

The Impact of Horizontal Merger Between Manufacturers on Channel Pricing Behaviors*

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Abstract

This paper studies the impact of a horizontal merger between two manufacturers on channel pricing behaviors. We utilize the new empirical industrial organization approach in which demand and supply side behaviors are derived from economic theories. We apply our model to a market data set obtained from the toilette paper category in which a major merger between Kimberly Clark and Scott happened. We find the impact of the merger on retailer-manufacturer interaction is heterogeneous across manufacturers. The merged manufacturer turns out to become tougher in its pricing. However, we do not find any evidence that the merge makes other manufacturers tougher.

Keywords: pricing, channel interaction, horizontal merger, new empirical industrial organization

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INTRODUCTION

Quite often, we hear on the news that a retailer has asked its manufacturers to reduce the wholesale prices of their products. While small manufacturers are forced to accept the retailer's demand, some big manufacturers have the power to refuse the retailer's unfair request. Sometimes in the extreme case, manufacturers decide to stop supplying their products to the retailer who asks for unacceptably low prices. This is especially the case with the consumer goods market. This might be because of a relatively low level of differentiation and fierce competition among manufacturers. The power game between giant manufacturers and mega-retailers has been one of great interest to both marketing researchers and marketing managers. As retailers become bigger, they have begun to exert influence on the manufacturers who have taken the leadership stemming from their high market shares. Moreover, retailers have attempted to obtain a dominant position by introducing private labels, which fight against national brands with lower prices. Manufacturers have responded through aggressive promotions and new product introduction to defend their profits. For the last few decades, both sides have tried to take the leadership in channel interaction like this. It seems that they have maintained a narrow equilibrium, so the marginal changes in market structure are likely to affect the power balance between manufacturers and retailers. In this sense, the changes in market structure are worthy of investigation to understand the nature of vertical relationship. This study tries to uncover the nature of channel interactions in terms of the pricing behavior of retailer and manufacturer before and after an event that seems to have a considerable impact on competitive nature in the market such as a merger and a new brand entry.

On July 15, 1995, a merger between the Kimberly-Clark Corporation and the Scott Paper Company was announced. Kimberly-Clark was one of the largest consumer products companies in the U.S, whose product portfolio includes facial tissue, toilet tissue, and diapers. Scott was also one of the leading manufacturers of tissue products, such as toilet tissue, paper towels, and paper napkins. As a result of the merger, a new giant tissue company was born. This company seemed to hold equal power in the market with

the other major player, Procter & Gamble (P&G). At the time of the merger, the combined company had approximately half of the facial tissue market and one quarter of the toilet tissue market (All the figures—market share and market size—come from the article of July 18, 1995 “Scott’s Dunlap: no paper tiger” in *The Free Lance-Star*). Among paper product industries, the toilet paper market was the biggest market in the U.S., amounting to \$2.96 billion sales in 1994. Kimberly had the second highest market share in the toilet tissue market as a result of the merger. Therefore, it is expected that some changes among market participants, both large and small, occurred. For example, Kimberly might behave more aggressively by utilizing more plentiful resources than before, or they might act collusively with other major players. In addition to a change in the relationship among the manufacturers of toilet tissue, Kimberly’s stance on their relationship with retailers is also likely to change after the merger.

Such an event provides an ideal opportunity to study the impact of a merger on strategic interactions among channel members. This study examines the pricing behaviors of both the retailer and manufacturer in the toilet tissue market, using the new empirical industrial organization (NEIO) framework. We compare the pricing behaviors in the pre-merger market with those in the post-merger market to test alternative scenarios. The merger could make the competition between manufactures more intense, which would lead them to behave more cooperatively with retailers. They could lower their wholesale prices, enduring the decline of their margins. Otherwise, the decrease in the number of manufacturers would allow manufactures to have more power against retailers than they had before the merger. The merger could have a different impact on each manufacturer.

This study shows that channel members interact with one another and changes in market structure have an impact on which party seizes the market pricing initiative. We find that the merged manufacturer price more competitively for its brand after the merger. Many studies have examined the interactions between channel members and the effects of the merger and our study can also contribute to the literature by adding knowledges on the impact of a manufacturer level merger on the relationship among vertical channel members.

The rest of this paper is organized as follows. In section 2, we discuss the related literature. In the third section, we present our

model followed by the description of the estimation strategy in section 4. In section 5, we introduce the data. Section 6 presents the results of the study and section 7 concludes the paper.

REVIEW OF LITERATURE

We investigate the changes in the pricing behaviors of one common retailer and manufacturers within NEIO framework. The NEIO framework allow us to evaluate the impact of a firm's strategic marketing decisions on other market participants' strategic decisions as well as on consumer demands (Kadiyali et al. 2001). A large amount of theoretical research has been conducted to study specific industries rather than using cross-sectional data across industries. These theoretical works reveal that market outcomes are affected by industry and firm-specific demand and cost characteristics that are difficult to model in the cross-sectional analysis (Kadiyali et al. 2001). As a result, researchers have focused on studying specific industries. The NEIO literature incorporates more industry- and firm-specific details in modeling demand, cost, and competition, to capture the possible heterogeneity across industries (Kadiyali et al. 2001). Another distinct characteristic of NEIO is to use structural econometric models. According to Chintagunta et al. (2006), the structural models rely on economic and/or marketing theories of consumer or firm behavior to derive the econometric specification that can be taken to data. In particular, structural models are typically derived based on optimizing behavior of agents such as utility maximizing behaviors by consumers and profit maximizing behaviors by firms.

Choi (1991) is among the first researchers who investigate the price competition in a market with a common retailer. His theoretical model considers three noncooperative games with different power structures—vertical Nash, manufacturer Stackelberg, and retailer Stackelberg. He assumes that competition between manufacturers is Bertrand Nash. Utilizing Choi's framework Besanko et al. (1998) empirically study the pricing behaviors of retailers and manufacturers. They use the vertical Nash model among the three scenarios of Choi to describe the noncooperative interactions between oligopolistic manufacturers and the common retailer. Their work reveals the importance of incorporating endogeneity in price

to make unbiased inferences on demand. Sudhir (2001) studies manufacturers' pricing behaviors in the presence of a strategic retailer. He assumed two scenarios—vertical Nash and manufacturer Stackelberg. His model is applied to the market data obtained from the yogurt and the peanut butter categories. He finds manufacturer Stackelberg game best fits the data, and the manufacturer pricing is tacitly collusive. The categories he studies are highly concentrated, so a cooperative outcome can be achieved in noncooperative game because it is easy to punish the firm that deviates from cooperative behavior. Villas-Boas (2007) investigates the vertical relationship between manufacturer and retailer. She assumes seven different scenarios, including manufacturer-Stackelberg, manufacturer collusion, and retailer collusion. She finds that the models assuming zero wholesale margin, in which retailers make pricing decisions, are supported by data and that the retail pricing may lie between Bertrand Nash and collusive retail pricing. This result is consistent with the high bargaining power of retailers that forces wholesale prices down to marginal cost.

Kadiyali et al. (2000) utilize the conduct parameter approach, extending Choi's model in three ways. First, they introduce a more general model of interactions between manufacturers instead of assuming Bertrand Nash game. Second, their model allows for heterogeneity in manufacturer-retailer interaction while Choi implicitly assumes that all manufacturers follow the same game rule. For instance, depending on the channel power and pricing strategies, some manufacturers might be Stackelberg leaders whereas other manufacturers are Stackelberg followers. Finally, they utilize the conduct parameter approach. Stackelberg games are not nested in the conduct parameter model, whereas Nash is nested in the conduct parameter model. They apply their model to market data on refrigerated juice and tuna and find that the retailer had pricing power. Chintagunta et al. (2002) investigate the effects of store brand introduction on retailer demand and pricing behavior. They examine whether manufacturer-retailer interaction changes after the introduction of a store brand by estimating demand and pricing equations twice—before and after store-brand entry. They find that the national-brand manufacturers appear to behave in a more accommodating manner after the introduction of store-brand.

There is extensive literature on the topic of horizontal mergers in the field of economics. While many studies focus on antitrust

issues resulting from mergers, some studies investigate horizontal mergers from different points of view. For example, Salant et al. (1983) study losses from horizontal mergers, assuming a Cournot equilibrium. They argue that there is the possibility that mergers reduce the joint profits of the merging parties because merging firms contract their output while other firms in the market expand. Perry and Porter (1985) discuss the incentives for horizontal merger in an oligopolistic industry. They claim that since new firms have access to the combined resources of both firms, mergers can be profitable in many circumstances. There are studies analyzing Kimberly-Scott merger case. The study of Hausman and Leonard (1997) is one of them. Like typical papers focusing on antitrust issues, they also focus on the effect of the merger on price level. They investigate whether unilateral effects arise after merger. Unilateral effects arise when the products of the merging parties place significant competitive constraints on each other prior to the merger. The merged firm may then be able to raise prices post-merger. They conclude that no unilateral effects arose after Kimberly bought Scott, which means that there was no price increase after the merger.

THE MODEL

This paper investigate pricing behaviors of channel members before and after horizontal mergers between manufacturers. We estimate the parameters of demand equation first, and then use these parameters to recover price-cost margin from pricing equation under the different scenarios. We use the same set of scenarios as in Choi (1991)—vertical Nash, manufacturer Stackelberg, and retailer Stackelberg. In addition to these three scenarios, we also estimate the conduct parameter model because there is a possibility that the three discrete games are not sufficient to capture a wide enough range of possible interactions. We estimate cost coefficients and conduct parameters twice with pre-merger data and post-merger data as done in Chintagunta et al. (2002). However, when we estimate demand parameters we do not divide the data into two parts because we expect consumer behavior is unlikely to be influenced by the merger between manufacturers. This particularly makes sense because Kimberly decided to maintain the brand

“Scott,” so there was no outward change in the toilet tissue market after the merger in consumer’s point of view.

Demand Equations

The demand model used in this paper is similar to that of Chintagunta et al. (2002). We start from the specification of the utility function consumers who are possibly heterogeneous in preferences. The utility of consumer *i* from choosing brand *j* at time *t* is given as follows:

$$u_{ijt} = \alpha_{ij} + \beta_i p_{jt} + \gamma d_{jt} + \mu_{jt} + \epsilon_{ijt}, \tag{1}$$

where p_{jt} is the price of brand *j* at time *t*, d_{jt} is a dummy variable which equals one if brand *j* is sold on a promotion such as bonus buy, or price reduction at time *t*, β_i is consumer specific price sensitivity, α_{ij} is a brand-specific preference parameter, and γ is the sensitivity to the retailer’s deal activity. μ_{jt} is a mean zero demand shock. This unobserved demand shock is specific to each store, each brand, and each time period. Since it comes from factors such as changes in shelf location and other unobserved promotions than ones included in d_{jt} , μ_{jt} can be correlated with the prices. ϵ_{ijt} indicates the consumer-, brand-, and time-specific error term that is observed by consumer, but not by researchers. We also include a time dummy for every three month that can capture overall demand shock affecting all the stores. Besides error term ϵ_{ijt} , we allow for consumer heterogeneity with respect to intrinsic brand preferences and price sensitivity by introducing random coefficients for intrinsic brand preferences (α_i) and for price sensitivity (β_i). We assume that these parameters are distributed according to a multivariate normal distribution. However, we impose some restrictions on parameters of the heterogeneity distribution because unconstrained variance-covariance matrix requires the estimation of a larger number of parameters. Specifically, we impose the following structure on heterogeneity parameters to reduce the model parameters while keeping the heterogeneity structure as flexible as possible:

$$\begin{aligned} \alpha_{ij} &= \alpha_j + \rho_j \nu_{ij} \\ \beta_i &= \beta + \rho_\beta \nu_{i\beta} \\ \text{where } \nu_{ij}, \nu_{i\beta} &\sim N(0,1) \end{aligned} \tag{2}$$

In this specification, a_i is the mean value of preference of brand j , v_{ij} is a variance component that varies by both consumers and brands, β is the mean value of price sensitivity, and $v_{i\beta}$ is a variance component that varies by consumers. α_j , β , ρ_j , and ρ_β are parameters to be estimated. Consequently, the implied variance of a_{ij} is ρ_j^2 and that of β is ρ_β^2 . With this heterogeneity distribution, we estimate much less number of mean parameters and covariance parameters. One can rewrite the utility function in equation (1) in the following form:

$$u_{ijt} = \delta_{jt} + \rho_j v_{ij} + \rho_\beta v_{i\beta} + \epsilon_{ijt}. \quad (3)$$

where δ_{jt} is the utility common to all consumers and the remaining terms reflect individual taste.

Specification of the demand system is completed with the option of an "outside good." The introduction of an outside good allows for the possibility that consumers decide not to purchase any of the brands. The indirect utility for the outside good is given as follows:

$$u_{i0t} = \alpha_{i0} + \epsilon_{i0t}, \quad (4)$$

where α_{i0} is set to zero. The mean utilities of included brands can be identified and estimated relative to the mean utilities of the outside good.

In terms of the distribution of idiosyncratic error term ϵ_{ijt} and ϵ_{i0t} , we assume they are identically and independently distributed with a Type 1 extreme value distribution. Given this assumption, the probability of consumer i purchasing brand j at time t is given by the multinomial logit model:

$$P_{ijt} = \frac{\exp(V_{ijt})}{1 + \sum_{k=1}^J \exp(V_{ikt})}, \quad (5)$$

where $V_{ijt} = \alpha_{ij} + \beta_i p_{jt} + \gamma d_{jt} + \mu_{jt}$ and J is the number of brands in the category. The market level demand are obtained by aggregating the individual-level choice probabilities over all consumers in a given time t . While the homogenous logit model suffers from the well known independence of irrelevant alternatives (IIA) property, the

market level demand from our model is free from the IIA property since consumer taste parameter is modeled as heterogenous. This heterogenous logit model results in more flexible substitution patterns between brands than homogeneous logit model.

Pricing Equations

The supply side equations are derived from the pricing decisions of the retailer and the manufacturers. The retailer chooses a retail price which maximizes the retail level category profit and each manufacturer picks the profit maximizing wholesale prices of its own products. We investigate how channel members interacted with one another before the merger and after the merger respectively and apply both the menu approach and the conduct parameter approach discussed in section two. First, we examine three possible scenarios: vertical Nash, manufacturer Stackelberg, and retailer Stackelberg. Interactions between manufacturers are assumed to be Bertrand Nash.

In vertical Nash (VN) game, each manufacturer chooses its wholesale price conditional on both the retailer’s margin on its own product and the observed retail prices of the competing brands. The retailer determines the margin of each brand conditional on the respective wholesale prices (Choi 1991). Let there be one retailer and N multi-brand manufacturers competing in the market. The retailer’s profit function in time t is given by

$$\pi_t = \sum_{j=1}^J [p_{jst} - w_{jt} - c_{jst}^r] s_{jst} M_{st}, \tag{6}$$

where p_{jst} is retail price of brand j at store s at time t , w_{jt} is wholesale price of brand j , c_{jst}^r is the retailer’s marginal cost of brand j at store s at time t , s_{jst} is the market share of brand j , and M_{st} is market size of store s at time t . Since the data we use include the sales records of individual stores that cover the local market, we assume that each store determines its own retail price. Thus, we use subscript “s” for store-specific variable. The first order conditions, assuming vertical Nash equilibrium in price, are given by

$$s_{jst} + \sum_{k=1}^J [p_{kst} - w_{kt} - c_{kst}^r] \frac{\partial s_{kst}}{\partial p_{jst}} = 0 \quad \forall j \in \{1, 2, \dots, J\}. \tag{7}$$

In vector notation, the first-order conditions become

$$s - \Omega(p - w - c^r) = 0,$$

where s , p , w and c^r are $J \times 1$ vectors of market shares, retail prices, wholesale prices, and marginal costs of retailer respectively. And we define a $J \times J$ matrix Ω whose (j, k) th element is given by $\Omega_{jk} \equiv -(\partial S_{ks} / \partial P_{js})$. Rearranging this equation, we obtain a retailer's markup equation.

$$p - w - c^r = \Omega^{-1}s. \quad (8)$$

Using estimates of the demand parameters, we can compute the price-cost margin of the retailer. The marginal cost of the retailer is modeled as $c_{jst}^r = \gamma_j^r + \psi_s^r + \tau^r l_t^r + \omega_{jst}^r$ where λ_j^r is brand-specific marginal cost, ψ_s^r is store-specific marginal cost, l_t^r is labor cost of retailing at time t , τ^r is coefficient of the cost variable, and ω_{jst}^r is an error term that is the marginal cost unobserved by the researcher, but observed by the retailer.

We derive a manufacturer's markup equations in a similar manner. Each manufacturer chooses the wholesale prices that maximize its profit. There are N manufacturer level profit functions

$$\pi_{mt} = \sum_{j \in S_m} [w_{jt} - c_{jt}^m] s_{jt} M_t. \quad (9)$$

In the above equation, S_m denotes the set of products that manufacturer m owns, and c_{jt}^m denotes the manufacturer's marginal cost of brand j . Unlike the retailer, manufacturers set equal price across stores, so we drop subscript s . Market shares in manufacturer's pricing equation are ones which are weighted by store level market sizes. The first order condition for brand j is given by.

$$s_{jt} + \sum_{k \in S_m} [w_{kt} - c_{kt}^m] \frac{\partial s_{kt}}{\partial w_{jt}} = 0 \quad \forall j = \{1, 2, \dots, J\}. \quad (10)$$

In vertical Nash game, manufacturers take as given the competing brands' retail prices and the retailer's margin on its own brand, thus $\partial s_{kt} / \partial w_{jt} = \partial s_{kt} / \partial p_{jt}$. This leads to manufacturer's markup equation

as follow:

$$w - c^m = (T_m \cdot * \Omega)^{-1} s \tag{11}$$

where T_m is the manufacturer m 's ownership matrix with the element $T_m(i, j)$ being 1 when both brand i and j are produced by manufacturer m and 0 otherwise and the operator ' $*$ ' indicagtes element-by-element multiplication of two matrices. We model the manufacturer's marginal cost of brand j as $c_{jt}^m = \lambda_j^m + \tau_1^m l_t^m + \tau_2^m ppi_t^m + \omega_{jt}^m$, where λ_t^m is brand-specific marginal cost, l_t^m is labor cost of manufacturing at time t , ppi_t^m is the Producer Price Index of pulp at time t , τ_1^m and τ_2^m is coefficient of cost variables, and ω_{jt}^m is an error term that is unobservable to the researcher, but observable to the manufacturers.

The Manufacturer-Stackelberg (MS) scenario models a market in which each manufacturer chooses the wholesale price taking into account the response function of the retailer, conditional on the observed wholesale price of the competitor's product. The retailer determines the price of each product given the respective wholesale prices (Choi 1991). As for the retailer's margins in MS game, they are the same as those in VS case because the retailer's strategy is to choose the best price in response to wholesale prices set by manufacturers in MS games as well as in VN game. Manufacturers do not change their wholesale prices in response to retailer's price setting behavior. On the other hand, the manufacturers' markups change. Each manufacturer decides its wholesale price to maximize profit from all the products that it possesses, knowing that retailer behaves according to equation (7). The first-order condition of each brand is as follows:

$$\sum_s M_{st} s_{jst} + \sum_{k \in S_m} \left\{ [w_{kt} - c_{kt}^m] \sum_s M_{st} \frac{\partial s_{kst}}{\partial w_{jt}} \right\} = 0 \quad \forall j = \{1, 2, \dots, J\}. \tag{12}$$

The derivatives of the market shares of all brands with respect to all wholesale prices, $\partial s_{kts} / \partial w_{jt}$, contain the cross price elasticities of demand and the effects of cost pass-through (Villas-Boas 2007). In other words, $\partial s_{kst} / \partial w_{jt} = (\partial s_{kst} / \partial p_{lst}) (\partial p_{lst} / \partial w_{jt})$. To compute $\partial s_{kst} / \partial w_{jt}$, we need to compute $\partial p_{lst} / \partial w_{jt}$ first. The first-order conditions of retailer's maximization functions are

$$\begin{aligned}
 FOC_r &= s_{jst} + \sum_{k=1}^J [p_{kst} - w_{kst} - c_{kst}^r] \frac{\partial s_{kst}}{\partial p_{jst}} = 0 \\
 F_{JS}(p_{1s}(w_1, \dots, w_j), \dots, p_{Js}(w_1, \dots, w_j), w_1, \dots, w_j) &= 0
 \end{aligned}
 \tag{13}$$

They are a function of retail prices and wholesale prices. Thus, we can get the below equation by implicit function theorem.

$$\sum_{k=1}^J \frac{\partial F_{js}}{\partial p_{ks}} \frac{\partial p_{ks}}{\partial w_j} + \frac{\partial F_{js}}{\partial w_j} = 0 \quad \begin{cases} j = 1, 2, \dots, J \\ s = 1, 2, \dots, S \end{cases},
 \tag{14}$$

where J is the number of brands and S is the number of stores. The left-side of this equation can be rewritten as follows:

$$\begin{bmatrix} \sum_{k=1}^J \frac{\partial s_{1s}}{\partial p_{ks}} \frac{\partial p_{ks}}{\partial w_j} - \frac{\partial s_{js}}{\partial p_{1s}} + \sum_{k=1}^J \frac{\partial s_{ks}}{\partial p_{1s}} \frac{\partial p_{ks}}{\partial w_j} + \sum_{k=1}^J \left[(p_{ks} - w_k - c_{ks}^r) \sum_{l=1}^J \frac{\partial^2 s_{ks}}{\partial p_{1s} \partial p_{ls}} \frac{\partial p_{ls}}{\partial w_j} \right] \\ \vdots \\ \sum_{k=1}^J \frac{\partial s_{Js}}{\partial p_{ks}} \frac{\partial p_{ks}}{\partial w_j} - \frac{\partial s_{js}}{\partial p_{Js}} + \sum_{k=1}^J \frac{\partial s_{ks}}{\partial p_{Js}} \frac{\partial p_{ks}}{\partial w_j} + \sum_{k=1}^J \left[(p_{ks} - w_k - c_{ks}^r) \sum_{l=1}^J \frac{\partial^2 s_{ks}}{\partial p_{Js} \partial p_{ls}} \frac{\partial p_{ls}}{\partial w_j} \right] \end{bmatrix}.$$

We express the above equations as vector notation and rearrange them, and then they become

$$\frac{\partial p_{Js}}{\partial w_j} = (-\Omega_{JS} - \Omega'_{JS} + Z_{JS})^{-1} [(-\Omega')_j].
 \tag{15}$$

where

$$\begin{bmatrix} \sum_k (p_{ks} - w_k - c_{ks}^r) \frac{\partial s_{ks}^2}{\partial p_{1s} \partial p_{1s}} & \dots & \sum_k (p_{ks} - w_k - c_{ks}^r) \frac{\partial s_{ks}^2}{\partial p_{1s} \partial p_{Js}} \\ \vdots & \ddots & \vdots \\ \sum_k (p_{ks} - w_k - c_{ks}^r) \frac{\partial s_{ks}^2}{\partial p_{Js} \partial p_{1s}} & \dots & \sum_k (p_{ks} - w_k - c_{ks}^r) \frac{\partial s_{ks}^2}{\partial p_{Js} \partial p_{Js}} \end{bmatrix}$$

and $(-\Omega')_j$ is j th column of $-\Omega'$. Now define $\Omega_{ij}^m = -\left(\sum_{k=1}^J \frac{\partial s_{js}}{\partial p_{ks}} \frac{\partial p_{ks}}{\partial w_i} \right)_{ij}$.

Collecting terms and solving for the manufacturers' price-cost

margin yields

$$w - c^m = (T_m \cdot \Omega^m)^{-1} s. \tag{16}$$

In the Retailer-Stackelberg (RS) game, each manufacturer chooses its wholesale price conditional on both the retailer’s margin on its own brands and the observed retail prices of the competing brands. The retailer chooses the margin of each brand using the reaction functions of all manufacturers (Choi 1991). Contrary to MS game, the manufacturer’s markup in RS is the same as one in VN game and the retailer’s markup is different from that in VN scenario. Since $\partial s_{kt} / \partial p_{jst} = (\partial s_{kst} / \partial w_{it})(\partial w_{it} / \partial p_{jst})$, we need to compute $\partial w_{it} / \partial p_{jst}$. By differentiating the first order conditions of manufacturer with respect to retail price of brand j at store r , we obtain equation (17) using the implicit function theorem.

$$\sum_{k=1}^J \frac{\partial F_m}{\partial w_k} \frac{\partial w_k}{\partial p_{jr}} + \frac{\partial F_m}{\partial p_{jr}} = 0, \quad m = 1, \dots, M. \tag{17}$$

The derivative of the first manufacturer’s first order condition with respect to p^{jr} becomes

$$\left[\sum_{l=1}^J \sum_s M_s \frac{\partial s_{1s}}{\partial w_l} \frac{\partial w_l}{\partial p_{jr}} + M_r \frac{\partial s_{1r}}{\partial p_{jr}} + \sum_{k \in S_m} \sum_s M_s \frac{\partial s_{ks}}{\partial p_{1s}} \frac{\partial w_k}{\partial p_{jr}} \right. \\ \left. + \sum_{l=1}^J \left[\sum_{k \in S_m} (w_k - c_k^m) \sum_s M_s \frac{\partial^2 s_{ks}}{\partial p_{1s} \partial w_l} \frac{\partial w_l}{\partial p_{jr}} \right] + \sum_{k \in S_m} (w_k - c_k^m) \sum_s M_s \frac{\partial^2 s_{ks}}{\partial p_{1s} \partial p_{jr}} \right].$$

From the above equation, we obtain $\partial w_{it} / \partial p_{jst}$ and use these to solve the retailer’s margin. The retailer’s price-cost margin is given as follows:

$$p - w - c^r = (\Omega^r + H)^{-1} s \tag{18}$$

where $\Omega^r = \begin{bmatrix} M_1 \Omega_1 & 0 & \dots & 0 \\ \vdots & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ 0 & \dots & \dots & M_S \Omega_S \end{bmatrix}$ is a block diagonal matrix in which

$$\Omega_s = \begin{bmatrix} \frac{\partial s_{1s}}{\partial p_{1s}} & \frac{\partial s_{2s}}{\partial p_{1s}} & \dots & \frac{\partial s_{js}}{\partial p_{1s}} \\ \vdots & \ddots & \ddots & \vdots \\ \frac{\partial s_{js}}{\partial p_{1s}} & \dots & \dots & \frac{\partial s_{js}}{\partial p_{js}} \end{bmatrix}, \text{ and } H = \begin{bmatrix} \sum_l \frac{\partial s_{1l}}{\partial w_l} \frac{\partial w_l}{\partial p_{11}} & \dots & \sum_l \frac{\partial s_{js}}{\partial w_l} \frac{\partial w_l}{\partial p_{11}} \\ \sum_l \frac{\partial s_{1l}}{\partial w_l} \frac{\partial w_l}{\partial p_{21}} & \dots & \sum_l \frac{\partial s_{js}}{\partial w_l} \frac{\partial w_l}{\partial p_{21}} \\ \vdots & \ddots & \vdots \\ \sum_l \frac{\partial s_{1l}}{\partial w_l} \frac{\partial w_l}{\partial p_{js}} & \dots & \sum_l \frac{\partial s_{js}}{\partial w_l} \frac{\partial w_l}{\partial p_{js}} \end{bmatrix}.$$

Now let us present the conduct parameter model. Introducing a conduct parameter makes the pricing equation different. The first-order condition of retailer’s pricing equation is

$$s_{jst} + \sum_{k=1}^J [p_{kst} - w_{ks} - c_{kst}^r] \frac{\partial s_{kst}}{\partial p_{jst}} [1 + \theta(w_j, r_j)] = 0 \tag{19}$$

where $r_{jst} = j_{st} - w_{jt} - c_{jst}^r$ and $\theta(w_j, r_j) = \partial w_j / \partial r_j$. $\theta(w_j, r_j)$ is called as a “conduct parameter.” This parameter represents how manufacturers respond to the change in retailer margin. When vertical Nash is assumed, these parameters equal zero, and equation (19) becomes same with equation (7). Kadiyali et al. (2001) estimate the conduct parameters that capture the response of manufacturer in response to changes in other brands’ retail margin, $\partial w_j / \partial r_k (k \neq j)$, as well as those that capture the response of manufacturer in response to changes in retail margin of own products. However, we assume those conduct parameters to be zero for the sake of simplicity because we have six brands, which requires estimation of 36 conduct parameters. This simplification assumes that manufacturers do not react to the changes in other brands’ retailer margins. The pricing equations of manufacturers in the conduct parameter model are given as follows:

$$s_{jt} + \sum_{k \in S_m} [w_k - c_k^m] \frac{\partial s_{kt}}{\partial p_{jt}} [1 + \theta(r_j, w_j)] = 0 \tag{20}$$

where $\theta(r_j, w_j) = \partial r_j / \partial w_j$. This parameter indicates how retailer behaves in response to the change in wholesale price. We also assume that the conduct parameters which represent the reaction of retailer and manufacturers in response to changes in the other brands’ wholesale prices equal zero, $\partial p_j / \partial w_k = 0, (k \neq j)$. Therefore,

we estimate only six conduct parameters. As noted before, the conduct parameters are zero in vertical Nash scenario. For the values of θ between 0 and -1, the retailer and manufacturers make higher margins than those under VN game and for values greater than 0, the margins are below those corresponding to VN.

ESTIMATION PROCEDURE

We utilize the estimation procedures by Berry et al. (1995) and Nevo (2001) in estimating demand parameters. We follow a two-step approach utilized by Chintagunta et al. (2002) and also by Villas-Boas (2007). In the first step, we estimate the parameters of demand equation, and then using these estimated parameters, we compute margins of the retailer and the manufacturers and estimate coefficients of cost and conduct parameters as the second step. This procedure makes the estimation procedure simple because the demand equation is not needed to be re-estimated whenever different market structures are tested. More importantly demand parameters are not affected by possible misspecification in the supply side.

One important issue in parameter estimation is the consumer heterogeneity. Since we have market-level data that contain brand shares, price, and promotion activities at store-level, we do not observe individual brand choices. Our parameter estimation would involve comparison between observed market shares and predicted market shares by integrating consumer level choice probabilities using consumer heterogeneity distribution as implicit weights. We rely on the simulation method in order to aggregate consumer level probabilities. The estimation consists of the following steps:

Step 1. Pick starting values for the set of parameters $\theta_2 = \{\rho_j, \rho_\beta\}$. These parameters are labelled as nonlinear parameters as they are subject to nonlinear search in the optimization procedure to be discussed later, we distinguish these from the linear parameters.

Step 2. Make R draws from distribution of $v = \{v_{ij}, v_{i\beta}\} \sim N(0, 1)$.

Step 3. Given the values of θ_2 , numerically compute δ that equates observed brand shares to predicted shares by using the contraction mapping suggested by Berry, Levinsohn, and Pakes. (1995).

Step 4. Estimate parameters included in δ_{jt} , $\theta_1 = \{a_j, \beta, \gamma\}$. These parameters can be estimated easily by regression. However, μ_{jt} is an

error term and possibly correlated with prices, so we use two-stage least squares.

Step 5. Compute moment conditions by interacting the error term, μ_{jt} , obtained from the two-stage least squares with instrumental variables. Then the GMM estimator can be obtained by minimizing the GMM objective function as follows:

$$\hat{\theta}_{GMM} = \operatorname{argmin}(Z'\mu(\theta))'AZ\mu(\theta) \quad (21)$$

where Z is instrumental variables, and A is the weighted matrix given by $A = (Z'Z)^{-1}$. Following Chintagunta et al. (2002), we adjust the demand equation based on the information on average demographics for each store in order to allow for systematic store-level differences in brand preferences and price sensitivity. Specifically, the brand preferences and price sensitivities for consumer i at store s are given by

$$\begin{aligned} \alpha_{ijs} &= \alpha_j + X_s\phi_j + \rho_j\nu_{ij} \\ \beta_{is} &= \beta + X_s\phi_\beta + \rho_\beta\nu_{i\beta} \end{aligned} \quad (22)$$

where X_s indicates the average demographics for store s , and ϕ_j and ϕ_β represent coefficient of interactions between brand preferences and price sensitivity with store-level demographics.

Using the values of parameters estimated in the first step, we compute price-cost margins of retailer and manufacturers under three assumed market structures. The markups are easily computed with estimated market shares and the first derivatives of shares with respect to retail prices. Next, subtracting these markups from the observed retail (wholesale) prices generates marginal costs of the retailer (manufacturers), c^r (c^m). And then we estimate parameters in cost equations, λ_j^r , ψ_s^r , τ^r , λ_j^m , and τ^m with ordinary least square, assuming that the error terms in cost equations are not correlated with brand and store dummies, and other cost variables.

In terms of the estimation of conduct parameter, we employ nonlinear least squares, since the conduct parameters enter nonlinearly in the pricing equations. The estimation strategy is to minimize the sum of squares, $E(\omega'\omega)$. The logic used to obtain the estimates of the conduct parameters are similar to that applied to estimate demand parameters; linear parameters and nonlinear parameters are estimated separately. The first order condition of the

minimization problem with respect to λ_j^r , ψ_s^r , τ^r , λ_j^m and τ^m are linear in these parameters. Thus, these linear parameters can be solved as a function of the conduct parameters with ordinary least square and plugged into the rest of the first-order conditions, limiting the nonlinear search to the conduct parameters only. We use the likelihood-ratio test for nested hypothesis and Vuong (1989) test for nonnested hypothesis to infer which game fits the data best.

DATA

We used store level scanner data from a large supermarket chain, Dominick's Finer Foods. This data set is publically available at the webpages of Kilts Center at University of Chicago. The retail chain has 96 stores around Chicago, Illinois, and is one of the two largest supermarket chains in the area (Chintagunta et al. 2002). The scanner data contain weekly observations on units sales at the UPC level, retail and wholesale prices, promotion activities, and store traffic for each store. The data set also contains information on demographics of households for each store.

Of the 399 weeks of available data, we choose to use two sets of 46-week long time series data; one set is for the pre-merger estimation from 06/30/94 to 06/28/95, and the other is for post-merger from 01/04/96 to 01/01/97. Note that the merger was announced on July 15, 1995. The pre-merger sample contains the data from one year before the merger and the post-merger sample starts six months after the announcement of merger. The actual date the merger was finalized is December 12, 1995. Nevertheless, during six months after the announcement, the market had time to recover to equilibrium. All market participants such as retailers, competing firms, and consumers knew that the two companies would merge from the date of the announcement. Thus, we select the period just after the finalization of the merger contract.

The toilet tissue data have sales records from 93 stores. We include six brands from the category for analysis. However, only the data of 73 stores were available for all the brands for the entire sample period. Moreover, the store demographic data are missing for three stores among 73. Thus, we remove observations from 23 stores, and keep data from other 70 stores for analysis. There was no entry or exit of any brands during the estimation period.

We aggregated the sales data at UPC level across both size (e.g., 4 rolls and 12 rolls) and brand variant to brand level. We also make a definition on market size to compute the market share of the outside good. We assume that every customer visiting the store may potentially purchases four rolls of toilet tissue which is the average package size of toilet tissue, i.e., the market size at store s at week t (M_{st}) = store traffic at store s during week t \times average package size of toilet tissue. The brand level market share observations are obtained by dividing brand sales by the market size.

As mentioned earlier we utilize information on the market characteristics for each of the 70 stores. For each store, we utilize information on the following five variables: (a) the fraction of the population that is educated, (b) the median income, (c) the average household size, (d) the fraction of the population that is unemployed, and (e) the average driving time to the store. We choose these variables because we expect those variables are related to cross-store differences in consumer preferences as suggested by Hoch et al. (1995). We use mean-centered measures in estimation.

We need exogenous variables to estimate parameters in the demand equation to account for the possible endogeneity in prices. The instruments we use are lagged retail prices, lagged wholesale prices, current values of the producer price indices (PPI) for the toilette tissue category and the average retail prices of other stores. Lagged retail price is unlikely correlated with the current demand shock. Sudhir (2001) also used lagged retail price as an instrument. Since lagged wholesale price and PPI reflect the costs of manufacturers, they are likely to be correlated with retail price, but uncorrelated with demand shock. Variables related to the manufacturer's costs are widely used as an instrument for retail price (e.g. Chintagunta et al. 2002; Villas-Boas 2007). According to the study of Walters and MacKenzie (1998), loss leader promotion or in-store price specials in paper product categories (e.g., paper towels, toilet tissue) have no effect on store traffic. The stores are unlikely to respond to the activities of other stores because customers do not go to other stores due to the promotions. Thus, the demand shock in one specific store does not seem to affect the retail prices of the rest of the other stores. We interact those variables with brand dummies to generate brand specific instruments. In addition to these four variables, we also include all other exogenous explanatory variables as instruments.

Table 1. Descriptive Statistics

		Sales (roll)	Retail price (\$/roll)	Wholesale price (\$/roll)	Retailer margin (%)	Promotion	Share
A. Before							
Angel	Mean	413	0.250	0.201	19.60	0.551	0.004
Soft	S.D	1253	0.025	0.030		0.498	0.012
Kleenex	Mean	465	0.577	0.490	15.08	0.175	0.005
	S.D	273	0.023	0.016		0.283	0.003
Charmin	Mean	2256	0.354	0.305	13.84	0.178	0.023
	S.D	2635	0.057	0.042		0.252	0.029
Store brand	Mean	646	0.266	0.187	29.70	0.060	0.006
	S.D	585	0.034	0.018		0.153	0.005
Quilted	Mean	1788	0.303	0.255	15.84	0.172	0.018
Northern	S.D	2406	0.028	0.019		0.256	0.024
Scott	Mean	1010	0.581	0.511	12.05	0.171	0.010
	S.D	1511	0.050	0.038		0.288	0.012
B. After							
Angel	Mean	573	0.294	0.231	21.43	0.391	0.003
Soft	S.D	1376	0.028	0.020		0.474	0.014
Kleenex	Mean	1070	0.528	0.463	12.31	0.296	0.011
	S.D	1132	0.080	0.073		0.353	0.012
Charmin	Mean	1641	0.400	0.335	16.25	0.110	0.018
	S.D	1369	0.050	0.038		0.266	0.012
Store brand	Mean	503	0.365	0.296	18.90	0.153	0.005
	S.D	225	0.040	0.030		0.244	0.002
Quilted	Mean	2216	0.381	0.270	29.13	0.241	0.021
Northern	S.D	2415	0.038	0.018		0.364	0.022
Scott	Mean	710	0.645	0.548	15.04	0.210	0.007
	S.D	447	0.045	0.047		0.342	0.004

Note: Retailer margins are calculated by subtracting wholesale price from retail price and dividing by retail price. These do not take into account retailer's other costs than wholesale price such as labor cost.

In the specification of the cost function, we include hourly wages of retailing for retailer's cost function and those of manufacturing for manufacturers' cost functions. These data gathered from Current Employment Statistics (CES) surveyed by Bureau of Labor Statistics in the U.S. In addition to the hourly wages, the PPI for pulp are used as a cost variables in the cost function of manufacturer because the pulp is the main raw material for producing tissue.

Table 1 provides descriptive statistics for the data with a comparison of before and after the merger. We have some interesting observations. Although Scott is classified as an economy brand (Hausman and Leonard 1997), its unit price is the highest among the six brands. This may be attributed to Scott's package size. The package size of the other brands is normally four whereas Scott's products consist of one roll. Quantity discount practice seems to make Scott's unit price look higher than that of the other brands. Second, after the merger the retail and wholesale prices of Kleenex went down while all the other brands' retail and wholesale prices rose. In addition, Kleenex's promotion activities increased by 69% post-merger. This may imply that Kleenex marketed its products aggressively to expand its market share. Its strategies seem successful. The quantity sold grew by 130%, and the market share doubled. At the same time, after the merger the retail price for Kleenex dropped more than the decrease of the wholesale price. Scott, Kimberly's another brand, shows records opposite of Kleenex's. Not only sales but market share fell by 30%. The standard deviation of sales decreased sharply. We guess Kimberly focused on boosting the sales of Kleenex. Consequently Scott's sales dropped. However, Scott's sales stabilized because regular consumers who liked Scott continuously bought Scott's products. Finally, we evaluate the statistics for Kimberly's competitors; we observe interesting contrast between two brands, Charmin and Quilted Northern. Charmin manufactured by P&G was the pre-merger market leader while Quilted Northern produced by James River Corporation (acquired by Georgia-Pacific in 2000) was the post-merger leader. It appears that Quilted Northern acted more competitively and took a softer stance towards the retailer in response to the merger between its rivals. Quilted Northern provided the retailer with a much greater margin compared to Charmin. Moreover, the former increased promotions by 40% whereas the latter cut promotions by 38%. Another aggressive brand is a private label, Dominick's. The retailer enjoyed a much higher margin from its private label—almost 30%—than the national brands, but the margin shrank considerably after the merger. Also, the promotion for the store brand soared by 155%. It seems that the retailer marketed its store-brand aggressively at the expense of its margin.

RESULTS

Table 2 presents the parameter estimates and the standard errors for the mean effects of brand preferences, price sensitivity, and deal sensitivity. The price and deal sensitivity appear to have expected signs and are statistically significant. Some of the interaction terms are also statistically significant. Specifically, the direction of interactions between income and the store brand preference is predictable. The estimates for the interactions between income and the private label is -1.123. This means that the preference for this brand is higher in the areas with lower incomes. It makes sense that consumers with lower than average income prefer the store brand to national brands. The interaction between income and price sensitivity is also statistically significantly different from zero, and the sign of this term is positive as expected. It is a reasonable result that consumers residing in the higher-than-average are less sensitive to price.

Table 3 reports the estimates and the standard errors for the heterogeneity parameters in the demand equation. Only two estimates, brand preference for Charmin and price sensitivity, are statistically significant. The other five estimates are insignificant. This results seems to suggest that consumer preference ordering is stable. That is, the level of differentiation appears low in this market, and each brand does not seem to give a distinct value to consumers. Instead, consumers are likely to habitually purchase the same brand as one they purchased previously. This is consistent with the fact that the ranking of brands in market share was stable over the estimation period. There is, however, an exception; Kleenex ranked the third after the merger, rising from the fifth before the merger.

The rise of Kleenex's market share is attributed to the decrease in its retail price. Note that only Kleenex's average retail price declined after the merger whereas that of the other brands rose. Thus, some consumers who liked Kleenex, but did not buy it due to its high price were likely to switch to Kleenex. This idea seems to be supported by the results of the price elasticity estimates. Table 4 presents the cross-price elasticity matrix. The elasticities were computed for each store week and then averaged across store week. We compute standard errors of the elasticity estimates using a bootstrap procedure. We draw values from the estimated variance-

Table 2. Mean Preference and Response Parameter Estimates

Variable	Parameter estimate	Standard error
Angel Soft	-2.442*	0.242
Angel Soft × Fraction educated	1.113*	0.478
Angel Soft × Median income	-1.102*	0.337
Angel Soft × Family size	0.421*	0.192
Angel Soft × Fraction unemployed	-5.736*	2.251
Angel Soft × Driving time	-0.016	0.054
Kleenex	1.114*	0.225
Kleenex × Fraction educated	-0.294	0.866
Kleenex × Median income	-0.361	0.626
Kleenex × Family size	-0.026	0.352
Kleenex × Fraction unemployed	-7.066	4.156
Kleenex × Driving time	-0.049	0.091
Charmin	0.632*	0.219
Charmin × Fraction educated	0.080	0.617
Charmin × Median income	-0.022	0.465
Charmin × Family size	-0.020	0.257
Charmin × Fraction unemployed	-4.642	2.965
Charmin × Driving time	-0.039	0.063
Store brand	-0.784*	0.232
Store × Fraction educated	-0.802	0.512
Store × Median income	-1.123*	0.347
Store × Family size	0.229	0.194
Store × Fraction unemployed	-4.471	2.356
Store × Driving time	-0.032	0.053
Quilted Northern	0.116	0.141
Quilted Northern × Fraction educated	0.442	0.508
Quilted Northern × Median income	0.073	0.394
Quilted Northern × Family size	-0.030	0.229
Quilted Northern × Fraction unemployed	-4.347	2.696
Quilted Northern × Driving time	-0.039	0.054
Scott	1.412	0.735
Scott × Fraction educated	-1.542	0.997
Scott × Median income	-1.535	0.817
Scott × Family size	0.140	0.408
Scott × Fraction unemployed	-7.233	4.598
Scott × Driving time	-0.102	0.099
Price	-0.188*	0.010
Price × Fraction educated	0.008	0.016
Price × Median income	0.025*	0.012
Price × Family size	-0.006	0.007
Price × Fraction unemployed	0.157*	0.076
Price × Driving time	0.001	0.002
Promotion	0.598*	0.022

Note: Estimates of time dummies are not reported. All seven dummies are statistically significant at the 5% level of significance.

* Significant at the 5% level of significance

Table 3. Heterogeneity Parameter Estimates

Variable	Parameter estimate	Standard error
$\rho_{Angel\ Soft}$	-0.070	3.073
$\rho_{Kleenex}$	0.243	1.041
$\rho_{Charmin}$	0.804*	0.381
ρ_{Store}	-0.054	4.545
$\rho_{Quilted\ Northern}$	0.070	1.928
ρ_{Scott}	-0.928	1.279
ρ_{Price}	0.068*	0.005

* Significant at the 5% level of significance

covariance matrix of the parameter estimates and computed the implied variances of the elasticity estimates as done in Song and Chintagunta (2006). The post-merger elasticities of other brands with respect to Kleenex’s price are all statistically significant. That is, some of consumers who used to buy other brands switched to Kleenex after the merger.

Turning to the results in table 3, the statistically significant estimate for price sensitivity suggests that consumers are considerably heterogeneous in price sensitivities. While some consumers are likely to buy products without discount, others tend to purchase products when they are discounted. Some of these price-sensitive consumers probably switch to Kleenex after the merger.

In summary, consumers are not much heterogeneous in brand preferences, except for one brand. On the other hands, consumers show a high degree of heterogeneity in price sensitivity, which means that very price-sensitive consumers exist in the market. In addition, the own-elasticities of toilet tissue brands are relatively high. According to Tellis (1988), the average own-elasticity is -1.76 across categories. The elasticities of all the brands in the analysis are greater than this. Compared with the averages for detergent (-2.77) and toiletries (-1.38) that seem to have similar characteristics—commodity and storable goods—the elasticities of toilet tissue brands are still larger. With all these results—homogeneous brand preferences and large own-elasticities—taken into account, it implies that competition between manufacturers seems very intense in the toilet tissue market.

For the supply side results, we first compare the model fit to data

Table 4. Price Elasticities

		A. Before				
	Angel Soft	Kleenex	Charmin	Store	Quilted Northern	Scott
Angel Soft	-2.870*	0.022	0.025	0.027	0.027	0.021
	(0.705)	(0.032)	(0.043)	(0.047)	(0.045)	(0.033)
Kleenex	0.078*	-2.966*	0.096*	0.083*	0.095*	0.115
	(0.031)	(0.715)	(0.039)	(0.040)	(0.040)	(0.066)
Charmin	0.206*	0.209*	-2.948*	0.212*	0.223*	0.203*
	(0.067)	(0.054)	(0.398)	(0.071)	(0.060)	(0.058)
Store brand	0.053	0.050	0.053	-2.911*	0.056	0.048
	(0.066)	(0.038)	(0.050)	(0.870)	(0.058)	(0.042)
Quilted Northern	0.159*	0.153*	0.161*	0.161	-2.945*	0.148*
	(0.073)	(0.047)	(0.049)	(0.081)	(0.532)	(0.052)
Scott	0.151*	0.233*	0.184*	0.158*	0.179*	-2.921*
	(0.067)	(0.085)	(0.057)	(0.072)	(0.071)	(0.695)
		B. After				
Angel Soft	-3.142*	0.042	0.046	0.048	0.048	0.037
	(0.752)	(0.038)	(0.045)	(0.051)	(0.050)	(0.036)
Kleenex	0.170*	-3.163*	0.194*	0.198*	0.183*	0.208*
	(0.059)	(0.602)	(0.050)	(0.079)	(0.062)	(0.084)
Charmin	0.200*	0.224*	-3.217*	0.221*	0.209*	0.207*
	(0.067)	(0.055)	(0.454)	(0.076)	(0.060)	(0.062)
Store brand	0.067	0.076	0.071	-3.334*	0.070	0.070
	(0.083)	(0.057)	(0.064)	(0.955)	(0.075)	(0.057)
Quilted Northern	0.207*	0.201*	0.205*	0.216*	-3.070*	0.180*
	(0.081)	(0.050)	(0.049)	(0.091)	(0.566)	(0.056)
Scott	0.140*	0.208*	0.170*	0.173*	0.152*	-3.118*
	(0.069)	(0.082)	(0.066)	(0.082)	(0.071)	(0.778)

Note: Effect of row prices on column shares. Numbers in parentheses are standard errors.

* Significant at the 5% level of significance

for the four different pricing equations, and then discuss the results from the best-fitting model. Table 5 summarizes the minimized sum of squared errors for each model and test statistics. It appears that the model incorporating conduct parameters fits the data best, when the smallest sums of squared errors are taken into account. The test statistics also supports the model as the best-fitting game. That is, all the three discrete games—vertical Nash, manufacturer-Stackelberg, and retailer-Stackelberg—are rejected in favor of the

Table 5. Model Fit Statistics

Model	Before		After	
	Sum of squared errors	Test statistic	Sum of squared errors	Test statistic
A. Retailer				
Vertical Nash	814,594,900	165,611*	1,387,207,300	173,173*
Manufacturer Stackelberg	814,594,900	595.69	1,387,207,300	622.90
Retailer Stackelberg	234,119,580	509.04	210,447,940	491.84
Conduct parameter	154,232	-	177,574	-
B. Manufacturer				
Vertical Nash	1,677.11	41,697.50*	2,122.31	44,456.68**
Manufacturer Stackelberg	36,415,476,000	10,979.40	35,133,876,000	10,904.72
Retailer Stackelberg	1,677.11	1,156.49	2,122.31	1,239.53
Conduct parameter	1390.01	-	1,524.90	-

Note: The three discrete games are tested against the conduct parameter model.

* χ^2 (6 degrees of freedom) critical value = 12.59

** χ^2 (8 degrees of freedom) critical value = 15.51

conduct parameter specification. Following Kadiyali et al. (2000), we infer the best-fitting game based on the likelihood-ratio test for nested hypothesis and Vuong (1989) test for nonnested hypothesis. The Vuong test statistic is as follows:

$$V = \frac{1}{\sqrt{n}} \left\{ \ln \left(\frac{f}{g} \right) - (p - q) \right\},$$

where n is the number of observation, f and g are likelihood values of two nonnested models, and p and q are the number of parameters in each model, respectively. V follows the standard normal distribution. If V is greater than the pre-determined critical value, then the model corresponding to g is rejected in favor of the

Table 6. Conduct Parameters

	Before		After	
	Parameter estimate	Standard error	Parameter estimate	Standard error
Conduct parameters				
$\theta_1(w_{as}, r_{as})$	2.230*	0.361	1.441*	0.348
$\theta_2(w_{kl}, r_{kl})$	198.308*	0.248	22.486*	0.200
$\theta_3(w_{ch}, r_{ch})$	43.573*	0.444	269.114*	0.381
$\theta_4(w_{sb}, r_{sb})$	-	-	-	-
$\theta_5(w_{qn}, r_{qn})$	45.205*	0.383	2.208*	0.404
$\theta_6(w_{sc}, r_{sc})$	455.363*	0.102	58.421*	0.170
$\theta_7(w_{as}, r_{as})$	-0.151	0.136	1.056*	0.118
$\theta_8(w_{kl}, r_{kl})$	12.324*	0.144	-0.456*	0.129
$\theta_9(w_{ch}, r_{ch})$	-0.561*	0.119	-0.697*	0.138
$\theta_{10}(w_{sb}, r_{sb})$	-	-	-	-
$\theta_{11}(w_{qn}, r_{qn})$	0.088	0.175	-0.133	0.111
$\theta_{12}(w_{sc}, r_{sc})$	0.323	0.177	-0.088	0.133

Note: as-Angel Soft, kl-Kleenex, ch-Charmin, sb-Store brand, qn-Quilted Northern, sc-Scott.

* Significant at the 5% level of significance

model corresponding to f . The values of V for two nonnested games, manufacturer-Stackelberg and retailer-Stackelberg, are larger than the critical value of the 5% significance level (1.64). Thus, the conduct parameter specification describes the pricing behavior of the channel members best.

Table 6 reports the estimation results from the supply side model. We assume the pricing decision for store brands are non-strategic in the sense that the retailer has the sole control on the pricing of the brand. So we assume that the conduct parameters related to store brands are zero. As presented in the table, many conduct parameters are estimated to be statistically significant, implying that the pricing setting in the category is not well explained by the vertical Nash game. Recall that the vertical Nash game is nested in the conduct parameter model: when θ equals zero, the game is vertical Nash. The conduct parameters in the retailer's pricing equation are all positive, indicating that the retailer behaves in a more accommodating manner than in a vertical Nash game. However, some conduct parameters in the manufacturers' pricing equations are estimated to be negative, indicating that those

manufacturers may set their prices more aggressively than in a vertical Nash game.

Probably the most important observation we want to make from the table is the change in the estimated conducts with the merger. For the retailer side, there is no sign reversal with the merger. All conducts are positive before and after merger. We do have a few sign reversal cases for the manufacturers. First, Kleenex's conduct, θ_8 , is positive before the merger but becomes negative after the merger. That is, Kimberly-Clark set Kleenex prices in an accommodating manner before the merger but starts to price more aggressively after the merger. It turns out that the merger is related to a larger pricing power for Kimberly-Clark. We have a similar observation for Scott brand. The conduct for Scott, θ_{12} , shows a similar change pattern as Kleenex. Combined together, we can conclude that the merger between Kleenex and Scott brings more pricing power toward the merged manufacturer. Note that we do not observe such a dramatic sign reversal for other brands than Kleenex and Scott. As for this particular category, the possible increase in pricing power for the manufacturers seems to be limited to the merged manufacturers only. Instead, Angel Soft appears to become softer after the merger as indicated by the change in its conduct parameter θ_7 .

CONCLUSION

This paper empirically studies the channel interactions before and after a horizontal merger between manufacturers. We apply the random coefficient logit model to specify the demand. Employing the notion of equilibrium, we also specify the pricing behavior of both retailer and manufacturer. We test three discrete games—vertical Nash, manufacturer Stackelberg, and retailer Stackelberg. In addition to testing these scenarios, we also estimate a conduct parameter model. The model selection test supports the conduct parameter model.

The results from the conduct parameter estimates show that the competitive landscape for the wholesale market of toilet tissue has changed as a result of the merger between Kimberly and Scott. We find that the interaction between channel members is not fixed and can change depending on the market structure. Consistent with our intuition, the merged manufacturer in this category takes a

tougher stance toward the retailer with the merger. This implies that a horizontal merger between influential manufacturers could be a threat to a retailer.

There are some limitations to our research. First, we do not consider interactions between manufacturers. The assumption of Bertrand Nash between manufacturers might not be realistic as reported Sudhir (2001) and Kadiyali et al. (2000). Actually, some big manufacturers in the paper industry have been accused of raising and fixing prices in the commercial markets (Telegraph Herald 1997), and the Justice Department investigated possible anti-competitive practices among paper companies (New York Times 1994). Although the suspicion was limited in the commercial market, there is a possibility that toilet tissue companies collusively set price in the consumer market as well.

Second, because of the multi-market contact nature, studying several categories might be required to reveal the nature of retailer-manufacturer interaction more completely. Big consumer goods manufacturers commonly interact with the retailer in multiple categories. Generally, many consumer goods companies are in rivalry in various markets. For example, Kimberly competes against P&G in markets other than toilet tissue such as facial tissue and paper towel. They might keep an eye on the other party's behavior, and consider other competing markets when they develop a strategy for one market, resulting in multi-market contact behaviors. Thus, the fact that they supply products to several categories might affect the relationship with retailer. Manufacturers might endure losses in one category for gains in other categories. In this sense, this research can be extended to analyzing several categories at the same time.

In summary, our study measures how a horizontal merger between manufacturers change the pricing behavior of retailer and manufacturers. This study seems to generate reasonable results that help marketing managers better understand the nature of the interactions between channel members.

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