

Pricing and Pack Size

Brand, Quantity, and Cost Considerations in Pricing Multipacks of Toothpaste

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Abstract

The US market for toothpaste, like many other goods, is shifting towards selling in bulk. Multipacks of toothpaste require quantity discounts to incentivize consumers, making buying in bulk a great deal for the savings-minded toothpaste-shopper. It is more difficult to understand, however, producers' willingness to sell multipacks of toothpaste, when margins are necessarily slimmer than single tubes due to quantity discounts. This paper explores the consumer's decision in purchasing toothpaste as an interaction between savings on price and inventory considerations, like shopping and carrying costs. My model combines aspects of prior works on second degree price discrimination and quantity discounts with alterations to fit the intricacies of the market for toothpaste. The model's predictions support the possibility of pack size as a tool for second degree price discrimination as shopping and carrying costs constitute two markets with different price elasticities of demand for single and multipacks of toothpaste. This work adds to the existing literature on storable goods and non-linear pricing and brings a new economics-based approach to a question faced by toothpaste producers.

JEL classification: L11; L42; D4

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I. Introduction and Motivation

From paper towels to potato chips and everything in between, bulk packaged goods are becoming increasingly popular. Toothpaste is no exception to the trend. From 6 packs at Costco to twin (2) and triple (3) packs at grocery stores, drug stores, and Walmart alike, toothpaste multipacks are taking over the American toothpaste market.

Total toothpaste sales in the US in 2018 (excluding online sales, Costco, and Kroger), exceeded \$2.8 billion, with over \$2 billion attributable to single tubes of toothpaste. Though the sales of multipacks seem miniscule in comparison to the sales figure for single tubes, the growth rates present a quite literally growing concern. Five packs, for example were first introduced around 2015 and have consistently grown over 50% year over year – 68% in 2018 alone.

Table 1

2018 US Toothpaste Pack Price and Growth

	<i>\$ Sales</i>	<i>Pack Price</i>	<i>Tube Price</i>	<i>Volume Growth</i>
<i>PACK SIZE</i>				
<i>1</i>	\$ 2,194,644,118.14	\$3.09	\$3.09	-3.7%
<i>2</i>	\$ 419,130,230.30	\$ 5.91	\$ 2.96	9.0%
<i>3</i>	\$ 116,838,112.57	\$7.21	\$2.40	13.6%
<i>5</i>	\$ 77,113,176.62	\$10.55	\$2.11	68.8%
<i>Tot/AVG</i>	\$ 2,807,725,637.63		\$2.97	-0.1%

Source: Nielsen Retail Scanner Data

The issue is not the growth of multipacks themselves, but that the growth detracts from single pack sales. Total toothpaste sales in terms of volume, are nearly static: Americans are not buying more toothpaste overall, so single pack sales must decline to counter the growth in multipacks. For producers, this means losing margin on every consumer switching from single to multipacks. Though it differs slightly across brands, on average, the per-tube price in a pack of three is 20% lower than buying a single tube.

Buying in bulk is cheapest for the consumer. Indeed, quantity discounts are required to incentive consumers to purchase larger packs. What is difficult to understand is the producer's willingness to continue offering and promoting multipacks of toothpaste, given the necessarily smaller margins from quantity discounting.

Unlike with many goods, toothpaste multipacks have little to no cost advantage for producers. Multipacks of toothpaste are merely single packs wrapped together. One could argue the increase in amount of toothpaste sold through multipacks brings returns to scale in the manufacturing process, but as seen in Table 1, the overall volume sold, or number of tubes, is nearly constant. The method of sale is simply shifting from single tubes to multipacks. Per a quick back-of-the-envelope calculation, the toothpaste market lost an estimated \$18 million in retail sales in 2017 as total volume sales shifted to multipacks from single tubes.

This paper presents a model of the consumer's decision in purchasing toothpaste and explores the possibility of using multipacks of toothpaste as a tool for second degree price discrimination in the market. Per the model, consumers face shopping and carrying costs: if they did not, they would buy the largest available packs to take advantage of per ounce price discounts, but that is not what we see in the market. Differences in shopping and carrying costs

cross consumers allow for the treatment of multipack and single pack buyers as two different markets.

Plenty of past work examines second degree price discrimination and quantity discounts, but none directly look at pack size, carrying costs, and shopping costs. Understanding the interplay between carrying and shopping costs and quantity discount savings is an important step in establishing the possibility of pack size as a tool for price discrimination. The findings and model could be valuable across industries, to regulators, consumers, and producers alike.

II. Literature Review

Relevant existing literature is both theoretical and empirical in nature. Theoretical works like Villas-Boas (2007) and Hendel & Nevo (2014) study the theoretical justification and existence of stockpiling given consumer and seller optimization. Empirical works like McManus (2007), Hendel & Nevo (2003) and Erdem et al. (2003) structurally estimate consumers' decisions in purchasing quantities of a good given an array of preference factors. I use these papers to ground the assumptions of my model and lay the framework for my empirical estimations.

McManus (2007) studies non-linear pricing in an oligopoly of non-durable goods, namely, specialty coffee at the University of Virginia. McManus (2007) is an empirical study of product design efficiency under nonlinear pricing, estimating patterns of allocative distortions in an oligopolistic market with product menus and quantity discounting. McManus creates an estimated utility function accounting for consumers' vertical preferences in types of coffee and horizontal preferences regarding consumers' physical distances from the nearest coffee shops.

He compares the change in utility from increasing coffee sizes to the producers increase in cost. McManus finds empirical evidence of the Mussa-Rosen model prediction of “no distortion at the top,” meaning the smallest menu options are “too small”, while the large options with the widest cost-price spread are the closest to efficient in matching marginal utility and marginal cost. McManus allows for a discrete menu of sizes and kinds of coffee, and draws preferences from a standard normal distribution. This approach of assigning preferences and evaluating against market shares may is used in my model.

Villas-Boas (2007) uses a theoretical model of firm and consumer profit (utility) maximization with varying levels of differentiation to show stockpiling is not an equilibrium outcome in a competitive market. Per the model, a price discount in period one causes consumers with strong preferences to purchase large quantities in the first period to save for future consumption, while relatively indifferent consumers purchase small quantities and cause more intense price competition in future periods. Both the consumer with strong preferences choosing between purchasing and consuming from storage, and the indifferent consumer choosing between brands cause overall prices to fall in all periods. Because of this inevitable outcome, producers maximize profit by charging the same price in both periods. Villas-Boas (2007) is refuted by work looking beyond a two period decision, such as Hendel, Lizzeri & Roketskiy (2014) and Hendel & Nevo (2003). It is important to factor Villas-Boas (2007) and dynamic multi-period approach findings in assessing the validity of my model. Additionally, quantity discounts on multipacks of toothpaste could be viewed as a “buy one, get one x% off” deal, which, per Villas-Boas (2007) would be inefficient for the producer.

Hendel and his co-authors have three papers examining similar issues around stockpiling theory. In Hendel & Nevo (2002) retail data is used to verify theoretical models' predicted effects of stockpiling, namely, changes in demand with time from last purchase and distributions of storage capacity. Hendel & Nevo (2002) provides evidence of stockpiling tendencies in an industry similar to that of toothpaste: laundry detergent. Hendel, Lizzeri, and Roketskiy (2014) examines non-linear pricing of storable goods through a theoretical model of participation and selection constraints. The paper finds the consumer's ability to store goods for future consumption resembles that of a resale market and undoes the monopolist's ability to extract consumer surplus through bundling or second degree price discrimination. I use these theoretical frameworks to build my model and better understand the assumptions and outcomes.

Hendel & Nevo (2003) builds on Hendel & Nevo (2002) by structurally estimating a dynamic model of consumer choice in the market for laundry detergent. Hendel and Nevo develop the consumers problem as maximizing expected utility given state variables of inventory, current prices, shocks to utility from added consumption, and a vector of brand specific shocks affecting the consumer's choice. Utility is dependent on consumption (independent of brand) storage cost, marginal utility of income, brand specific preferences, and an advertising factor. To solve the optimization problem, Hendel & Nevo (2003) uses Rust (1987) and a nested algorithm to derive a likelihood of observing each consumer's series of decisions given the state variable, it then "nests" this likelihood computation in a non-linear search procedure that estimates the parameters to maximize the likelihood of the observed sample. Because this is computationally difficult and the state space is too large (too many brand/size combinations), Hendel & Nevo break this into a three step process of maximizing the

likelihood of an observed brand choice conditional on quantity to recover all parameters dependent on brand through a logit model computing inclusive values and transition probabilities for each decision and, finally, applying the nested algorithm to compute the quantity decision parameters. The key findings are that prior models not considering pre-temporal purchases and inventory overestimate consumer's own price elasticity, underestimate cross-price elasticity, and overestimate the likelihood consumers will select the outside option to not purchase any detergent at a given time, regardless of their stockpiling capacity and tendencies.

Erdem, Imai, & Keane (2003) develop and estimate a model of consumer choice behavior in the market for ketchup. Similar to toothpaste, ketchup is frequently purchased, branded, storable, and often on sale or promotion. Erdem et al. (2003) focuses on the optimal decision given past and current prices fueling future expectations. Erdem et al. (2003) defines a household utility dependent on consumption, income (the outside option and numeraire good), price of ketchup, a fixed cost of going to the store to purchase, a carrying cost, and a cost of stocking out (running out of ketchup). Erdem et al. (2003) uses an exogenous rate assumption for consumption of ketchup, an assumption I will employ in my model for toothpaste. Consumers are split into four levels of ketchup consumption. The rate of consumption for each level is a function of family size, a draw from a normal distribution, and the probability of switching between the 4 levels of consumption rates. The key structural parameters are preference weights, means of log usage requirements, inventory carrying cost parameters, fixed cost of purchase parameters, and a stock out cost parameter. Erdem et al. (2003) then defines a price process: how retailers change prices based on prior prices, promotional activity, and seasonality. Using Bellman's principle (maximizing forward looking payoffs, not just today's)

and a value function with inventory and knowledge of pricing scheme as priors, they are able to write the probability a household chooses to buy a particular brand/size combination conditional on the state variables. When aggregated across consumers, these probabilities are directly comparable to observed market shares in a given period. Since initial inventory is unobservable, Erdem et al. (2003) simulates the household's purchase and consumption decisions for weeks prior to the data M times given initial usage rate and preference type assigned to generate a series of initial inventory draws for each household. Using simulated maximum likelihood estimates, Erdem et al (2003) forms the likelihood of the household's observed choice history. From Erdem, Imai, & Keane (2003) I borrow the exogenous rate assumption framework. My model resembles Erdem, Imai, & Keane (2003) in the analysis of a Markov decision process through value function iteration, but does not contain dynamic pricing factors.

Despite all the literature surrounding pricing strategies and stockpiling, none have brought all the elements of the toothpaste multipack question together. McManus' model examines a non-storable good and one-period purchase decision. Hendel & Nevo (2002) and Hendel, Lizzeri, & Roketskiy (2014) lack competition and brand preferences. Hendel & Nevo (2003) examines the laundry detergent market, one similar in many regards to the toothpaste market; however, Hendel & Nevo (2003) focuses on a market in which sizes are not discrete and consumption is more differentiated across consumers than toothpaste. My research will bring components from all these prior works (non-linear pricing, storability, horizontal differentiation) together to better understand how stockpiling and pricing schemes affect a consumer's decision in buying multipacks. I use the theoretical frameworks of Villas-Boas (2007), and Hendel & Nevo (2014) to consider the validity of many of my model's assumptions and structure and the

empirical works of Hendel & Nevo (2003) and Erdem, Imai, & Keane (2003) to structure the empirical model and the method of solving for parameter estimates.

III. Market and Data

3.1 Market Structure

Toothpaste is an interesting market to explore the dynamics of multipacks and stockpiling because it is a relatively simple market which allows for some simplifying assumptions. First, consumer consumption is significantly more limited in variation than food products for example, making modeling easier, since consumption can be taken as an exogenous variable. Research by the American Dental Association and other organizations¹ shows relationships between gender or socioeconomic status and the frequency with which one reports brushing their teeth, but there is truly very little variance in the amount of toothpaste consumed by American adults.

Unlike with many goods, marginal utility with toothpaste is hardly the utility gained from consuming one more unit, since there's such limited variation in amount consumed (and who really loves brushing their teeth?). Instead utility comes from a premium from consuming a preferred brand, not having to return to the store to buy another tube of toothpaste when one runs out, and cost savings from stockpiling at a lower price. While there is some research on stockpiling behaviors increasing consumption of goods due to the psychology of having more available, it is unlikely most Americans' toothpaste use falls much beyond the American Dental

¹ Delta Dental (2014)

Association's recommended brushing teeth twice a day, and only so much toothpaste fits on a toothbrush.

The toothpaste market is highly concentrated with limited vertical differentiation. Colgate Palmolive, GlaxoSmithKline, and Procter & Gamble, manufacturers of Colgate, Sensodyne, and Crest respectively account for over 95% of market share with limited variation over time. Differences between sales volume and dollar sales shares show slight vertical differentiation between Colgate, Crest, and Sensodyne. The pattern is consistent with P&G's known strategy of positioning their products as slightly more luxury and GSK's positioning of Sensodyne as a specialty toothpaste. The large and very consistent market shares align with preferences being horizontally heterogeneous with strong brand loyalties.

One notable example of extreme brand loyalty is the US Hispanic brand loyalty to Colgate. In the Houston toothpaste market (a market with a large Hispanic population), Colgate has a 62% sales share of Hispanic shoppers in terms of toothpaste volume, yet only 44% sales share of non-Hispanic shoppers in the same area: a pattern that holds nation-wide, even when prices are identical.

The toothpaste market can be broken down into discrete categories for relevant analysis of multipacks, more so than the market for laundry detergent Hendel and Nevo tackle in their 2003 work. If considering only Crest and Colgate, which make up 70% of total sales, the market can be completely broken into 1, 2, 3, 5, and 6 packs with the main product lines being base toothpaste, whitening, complete/health, and sensitive. There are some small, non-bulk, very premium items that will fall outside this scope, like Crest's 2-step 3D White product, but these move in relatively small quantities and are not central to the question of this research.

3.2 Data

Data access has been a major obstacle in the building and testing of this model. The initial specification required Nielsen retail scanner data and household scanner data to estimate the factors guiding consumer decisions in purchasing toothpaste through an initial multinomial logit regression across all sampled households. Household level “HomeScan” data is prohibitively expensive, to the tune of \$10,000, so I instead use only Nielsen retail scanner data for all Procter & Gamble brands and their direct competitors. This data set is collected by Nielsen and tracks the purchase of a variety of goods by collecting data on what bar codes scan at what store on a given date. The data set includes sales in volume, units, and dollars, as well as a brand or product’s share of the market for a type of good, base and average prices, percent and number of units/dollars sold through promotional programs, several distribution statistics, and many more specifications for an expanse of consumer household goods, though I will be focusing on toothpaste.

Nielsen allows for the breakdown of the data by retailer, city, region, type of store (Food, Drug, Mass), or total US; however, the data excludes three of perhaps the largest sellers of toothpaste: Kroger, Costco, and Amazon. Market shares excluding these retailers will be used to test the fit of the model, so purchases at the missing retailers are counted as an “outside option” and do not affect the fit of the model. If the data for these additional retailers becomes available, it is easy to expand this model to include the additional three retailers².

² Costco also presents a theoretical issue with shopping costs because of the fixed cost of membership

With the large amount of data available and inconsistencies in pricing and brand bias in some regions, the size of the market is pared down to all retailers in one city as outlined below. I use retail data to track prices, promotions, and market shares, variables needed to test the fit of the model and estimate the utility function parameters.

I choose to use summary statistics of toothpaste sales in the Raleigh-Durham area for 2018. With limited variation in market shares and sales numbers, there should be no year-specific effects in the consumer's decision. After all, toothpaste consumption independent of brand, is unaffected by macro changes, like recessions or political changes. Consumers may change their price sensitivity in picking a brand, which would be reflected in the coefficient on price, but the need for clean teeth and fresh breath does not change with the political and economic climate.

Raleigh-Durham is a great market to examine predominantly because it is home to the best university, but also because it fits the national averages in terms of brand shares and consumer price index. Changing the city or year used would not drastically change the design or outcome of the model.

IV. Theoretical Foundation

4.1 Initial Setup and Value Function Iteration

The underlying theory of my research is that of intertemporal consumer utility maximization. In observing the per-ounce prices of toothpaste, purchasing multipacks is clearly the cheapest option, regardless of what brand is chosen. The price differential leads to one of two conclusions: consumers are irrational in their purchasing toothpaste, or there are other

factors significantly influencing the decision to buy multipacks versus single tubes of toothpaste. The model aims to estimate these significant other factors and the subsequent optimal purchase patterns. If these factors prove to exist and be significant, producers can work to change prices and pack sizes to regain profits in a market of shrinking margins.

The consumer maximizes her utility function with respect to a quantity or choice of the underlying good to make a purchase or consumption decision.

$$u(a, i) = \gamma_a - \alpha p_a + SC \mathbb{1}(i < c) + CC(i) \quad (1)$$

The consumer derives utility from choosing a brand-quantity bundle a , given a starting inventory i . For simplicity, and in accordance with this paper’s title, $a \in [0,4]$ are as follows in Table 2:

Table 2

Brand-Quantity Bundles

0 = no toothpaste purchase	Crest	Colgate
Single Pack	1	2
Multipack	3	4

Since toothpaste is a necessity, or a good with very rapidly decreasing marginal utility from consumption beyond a set level, the utility from actually using the toothpaste is relatively flat and unchanging. Because of this feature of toothpaste, utility is derived from purchasing a preferred brand. In (1), γ is a brand premium associated with the chosen brand/size option.

The consumer, like in most utility functions, loses utility in having to pay for the good. Income is not a variable in the function, since toothpaste is a good for which consumers have quasilinear preferences and there are no income effects. In equation (1), α is the marginal utility of income spent on the good multiplied by the price of the size/brand option chosen.

Shopping and carrying costs are the key components of the model and analysis. The consumer makes her quantity purchase choice considering current inventory level. If the consumer runs out of inventory during the period, she must go to the store and buy more immediately, as she cannot simply not brush her teeth until the next shopping trip. This cost is incorporated in the term SC , an indicator variable with a positive value when inventory in the period falls below consumption level. SC can be interpreted as either a stock out cost or a shopping cost. Finally, CC is the implicit cost of storing an inventory of toothpaste. Though it does not literally cost anything to store a tube of toothpaste in a bathroom cupboard, without an implicit carrying cost, the consumer would buy an unlimited amount of toothpaste when the price is perceived to be the lowest. The carrying cost can be interpreted as the opportunity cost of storing another good in the cupboard: storing toothpaste instead of, say, an extra box of tissues.

The state variables of the model are initial inventory and consumption. Initial inventory is unobservable, but with long horizon dynamic models like this one, the initial inventory is eventually quite insignificant as purchase decisions are made. Consumption is similarly difficult to observe. I work under the industry standard assumption that a tube of toothpaste lasts about 8 weeks.

In a dynamic model, consumers do not simply maximize the period's utility but look to future periods and maximize across all periods. The indirect utility function, or value function,

is the utility derived from maximization as a function of the state variables, and shows what value a consumer derives acting optimally across all periods. The value function is the sum of the consumer's utility in each period, discounted to present value.

$$V(i) = \max_a \sum_{t=1}^T \beta^{t-1} u(a, i) \quad (2)$$

This sequence problem is maximized subject to a transition equation of the state variable, inventory. Each period, the consumer buys a and consumes c , bringing her to a new inventory level, i .

$$i_{t+1} = i_t + a_t - c_t$$

Equation (2) can be directly solved on a finite horizon with recursion based on the assumption that inventory at the end of the sequence is zero, as it is inefficient to leave anything behind. Assuming the average consumer does not plan to end life with no toothpaste left in the cabinet, I work on an infinite horizon and redefine the value function to impose stationarity, meaning the decision is the same in every period that the state variables are the same. The t subscript is removed, so i' denotes next period's inventory.

$$V(i) = \max_a u(a, i) + \varepsilon_a + \beta V(i') \quad (3)$$

The consumer's value today is the utility derived from making the optimal decision " a " plus an exogenous taste shock and the discounted value of the next period's choice. The value function is the same for each period, so implies optimality across the whole horizon³. The next step is solving for the value function $V(i)$.

³ Bellman's Principle of Optimality

Solving for the value function requires a technique called value function iteration, in which the value function is based on an initial guess and loops through a simulated maximization problem to converge on the true value.

First, using the framework of Adda & Cooper (2003), I define the choice specific valuation W :

$$W_a(i) = u(a, i) + \beta E(V(i'))$$

The choice specific value function is the value received for choosing brand-quantity bundle a plus the expected value of the next period. The expected value is the inventory transition probability times the value of the new inventory level. Since the next period's inventory is a linear transformation of today's ($i' = i + a - c$), this probability is just the probability the consumer chooses action a conditional on initial inventory, so (4) can be rewritten as:

$$W_a(i) = u(a, i) + \beta \pi_a V(i') \quad (4)$$

Though the parameters of the utility function were not estimated with a multinomial logit due to the lack of consumer-level data, the same techniques can be used to calculate the choice probabilities.

$$\pi_a = \frac{e^{W_a}}{\sum_a e^{W_a}} \quad (5)$$

Finally, the value function can be defined as the expected choice specific value, plus the expected exogenous taste shock, linked to the specific choice. The exogenous taste shock is represented by Euler's constant and the sum of the log of weights: a simplification from

Aguirregabiria (2006). Essentially, Equation (7) embeds probabilities into Equation (3) to mimic maximization conditional on the draw of ϵ .

$$V(i) = \sum_a W_a(i)\pi_a + \gamma + \sum_a \ln\pi_a \quad (6)$$

With Equation (1), Equation (4), Equation (5), and Equation (6), I can use value function iteration to estimate the true value function, Equation (3). The process begins with assigning parameter values and initializing a vector of zeros to serve as V , the initial value function guess and placeholder for the true value function. Choice-specific value functions, Equation (4), can then be calculated for each $a \in A$, as $V(\cdot)$ is 0, making the absence of π_a a non-issue. With these choice-specific value functions, we can calculate a probability matrix and the first iteration of the estimated value function, Equation (6). The first iteration is stored as $V(i)$ and we go back to Equation (4) and repeat the process, using the appropriate column from the choice-specific value function matrix and the probability matrix for each inventory. The process is repeated until two value function outputs are close enough together.

4.2 Generalized Method of Moments

The initial parameters of the utility function, without access to consumer-level data, cannot be directly estimated through a multinomial logit. Instead, Generalized Method of Moments (GMM) is sufficient to estimate the values of the parameters.

$$\min_c ((\widehat{MarketShare} - MarketShare)^2 + (\widehat{OutsideProb} - OutsideProb)^2) \quad (7)$$

Through GMM, I minimize the sum of the squared differences between summary statistics, or moments, estimated through the model and the observed summary statistics in the market with respect to the target parameters, like the cost coefficients (SC and CC) and brand

coefficients (γ). Market share and probability of purchase are the most relevant summary statistics in the retail scanner data set.

V. Estimates

I start the estimation process by significantly paring down the market. I allow for only single and twin packs of Crest and Colgate. The model can easily be expanded to contain larger size options and more brands. The model allows inventory of 0 to 10, but can be altered to allow more inventory. Here, if the consumer's inventory exceeds 10, the consumer must dispose of the excess and receives disutility from the waste. I initially set the consumption level to one tube. This assumption sets the time horizon at about 8 weeks, which is the industry standard assumption for the time it takes to use one tube of toothpaste. The process is later repeated with greater consumption and inventory assumptions to check fidelity, but the one tube timeline results are reported below.

Without household level purchase data, I make initial guesses for the parameters to reduce the computation time searching for a minimum across 10 variables (4 brand premiums, 4 price elasticities, shopping cost, carrying cost).

The initial guess for γ , the utility received from brand selection at the moment of purchase, reflects the known market shares in terms of volume for Crest and Colgate twin and single packs. Volume share is used rather than unit or dollar share such that twin and single sales can be directly compared.

Price elasticity, α , is estimated from Lerner's Index and the markup rule using market shares and prices.

$$L = \frac{P - MC}{P} = \frac{-1}{\varepsilon}$$

Marginal cost is set at \$1.30, the average cost of producing a completed boxed product known from my time at P&G. Though I would love to say Crest has a significant edge in the production process, I assume Colgate and Crest face the same marginal cost. The least elastic option is Crest single packs, while the most elastic is the Colgate dual, though all four options are only slightly elastic with estimates around -1.6.

Table 3

Price Elasticity Estimates

	<i>No Purchase</i>	<i>Crest Single</i>	<i>Colgate Single</i>	<i>Crest Dual</i>	<i>Colgate Dual</i>
α	0	-1.56	-1.57	-1.64	-1.60

Note: The coefficients, α , used on price term in utility function are elasticities estimated from Lerner's index.

Upon running the value function iteration process with the starting estimates for brand and price coefficients, the value function converges⁴ in 40 iterations, showing the scaling of the variables is appropriate and the guesses are reasonable⁵.

I nest the value function iteration process in the GMM minimization to estimate the carrying costs, shopping costs, and more precise brand coefficients. In GMM, the true market shares are 45.3%, 22.8%, 22.2% and 9.7% for Crest single, Colgate single, Crest multi, and

⁴ Difference of <.0001 between two iterations.

⁵ As learned from experience, if the initial guesses are not close enough, the value function does not converge

Colgate multipacks respectively as pulled from the Nielsen dataset. The “true” probability of no purchase, *OutsideProb*, is estimated to be 20%. HomeScan data would allow for more accurate estimation of the true probability, but 80/20 is reasonable for now.

After the minimization, the brand premium coefficients continue to reflect the market share in magnitude.

Table 4

Brand Parameter Coefficients

	<i>No Purchase</i>	<i>Crest Single</i>	<i>Colgate Single</i>	<i>Crest Dual</i>	<i>Colgate Dual</i>
γ	0	104.8	44.7	88.1	0.5

Note: Brand parameter coefficients estimated through minimization GMM starting with initial guess of market shares

The shopping cost at 164, as expected, is significantly higher than carrying cost of 5.9 per unit, per period. There is no direct interpretation of the shopping and carrying cost parameters, as the parameters for price elasticity and market share are in percentage terms.

Table 5

Cost Parameter Estimates

<i>Consumption</i>	<i>Shopping Cost</i>	<i>Carrying Cost</i>
<i>1 tube (8 weeks)</i>	164	5.9

2 tubes (16 weeks)

7.68

19.66

Note: Cost parameters estimated through GMM, first with consumption set to one tube (8 weeks), and then 2 tubes (16 weeks).

I rerun the optimization problem changing consumption. The difference in magnitude of carrying and shopping cost parameter estimates decreases as level of consumption, or time horizon of the model, increases, consistent with accrual of storage cost over time but constant cost of stocking out.

With the optimized parameters, I estimate own and cross-price elasticities, presented in Table 6 below. The elasticities are the percent change in market volume share for a 1% change in the pack's price. I use volume share so multipacks and single packs can be directly compared. The "No Purchase" column shows the % change in the probability of not making a purchase for an associated 1% change in price. These estimates for the outside option elasticity are unsurprisingly inelastic because toothpaste is such a necessary good.

Table 6

Own and Cross Price Elasticities of Market Share

<i>1% Price Change</i>	<i>Crest Single</i>	<i>Colgate Single</i>	<i>Crest Dual</i>	<i>Colgate Dual</i>	<i>No Purchase</i>
<i>Crest Single</i>	-0.037%	0.035%	0.034%	0.036%	.027%
<i>Colgate Single</i>	0.035%	-0.107%	0.034%	0.036%	.027%
<i>Crest Dual</i>	0.070%	0.071%	-0.234%	0.034%	.077%

<i>Colgate Dual</i>	0.054%	0.053%	0.010%	-0.672%	.065%
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Note: percent change in market share of a product for a 1% change in the price of the product in Column 1

Crest demand is much less elastic with own price elasticities roughly one third of Colgate's. Crest single tubes are by far the least elastic with an estimate of only a -.037% share loss for a 1% increase in price, versus Colgate single's -0.107% loss.

Changes in the price of single packs cause almost exactly equal substitutions toward other options. Changes in the prices of twin packs of both Crest and Colgate cause substitution towards single packs, rather than cross-brand in multipacks. The most elastic estimation is Colgate dual packs with an own-price elasticity of -0.672%. The (relatively) large estimate, at 3 times Crest dual and 6 times Colgate single, suggests the consumers buying Colgate dual packs are heavily focused on price, whereas Crest shoppers tend to stick to their preferred brand.

Crest dual packs show the greatest increase in the probability of not purchasing and consuming from inventory. This prediction makes sense with the extreme brand loyalty observed in the market: consumers will not commit to multiple tubes of their least preferred brand, rather, they buy single packs or consume from storage.

Though the changes in market shares are small, at around only 1%, when scaled to all types of toothpaste offered by Crest and Colgate in multipacks, and in markets beyond just Raleigh-Durham, the changes in prices yield millions of dollars in lost sales. For example, a 1% change in the price of a Crest single tube, or an increase of about 3 cents, leads to \$40,000 of lost

sales in the Raleigh-Durham market for whitening toothpaste only. Scaled to the US market for all toothpaste, the loss grows to over \$13 million.

5.2 Predictions

Now equipped with a model specified to current market conditions, I return to the original question and purpose of creating the model: understanding dynamics between pack size, demand, and pricing.

Differing shopping costs suggest possible pricing schemes, like Second Degree Price Discrimination, to increase profits. Under Second Degree Price Discrimination, the producer knows two different types of consumers exist with different demand curves but does not know who is who. The producer sets prices such that consumers self-select into the appropriate group.

In the market for toothpaste, it is possible consumers with high shopping costs (SC) and low shopping costs, as well as high and low carrying costs, constitute different types of consumers. Producers can treat pack size as a menu of size offerings, like typical Second Degree Price Discrimination examples of movie theater popcorn and high and low coverage car insurance. Generally, the smallest option is “too small” to discourage cross purchasing and preserve profits. Prices are set to ensure both types of consumers purchase a good and self-select into the appropriate group.

Using the model and parameters estimated through the Value Function Iteration and Generalized Method of Moments processes outlined above, I test higher and lower shopping and carrying costs to first observe changes in market share.

Higher shopping costs shift market share from single packs to multipacks and increase the probability of making a purchase. Customers are more likely to buy something, but the increased demand is entirely directed to multipacks. The market share of Crest multipacks grows more quickly with increases in shopping costs than does the share of Colgate multipacks.

At low levels of shopping costs, the market is more heavily weighted toward single packs and is very insensitive to small changes in shopping cost.

Carrying costs have the inverse relationship of shopping costs. High carry costs push consumers toward single packs, while low carry costs have little to no impact on the sales break down. High carry costs increase the probability not of making a purchase and instead reducing inventory.

Increased shopping and carrying costs change the optimal inventory. At the base level, the model predicts an optimal inventory of 4 tubes in storage. Increasing shopping costs by 50% shifts the optimal inventory to 5 tubes. Decreasing shopping costs by 50% or increasing carrying costs by 50% drop the optimal inventory to 3 tubes, while a drop in carrying costs have no impact on the optimal level of inventory. Market shares reflect the purchases needed to get to the optimal inventory from all possible starting inventories.

After confirming costs alter market shares as expected, I calculate new price elasticities. Though there are many other possible relationships to test, I choose to look at the impact of changing the prices of both Crest and Colgate multipacks at different levels of shopping and carrying costs.

Low shopping and carrying cost consumers have more elastic demand for multipacks. Interestingly, low cost consumers' elasticity is greater for Crest multipacks than Colgate multipacks, suggesting they are perhaps just in search of the best deal.

The most significant finding from this exercise in increasing the cost of both Crest and Colgate multipacks is the difference in "No Purchase" probability increase between low shopping cost and high shopping cost consumers. Low shopping cost consumers are relatively unaffected by increases in the cost of multipacks: the increase in consumers not purchasing in a period is countered by an equal increase in consumers switching to single packs.

Table 7

Own and Cross-Price elasticities for Multipacks at different cost levels

	<i>Crest Single</i>	<i>Colgate Single</i>	<i>Crest Multi</i>	<i>Colgate Multi</i>	<i>No Purchase</i>
<i>Base</i>	.05	.04	-.08	0	.12
<i>High SC</i>	.05	.05	-.11	-.08	.14
<i>Low SC</i>	.05	.04	-.13	-.10	.05
<i>High CC</i>	.04	.04	-.09	-.11	.05
<i>Low CC</i>	.07	.04	-.12	-.09	.06

Note: % change in market share for a 1% increase in Crest Multipack price at high and low Shopping and Carrying cost levels

These elasticities present a promising opportunity to regain margin through pricing changes by considering high and low cost shoppers independently. Again, there are many

possible ways to test the impacts of the differing elasticities. Because of my interest in helping Procter & Gamble, I test the effect of raising Crest multipack price 1% in a market with high and low shopping cost consumers and report the elasticities in Table 6.

Table 8

Crest Own and Cross-Price Elasticities

	<i>Crest Single</i>	<i>Colgate Single</i>	<i>Crest Multi</i>	<i>Colgate Multi</i>	<i>No Purchase Prob</i>
<i>High Shopping Cost</i>	0.03%	0.05%	-0.11%	0.00%	0.07%
<i>Low Shopping Cost</i>	0.02%	0.00%	-0.13%	0.00%	0.05%

Note: own and cross-price elasticities for a 1% change in the price of Crest multipacks at high and low shopping costs. High shopping costs are 2X the model-predicted market cost, and low shopping costs are ½ the total market shopping cost.

In terms of revenue, the shift to single packs and increase in price of multipacks outweighs the loss of low cost multipack purchasers and those who choose to consume from storage. A 1% increase in price of Crest dual packs increases Crest revenues by 0.5%, or \$58,000 while only increasing Colgate sales \$1,400, assuming the market is 80% high shopping cost consumers and 20% low shopping cost consumers as the model predicts. While this gain is small relative to the \$7 million Raleigh-Durham market considered, when scaled to the US market for toothpaste, the increase in sales nears \$25 million for a 1%, or 7, cent increase in price. This same exercise can be repeated with differing levels of shopping and carrying costs and different product's prices changing. The output is a new way of looking at price impacts on toothpaste demand, as the presence of different elasticities for high and low carrying and

shopping cost consumers suggests the possibility of new markup rules for single and multipacks by treating high and low cost consumers as different markets.

5.3 Possible Extensions

The model can easily be extended to a broader time horizon by increasing the number of possible inventory levels and consumption level. The number of purchase options can be increased to account for packs of 3, 4, 5, and 6, as well as to include more brands, like Sensodyne and Arm&Hammer. The utility function can be expanded to include other factors, such as promotional activity, as in Hendel & Nevo (2003), price pattern expectations as in Erdem, Imai, & Keane (2003), and a factor for toothpaste benefit, like whitening, health, base, and sensitive.

If HomeScan data was to become available, the estimation of parameters could be done directly through a multinomial logit regression rather than Generalized Method of Moments as in Equation (8). HomeScan data would allow for better estimation of frequency of purchases and consumption levels as well.

VI. Conclusion

Toothpaste multipacks sales have grown year over year in the US market. Bulk packaging, multipacks included, require quantity discounts to incentivize consumers. While this is a great deal for consumers, producers lose profits with every sale of a multipack instead of a single pack.

In this paper, I explore the dynamics of the market for toothpaste through a model of consumer demand. Consumers face shopping and carrying costs in choosing how much

toothpaste to buy and how much to store. Using summary statistics for the Raleigh-Durham toothpaste market, I estimate the parameters for brand and costs factored in the consumer's purchase decision. I then estimate the own and cross-price elasticities for Crest and Colgate single and dual packs. By altering the shopping and carry cost weights, we find high shopping and carrying costs lead to greater price elasticities of demand, and increased probabilities of consuming from storage. The different elasticities of demand suggest second degree price discrimination is possible through pack size. I suggest a possible pricing scheme to grow profit margins in the multipack market.

The work in this model can be expanded to include more product options, longer time horizons, and other decision-making factors. Access to Nielsen HomeScan data would provide better parameter estimates and summary statistics, like the true frequency of purchase.

During my time at Procter & Gamble, I saw pricing based largely off of fixed markup rules. This model presents evidence of differing consumer elasticities, that suggests different markups for single and multipacks could generate more profit when treating high and low cost consumers as separate markets. Finally, the work of this paper adds to a breadth of literature on pricing and quantity discounts by examining pack size as a tool for non-competitive pricing.

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