32%***	***2.13%***	***1.66%***	***0.61%***	***0.07%***	***2.07%***	***0.04%***	***1.52%***
Colgate2	***0.73%***	-	***2.12%***	***1.65%***	***0.60%***	***0.07%***	***2.06%***	***0.04%***	***1.52%***
Colgate3	***0.74%***	***0.32%***	-	***1.72%***	***0.62%***	***0.07%***	***2.13%***	***0.04%***	***1.57%***
Colgate4	***0.74%***	***0.32%***	***2.18%***	-	***0.61%***	***0.07%***	***2.13%***	***0.04%***	***1.56%***
Crest1	***0.73%***	***0.32%***	***2.13%***	***1.66%***	-	***0.07%***	***2.07%***	***0.04%***	***1.52%***
Crest2	***0.73%***	***0.31%***	***2.11%***	***1.65%***	***0.60%***	-	***2.05%***	***0.04%***	***1.51%***
Crest3	***0.74%***	***0.32%***	***2.19%***	***1.72%***	***0.62%***	***0.07%***	-	***0.04%***	***1.57%***
Crest4	***0.73%***	***0.31%***	***2.11%***	***1.65%***	***0.60%***	***0.07%***	***2.05%***	-	***1.51%***
5A1	***0.74%***	***0.32%***	***2.17%***	***1.70%***	***0.61%***	***0.07%***	***2.11%***	***0.04%***	-

Note: The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 2.6B: Online Market Share Recovered from Stockouts

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Darlie1	Darlie2	Darlie3	Lion1	Lion2	Lion3
Colgate1	-	***0.66%***	***0.70%***	***2.53%***	***0.76%***	***0.16%***	***1.04%***	***0.16%***	***0.61%***	***0.20%***	***0.19%***	***2.12%***	***1.08%***
Colgate2	***1.22%***	-	***0.70%***	***2.50%***	***0.75%***	***0.16%***	***1.03%***	***0.16%***	***0.61%***	***0.20%***	***0.19%***	***2.10%***	***1.07%***
Colgate3	***1.22%***	***0.66%***	-	***2.50%***	***0.76%***	***0.16%***	***1.03%***	***0.16%***	***0.61%***	***0.20%***	***0.19%***	***2.11%***	***1.08%***
Colgate4	***1.26%***	***0.67%***	***0.72%***	-	***0.78%***	***0.17%***	***1.08%***	***0.17%***	***0.63%***	***0.21%***	***0.19%***	***2.16%***	***1.11%***
Crest1	***1.22%***	***0.66%***	***0.70%***	***2.51%***	-	***0.16%***	***1.03%***	***0.16%***	***0.61%***	***0.20%***	***0.19%***	***2.11%***	***1.08%***
Crest2	***1.21%***	***0.65%***	***0.69%***	***2.48%***	***0.75%***	-	***1.02%***	***0.16%***	***0.60%***	***0.20%***	***0.19%***	***2.09%***	***1.07%***
Crest3	***1.23%***	***0.66%***	***0.70%***	***2.53%***	***0.76%***	***0.16%***	-	***0.16%***	***0.61%***	***0.20%***	***0.19%***	***2.12%***	***1.08%***
Darlie1	***1.21%***	***0.65%***	***0.69%***	***2.48%***	***0.75%***	***0.16%***	***1.02%***	-	***0.60%***	***0.20%***	***0.19%***	***2.09%***	***1.07%***
Darlie2	***1.22%***	***0.66%***	***0.70%***	***2.49%***	***0.75%***	***0.16%***	***1.03%***	***0.16%***	-	***0.20%***	***0.19%***	***2.10%***	***1.07%***
Darlie3	***1.21%***	***0.65%***	***0.69%***	***2.48%***	***0.75%***	***0.16%***	***1.02%***	***0.16%***	***0.60%***	-	***0.19%***	***2.09%***	***1.07%***
Lion1	***1.21%***	***0.65%***	***0.69%***	***2.48%***	***0.75%***	***0.16%***	***1.02%***	***0.16%***	***0.60%***	***0.20%***	-	***2.09%***	***1.07%***
Lion2	***1.24%***	***0.67%***	***0.71%***	***2.54%***	***0.77%***	***0.17%***	***1.05%***	***0.17%***	***0.62%***	***0.20%***	***0.19%***	-	***1.10%***
Lion3	***1.23%***	***0.66%***	***0.70%***	***2.52%***	***0.76%***	***0.16%***	***1.04%***	***0.16%***	***0.61%***	***0.20%***	***0.19%***	***2.12%***	-

Note: The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 2.7: Price Elasticities and Production Substitution

Markets	Average Own-Price Elasticity	Average Cross-Price Elasticity	Average Market Share Recovered by the Common Products under Stockout
Online	-0.87	0.04	6.05%
Offline	-1.74	0.17	6.55%

Table 2.8A: Offline Revenue Changes due to Price Increases

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Net Change
Colgate1	***-295.69***	***28.93***	***38.64***	***11.19***	***47.48***	***8.73***	***34.80***	-125.93
Colgate2	***32.09***	***-111.44***	***13.95***	***4.20***	***16.35***	***3.67***	***12.75***	-28.44
Colgate3	***56.25***	***18.35***	***-72.46***	***13.02***	***32.43***	***6.56***	***35.87***	90.01
Colgate4	***21.63***	***7.33***	***17.30***	***-13.02***	***13.56***	***2.47***	***17.28***	66.55
Crest1	***45.66***	***14.19***	***21.39***	***6.73***	***-163.49***	***5.40***	***19.90***	-50.20
Crest2	***7.76***	***2.95***	***4.05***	***1.15***	***5.03***	***-42.10***	***3.61***	-17.55
Crest3	***41.93***	***13.88***	***29.70***	***10.76***	***24.97***	***4.85***	***-56.29***	69.81

Note: Based on 10,000 units in sales as the market. The numbers are the effects of a 10% price change in the row product on the column product's revenue in dollars. Revenue calculation is based on descriptive statistics in Table 2.2 and estimates in Table 2.4A. The last column shows the net change in revenue in the common products at the store.

Table 2.8B: Online Revenue Changes due to Price Increases

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Net Change
Colgate1	***-20.23***	***4.67***	***7.07***	***2.29***	***3.91***	***2.08***	***8.80***	8.59
Colgate2	***6.19***	2.12	***4.67***	***1.52***	***2.62***	1.00	***5.93***	24.06
Colgate3	***4.99***	***2.48***	***-18.70***	***1.21***	***2.04***	***1.10***	***4.60***	-2.26
Colgate4	***8.17***	***4.01***	***6.12***	***1.17***	***3.45***	***1.78***	***7.98***	32.68
Crest1	***4.84***	***2.43***	***3.58***	***1.20***	***-9.66***	***1.08***	***4.49***	7.95
Crest2	***1.53***	0.56	***1.16***	***0.38***	***0.65***	0.22	***1.47***	5.97
Crest3	***5.65***	***2.83***	***4.18***	***1.43***	***2.33***	***1.26***	***-16.64***	1.05

Note: Based on 10,000 units in sales as the market. The numbers are the effect of a 10% price change in the row product on the column product's revenue in dollars. Revenue calculation is based on descriptive statistics in Table 2.2 and estimates in Table 2.4B. The last column shows the net change in revenue in the common products at the store.

Table 2.9A: Offline Revenue Changes due to Stockouts

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Net Change
Colgate1	***-2307.00***	***4.84***	***8.80***	***3.49***	***6.57***	***1.87***	***6.64***	-2274.78
Colgate2	***5.30***	***-694.47***	***3.83***	***1.59***	***2.59***	***0.66***	***2.94***	-677.55
Colgate3	***18.86***	***7.51***	***-1109.88***	***12.97***	***12.38***	***2.13***	***21.57***	-1034.46
Colgate4	***11.39***	***4.76***	***19.69***	***-451.19***	***8.26***	***1.24***	***16.67***	-389.18
Crest1	***8.48***	***3.05***	***7.41***	***3.25***	***-878.11***	***1.03***	***5.82***	-849.07
Crest2	***1.53***	***0.49***	***0.81***	***0.31***	***0.65***	***-321.75***	***0.61***	-317.33
Crest3	***16.59***	***6.74***	***25.14***	***12.80***	***11.34***	***1.85***	***-842.25***	-767.80

Note: Based on 10,000 units in sales as the market. The numbers are the effect of the stockout in the row product on the column product's revenue in dollars. Revenue calculation is based on descriptive statistics in Table 2.2 and estimates in Table 2.4A. The last column shows the net change in revenue in the common products at the store.

Table 2.9B: Online Revenue Changes due to Stockouts

	Colgate1	Colgate2	Colgate3	Colgate4	Crest1	Crest2	Crest3	Net Change
Colgate1	***-1130.38***	***6.40***	***4.09***	***11.12***	***8.18***	***1.82***	***4.86***	-1093.92
Colgate2	***7.55***	***-754.76***	***2.29***	***5.52***	***4.47***	***1.14***	***2.58***	-731.21
Colgate3	***7.32***	***3.48***	***-325.44***	***6.42***	***4.60***	***0.99***	***2.75***	-299.89
Colgate4	***23.38***	***9.80***	***7.55***	***-654.69***	***15.70***	***2.78***	***9.81***	-585.67
Crest1	***7.73***	***3.59***	***2.43***	***7.03***	***-608.27***	***1.02***	***2.96***	-583.51
Crest2	***1.86***	***0.99***	***0.56***	***1.36***	***1.10***	***-215.10***	***0.64***	-208.60
Crest3	***10.27***	***4.63***	***3.25***	***9.82***	***6.62***	***1.32***	***-334.23***	-298.32

Note: Based on 10,000 units in sales as the market. The numbers are the effect of the stockout in the row product on the column product's revenue in dollars. Revenue calculation is based on descriptive statistics in Table 2.2 and estimates in Table 2.4B. The last column shows the net change in revenue in the common products at the store.

Table 2.10: Changes in Consumer Welfare at Product-Level

	Offline		Online	
	10% Price Increase		10% Price Increase	
	Absolute Change	Percentage Change	Absolute Change	Percentage Change
Colgate1	***-$0.03***	***-4.69%***	***-$0.01***	***-2.49%***
Colgate2	***-$0.01***	***-1.34%***	***-$0.01***	***-1.87%***
Colgate3	***-$0.01***	***-2.25%***	***$0.00***	***-1.30%***
Colgate4	***$0.00***	***-0.96%***	***$0.00***	***-2.74%***
Colgate	***-$0.05***	***-9.53%***	***-$0.02***	***-8.86%***
Crest1	***-$0.01***	***-1.71%***	***$0.00***	***-1.29%***
Crest2	***$0.00***	***-0.57%***	***$0.00***	***-0.46%***
Crest3	***-$0.01***	***-1.71%***	***$0.00***	***-1.57%***
Crest4	***$0.00***	***-0.05%***	-	-
Crest	***-$0.02***	***-4.12%***	***-$0.01***	***-3.49%***
5A1	***-$0.01***	***-1.61%***	-	-
Darlie1	-	-	***$0.00***	***-0.75%***
Darlie2	-	-	***-$0.01***	***-1.58%***
Darlie3	-	-	***$0.00***	***-0.96%***
Lion1	-	-	***-$0.02***	***-6.26%***
Lion2	-	-	***-$0.01***	***-2.54%***
Lion3	-	-	***$0.00***	***-0.43%***
Local Brand(s)	***-$0.01***	***-1.61%***	***-$0.04***	***-12.53%***

Note: Numbers in bold and italic are significant at the 5% significance level. Local brand includes 5A offline, and other brands include Darlie and Lion online.

3. Are Complements Really Complementary? An Empirical Structural Estimation of Consumer Purchase Behavior across Product Categories

3.1 Introduction

Consumers purchase products from multiple categories during a shopping trip. Examples include families purchasing both toothbrushes and toothpastes which are complements-in-use that provide superior results when used together (Shocker et al. 2004). Understanding substitutability and complementarity of cross-category demand is of great importance to the retailers who determine the inventory level of different categories to maximize revenue and to the multicategory manufacturers who rationalize their pricing and supply chain strategies across product categories. The rationale is that a change in the marketing (e.g., pricing) and supply chain strategies (e.g., inventory policies) of one category may affect the demand for other categories through cross-category effect.

Price and product availability are two factors that affect consumer purchase decisions regarding the focal products and other products. An increase in price is often related to a reduction in demand for the focal product with an increased price, and product stockout can result in loss of sales or backorders. Price and product availability of the focal product may affect consumer demand for other product categories. For example, if laundry detergent and fabric softener are complements, and cake mix and cake frosting are complements, a price reduction on detergent may increase the sales of fabric softener, and stockout of cake mix may reduce the sales on cake frosting. Researchers have studied effects of various marketing mix variables (e.g., Manchanda et al. 1999, Song and Chintagunta 2006, Wedel and

Zhang 2004) and find cross-category effects on other product categories by changing marketing efforts on the focal category. For example, Song and Chintagunta (2006) find complementarity between softeners and detergents: a reduction in softener price increases demand for detergents.

Despite the literature studying multicategory demand, the understanding of how product availability affects consumer purchase behavior across product categories is much limited. Specifically, does the product availability status of one category (e.g., toothbrush) affect demand for another category (e.g., toothpaste)? If there exists a cross-category effect, will stockouts in one category increase or decrease demand for other categories? Furthermore, how does the product availability status affect the demand for products of the same brand but other category and the demand for products of another brand and another category? For example, does the stockout of Colgate toothbrushes have different effects on the demand for Colgate toothpastes and the demand for Crest toothpastes?

In this chapter, we address the above questions by using large-scale transaction level data from one of the largest supermarket chains in China. We apply a structural demand framework to examine consumer purchase behavior across two complements-in-use categories, toothbrush products and toothpaste products. Based on our estimation, we conduct counterfactual analyses on consumer response to price change and stockout. We find that consumers do not have superior utility to purchase toothbrushes and toothpastes together. Through cross-price elasticity computation, we find that most of the cross-category cross-price elasticities are positive. This suggests products that are complements-in-use may not be complements-in-purchase. We further conduct consumer welfare analyses and show that consumers are hurt by price increases.

Our study makes a number of important contributions. First, our research is among the small stream of papers studying multicategory demand. Despite a rich body of literature on demand estimation where consumers choose a single product within a product category (e.g., Berry 1994, Berry et al. 1995, Nevo 2001), understanding of how consumers make purchase decisions of products across product categories are much limited (a review of multicategory demand models can be found in Seetharaman et al. (2005)). Second, our study is among the first papers to examine the effect of product availability in the context allowing multi-category consumer demand. Neglecting stockouts may lead to biases or incorrect managerial implications in structural models (e.g., Bruno and Vilcassim 2008, Conlon and Mortimer 2013, Musalem et al. 2010). Third, our Point-of-Sale (POS) data provides information on the products a consumer buying in each shopping trip that helps examine cross-category effects whereas most papers only use product-level aggregate data. Song and Chintagunta (2006) point out that joint purchase incidence probability during a shopping trip cannot be identified with aggregate level data as different joint purchase incidence outcomes can result in the same aggregate sales data in each category. Using transaction-level data, we directly observe whether consumers have made multicategory purchases and are able to uncover consumer purchase pattern during a shopping trip.

The rest of the chapter is organized as follows. Section 3.2 gives an overview of the relevant literature. Section 3.3 develops the structure model.

Section 3.4 details our empirical context and data. Section 3.5 discusses the estimation. Section 3.6 presents results. Section 3.7 presents the analysis of consumer welfare estimation. Finally, Section 3.8 discusses the results, theoretical and managerial implications, research limitations, and future research.

3.2 Literature and Theory

3.2.1 Marketing Mix and Multicategory Demand

Multicategory demand has drawn increasing research attention. To capture cross-category effect, a common measure is the cross-price elasticity— the percentage change of demand for a product in one product category caused by a one percent change in the price of a product in another product category. Products are considered as complements if the reduction of the price of a product in one product category leads to an increase in sales of a product in another product category (e.g., Bucklin et al. 1998; Russell and Bolton 1988; Russell and Petersen 2000). While the price elasticity measures the inter-product relationships in demand, it cannot fully capture the richness of cross-category relationships, for example, the inter-product relationships in use. Shocker et al. (2004) categorize the possible cross-category relationships as substitutes-in-use, which serves similar purpose of usage; occasional substitutes, which may be used in a similar way for a higher-order purpose (e.g. granola can be placed at the breakfast section in a retail store but it can also be used as a substitute for snacks); complements-in-use; and occasional complements, which are intended to be used together to exert design influences on each other (e.g., the size of a briefcase should reflect the size and nature of other products to be contained). Shocker et al. (2004) argue that promotions can also affect consumer purchase behavior across product categories. For example, the promotion on certain categories can induce store traffic and stimulate consumer occasionally substitute one category (granola) for another (cookies).

Manchanda et al. (1999) use household scanner data and study consumer purchase on four product categories: cake mix, cake frosting, detergent, and fabric softener, among which cake mix and cake frosting, detergent and fabric softener are complements-in-use pairs. They find significant complementarity regarding price and promotion: the price reduction and/or promotion of one product category increases the demand for the other product category. The complementarity is stronger between cake mix-cake cake frosting pair than that between detergent-fabric softener pair. Lee et al. (2013) also use household scanner data and studied the consumer multicategory demand for milk and cereal. In their empirical direct utility model, Lee et al. (2013) assume a superadditive utility structure for complementary products that favors purchases of products in both categories than purchases of either product in a category. That is, consumers obtain higher utilities when purchasing both milk and cereal than the summation of the utilities of either milk or cereal. Their findings suggest significant yet asymmetric complementary cross-category effects of price and promotion between milk and cereal: the effects of milk price and/or promotion on cereal are larger than those of cereal on milk.

Song and Chintagunta (2006) argue that store-level data are sufficient to study multicategory demand for the purpose of pricing and category management. They investigate consumer purchase behavior across four laundry categories using weekly product-store level data and proposed a model where consumers maximize their utility by purchasing either one product or products from different categories. They find complementarity regarding price and promotion between the liquid softener-liquid detergent pair and between the liquid softener-powdered detergent pair but not between liquid/powdered detergent-liquid/sheet softener pairs. The advantage of Song and Chintagunta (2006)'s model is that they extend standard discrete choice model to allow consumer multicategory purchase decisions so that they are able to estimate complementarity with respect to price across categories. By contrast, choices of a single product or an outside good is allowed in standard discrete choice models, thus only the substitutability can be estimated. Using a model similar to Song and Chintagunta (2006)'s model that allows cross-category demand, we apply our structural model estimation to transaction-level data. Compared to Song and Chintagunta (2006), the transaction-level data allow us to directly observe cross-category purchases, thus we are able to uncover consumer purchase behavior across categories in a shopping trip, which cannot be analyzed at the aggregate level. For example, Song and Chintagunta (2006) cannot observe cross-category purchases in a shopping trip, thus different multicategory demand at consumer level can result in same aggregate multicategory demand at the store level. We apply our model to study consumer purchase behavior across complementary-in-use categories— toothbrushes and toothpastes— and examine the cross-category complementarity regarding price during a shopping trip.

3.2.2 Product Availability and Multicategory Demand

There is limited yet increasing number of literature to study how product availability affects consumer purchase behavior. On one hand, consumers may choose to buy other available products when a product is out-of-stock (e.g., Corstjens and Corstjens 1995, Musalem et al. 2010, Vulcano et al. 2012). On the other hand, the availability of the focal product may increase consumer demand for other products (Shocker et al. 2004). For example, consumers may purchase Colgate toothbrushes to pair with Colgate toothpastes.

Musalem et al. (2010) study consumer substitution pattern within a product category when a product stockouts. They use daily sales data of shampoo products and derived consumer purchase likelihoods given different product availability statuses. They find evidence of important biases in model parameters without accounting for product availability, especially when stockouts are frequent. Conlon and Mortimer (2013) use exact product availability information on a network of vending machines and estimated consumer substitution pattern when products stockout. They also report evidence of bias in sales prediction and consumer substitution pattern by ignoring stockouts. Specifically, they report a 32% larger negative stockout effect on profit by using a model that accounts for stockouts than that by using models that do not consider stockouts. Biases or incorrect managerial implications in structural models are also reported in other literature when neglecting stockouts (Bruno and Vilcassim 2008, Conlon and Mortimer 2013, Musalem et al. 2010).

While the above literature has studied consumer substitution pattern within a product category, to the best of our knowledge, none has examined the cross-category effect of product availability. Despite the research in one product category, Kim et al. (2002) propose a random utility structural model that allows consumers to purchase more than one product in a category. They study consumers' trade-off between price and product variety across different yogurt flavors by using household-level data. Though they do not observe product availability, they conduct counterfactual analyses on consumer response to the absence of each yogurt flavor and suggest that consumers need to be compensated by price reduction following a reduction in product variety. In this chapter, we leverage the information on product availability in our data and apply a random coefficients discrete choice model to examine the effect of product availability on consumer multicategory demand. Based on our estimation result, we conduct counterfactual analyses on consumer response to product stockout within and across product categories.

3.3 The Model

3.3.1 The Setup

Following Song and Chintagunta (2006), we develop a multicategory choice model that allows consumer demand to depend on utilities from two categories. We assume consumer *i*'s utility of purchasing a single product *j* in store *s* at time *t* is

$$U_{ist,cj} = \alpha_{cj} + \beta_{ic} PRICE_{st,cj}, \tag{3.1}$$

where α_j is consumer *i*'s intrinsic preference of product j. $PRICE_{st,cj}$ is the price of product j in category $c \in \{1,2\}$. Let toothbrush products $c_1 j \in c_1 = \{0, c_1 1, c_1 2, \dots, c_1 N_1\}$ be in category 1 and toothpaste products $c_2 j \in \{0, c_2 1, c_2 2, \dots, c_2 N_2\}$ be in category 2. N_1 and N_2 are the number of products in the two categories respectively. We capture consumers' heterogeneous tastes for price by allowing β_{ic} to vary across consumers and categories around its population mean $\overline{\beta_c}$ and variance σ_{jc} as follows:

$$\beta_{ic} \sim N\left(\overline{\beta_c}, \sigma_c\right). \tag{3.2}$$

We model multicategory demand as a bundle choice, where a consumer can choose one product from either category or one from both categories. When there are N_1 products in category 1 and N_2 products in category 2, the number of potential bundles is $(N_1 + 1)(N_2 + 1)$. We assume consumer i's utility of a bundle choice $b \in B$ is

$$V_{ist,b} = U_{ist,b} + \varepsilon_{ist,b} = d_1 U_{ist,c_1 j} + d_2 U_{ist,c_2 j} + d_1 d_2 \gamma(c_1 j, c_2 j) + \varepsilon_{ist,b}, \tag{3.3}$$

where and $\varepsilon_{ist,b}$ is the unobserved utility and $\gamma(c_1 j, c_2 j)$ is the additional (dis)utility that consumers get if purchase both the product $c_1 j$ in the category 1 and the product $c_2 j$ in the category 2. d_1 is a dummy variable with 1 indicating a consumer has purchased a product in the category 1 and 0 otherwise. d_2 is a dummy variable with 1 indicating a consumer has purchased a product in the category category 2 and 0 otherwise. In our baseline specification, we will allow $\gamma(c_1 j, c_2 j)$ to flexibly vary by $c_1 j$ and $c_2 j$. Assuming a simple two-product case where consumers can choose neither, either category or both categories. In this case, Gentzkow (2007) and Berry et al. (2016) have proved that the two categories are complements-in-purchase, that is the cross-price elasticities are negative if $\gamma(c_1 j, c_2 j)$ is positive. The two categories are substitutes-in-purchase, that is the cross-price elasticities are positive if $\gamma(c_1 j, c_2 j)$ is negative. The two products are independent, that is the cross-price elasticities are zero if $\gamma(c_1 j, c_2 j)$ is zero.

Substituting (3.1) into (3.3), consumer i's utility of purchasing bundle b becomes

$$\begin{aligned} V_{ist,b} &= d_1(\alpha_{c_1 j} + \beta_{ic_1} PRICE_{st,c_1 j}) + d_2(\alpha_{c_2 j} + \beta_{ic_2} PRICE_{st,c_2 j}) \\ &\quad + d_1 d_2\, \gamma(c_1 j, c_2 j) + \varepsilon_{ist,b} \end{aligned} \tag{3.4}$$

The probability that consumer i purchases product b is

$$Prob_{ist,b} = \frac{\exp\,(U_{ist,b})}{\sum_{b' \in B} \exp\,(U_{ist,b'})}. \tag{3.5}$$

The probability that consumer i purchases product j is

$$Prob_{ist,cj} = \frac{\sum_{b \in B_{cj}} \exp\,(U_{ist,b})}{\sum_{b' \in B} \exp\,(U_{ist,b'})}. \tag{3.6}$$

3.3.2 Price Elasticities

In the following, we focus on price elasticities of demand during a shopping trip. We drop subscript s and t for convenience without loss of generality. We consider price elasticities of demand of three types: 1) the own-price elasticity, 2) the cross-price elasticity within the category, and 3) cross-price elasticity between the categories. The price elasticity is defined as

$$\eta_{cj,c'j'} = \frac{\partial Prob_{cj} \cdot PRICE_{c'j'}}{\partial PRICE_{c'j'} \cdot Prob_{cj}}$$

$$= \begin{cases} \dfrac{PRICE_{c'j'}}{Prob_{cj}} \displaystyle\int \beta_{ic} Prob_{icj}(1 - Prob_{icj}) dF(\beta_{ic_1}, \beta_{ic_2}) & if\ j = j', \\ -\dfrac{PRICE_{c'j'}}{Prob_{cj}} \displaystyle\int \beta_{ic'} Prob_{icj} Prob_{icj'} dF(\beta_{ic_1}, \beta_{ic_2}) & if\ j, j' \in c_1\ or\ j, j' \in c_2, \\ \dfrac{PRICE_{c'j'}}{Prob_{cj}} \displaystyle\int \beta_{ic'} (Prob_{icj,cj'} - Prob_{icj} Prob_{icj'}) dF(\beta_{ic_1}, \beta_{ic_2}) & otherwise, \end{cases} \tag{3.7}$$

where

$$Prob_{cj} = \int \frac{\sum_{b \in B_{cj}} \exp\,(U_{ib})}{\sum_{b' \in B} \exp\,(U_{ib'})} dF(\beta_{ic_1}, \beta_{ic_2}), \tag{3.8}$$

and $Prob_{cj,c'j'}$ is the probability that consumer i purchases both products cj and $c'j'$. The first line is the own-price elasticity. The second line is the cross-price elasticity within the product category. In the following, we analyze the sign of the elasticities. Consumers' heterogeneous tastes of prices β_{ic_1} and β_{ic_2} are expected to be negative, therefore the own price elasticity is expected to be negative: a higher price of product cj reduces the utility consumers get from bundles containing product cj and thus reduces the demand for the product cj. If β_{ic_1} and β_{ic_2} are negative, the cross-price elasticity of two products within a product category is positive, that is the competing varieties within a product category are substitutes during a shopping trip. The last line is the cross-price elasticity between the two categories. Compared with the cross-price elasticity within the category, the cross-price elasticity between two categories carries an additional term $\frac{PRICE_{c'j'}}{Prob_{cj}} \int \beta_{ij'} Prob_{icj,c'j'} dF(\beta_{ic_1}, \beta_{ic_2})$, the probability of consumers choosing the bundle containing both products cj and $c'j'$. The sign and magnitude of the cross-price between categories are not guaranteed and depend on the comparison between the additional term $Prob_{icj,c'j'}$ and $Prob_{icj}Prob_{ic'j'}$.

Consider a simple two-product case where consumers can only choose from two products *j* and *k*, with each product from different product categories. The difference between the additional term $Prob_{ij,k} - Prob_{ij}Prob_{ik}$ becomes

$$\frac{e^{U_{ij}+U_{ik}+\gamma(j,k)} - e^{U_{ij}}e^{U_{ik}}}{\left[1 + e^{U_{ij}} + e^{U_{ik}} + e^{U_{ij}+U_{ik}+\gamma(j,k)}\right]^2}.$$

If $\gamma = 0$, the cross-price elasticity between two categories becomes zero and products *j* and *k* are independent. If $\gamma > 0$, $Prob_{ij,k} > Prob_{ij}Prob_{ik}$ and products

j and k are complements. If $\gamma < 0$, and $Prob_{ij,k} < Prob_{ij}Prob_{ik}$ and products j and k are substitutes.

It becomes complex when there are multiple products within each category. Suppose there are two products j_1 and j_2 in the category of c_1, and there is only one product k in the category of c_2. The set of bundles that consumers can choose from is $\{0, j_1, j_2, k, (j_1, k), (j_2, k)\}$. The difference between $Prob_{ij_1,k}$ and $Prob_{ij_1}Prob_{ik}$ becomes

$$\frac{e^{U_{ij_1}+U_{ik}} \cdot \left(e^{\gamma(j_1,k)} + e^{U_{ij_2}+\gamma(j_1,k)} - 1 - e^{U_{ij_2}+\gamma(j_2,k)}\right)}{\left(1 + e^{U_{ij_1}} + e^{U_{ij_2}} + e^{U_{ik}} + e^{U_{ij_1,k}} + e^{U_{ij_2,k}}\right)^2}. \tag{3.9}$$

Clearly, the cross-price elasticity of demand between categories for product A regarding the price of product k does not only depend on the direct (dis)utility between product j_1 and product k, but also the (dis)utilities of all possible pairs of product k. Assume $U_{j_1} = 5,\ U_{j_2} = 6, U_k = 4, \gamma(j_1, k) = -2, \gamma(j_2, k) = -1$. The disutility comes in as consumers may have different shopping cycle of products in different categories. The numerator of equation (3.9) becomes

$$e^{\gamma(j_1,k)} + e^{U_{ij_2}+\gamma(j_1,k)} - 1 - e^{U_{ij_2}+\gamma(j_2,k)} = e^{-2} + e^4 - 1 - e^5 < 0.$$

Hence, the cross-price elasticity of demand between categories for product j_1 regarding the price of product k in equation (3.9) is positive, indicating product j_1 and product k are substitutes. This can happen if consumers get a lower utility to purchase both categories together. When one category increases its price, consumers become more reluctant to purchase both categories together and switch to the other category.

Consider another case when consumers still have disutility of purchasing products in both product categories: $U_{j_1} = 5,\ U_{j_2} = 6, U_k = 4, \gamma(j_1, k) = -1, \gamma(j_2, k) = -3$

$$e^{\gamma(j_1,k)} + e^{U_{ij_2}+\gamma(j_1,k)} - 1 - e^{U_{ij_2}+\gamma(j_2,k)} = e^{-1} + e^5 - 1 - e^3 > 0.$$

Hence, the cross-category cross-price elasticity of demand for product j_1 regarding the price of product k in equation (3.9) is negative, indicating product A and product k are complements even though consumers have subadditive utility when purchasing product j_1 and product k together. Zhou (2014) suggests a joint-search effect when the cost of search is incurred jointly for all products (e.g., consumers can easily examine the products once they are at the store). As a result, the intrinsically independent products can be priced like complements. Berry et al. (2016) has shown that independent or even competing products can be complementary if other products exhibit superadditive utilities. One example is that consumers may prefer one-stop shopping than to make purchases at different stores. With more than one product to choose from a product category, the substitutability of products does not only depend on their direct interaction in utility within a bundle but also their indirect interaction via other products (Gentzkow 2007, Ogaki 1990, Samuelson 1974).

3.3.3 Stockout Effect

The change in the market share of product j following the stockout of product j' is defined as

$$\Delta = Prob'_{cj} - Prob_{cj}$$

$$= \begin{cases} -\int Prob_{icj} dF(\beta_{ic_1}, \beta_{ic_2}) & if\ j = j', \\ \int \left[\frac{\sum_{b \in B_{cj}} \exp(U_{ib})}{\sum_{b \in B} \exp(U_{ib}) - \sum_{b \in B'_{cj}} \exp(U_{ib})} - Prob_{icj} \right] dF(\beta_{ic_1}, \beta_{ic_2}) & if\ j, j' \in c_1\ or\ j, j' \in c_2, \\ \int \left[\frac{\sum_{b \in B_{cj}} \exp(U_{ib}) - \exp\,(U_{icj,cj'})}{\sum_{b \in B} \exp(U_{ib}) - \sum_{b \in B'_{cj}} \exp(U_{ib})} - Prob_{icj} \right] dF(\beta_{ic_1}, \beta_{ic_2}) & otherwise, \end{cases}$$

where $Prob'_{cj}$ is the probability that product j is purchased following the stockout of product j'. The first line is the loss of market share when product j itself is out-of-stock. The second line is the change in the market share product j following the stockout of another product j' in the same product category. The second line is expected to be positive because $\frac{\sum_{j \in b} \exp(V_{ist,b})}{\sum_b \exp(V_{ist,b}) - \sum_{k \in b} \exp(V_{ist,b})} > \frac{\sum_{j \in b} \exp(V_{ist,b})}{\sum_b \exp(V_{ist,b})}$, suggesting that the loss of market share should be recovered by the products in the same product category. The third line is the change in the market share following the stockout of a product in the other product category. Similar to the cross-category cross-price elasticity, the comparison between $\frac{\sum_{b \in B_{cj}} \exp(U_{ib}) - \exp\,(U_{icj,cj'})}{\sum_{b \in B} \exp(U_{ib}) - \sum_{b \in B'_{cj}} \exp(U_{ib})}$ and $Prob_{icj}$ depends on the direct interaction between product j and product j' and their indirect interaction via other products. There can be positive or negative changes in the market share of products in other categories.

3.4 Empirical Context and Data

We collect data from one of the largest supermarket chains in China from August 8, 2011 to December 31, 2014. The supermarket chain has annual sales of \$4.37 billion in 2011. It operates a network of 34 supermarket stores located in Shanghai metropolitan area. A distribution center located in the rural area in Shanghai supplies all 34 supermarket stores.

In this chapter, we focus on consumer packaged goods and studied consumer demand across product categories. We collect POS data for two complements-in-use categories: toothbrush and toothpaste. Toothbrushes and toothpastes are chosen because they are common consumer packaged goods that are in supply over a long-term and year-round (not the products on the market for a few months and then discontinued, or on the market only for a few months a year), which helps us to focus on consumer demand for mature products. The POS data consist of detailed information on each transaction, including the amount bought and the price paid by SKU and transaction time. We have daily inventory data for each SKU in each store, which help us to directly measure product availability. Additionally, we have order and shipment data including the wholesale price paid by each store to the distribution center.

We select consumer transactions with purchases of either a toothbrush or a toothpaste product from August 8th, 2011 to September 8th, 2014. In this time period, the data record 190,872 transactions made by 186,159 consumers. We focus on consumer choices of brands with more than 10% of market shares in toothbrush and toothpaste categories separately and treat the remaining brands as outside good. Three brands, Crest, Colgate, and 5A, account for 90 SKUs and 97.56% of total sales in the toothbrush category; and four brands, Crest, Colgate, Shanghai and Zhonghua, account for 163 SKUs and 94.67% of total sales in the toothbrush category. 5A, Shanghai, and Zhonghua are local brands sold in China and only specialize in one product category (i.e., 5A specializes in toothbrush products. Shanghai and Zhonghua specialize in toothpaste products). Products are sold in various package sizes. Different package sizes follow a nonlinear pricing scheme that may affect consumer purchase behavior (Hendel and Nevo 2006). We treat different package sizes as different products and assume consumers derive their utility from different brand-size combinations. We operationalize the price as the weighted (by average monthly unit sales of all SKUs in the brand-size combination during the whole data period) average unit price per toothbrush or per 100g toothpaste. Products are later referred to as brand-size combination in this chapter. Table 3.1 presents the descriptive statistics on the average unit prices and relative market shares of products. Table 3.2 shows the number of transactions in which consumers purchased either toothbrush, toothpaste or both products. Transactions with a single product are more prevalent than those with products from both product categories. In particular, only 6.49% transactions involve purchases of both categories, smaller than the percentage of outside good transactions. To further investigate the joint purchase of a toothbrush and a toothpaste, we run ordinary least squares (OLS) regressions of a product's daily sales quantity on the average price of the other category. There is potential endogeneity if the price is correlated with unobserved product attributes. For example, the attractiveness of the package design or the quality of a product may be correlated with both prices and consumer demand. These product attributes can be observed by consumers but not by the researchers. Following Song and Chintagunta (2006), we use the wholesale price as an instrumental variable (IV) to deal with the endogeneity. The wholesale price reflects supply-side shocks, such as production cost, which is unlikely correlated with consumer demand. Table 3.3 presents both OLS and IV estimation results.

None of the price coefficients is significant, offering no evidence on either complementarity or substitutability between the toothbrush and the toothpaste categories. Figure 3.1 presents the average unit price, daily sales and stockout of a sample product (Crest 4 Pack) in a sample store. The price varies from time to time and daily sales move opposite to the price: when the price is low, there are more sales. To deal with the endogeneity of the price, we use wholesale price as IV. Wholesale price provides supply-side shocks, such as the production cost, that is unlikely to correlate with consumer demand. The IV is weighted (by average monthly shipment quantity in the whole data period) average unit wholesale price.

3.5 Estimation

The nonlinearity of the structural model makes it invalid to use traditional linear Two-Stage Least Squares (2SLS) to control for endogeneity. We adopt the control function approach (Petrin and Train 2010) to purge out the correlation between price and the unobserved component of the indirect utility. We decompose the unobserved component $\varepsilon_{ist,b}$ into an unobserved error $\eta_{ist,b}$, which is correlated with price and an error $\bar{\varepsilon}_{ist,b}$, which is uncorrelated with price and has i.i.d Type I extreme value distribution as follows,

$$\varepsilon_{ist,b} = \eta_{ist,b} + \bar{\varepsilon}_{ist,b}. \tag{3.10}$$

We specify the following projection of $PRICE_{st,j_1}$ on the instrumental variable Z_{st,j_1},

$$PRICE_{st,cj} = \varphi_0 + \varphi_1 Z_{st,cj} + \mu_{st,cj}, \tag{3.11}$$

where φ_0 is the intercept and $Z_{st,cj}$ is the IV for $PRICE_{st,cj}$. $\mu_{st,cj}$ is the residual correlated with the unobserved error $\eta_{ist,b}$. The control function is specified by projecting $\eta_{ist,b}$ on μ_{st,c_1j} and μ_{st,c_2j},

$$\eta_{ist,b} = \lambda_1 d_1 \mu_{st,c_1j} + \lambda_2 d_2 \mu_{st,c_2j} + u_{ist,b}, \tag{3.12}$$

where $u_{ist,b}$ has i.i.d standard normal distribution and is not correlated with prices. Plugging (3.12) into (3.4)

$$\begin{aligned} V_{ist,b} = d_1(\alpha_{c_1j} + \beta_{i1} PRICE_{st,c_1j} + \lambda_1 \mu_{st,c_1j}) + d_2(\alpha_{c_2j} \\ + \beta_{i2} PRICE_{st,c_2j} + \lambda_2 \mu_{st,c_2j}) + u_{ist,b} + \bar{\varepsilon}_{ist,b}. \end{aligned} \tag{3.13}$$

Hence, conditional on $\mu_{ist,b}$, $PRICE_{st,j_1}$ and $PRICE_{st,j_2}$ are uncorrelated with the unobserved error.

The control function approach consists of two steps.

Step 1: Run linear regressions of price on IV for toothbrush and toothpaste separately according to equation (3.11). Predict the value of the residuals.

Step 2: Substitute μ_{st,j_1} and μ_{st,j_2} with the predicted residuals $\widehat{\mu_{st,J_1}}$ and $\widehat{\mu_{st,J_2}}$ into Equation (3.13) and use maximum simulated likelihood (MSL) to estimate the parameters.

We treat outside good as our base group and normalize the utility of purchasing outside good to zero. The natural way to estimate a structural model like ours is to use maximum-likelihood to maximize the following log-likelihood:

$$L(\Theta)=\sum_s \sum_t \sum_i ln \int Prob_{ist,b}\, dF(\beta_{i1}, \beta_{i2}), \tag{3.14}$$

where Θ is a vector of all model parameters. However, there is no closed form solution for Equation (3.14). We, therefore, estimate our model by maximum simulated likelihood (Train 2003). We maximize the following simulated log-likelihood:

$$L(\Theta)=\sum_s \sum_t \sum_i ln \sum_S \frac{1}{S} \widehat{Prob_{ist,b}}\,, \tag{3.15}$$

where $\widehat{Prob_{ist,b}}$ is the simulated probability for $Prob_{ist,b}$ and S is the number of simulation draws. We use 100 Halton draws of β_{i1} and β_{i2} for the estimation. The Halton draws have two desirable features (Cameron and Trivedi 2005, Train 2003): 1) they give fairly even coverage over sampling distribution domain, which makes the simulated probabilities vary less than those generated with random draws, and 2) the draws for an observation are created to fill in the spaces left empty by the previous observations, which provides a better coverage than random draws.

3.6 Estimation Results

Table 3.4 presents the estimation results. The intrinsic preference measures a consumer's utility of purchasing a product: a higher intrinsic preference means a higher utility. Most of the intrinsic preference estimates are negative because the data show that consumers are more likely to choose the outside option than bundles containing a certain product. This is because the outside option accounts for 14.84% purchase incidents. Among toothpaste products, the largest coefficient of the intrinsic preference is that of Colgate Medium Pack toothpaste (α =0.39, *p*<0.001), and the smallest coefficient is that of Shanghai Small Pack toothpaste (α = -2.45, *p*<0.001). Among toothbrush products, the largest coefficient of the intrinsic preference is that of Colgate 1 Pack toothbrush (α =-0.08 but not statistically significant), and the smallest coefficient is that of Crest 4 Pack toothbrush (α = -4.55, *p*<0.001). The estimates of intrinsic preference parameters are partially identified by the relative market shares in each product category (e.g., 20.70% for Colgate Medium Pack toothpaste, 2.38% for Shanghai Small Pack toothpaste in toothpaste category, 25.70% for Colgate 1 Pack toothbrush and 0.01% for Crest 4 Pack toothbrush in the toothbrush category).

All γ's are negative and statistically significant at the 5% significance level, suggesting consumers obtain subadditive utilities when purchase toothbrush and toothpaste together. For example, γ between 5A toothbrush and Crest toothpaste is -2.25, *p*<0.001. Since the substitutability between two products does not only depend on the direct interaction between the bundles containing these two products but also on the indirect interactions via other bundles, we compute cross-price elasticities to examine the product substitutability across products and product categories in the next subsection. The price coefficients for both categories are both negative and significant ($\overline{\beta_{J_1}}$ =-0.16, p<0.001 for toothbrushes and $\overline{\beta_{J_2}}$ =-0.07, p<0.001 for toothpastes) disutility on price. The standard deviation of both price coefficients are significant (σ_{j_1} =0.13, p<0.001 for toothbrushes and σ_{j_2} =0.20, p<0.001 for toothpastes) suggesting large consumer heterogeneous tastes on prices.

3.6.1 Price Effect

Because the estimation results of the structural model are not immediately interpretable (Cameron and Trivedi 2005), we compute the own- and cross-price elasticities using the estimates in Table 3.4. The associated standard errors are estimated by taking the asymptotic distribution of the estimated parameters $\widehat{\beta_{\iota J_1}}$ and $\widehat{\beta_{\iota J_2}}$, computing the statistic in question at each draw, and calculating the sample standard deviation (Berry et al. 1999, Nevo 2000). Tables 3.5 present the own- and cross-price elasticities. The diagonal numbers are the own-price elasticities, and the off-diagonal numbers are the cross-price elasticities. The results show the demand for the focal product and its price are inversely related: the demand decreases when the price increases. For example, the own-price elasticity for Colgate 1 Pack toothbrush is -0.50, indicating that a 1% increase in the price of Colgate 1 Pack toothbrush results in 0.50% decrease in its demand. The results are in the similar ranges to the findings in the literature that the price elasticities are typically between -4 and 0 (e.g., Bijmolt et al. 2005, Ghose and Yao 2011, Granados et al. 2012). All of the own-price elasticities are significant at the 5% significance level.

Most within-category cross-price elasticities are positive and statistically significant at the 5% significance level, suggesting competing varieties within the product category are substitutes during a shopping trip. For example, within the toothbrush category, the cross-price elasticity of the Colgate 3 Pack toothbrush (row) on the 5A 1 Pack toothbrush (column) is 0.02, suggesting that a 1% increase in the price of the Colgate 3 Pack toothbrush results in a 0.02% increase in the demand for the 5A 1 Pack toothbrush. To take an example in toothpaste category, the cross-price elasticity of the Crest Large Pack toothpaste (row) on the Zhonghua Large Pack toothpaste (column) is 0.03, suggesting that a 1% increase in the price of the Crest Large Pack toothpaste results in 0.03% increase in the demand for the Zhonghua Large Pack toothpaste. The substitution pattern is asymmetric. This is because the price elasticities are influenced by the price of the related product and all the model parameters. The cross-price elasticity of 5A 1 Pack toothbrushes (row) on the Colgate 3 Pack toothbrush (column) on is 0.02. The cross-price elasticity of

Zhonghua Large Pack toothpaste (row) on Crest Large Pack toothpastes (column) on is 0.01.

The cross-price elasticities between categories range from -0.01 to 0.71. Most of the cross-price elasticities between categories are positive, suggesting products in complements-in-use categories can be substitutes. For example, cross-price elasticities between the Colgate 1 Pack toothbrush (row) on the Zhonghua Large Pack toothpaste (column) show that a 1% increase in the price of the Colgate 1 Pack toothbrush results in 0.03% increase in the demand for the Zhonghua Large Pack toothpaste; and a 1% increase in the price of the Zhonghua Large Pack toothpaste results in 0.01% increase in the demand for the Colgate 1 Pack toothbrush.

3.6.2 Stockout Effect

To estimate the effects of stockouts on consumer demand, we conduct counterfactual analyses using the estimates in Table 3.4. We simulate the stockout effects when a product is not available in the consumers' choice set. Each row in Table 3.6 presents the change in absolute markets shares[8] of other products following the stockout of one product. The diagonal cells are omitted as the focal out-of-stock product loses all its market share.

The stockouts of a product induce consumers switching to products within the same category and in the other category. As expected, changes in all product market shares due to the stockout of a product in the same category are positive.

[8] The market shares of all bundles add up to 1.

For example, when the Colgate 1 Pack toothbrush is out-of-stock, the market share of the Colgate 2 Pack toothbrush increases by 0.03%; when the Colgate Large Pack toothpaste is out-of-stock, the market share of the Colgate Medium Pack toothpaste increases by 0.09%. The stockout of a product in one category also positively affects the market shares of products in the other category. For example, the market share of the Colgate Small Pack toothpaste increases by 0.01% following the stockout of the Colgate 1 Pack toothbrush.

There are also statistically significant switching into other brands when stockouts happen. For example, when the Colgate 1 Pack toothbrush is out-of-stock, as a brand, Colgate's market share decreases by 6.43% and Crest's increases by 0.18%. Decomposing the change in market shares of toothbrush and toothpaste product, Colgate loses 6.51% market shares in toothbrush products but gain 0.08% market shares in toothpaste products, slightly making up its loss. At the same time, market shares of Crest increases by 0.12%, 0.06% in toothbrush products and 0.08% in toothpaste products.

3.6.3 Economic Impact

While the results are statistically significant, it is important to show that the results are also economically significant. We calculate the effects on dollar revenue due to price increases. We assume that the total market size for toothbrush and toothpaste products is 12,828[9] units and compute the dollar amount of revenue changes by using the statistics in Table 3.1 and price elasticities in Table 3.5. Table 3.7 presents

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[9] The average sales of toothbrush and toothpaste products are 12,828 units in the supermarket chain during the data collection period.

the changes in revenue in dollars due to a 10% price increase[10]. For example, when Colgate 2 Pack toothbrush's price increases by 10%, the revenue for the Colgate 2 Pack toothbrush increases by $11.80 or 4.72%. Besides the revenue increase in the Colgate 2 Pack toothbrush, Colgate's revenue also increases by consumer switching to other Colgate product. The revenue of the all Colgate product increases by $18.63 or 0.48%. Other brands also benefit from the price increase of Colgate 2 Pack toothbrush: the revenue increases by $1.60 or 0.06% for Crest products, $117.18 or 22.10% for Shanghai products, $16.70 or 1.22% for Zhonghua products. The focal brand which increases its price is better off because of the revenue compensation from its other products.

Similar to the price increase, we further calculate the effects on revenue in dollars due to stockouts. Table 3.8 shows the results. For example, when the Colgate 2 Pack toothbrush stocks out, the revenue of the Colgate 2 Pack toothbrush and all brands in the entire store decrease by $250.18 or 100% and $230.01 or 2.60%, respectively. In this case, the revenue decreases by $240.68 or 6.20% for all Colgate products including toothbrushes and toothpastes, while the revenue increases by $5.91 or 0.21% for Crest products, $1.41 or 0.27% for Shanghai products, and $2.35 or 0.17% for Zhonghua products. Except when the Crest 4 Pack

[10] 10% price increase for Colgate 1 Pack, Colgate 2 Pack, Colgate 3 Pack, Colgate 4 Pack, Crest 1 Pack, Crest 2 Pack, Crest 3 Pack, Crest 4 Pack and 5A 1 Pack toothbrushes are $0.14, $0.13, $0.07, $0.04, $0.11, $0.17, $0.06, $0.07, $0.06 respectively. 10% price increase for Colgate Large Pack, Colgate Medium Pack, Colgate Small Pack, Crest Large Pack, Crest Medium Pack, Crest Small Pack, Shanghai Large Pack, Shanghai Medium Pack, Shanghai Small Pack, Zhonghua Large Pack, Zhonghua Medium Pack, and Zhonghua Small Pack toothpastes are $0.08, $0.10, $0.05, $0.07, $0.12, $0.12, $0.04, $0.06, $0.04, $0.05, $0.08, and $0.09 respectively.

toothbrush or the Shanghai Large Pack toothpaste is out-of-stock, the manufacturer loses its revenue when a product is out-of-stock.

3.7 Consumer Welfare Analyses

We estimate the changes in consumer welfare with respect to the price changes and stockouts. We use the compensating variation (CV), a standard welfare analysis approach, that measures the changes in consumer welfare when the characteristics of a product (e.g., price) are changed, or a product is removed from the consumers' choice set (Cameron and Trivedi 2005). The compensating variation is the amount that the consumer budget has to increase or decrease to keep consumer utility the same after her choice set changes (e.g., the introduction of a new product, the removal of the existing product or the price change of a product):

$$CV = E_{\varepsilon_{ist,b},\beta_{i1}\beta_{i2}}\left[\max_R\left(V_{ist,b}\right)\right] - E_{\varepsilon_{ist,b},\beta_{i1}\beta_{i2}}\left[\max_{R'}\left(V_{ist,b}\right)\right], \tag{3.16}$$

where $E_{\varepsilon_{ist,b},\beta_{i1}\beta_{i2}}[\cdot]$ is the expected value over random error $\varepsilon_{ist,b}$ and random coefficient β_{i1} and β_{i2}; R is the consumer's choice set before the change and R' is choice set after the change. With TIEV error $\varepsilon_{ist,b}$, an analytical solution for the above equation can be written as (Gentzkow 2007):

$$\begin{aligned} E_{\varepsilon_{ist,b},\beta_{i1}\beta_{i2}}\left[\max_R\left(V_{ist,b}\right)\right] &= E_{\beta_{i1}\beta_{i2}}\left[ln\sum_R e^{V_{ist,b}}\right] \\ &\approx \frac{1}{S}\sum_S\left(ln\sum_R e^{V_{ist,b}}\right). \end{aligned} \tag{3.17}$$

We convert CV to dollars by dividing CV by price coefficient β_i, and compute standard errors for welfare estimates by taking 100 draws from the asymptotic distribution of the estimated price parameter $\widehat{\beta_{i1}}$ and $\widehat{\beta_{i2}}$ (Gentzkow 2007).

Table 3.9 presents the absolute and percentage changes in consumer welfare due to a 10% price increase or the stockout of a product. Price increases have negative and significant effects on the consumer welfare. For example, the welfare of a consumer reduces by $0.009 or 2.83% when the Colgate 1 Pack toothbrush increases its price by 10%. Stockouts do not have significant effects to reduce consumer welfare.

3.8 Concluding Remarks

In this chapter, we examine consumer demand within and cross product category under product substitution and analyze the effects of price changes or a product stocks out during a shopping trip. We use a large-scale transaction-level dataset on consumer packaged goods and apply a general random coefficients discrete choice model that allows interdependence across consumer multicategory choice.

We find that the complements-in-use products such as toothbrushes and toothpastes can be substitutes during a shopping trip. This is because consumers may have different shopping cycle and prefer to purchasing different categories during different shopping trips. There exists asymmetric substitution pattern, i.e. the price effect of one product on the demand for the other product is not necessarily the same as the price effect of the other product on the demand for the first product. Our study uses transaction-level data and complements the current research of multicategory demand using aggregate data. This allows us to observe consumer multicategory choices during a shopping trip. Contrary to the findings that complements-in-use products are complements-in-purchase (e.g., Manchanda et al. 1999, Song and Chintagunta 2006), our finding suggests that during a shopping trip consumers do not necessarily consider purchasing complements-in-use products together. Facing a price increase, consumers may substitute their purchase with products in complementary product categories.

In addition to the price effect, another trigger for consumers to search for other products is product stockouts. Within the same product category, the market shares are mostly recovered in products of the big brands: Colgate and Crest, following a product stockout. The asymmetric effects of stockouts on the market shares still holds, i.e. the stockout effect of one product on the demand for the other is not necessarily the same as that of the other product on the demand for the first product. Our findings on cross-price elasticities and product substitutions under stockouts are consistent with Shocker et al. (2004) that the demand for the focal product depends on the other products' prices and availability.

Our results are not only statistically significant but also economically significant. Price increases may have a detrimental effect on the focal product's revenue (i.e., when Colgate 1 Pack toothbrush, Colgate 2 Pack toothbrush, Crest 1 Pack toothbrush, Crest 2 Pack or Crest Medium Pack toothpaste increases its price) but a positive effect to increase the brand's revenue. However, stockouts hurt the manufacturer's revenue no matter which product is out-of-stock.

Our findings have a number of managerial implications. First, retailers need to consider not only the focal product but also products within and cross product categories when devising their pricing strategies, especially that consumers may not necessarily purchase complements-in-use products during the same shopping trip. Product substitutions become complex given the existence of the competing varieties in the same product category and products in the other product categories. Retailers need to test product substitution pattern carefully before they set prices and the product inventory levels. Although retailers may lose some sales for the focal product due to price increases, it is possible that the lost revenues can be recovered by the revenue gained from products within and cross product categories. The retailers may be better off in terms of revenues of the major brands. Third, from a manufacturer's perspective, price increases and stockouts may decrease its revenue. One possible strategy to mitigate such a situation is that the manufactures should provide incentives for the retailers to keep their products in stock (Yao et al. 2010).

Finally, our research has several limitations. First, due to the limitation of our data, we cannot examine the consumer demand in response to other demand-triggering variables such as advertising. Given that marketing strategies may have different effects on the demand for products and the interactions between products, it would be interesting to extend our model to study the effect of other demand-triggering events on consumer multicategory demand. Second, our study uses the data collected from a supermarket chain for consumer packaged goods. Our findings should be generalized to other industry settings and other product categories with caution. Future studies may collect additional data from other industries and from other product categories to empirically study consumer multicategory demand.

Figure 3.1: Average Unit Price, Daily Sales and Stockout of Crest 4 Pack in a Sample Store

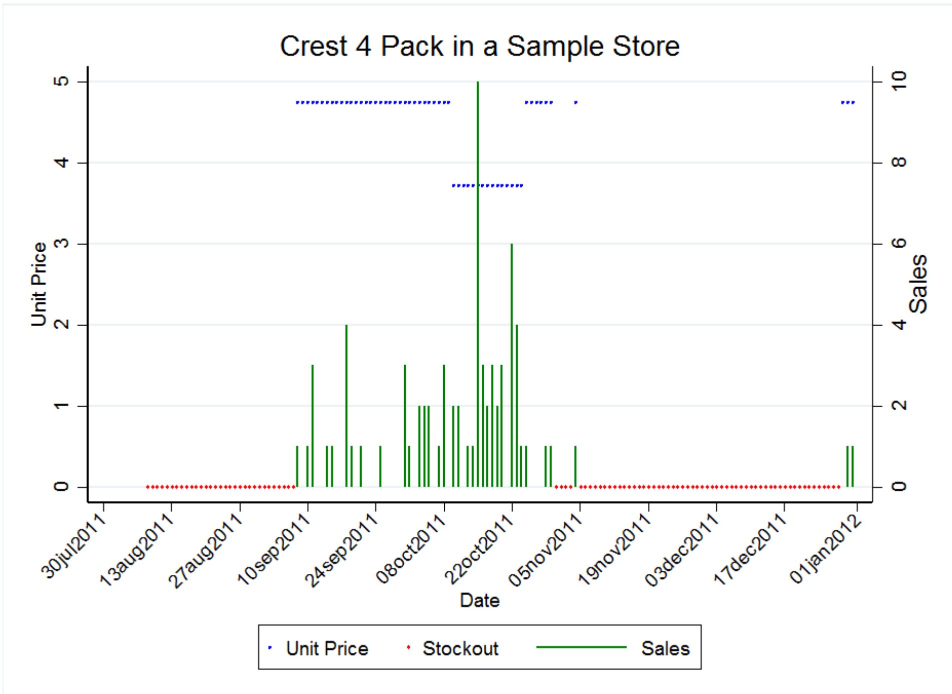

Table 3.1: Descriptive Statistics of Unit Price and Market Shares

	Toothbrush			Toothpaste	
	Average Unit Price	Market Share		Average Unit Price	Market Share
Colgate 1 Pack	1.37	25.70%	Colgate Large Pack	0.75	6.69%
Colgate 2 Pack	1.25	6.33%	Colgate Medium Pack	1.00	20.70%
Colgate 3 Pack	0.65	14.64%	Colgate Small Pack	0.49	3.33%
Colgate 4 Pack	0.43	6.82%			
Colgate	**0.95**	**53.49%**	**Colgate**	**0.75**	**30.72%**
Crest 1 Pack	1.06	12.69%	Crest Large Pack	0.72	10.09%
Crest 2 Pack	1.66	2.62%	Crest Medium Pack	1.23	11.23%
Crest 3 Pack	0.56	15.65%	Crest Small Pack	1.18	3.99%
Crest 4 Pack	0.72	0.01%			
Crest	**1.04**	**30.98%**	**Crest**	**1.05**	**25.32%**
5A 1 Pack	0.63	11.96%	Shanghai Large Pack	0.39	2.96%
5A	**0.63**	**11.96%**	Shanghai Medium Pack	0.62	9.69%
			Shanghai Small Pack	0.35	2.38%
			Shanghai	**0.46**	**15.02%**
			Zhonghua Large Pack	0.45	6.15%
			Zhonghua Medium Pack	0.84	15.15%
			Zhonghua Small Pack	0.92	2.31%
			Zhonghua	**0.73**	**23.62%**
Other Brands	**0.30**	**3.57%**	**Other Brands**	**0.59**	**5.33%**

Note: prices of toothpastes are normalized to unit price per 100g.

Table 3.2: Cross Tabulation of Toothbrush and Toothpaste

	Buy toothbrush	Didn't buy toothbrush
Buy toothpaste	12,386	111,821
Didn't buy toothpaste	38,342	28,323

Note: to be specific, consumers purchased outside good during 28,323 shopping trips.

Table 3.3: Reduced Form Estimation Results of Oral Products

(Robust Standard Errors in Parentheses)

	OLS		IV	
	(1) Toothbrushes	(2) Toothpastes	(3) Toothbrushes	(4) Toothpastes
Price	0.83	-0.11	0.46	-0.41
	(0.63)	(0.34)	(0.43)	(0.29)
Product Dummy	Included	Included	Included	Included
Store Dummy	Included	Included	Included	Included
Model Statistics				
R-squared	0.37	0.28	0.37	0.28
F Statistics	93***	146***	93***	146***

* $p < 0.05$; ** $p < 0.01$; ***$p<0.001$

Note: the dependent variables for Column (1) and (3) are daily sales quantity of toothbrushes, and the dependent variables for Column (2) and (4) are daily sales quantity of toothpastes. The independent variables for Column (1) and (3) are toothpaste price, and the independent variables for Column (2) and (4) are toothbrush price.

Table 3.4: Estimation Results

(Robust Standard Errors in Parentheses)

Intrinsic Preference of Toothpaste α		**Intrinsic Preference of Toothpaste α**	
Colgate Large Pack	-0.71***	5A 1 Pack	-1.16***
	(0.09)		(0.08)
Colgate Medium Pack	0.39***	Colgate 1 Pack	-0.08
	(0.11)		(0.14)
Colgate Small Pack	-2.33***	Colgate 2 Pack	-1.32***
	(0.06)		(0.13)
Crest Large Pack	-0.26**	Colgate 3 Pack	-0.88***
	(0.09)		(0.08)
Crest Medium Pack	-0.238	Colgate 4 Pack	-1.59***
	(0.13)		(0.06)
Crest Small Pack	-1.52***	Crest 1 Pack	-0.97***
	(0.13)		(0.11)
Shanghai Large Pack	-1.87***	Crest 2 Pack	-2.12***
	(0.05)		(0.16)
Shanghai Medium Pack	-0.57***	Crest 3 Pack	-1.00***
	(0.08)		(0.06)
Shanghai Small Pack	-2.45***	Crest 4 Pack	-4.55***
	(0.05)		(0.58)
Zhonghua Large Pack	-1.00***		
	(0.06)		
Zhonghua Medium Pack	0.03661		
	(0.10)		
Zhonghua Small Pack	-1.95***		
	(0.11)		
γ		**Mean Price Coefficients β**	
5A brush_Crest paste	-2.25***	Toothbrush Price	-0.16***
	(0.04)		(0.02)
5A brush_Colgate paste	-2.48***	Toothpaste Price	-0.07***
	(0.05)		(0.02)
5A brush_Shanghai paste	-2.37***		
	(0.08)		
5A brush_Zhonghua paste		**Standard Deviation of Price Coefficients σ**	
	-2.27***		
	(0.05)		
Crest brush_Crest paste	-1.96***	Toothbrush Price	0.13***
	(0.03)		(0.01)
Crest brush_Zhonghua paste	-2.26***	Toothpaste Price	0.20***
	(0.04)		(0.01)
Crest brush_Shanghai paste	-2.36***		
	(0.07)		

Crest brush_Colgate paste	-2.50***
	(0.03)
Colgatet brush_Crest paste	-2.42***
	(0.03)
Colgatet brush_Colgate paste	-2.25***
	-0.02294
Colgatet brush_Zhonghua paste	-2.58***
	(0.03)
Colgatet brush_Shanghai paste	-2.84***
	(0.06)
Model Statistics	
	1257731
N	3
Log Likelihood	-571541
$\chi2$	299***

** p < 0.05; ** p < 0.01; ***p<0.001*

Table 3.5: Price Elasticities

	5A 1	Colgate 1	Colgate 2	Colgate 3	Colgate 4	Crest 1	Crest 2	Crest 3	Crest 4
5A 1	***-0.50***	0.01	0.01	***0.02***	***0.02***	***0.01***	0.00	***0.02***	***0.02***
Colgate 1	0.02	***-0.50***	-0.02	***0.03***	***0.04***	-0.02	-0.05	***0.03***	0.02
Colgate 2	***0.01***	-0.01	***-0.48***	***0.01***	***0.01***	0.00	-0.01	***0.01***	***0.01***
Colgate 3	***0.02***	0.01	***0.01***	***-0.47***	***0.02***	***0.01***	0.01	***0.02***	***0.02***
Colgate 4	***0.01***	***0.00***	***0.00***	***0.01***	***-0.38***	***0.01***	0.00	***0.01***	***0.01***
Crest 1	***0.01***	-0.01	0.00	***0.01***	***0.02***	***-0.51***	-0.01	***0.01***	***0.01***
Crest 2	0.00	-0.01	0.00	0.00	***0.00***	0.00	-0.35	0.00	0.00
Crest 3	***0.02***	***0.01***	***0.01***	***0.02***	***0.02***	***0.01***	0.01	***-0.43***	***0.02***
Crest 4	***0.00***	0.00	0.00	***0.00***	***0.00***	***0.00***	0.00	***0.00***	***-0.54***
Colgate Large	***0.02***	***0.01***	***0.01***	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***	***0.03***
Colgate Medium	***0.03***	***0.03***	***0.04***	***0.04***	***0.04***	***0.03***	***0.03***	***0.03***	***0.06***
Colgate Small	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Crest Large	***0.02***	***0.02***	***0.02***	***0.03***	***0.03***	***0.02***	***0.02***	***0.02***	***0.04***
Crest Medium	***0.01***	0.00	***0.01***	***0.01***	***0.01***	***0.02***	***0.04***	***0.02***	***0.01***
Crest Small	***0.00***	***0.00***	***-0.01***	***-0.01***	***-0.01***	***0.01***	***-0.01***	***-0.01***	0.00
Shanghai Large	***0.01***	***0.01***	***0.01***	***0.01***	***0.01***	***0.01***	***0.01***	***0.01***	***0.01***
Shanghai Medium	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***	***0.03***
Shanghai Small	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Zhonghua Large	***0.01***	***0.01***	***0.01***	***0.01***	***0.02***	***0.01***	***0.01***	***0.01***	***0.02***
Zhonghua Medium	***0.03***	***0.02***	***0.03***	***0.03***	***0.03***	***0.02***	***0.03***	***0.03***	***0.05***
Zhonghua Small	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.01***

	Colgate Large	Colgate Medium	Colgate Small	Crest Large	Crest Medium	Crest Small	Shanghai Large	Shanghai Medium	Shanghai Small	Zhonghua Large	Zhonghua Medium	Zhonghua Small
5A 1	***0.19***	***0.01***	***0.27***	***0.01***	***0.01***	***0.00***	***0.31***	***0.01***	***0.33***	***0.01***	***0.01***	***0.13***
Colgate 1	***0.02***	***0.02***	***0.55***	***0.02***	***0.01***	***0.01***	***0.62***	***0.03***	***0.66***	***0.03***	***0.02***	***0.27***
Colgate 2	***0.01***	***0.00***	***0.49***	***0.01***	***0.00***	0.02	***0.56***	***0.40***	***0.59***	***0.56***	***0.01***	***0.24***
Colgate 3	***0.01***	***0.01***	***0.24***	***0.01***	***0.01***	0.01	***0.27***	***0.02***	***0.29***	***0.02***	***0.01***	***0.12***
Colgate 4	***0.01***	***0.00***	***0.16***	***0.01***	***0.00***	0.01	***0.19***	***0.13***	***0.20***	***0.19***	***0.01***	***0.08***
Crest 1	***0.33***	***0.01***	***0.46***	***0.01***	***0.00***	***0.00***	***0.52***	***0.37***	***0.55***	***0.53***	***0.01***	***0.23***
Crest 2	***0.42***	***0.23***	***0.59***	***0.00***	0.00	0.03	***0.67***	***0.48***	***0.71***	***0.67***	***0.31***	***0.29***
Crest 3	***0.01***	***0.01***	***0.20***	***0.01***	***0.00***	0.01	***0.23***	***0.01***	***0.24***	***0.01***	***0.01***	***0.10***
Crest 4	***0.20***	***0.11***	***0.29***	***0.19***	***0.03***	0.01	***0.33***	***0.23***	***0.35***	***0.33***	***0.15***	***0.14***
Colgate Large	***-0.17***	0.00	***0.01***	0.00	***-0.02***	***-0.02***	***0.02***	***0.01***	***0.02***	***0.02***	0.00	0.00
Colgate Medium	-0.02	0.02	0.02	***-0.03***	***-0.15***	***-0.17***	***0.03***	0.00	***0.03***	***0.03***	***-0.05***	***-0.05***
Colgate Small	***0.00***	0.00	***-0.25***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***
Crest Large	0.01	***-0.01***	***0.02***	***-0.14***	***-0.04***	***-0.04***	***0.03***	***0.01***	***0.03***	***0.03***	0.00	0.00
Crest Medium	***-0.07***	***-0.13***	***-0.03***	***-0.07***	***0.51***	***-0.28***	***-0.02***	***-0.05***	-0.01	***-0.02***	***-0.10***	***-0.10***
Crest Small	***-0.02***	***-0.04***	***-0.01***	***-0.03***	***-0.08***	***0.86***	***-0.01***	***-0.02***	***-0.01***	***-0.01***	***-0.03***	***-0.03***
Shanghai Large	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***-0.25***	***0.00***	***0.01***	***0.01***	***0.00***	***0.00***
Shanghai Medium	***0.01***	0.00	***0.02***	***0.01***	***-0.01***	***-0.02***	***0.02***	***-0.21***	***0.02***	***0.02***	0.00	0.00
Shanghai Small	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***-0.24***	***0.00***	***0.00***	***0.00***
Zhonghua Large	***0.01***	***0.00***	***0.01***	***0.01***	***0.00***	***0.00***	***0.01***	***0.01***	***0.02***	***-0.24***	***0.01***	***0.00***
Zhonghua Medium	0.00	***-0.03***	***0.02***	0.00	***-0.07***	***-0.08***	***0.03***	0.01	***0.03***	***0.03***	-0.07	***-0.02***
Zhonghua Small	0.00	***0.00***	***0.00***	0.00	***-0.01***	***-0.01***	***0.00***	0.00	***0.00***	***0.00***	***0.00***	-0.03

Note: The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 3.6: Absolute Changes in Demand due to Stockouts

	5A 1	Colgate 1	Colgate 2	Colgate 3	Colgate 4	Crest 1	Crest 2	Crest 3	Crest 4
5A 1	-	***0.04%***	***0.01%***	***0.03%***	***0.02%***	***0.02%***	***0.00%***	***0.03%***	***0.00%***
Colgate 1	***0.04%***	-	***0.03%***	***0.06%***	***0.03%***	***0.04%***	***0.01%***	***0.06%***	***0.00%***
Colgate 2	***0.01%***	***0.03%***	-	***0.02%***	***0.01%***	***0.01%***	***0.00%***	***0.02%***	***0.00%***
Colgate 3	***0.03%***	***0.06%***	***0.02%***	-	***0.02%***	***0.03%***	***0.01%***	***0.04%***	***0.00%***
Colgate 4	***0.02%***	***0.03%***	***0.01%***	***0.02%***	-	***0.01%***	***0.00%***	***0.02%***	***0.00%***
Crest 1	***0.02%***	***0.04%***	***0.01%***	***0.03%***	***0.01%***	-	***0.00%***	***0.02%***	***0.00%***
Crest 2	***0.00%***	***0.01%***	***0.00%***	***0.01%***	***0.00%***	***0.00%***	-	***0.01%***	***0.00%***
Crest 3	***0.03%***	***0.06%***	***0.02%***	***0.04%***	***0.02%***	***0.02%***	***0.01%***	-	***0.00%***
Crest 4	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	-
Colgate Large	***0.02%***	***0.02%***	***0.01%***	***0.02%***	***0.01%***	***0.02%***	***0.00%***	***0.02%***	***0.00%***
Colgate Medium	***0.03%***	***0.05%***	***0.01%***	***0.04%***	***0.02%***	***0.02%***	***0.01%***	***0.05%***	***0.00%***
Colgate Small	***0.01%***	***0.01%***	***0.00%***	***0.01%***	***0.00%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***
Crest Large	***0.02%***	***0.04%***	***0.01%***	***0.03%***	***0.02%***	***0.01%***	***0.00%***	***0.02%***	***0.00%***
Crest Medium	***0.01%***	***0.02%***	***0.01%***	***0.02%***	***0.01%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***
Crest Small	***0.00%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***
Shanghai Large	***0.01%***	***0.02%***	***0.00%***	***0.01%***	***0.01%***	***0.01%***	***0.00%***	***0.01%***	***0.00%***
Shanghai Medium	***0.02%***	***0.03%***	***0.01%***	***0.03%***	***0.02%***	***0.02%***	***0.00%***	***0.03%***	***0.00%***
Shanghai Small	***0.01%***	***0.01%***	***0.00%***	***0.01%***	***0.00%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***
Zhonghua Large	***0.01%***	***0.03%***	***0.01%***	***0.03%***	***0.02%***	***0.02%***	***0.00%***	***0.02%***	***0.00%***
Zhonghua Medium	***0.02%***	***0.05%***	***0.01%***	***0.04%***	***0.02%***	***0.02%***	***0.01%***	***0.03%***	***0.00%***
Zhonghua Small	***0.00%***	***0.01%***	***0.00%***	***0.01%***	***0.00%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***

	Colgate Large	Colgate Medium	Colgate Small	Crest Large	Crest Medium	Crest Small	Shanghai Large	Shanghai Medium	Shanghai Small	Zhonghua Large	Zhonghua Medium	Zhonghua Small
5A 1	***0.02%***	***0.03%***	***0.01%***	***0.02%***	***0.01%***	***0.00%***	***0.01%***	***0.02%***	***0.01%***	***0.01%***	***0.02%***	***0.00%***
Colgate 1	***0.02%***	***0.05%***	***0.01%***	***0.04%***	***0.02%***	***0.00%***	***0.02%***	***0.03%***	***0.01%***	***0.03%***	***0.05%***	***0.01%***
Colgate 2	***0.01%***	***0.01%***	***0.00%***	***0.01%***	***0.01%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***	***0.01%***	***0.01%***	***0.00%***
Colgate 3	***0.02%***	***0.04%***	***0.01%***	***0.03%***	***0.02%***	***0.01%***	***0.01%***	***0.03%***	***0.01%***	***0.03%***	***0.04%***	***0.01%***
Colgate 4	***0.01%***	***0.02%***	***0.00%***	***0.02%***	***0.01%***	***0.00%***	***0.01%***	***0.02%***	***0.00%***	***0.02%***	***0.02%***	***0.00%***
Crest 1	***0.02%***	***0.03%***	***0.00%***	***0.01%***	***0.00%***	***0.00%***	***0.01%***	***0.02%***	***0.00%***	***0.02%***	***0.02%***	***0.00%***
Crest 2	***0.00%***	***0.01%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***
Crest 3	***0.02%***	***0.05%***	***0.01%***	***0.02%***	***0.01%***	***0.01%***	***0.01%***	***0.03%***	***0.01%***	***0.02%***	***0.03%***	***0.01%***
Crest 4	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***	***0.00%***
Colgate Large	-	***0.09%***	***0.01%***	***0.06%***	***0.04%***	***0.01%***	***0.01%***	***0.04%***	***0.01%***	***0.03%***	***0.07%***	***0.01%***
Colgate Medium	***0.09%***	-	***0.02%***	***0.15%***	***0.14%***	***0.04%***	***0.03%***	***0.11%***	***0.02%***	***0.08%***	***0.19%***	***0.02%***
Colgate Small	***0.01%***	***0.02%***	-	***0.01%***	***0.01%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***	***0.01%***	***0.01%***	***0.00%***
Crest Large	***0.06%***	***0.15%***	***0.01%***	-	***0.07%***	***0.02%***	***0.02%***	***0.07%***	***0.01%***	***0.05%***	***0.11%***	***0.01%***
Crest Medium	***0.04%***	***0.14%***	***0.01%***	***0.07%***	-	***0.02%***	***0.01%***	***0.05%***	***0.01%***	***0.04%***	***0.09%***	***0.01%***
Crest Small	***0.01%***	***0.04%***	***0.00%***	***0.02%***	***0.02%***	-	***0.00%***	***0.01%***	***0.00%***	***0.01%***	***0.02%***	***0.00%***
Shanghai Large	***0.01%***	***0.03%***	***0.00%***	***0.02%***	***0.01%***	***0.00%***	-	***0.02%***	***0.00%***	***0.01%***	***0.03%***	***0.00%***
Shanghai Medium	***0.04%***	***0.11%***	***0.01%***	***0.07%***	***0.05%***	***0.01%***	***0.02%***	-	***0.01%***	***0.04%***	***0.08%***	***0.01%***
Shanghai Small	***0.01%***	***0.02%***	***0.00%***	***0.01%***	***0.01%***	***0.00%***	***0.00%***	***0.01%***	-	***0.01%***	***0.01%***	***0.00%***
Zhonghua Large	***0.03%***	***0.08%***	***0.01%***	***0.05%***	***0.04%***	***0.01%***	***0.01%***	***0.04%***	***0.01%***	-	***0.06%***	***0.01%***
Zhonghua Medium	***0.07%***	***0.19%***	***0.01%***	***0.11%***	***0.10%***	***0.02%***	***0.03%***	***0.08%***	***0.01%***	***0.06%***	-	***0.02%***
Zhonghua Small	***0.01%***	***0.02%***	***0.00%***	***0.01%***	***0.01%***	***0.00%***	***0.00%***	***0.01%***	***0.00%***	***0.01%***	***0.02%***	-

Note: The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 3.7: Revenue Changes due to Price Increases

	5A 1	Colgate 1	Colgate 2	Colgate 3	Colgate 4	Crest 1	Crest 2	Crest 3	Crest 4
5A 1	***10.57***	0.63	0.17	***0.47***	***0.16***	***0.33***	0.04	***0.46***	***0.00***
Colgate 1	24.34	***50.85***	-0.58	***0.83***	***0.34***	-0.64	-0.71	***0.87***	0.00
Colgate 2	***23.94***	-0.65	***11.80***	***0.25***	***0.10***	-0.09	-0.15	***0.25***	***0.00***
Colgate 3	***24.25***	0.93	***0.24***	***14.53***	***0.22***	***0.46***	0.07	***0.60***	***0.00***
Colgate 4	***23.98***	***0.47***	***0.12***	***0.27***	***5.35***	***0.22***	0.04	***0.26***	***0.00***
Crest 1	***24.06***	-0.59	-0.07	***0.40***	***0.15***	***18.90***	-0.16	***0.40***	***0.00***
Crest 2	23.79	-0.67	-0.12	0.06	***0.03***	-0.16	8.55	0.07	0.00
Crest 3	***24.20***	***0.90***	***0.23***	***0.56***	***0.19***	***0.44***	0.08	***14.62***	***0.00***
Crest 4	***23.77***	0.02	0.00	***0.01***	***0.00***	***0.01***	0.00	***0.01***	***0.01***
Colgate Large	***24.23***	***1.36***	***0.32***	***0.46***	***0.15***	***0.65***	***0.23***	***0.43***	***0.00***
Colgate Medium	***24.66***	***3.51***	***0.88***	***1.21***	***0.40***	***1.11***	***0.39***	***0.95***	***0.00***
Colgate Small	***23.85***	***0.35***	***0.08***	***0.12***	***0.04***	***0.14***	***0.05***	***0.11***	***0.00***
Crest Large	***24.36***	***2.28***	***0.54***	***0.76***	***0.25***	***0.75***	***0.29***	***0.60***	***0.00***
Crest Medium	***24.04***	0.45	***0.23***	***0.31***	***0.12***	***0.76***	***0.58***	***0.56***	***0.00***
Crest Small	***23.85***	***0.17***	***-0.23***	***-0.24***	***-0.07***	***0.29***	***-0.10***	***-0.26***	0.00
Shanghai Large	***23.91***	***0.56***	***0.13***	***0.19***	***0.06***	***0.22***	***0.07***	***0.17***	***0.00***
Shanghai Medium	***24.20***	***1.77***	***0.49***	***0.60***	***0.23***	***0.80***	***0.28***	***0.48***	***0.00***
Shanghai Small	***23.84***	***0.31***	***0.07***	***0.10***	***0.03***	***0.12***	***0.04***	***0.09***	***0.00***
Zhonghua Large	***24.04***	***1.13***	***0.35***	***0.38***	***0.16***	***0.58***	***0.19***	***0.31***	***0.00***
Zhonghua Medium	***24.49***	***2.68***	***0.65***	***0.92***	***0.30***	***0.97***	***0.39***	***0.78***	***0.00***
Zhonghua Small	***23.84***	***0.29***	***0.07***	***0.11***	***0.04***	***0.11***	***0.04***	***0.10***	***0.00***

	Colgate Large	Colgate Medium	Colgate Small	Crest Large	Crest Medium	Crest Small	Shanghai Large	Shanghai Medium	Shanghai Small	Zhonghua Large	Zhonghua Medium	Zhonghua Small
5A 1	***7.43***	***1.41***	***3.44***	***0.49***	***0.56***	***0.17***	***92.41***	***0.50***	***2.12***	***0.25***	***0.81***	***2.19***
Colgate 1	***0.89***	***2.89***	***6.91***	***1.28***	***1.50***	***0.51***	***95.20***	***1.45***	***4.26***	***0.70***	***2.31***	***4.40***
Colgate 2	***0.21***	***0.68***	***6.25***	***0.32***	***0.36***	0.90	***94.67***	***18.66***	***3.85***	***12.13***	***0.59***	***3.98***
Colgate 3	***0.46***	***1.49***	***3.03***	***0.72***	***0.84***	0.44	***92.08***	***0.81***	***1.87***	***0.38***	***1.30***	***1.93***
Colgate 4	***0.20***	***0.63***	***2.07***	***0.31***	***0.36***	0.30	***91.31***	***6.18***	***1.28***	***4.02***	***0.57***	***1.32***
Crest 1	***12.59***	***1.33***	***5.83***	***0.34***	***0.31***	***0.09***	***94.33***	***17.41***	***3.59***	***11.31***	***0.77***	***3.71***
Crest 2	***16.12***	***37.10***	***7.46***	***0.07***	0.05	1.08	***95.64***	***22.28***	***4.60***	***14.48***	***30.20***	***4.75***
Crest 3	***0.51***	***1.77***	***2.56***	***0.45***	***0.41***	0.37	***91.71***	***0.60***	***1.58***	***0.30***	***1.00***	***1.63***
Crest 4	***7.87***	***18.12***	***3.64***	***10.45***	***3.03***	0.53	***92.58***	***10.88***	***2.25***	***7.07***	***14.75***	***2.32***
Colgate Large	***31.27***	-0.66	***0.18***	0.26	***-1.94***	***-0.77***	***89.80***	***0.44***	***0.12***	***0.37***	0.06	0.00
Colgate Medium	-0.69	164.20	0.20	***-1.46***	***-16.24***	***-6.27***	***89.89***	-0.20	***0.21***	***0.58***	***-4.48***	***-0.82***
Colgate Small	***0.07***	0.08	***9.13***	***0.09***	***-0.12***	***-0.05***	***89.68***	***0.11***	***0.02***	***0.08***	***0.11***	***0.02***
Crest Large	0.31	***-1.68***	***0.27***	***47.14***	***-3.83***	***-1.51***	***89.88***	***0.61***	***0.18***	***0.56***	-0.22	-0.06
Crest Medium	***-2.54***	***-20.65***	***-0.39***	***-4.20***	***167.63***	***-10.24***	***89.48***	***-2.38***	-0.10	***-0.42***	***-9.66***	***-1.71***
Crest Small	***-0.86***	***-6.78***	***-0.14***	***-1.41***	***-8.72***	***71.35***	***89.58***	***-0.83***	***-0.04***	***-0.17***	***-3.20***	***-0.57***
Shanghai Large	***0.12***	***0.20***	***0.06***	***0.16***	***-0.11***	***-0.05***	***96.19***	***0.18***	***0.04***	***0.12***	***0.20***	***0.03***
Shanghai Medium	***0.37***	-0.16	***0.22***	***0.43***	***-1.53***	***-0.62***	***89.84***	***35.78***	***0.14***	***0.44***	0.36	0.05
Shanghai Small	***0.07***	***0.12***	***0.03***	***0.09***	***-0.04***	***-0.02***	***89.68***	***0.10***	***4.79***	***0.07***	***0.12***	***0.02***
Zhonghua Large	***0.32***	***0.49***	***0.16***	***0.40***	***-0.27***	***-0.13***	***89.78***	***0.45***	***0.10***	***15.94***	***0.52***	***0.08***
Zhonghua Medium	0.06	***-4.40***	***0.27***	-0.19	***-7.47***	***-2.91***	***89.90***	0.43	***0.20***	***0.60***	90.93	***-0.27***
Zhonghua Small	0.00	***-0.61***	***0.03***	-0.04	***-1.00***	***-0.39***	***89.68***	0.04	***0.02***	***0.07***	***-0.21***	15.85

Note: The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 3.8: Revenue Changes due to Stockouts

	5A 1	Colgate 1	Colgate 2	Colgate 3	Colgate 4	Crest 1	Crest 2	Crest 3	Crest 4
5A 1	***-237.55***	***7.65***	***1.99***	***2.53***	***0.94***	***2.54***	***1.01***	***2.14***	***0.06***
Colgate 1	***3.54***	***-1117.82***	***4.85***	***5.00***	***1.75***	***6.02***	***2.66***	***4.11***	***0.11***
Colgate 2	***1.00***	***5.25***	***-250.18***	***1.41***	***0.50***	***1.67***	***0.73***	***1.17***	***0.03***
Colgate 3	***2.45***	***10.49***	***2.74***	***-301.08***	***1.35***	***3.50***	***1.38***	***3.04***	***0.08***
Colgate 4	***1.39***	***5.56***	***1.46***	***2.04***	***-91.91***	***1.88***	***0.72***	***1.75***	***0.04***
Crest 1	***1.50***	***7.67***	***1.97***	***2.13***	***0.75***	***-426.88***	***1.06***	***1.76***	***0.05***
Crest 2	***0.38***	***2.15***	***0.55***	***0.53***	***0.18***	***0.67***	***-138.07***	***0.43***	***0.01***
Crest 3	***2.42***	***10.05***	***2.63***	***3.55***	***1.35***	***3.37***	***1.31***	***-276.21***	***0.08***
Crest 4	***0.05***	***0.21***	***0.06***	***0.07***	***0.03***	***0.07***	***0.03***	***0.06***	***-0.23***
Colgate Large	***1.80***	***3.67***	***0.90***	***1.51***	***0.59***	***2.32***	***0.83***	***1.59***	***0.05***
Colgate Medium	***2.65***	***8.39***	***2.02***	***3.32***	***1.27***	***3.38***	***1.96***	***3.60***	***0.12***
Colgate Small	***0.42***	***1.52***	***0.40***	***0.63***	***0.25***	***0.52***	***0.18***	***0.56***	***0.01***
Crest Large	***1.60***	***6.68***	***1.66***	***2.65***	***1.02***	***1.39***	***0.37***	***1.66***	***0.08***
Crest Medium	***0.87***	***3.89***	***0.94***	***1.46***	***0.55***	***0.66***	***0.09***	***0.81***	***0.05***
Crest Small	***0.19***	***0.86***	***0.44***	***0.64***	***0.25***	***0.11***	***0.20***	***0.57***	***0.01***
Shanghai Large	***0.76***	***2.73***	***0.71***	***1.14***	***0.45***	***0.94***	***0.33***	***1.00***	***0.02***
Shanghai Medium	***1.35***	***6.09***	***2.14***	***2.51***	***1.30***	***2.81***	***1.00***	***1.82***	***0.07***
Shanghai Small	***0.45***	***1.61***	***0.42***	***0.68***	***0.27***	***0.55***	***0.20***	***0.59***	***0.01***
Zhonghua Large	***1.18***	***4.98***	***1.89***	***2.09***	***1.16***	***2.47***	***0.89***	***1.59***	***0.06***
Zhonghua Medium	***1.82***	***8.22***	***2.05***	***3.27***	***1.26***	***2.19***	***1.51***	***2.45***	***0.10***
Zhonghua Small	***0.39***	***1.43***	***0.37***	***0.58***	***0.23***	***0.49***	***0.17***	***0.51***	***0.01***

	Colgate Large	Colgate Medium	Colgate Small	Crest Large	Crest Medium	Crest Small	Shanghai Large	Shanghai Medium	Shanghai Small	Zhonghua Large	Zhonghua Medium	Zhonghua Small
5A 1	***2.15***	***4.29***	***0.33***	***1.84***	***1.71***	***0.36***	***0.47***	***1.34***	***0.25***	***0.85***	***2.45***	***0.56***
Colgate 1	***1.98***	***6.14***	***0.53***	***3.47***	***3.49***	***0.73***	***0.77***	***2.73***	***0.41***	***1.62***	***5.01***	***0.94***
Colgate 2	***0.54***	***1.64***	***0.16***	***0.96***	***0.93***	***0.42***	***0.22***	***1.07***	***0.12***	***0.69***	***1.39***	***0.27***
Colgate 3	***1.73***	***5.18***	***0.47***	***2.93***	***2.78***	***1.17***	***0.68***	***2.39***	***0.36***	***1.45***	***4.24***	***0.81***
Colgate 4	***1.03***	***3.03***	***0.29***	***1.73***	***1.60***	***0.69***	***0.41***	***1.90***	***0.22***	***1.24***	***2.51***	***0.48***
Crest 1	***1.63***	***3.23***	***0.24***	***0.95***	***0.76***	***0.12***	***0.34***	***1.64***	***0.18***	***1.05***	***1.74***	***0.42***
Crest 2	***0.37***	***1.20***	***0.05***	***0.16***	***0.07***	***0.14***	***0.08***	***0.37***	***0.04***	***0.24***	***0.77***	***0.09***
Crest 3	***2.13***	***6.53***	***0.48***	***2.14***	***1.79***	***1.21***	***0.70***	***2.02***	***0.37***	***1.29***	***3.71***	***0.83***
Crest 4	***0.06***	***0.17***	***0.01***	***0.08***	***0.08***	***0.02***	***0.01***	***0.06***	***0.01***	***0.04***	***0.11***	***0.01***
Colgate Large	***-387.12***	***12.01***	***0.50***	***5.19***	***7.08***	***1.75***	***0.69***	***3.43***	***0.36***	***2.01***	***7.48***	***1.01***
Colgate Medium	***9.07***	***-1608.14***	***1.23***	***13.78***	***21.85***	***5.52***	***1.67***	***8.83***	***0.86***	***4.90***	***20.42***	***2.76***
Colgate Small	***0.75***	***2.47***	***-126.28***	***1.11***	***1.36***	***0.33***	***0.16***	***0.76***	***0.08***	***0.46***	***1.58***	***0.21***
Crest Large	***5.43***	***19.13***	***0.77***	***-560.26***	***11.46***	***2.84***	***1.06***	***5.38***	***0.56***	***3.12***	***11.84***	***1.59***
Crest Medium	***4.29***	***17.56***	***0.54***	***6.63***	***-1075.68***	***3.33***	***0.71***	***4.06***	***0.36***	***2.10***	***10.17***	***1.38***
Crest Small	***1.10***	***4.59***	***0.14***	***1.70***	***3.45***	***-366.47***	***0.18***	***1.04***	***0.09***	***0.53***	***2.64***	***0.36***
Shanghai Large	***1.30***	***4.20***	***0.20***	***1.93***	***2.24***	***0.54***	***0.00***	***1.32***	***0.15***	***0.82***	***2.70***	***0.36***
Shanghai Medium	***4.15***	***14.12***	***0.60***	***6.20***	***8.10***	***1.99***	***0.84***	***-465.28***	***0.44***	***2.47***	***8.88***	***1.19***
Shanghai Small	***0.75***	***2.41***	***0.12***	***1.11***	***1.27***	***0.31***	***0.16***	***0.77***	***-65.05***	***0.48***	***1.56***	***0.21***
Zhonghua Large	***3.33***	***10.74***	***0.51***	***4.94***	***5.74***	***1.39***	***0.72***	***3.39***	***0.38***	***-215.04***	***6.92***	***0.93***
Zhonghua Medium	***6.71***	***24.27***	***0.93***	***10.15***	***15.05***	***3.77***	***1.28***	***6.59***	***0.66***	***3.75***	***-984.85***	***2.00***
Zhonghua Small	***0.81***	***2.95***	***0.11***	***1.23***	***1.85***	***0.46***	***0.15***	***0.80***	***0.08***	***0.45***	***1.80***	***-164.39***

Note: The numbers are the effect of the row product on the column product. The numbers in bold and italic are significant at the 5% significance level.

Table 3.9: Changes in Consumer Welfare

	10% Price Increase	
	Absolute Change	Percentage Change
Toothbrush		
5A 1	***-$0.002***	***-0.77%***
Colgate 1	***-$0.009***	***-2.83%***
Colgate 2	***-$0.002***	***-0.78%***
Colgate 3	***-$0.003***	***-0.97%***
Colgate 4	***-$0.001***	***-0.38%***
Crest 1	***-$0.003***	***-1.11%***
Crest 2	***-$0.001***	***-0.34%***
Crest 3	***-$0.002***	***-0.82%***
Crest 4	***$0.000***	***-0.02%***
Toothpaste		
Colgate Large	***-$0.003***	***-1.09%***
Colgate Medium	***-$0.015***	***-4.21%***
Colgate Small	***$0.000***	***-0.16%***
Crest Large	***-$0.006***	***-1.85%***
Crest Medium	***-$0.013***	***-3.17%***
Crest Small	***-$0.004***	***-0.90%***
Shanghai Large	***-$0.001***	***-0.23%***
Shanghai Medium	***-$0.003***	***-1.14%***
Shanghai Small	***$0.000***	***-0.12%***
Zhonghua Large	***-$0.002***	***-0.58%***
Zhonghua Medium	***-$0.009***	***-2.66%***
Zhonghua Small	***-$0.001***	***-0.33%***

Note: Numbers in bold and italic are significant at the 5% significance level.

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Biography

Xingyue Zhang was born in Chengdu, China. She attended the School of Economics and Management at Tongji University, where she earned her bachelor degree in Management Science and graduated summa cum laude in 2011. She continued her graduate studies in the same field at Tongji University and earned her master degree in Management Science in 2013.

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