Channel Coordination and Manufacturer Competition:

Evidences from Management Change in a Retailing Store

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Abstract

This study examines the effect of a retailing management change on retail price and sales in a large Chinese department store, results of which will provide insights to channel coordination and manufacturer competition issues. The department store in our data switched one of its product categories from retailer-managed to manufacturer-managed retail system. We find that this change causes the retail price to decrease; the impact is significantly stronger for brands with smaller market share, more elastic demand, and larger demand fluctuations. These results imply the improvement of channel coordination but on the other hand also the intensification of price competition among manufacturers under the manufacturer-managed system. Retail sales increase due to the price change; in addition, the management change causes the sales to increase by a further 14 percent, perhaps implying an increase of the investment in selling effort from manufacturers. These results are consistent with the hypotheses we develop mainly based on a simple game-theoretic model.

1. INTRODUCTION

Consider a retailing store that sells multiple brands of a product produced by different manufacturers. Who should make the decisions about the retail price of each brand, and how many units to stock? Traditionally, the retailer makes both of the decisions. More specifically, manufacturers establish wholesale prices for individual brands. The retailing store orders with the manufacturer who fulfills these orders. After that, the store decides the retail prices of all the brands it has, and sells them to consumers. This retailer-managed retail system (RMR) may be justified with the argument that the retailer typically has better information about consumer demand and can manage the product category better because of its managerial expertise at the retailing level. Moreover, selling through an intermediary retailer may reduce the extent of manufacturer competition, and thus, is preferable to manufacturers whose products are highly competitive (McGuire and Staelin 1983). However, this system suffers from well-known problems such as double marginalization (Spengler 1950) and information distortion (Lee et al. 1997).

More recently, the manufacturer-managed retail (MMR) system has become popular in some retailing environments. For example, MMR is currently widely being used in China and Japan, especially in department stores where retailers have more bargaining power. A recent survey from 30 upscale department stores across major Chinese cities reveals that about 80% of categories sold in the stores are managed using MMR, and that this percentage has been increasing (Wu 2005). In an MMR system, the manufacturer is responsible for the retail price and the management of retailer inventory. Manufacturers are even required to have a sales staff inside the store. The store's revenue comes from a pre-set percentage revenue sharing contract.

MMR is part a retailing industry trend that encourages channel coordination and reduces the information distortion problem, which could benefit both the retailer and the manufacturer. Operations literature shows that MMR reduces the "bullwhip" effect (Lee et al. 1997) to the manufacturer, and that the primary beneficiary is the manufacturer, especially manufacturers with high demand variability. In addition, it is quite likely that manufacturers incur a smaller inventory holding cost than the retailer. If the manufacturers' inventory holding cost is sufficiently low, then the manufacturer and the channel as a whole would be better off under MMR than under RMR.

However, most of the conclusions in the current literature are drawn using a simple channel structure in which a manufacturer sells one product through one retailer. Competition is not considered. We contend that competition between manufacturers of competing brands may play a critical role when analyzing different types of retail management systems. In particular, under the manufacturer-managed retail system, there may be more price competition between competing brands, because manufacturers compete face-to-face inside the store without an intermediary. In this scenario, the retailer does not control retail price and the ensuring price competition between manufacturers may hurt the manufacturer at the end. Our study will investigate this issue. The central question of our study is: Does the manufacturer-managed retail system increase competition between manufacturers of competing brands, compared to the retailer-managed retail system? By addressing this issue, we intend to provide a better understanding of differences of competition behaviors and their impacts on sales under different retail management regimes.

To examine the issue at hand, we make use of a special dataset in a large Chinese department store for a single product category. All brands in this category were first sold under the store-managed retail system, and then were switched to the manufacturer-managed retail system *simultaneously*. This policy change provides us a context for empirically evaluating the effect on brand competition from the retail management change. Our empirical study finds both statistically and economically significant increases in brand competition as a result of this change.

We begin by developing a simple game-theoretic framework that takes into account the channel coordination and manufacturer competition issues discussed above. The framework is used to help us generate hypotheses for predicted changes in competition. After that, we conduct an empirical analysis to test whether the observational changes in our data are consistent with our hypotheses. In the empirical analysis, we first show that after switching to MMR, the overall retail price across all brands decreases by 10.7% on average, which causes sales to increase by 11.9% on average. These results provide strong empirical evidence that the manufacturer-managed retail system intensifies price competition between competing brands. However, the retail price may decrease because brand competition does in fact become more intense, or alternatively, because of inventory cost savings. The switch from RMR to MMR shifts the responsibility of retail inventory management from the store to manufacturers. Benefitting from centrally managed inventory in a market, manufacturers often incur a smaller inventory holding cost than retailers. As a result, manufacturers may reduce the retail price to consumers. To isolate this concern, we separately examine the effects on major brands and minor brands from the management change. If inventory cost saving is the main factor that causes the decline in retail prices, we would expect that price cuts for major brands are more significant than those for minor brands. This is because that major brands usually benefit more from the centrally managed inventory after the management change. However, our empirical estimation shows the opposite result: after the switch, the price decrease of minor brands is significantly larger than that of major brands. This implies that the management change does indeed cause more intense price competition. To further investigate the effect of the management change on brand competition, we also separately examine its effects on brands with different price elasticities. Our empirical results reveal that MMR intensifies the competition, especially between brands which are highly competitive. Under the retailer-managed retail system, this competition is mitigated by the presence of the channel intermediary, i.e., the store. MMR restores the competition between these highly competitive brands. This finding is consistent with, and lends support to the contention in the previous marketing literature that competing manufacturers prefer to sell through an intermediary if their products are highly competitive (McGuire and Staelin 1983).

In addition, we examine if the effects of the management change differ on brands according to demand uncertainty. Previous operations research shows that brands with higher demand variability benefit more from MMR. This is because compared to RMR, MMR reduces the “bullwhip” effect of brands with higher demand variability the most. Our results show, however, that brands with higher demand uncertainty also suffer from more intense price competition under MMR. This result demonstrates that there is a trade-off between costs and benefits under the different retail management systems.

To summarize, our findings reveal that (1) the switch from retailer-managed retail to manufacturer-managed retail significantly intensifies the brand competition between competing brands; (2) the impact on brands from the management change are heterogeneous; and (3) there is a trade-off for the competing brands between the benefits (better channel coordination and information sharing, lower inventory holding costs) and the costs (more intense brand competition) under the manufacturer-managed retail system. These findings provide a better understanding of the differences in competitive behaviors and their impacts on sales under different types of retail management, which should interest practitioners and researchers in marketing and operation alike.

The rest of the paper is organized as follows. In Section 2, we discuss related literature. A general description of our data, and its major feature -- a policy change in management, are summarized in Section 3, with an emphasis on describing sources of exogenous variation we rely on in our analysis. We describe and discuss our game-theoretic model in Section 4. In Section 5 we present our empirical analysis, as well as the estimation results. We conclude with a discussion of implications for researchers and managers in Section 6.

2. LITERATURE REVIEW

Our study is mainly related to two streams of research: channel selection, competition and coordination in marketing and inventory management in operations.

In marketing research, the channel selection decision of a manufacturer includes problems such as whether to vertically integrate retail activities or to use independent retailers and, in the latter case, whether to use exclusive franchised dealers or to use common retail stores that also sell competing brands. These marketing intermediaries are traditionally thought of as necessities primarily for the roles they play in relieving a manufacturer's financial burden, distributing products efficiently, and selling product assortments (Kotler 1988).

Different objectives of channel members, however, create conflicts within a channel. As a result, its members often fail to reach Pareto-optimal pricing decisions. This double marginalization problem was recognized a long time ago (Spengler 1950). Since then, numerous studies have focused on vertical coordination among channel members through such measures as various transfer pricing schemes or formal agreements (Zusman and Etgar 1981; McGuire and Staelin 1983, 1986; Jeuland and Shugan 1983, 1988a; Moorthy 1987), implicit understanding (Shugan 1985), and formation of conjectures (Jeuland and Shugan 1988b) to achieve maximum channel profit. Most of these studies have considered only one manufacturer (monopoly) and its channel intermediaries, and the analysis of competition and cooperation is confined to members in the same channel.

McGuire and Staelin (1983) show that when multiple manufacturers are considered, the price competition between the differentiated brands from different manufacturers plays a critical role in determining the channel structure. Specifically, they analyze a duopoly case, and show that for low degrees of product substitutability, a market with both manufacturers vertically integrated is shown to be a stable equilibrium channel structure, though it does not necessarily yield the highest profits. When the products are highly competitive, however, the intermediaries are found to be working as a buffer against intense price competition between producers, and therefore, are preferable by the manufacturers. Moorthy (1988) derives more general conditions for decentralization to be a Nash equilibrium; i.e., the manufacturers' products are either (1) demand substitutes and strategic complements (When products are strategic complements in price, a price increase of a firm leads to a price increase of the other. See Tirole (1988, pp. 207-208) for detail) at the manufacturer or retailer level, or (2) demand complements and strategic substitutes at the manufacturer or retailer level. Since prices are often strategic complements (Tirole 1988), manufacturers of highly substitutable goods prefer the independent intermediary to vertical integration.

Choi (1991) analyzes the channel structure in which two competing manufacturers, each producing one brand, sell their substitutable products through a common independent retailer. As in his study, our work also analyzes a channel involving multiple manufacturers and a common retailer. In fact, the linear demand Manufacturer-Stackelberg case in Choi (1991) is same as the pre-change game in our theoretical model, which is used to model the retailer-managed retail system. Since our study aims at better understanding the difference of competition behaviors under different types of retail management, we also add a post-change game to model the manufacturer-managed retail system, and the focus here is on comparing the difference of our pre- and post-change games in terms of retail prices and sales changes as a result of the retail management change.

The second set of related literature is the inventory management in operation and supply chain research. The research identifies two types of retailer inventories: cycle inventory and safe inventory. Cycle inventory of a retailer is the average inventory due to purchases in lot sizes that are larger than those demanded by the customers. Cycle inventory exists because purchasing in large lots allows the retailer to exploit economies of scale and lower cost. Thus, the retailer carries cycle inventory even if there is no demand variability. On the other hand, safety inventory is inventory carried by the retailer for the purpose of satisfying demand that exceeds the amount forecasted for a given period. Safety inventory exists because demand forecasts are uncertain and a product shortage may result if actual demand exceeds the forecast demand (Chopra and Meindl 2004).

The existence of demand uncertainty and safe inventory leads to an interesting phenomenon in the supply chain – the bullwhip effect. The bullwhip effect is a channel behavioral phenomenon that causes demand fluctuations to be more pronounced upstream than downstream in a chain. In a manufacturer-retailer supply chain, this phenomenon can be viewed as the demand variability is amplificated from the retailer to the manufacturer. In their seminal paper, Lee, Padmanabhan, and Whang (1997) identify four sources that can cause the bullwhip effect in a context where channel members behavior rationally. The four causes are: (1) Demand Signal Processing: The retailer overstocks because she overestimates retail demand surges; (2) Order Batching: The retailer combines orders to take advantage of, say, quantity discounts; (3) Price Fluctuations: The wholesale prices of the manufacturer varies (e.g., trade promotions); and (4) Shortage Gaming: The retailer orders more than needed in the face of supply restrictions.

The bullwhip effect has been viewed as one of the main forces that paralyze supply chains, and identified as most harmful to the efficiency of a supply chain. Consequently, numerous research and industry report focus on ways to mitigate the bullwhip, such as common data definitions, information sharing, electronic data exchanges, collaborative forecasting and planning, and reducing the number of intermediaries in a supply chain. This extensive literature includes Bourland et al. 1996, Cachon and Fisher (2000), Chen (1998), Gallego eta al (2000), Gavirneni et al. (1999), Lee et al. 1997, Lee et al. (2000), Raghunathan (2001), and Raghunathan and Yeh (2001), etc.

Vendor-managed inventory (VMI) is one of the solutions proposed by the operations research to achieve this purpose. In a VMI system, the vendor or manufacturer is responsible for the management of stock at eh retailer. The retailer provides the manufacturer with access to its real-time inventory level. The replenishment decisions, i.e., how much and how often to replenish, are mad by the manufacturer. VMI is similar to manufacturer-managed retail (MMR) discussed in this study in that in both systems, it is the manufacturer who take care of retail inventory. As a result, both systems have the effect on reducing the bullwhip effect at the manufacturer. Different from MMR, however, in a VMI system, the retailer still makes the retail price decision.

While advocated by most of the research, which also seems intuitive, that information sharing reducing the number of intermediaries in a supply chain are benefitable to trading partners, Iyer et al. (2007) show that having inventory in the channel can help the manufacturer to manage retail pricing behavior while better extracting retail surplus. Thus even if the information system is perfectly reliable, the manufacturer might not always want to institute an information enabled channel over a channel with inventory.

Except the two streams of literature discussed above, our study is also related to the some other research. Padmanabhan and Png (1997) show that, by offering a returns policy, a manufacturer intensifies the degree of retailer competition. Our research idea is similar to theirs in some sense. Our problem can be viewed that by removing itself from price and stock decisions, a retailer intensifies the competition between competing brands. But as opposed to downstream retailer competition considered by Padmanabhan and Png (1997), we consider upstream manufacturer competition.

3. DATA AND SUMMARY OF THE POLICY CHANGE

The data for this paper comes from a large Chinese department store, which is top-ranked in both sales and profits across the nation. The store sells product categories including Beauty, Jewelry & Watch, Shoes, Cigarettes & Wine, Women's Clothing, Men's Clothing, Handbags & Accessories, Home Furnishings, Bed & Bath, Fitness & Sports, Toys & Games, Appliances, Electronics & Computers, etc., with the total UPCs of approximate 250,000. Different from department stores in U.S., however, most of department stores in China, including the one providing us the data, operate in one location. That is, they are not chains.

The store provided us with transaction-level sales data including unit sales, list price, as well as final retail price, with a sample period of 4 years (To maintain confidentiality required by the store, we name them Year 1 – Year 4. Our data cover from January 1 of Year 1 to December 31 of Year 4). In addition to the sales data, we also obtained advertising information (typically feature ad on local newspapers) of the store for the same period of time.

In this study, we focus on the product category C. The key feature of our data on this product category is a policy change on retail management. Within the store, different product categories are managed under different retail management systems: some product categories are sold using the retailer-managed retail system (RMR), while others are managed by the manufacturer-managed retail system (MMR). Interestingly, the store decided to switch the retail management of category C from RMR to MMR at the early of Year 4. Before the switch, the store decided the retail prices of all brands in the category, as well as managed the retail inventory of the category. After the switch, however, the duties were shifted to individual manufacturers.

We consider this key feature of our data, i.e., the retail management change, to be an exogenous change of retail prices, due to the fact that it was rapid and unanticipated (by manufacturers). The timing of events is as follows:

- February 27, Year 4: In a store executive meeting, the store reviewed the sales of the product category in previous years, and made the switch decision.
- Mar 6, Year 4: The store began to inform individual manufacturers of the store decision, as well as negotiate new contracts with them.
- Mar 30, Year 4: The contract negotiations were completed.
- April 17, Year 4: The first brand began adopting the manufacturer-managed retail system to sell.
- April 30, Year 4: All brands were switched to the new management system.

During our discussion with the store management, they stressed that this management change incurred very fast and smoothly. They also confirmed that no other major factors that might also affect the retail price, such as the production cost, had notable change during the switch process. Please be noted that we do not claim that the management change is exogenous of sales. In fact, as we will discuss in the following section, this change in management is indeed exogenous of sales.

The unique feature of our data facilitates us to construct an empirical model to estimate the retail price and sales changes as a result of the management change, and generate implications regarding competition behaviors under different retail management regimes. We begin by developing a simple game-theoretic framework to help us generate hypotheses for predicted changes in competition. After that, we test whether the observational changes in our data are consistent with our hypotheses.

4. THE THEORETICAL MODEL AND HYPOTHSES GENERATION

The main goal of this research is to conduct an empirical study to investigate the impact of a major policy change on brand competition. Before doing that, however, we in this section describe and analyze a simple game-theoretic model. The purpose of building and discussing the model is to help us generate hypotheses for predicted changes.

To build a model that is consistent to our data in a simple way, we consider a market with two-level channel structure, i.e., the manufacturer and the retailer levels. Each manufacturer is assumed to produce only one product (brand). The retailer sells many competing brands with varying degrees of substitutability.

In particular, this paper studies a duopoly model of manufacturers who sell their products through a common independent retailer. For simplicity, we assume that there is only one retailer in one market area. That is, we consider a market consisting of two manufacturers and a retailer. The two manufacturers each produces and offers one brand of good, which sold (only) through the common retailer. Although it may be a strong assumption for some product markets, this assumption enables us to isolate the effect of the policy change on manufacturer competition, which is our main concern, from the effect of competition among retailers.

4.1 Model Set-Up

4.1.1 Demand Function

As in McGuire and staelin (1983) and Jeuland and Shugan (1988), our model uses the following linear duopoly demand function that captures product differentiation:

$$q_i = \alpha_i - \lambda_i p_i + \gamma p_j, \qquad i, j = 1, 2, \; j \neq i \qquad (4.1)$$

where q_i is the demand for brand i at price p_i given that the price of the other brand j is p_j. The parameters of (4.1) are assumed that $\alpha_i > 1$ and $0 < \gamma < \lambda_i$ ($i = 1, 2$), as explained in Jeuland and Shugan (1988). Note that to keep the model tractable, here we assume that γ is symmetric for the two brands. In this model, the difference $\lambda - \gamma$ is inversely related to the degree of product substitutability between the two products. That is, the smaller the difference, the more substitutable (i.e., less differential) the two products, therefore the more potential price competition. Linear demand imposes a particular structure on the effect of changes in wholesale prices on retail prices, as noted in Tyagi (1999). We acknowledge that other functional forms may lead to different outcomes but leave this to future research.

4.1.2 Cost Structure

We consider two types of cost in the model: production cost and selling cost. We assume that the two manufacturers produce the good at a same constant unit (marginal) production cost. This is arguable to be true for the product category under investigation. Following previous research, this production cost is normalized to zero.

On the other hand, the selling cost summarizes costs of selling a product to customers. It may include the total wage of salespersons, inventory monitoring and other overhead costs of managing the inventory, the opportunity cost of purchasing and stocking a particular product, and so on. This cost is crucial to and must be considered in our model. As a reminder, our study intends to discover the potential differences in brand competition under two different retail management regimes (retailer-managed retail and manufacturer-managed retail), one before and the other after a retailer policy change. Before the change, the retailer took the full responsibility to sell the product category, which incurred her several types of selling costs. For example, the store carried inventory costs for monitoring and maintaining retail inventory. In addition, an order cost incurred every time the store placed an order with the manufacturer. After the policy change, the store's role shifted from managing and selling the product category to simply renting retailing space. Now individual manufactures took control over the retailer to monitor and replenish retail inventory, as well as sell products to consumers. Consequently, those selling costs were carried by manufacturers rather than the retailer. To capture this feature, it is assumed in our model that there is a unit selling cost that is carried by the retailer before the management change. After the change, this selling cost is shifted to the manufacturer side, and the retailer does not have it any longer. For the two-manufacturer-one-retailer case, we assume that in the retail-managed retail system, the retailer has a selling cost of m_c per unit; after the management changes to the manufacturer-managed retail system, the two manufacturers have a unit selling cost of m_m^1 and m_m^2, respectively. This selling cost could be different among the retailer and the manufacturer, i.e., m_c ‡ m_m^1 ‡ m_m^2. In fact, from the viewpoint of inventory management, literature on operations management shows that in the one-manufacturer-one-retailer case, this selling cost for the manufacturer is less than for the retailer, i.e., $m^{MMR} < m^{RMR}$. Moreover, after the retail management changes from RMR to MMR, the decrease of the selling cost for large manufacturers is more than for small manufacturers. It is because by taking advantage of centrally managed inventory in a market, manufacturers, those large ones in particular, are more efficient in managing inventory. This selling cost saving would induce manufacturers to decrease the retail price. Since large brand benefits more from the cost saving, she has more incentive to cut the price. Therefore, if there is no manufacturer competition behavior change under RMR and MMR, we would expect the following:

Hypothesis 1. Suppose there is no manufacturer competition behavior change under retail-managed retail (RMR) and manufacturer-managed retail (MMR). Then the change from RMR to MMR will lead to a decrease in the retail price. The magnitude of the decrease is more significant for the larger brand than the small brand.

To isolate the effect of the management change on brand competition from its potential impacts on the cost side, we in the following assume that the selling cost is same within the channel, i.e., $m_c = m_m^1 = m_m^2$. In addition, we normalize other possible selling costs carried by the store and/or the manufacturers that do not change under the two types of retail management to zero.

One important source of the selling cost included in our model is the inventory cost. As already discussed in Section 3, the inventory cost is in general comprised of two components: cycle inventory cost, and safe inventory cost. Safe inventory helps a supply chain improve product availability in the presence of demand variability. But cycle inventory exists even when there is not demand uncertainty.

Since our demand function is deterministic, the selling cost in our model includes cycle inventory cost but not safe inventory cost.

Although our game-theoretic model does not include demand uncertainty, we will empirically test the effect on brands with heterogeneous demand variability. We expect that the high-risk brand would cut price more than the low-risk brand after the management is changed from RMR to MMR. Intuitively, the brand with higher demand variability has more incentive to promote due to the larger stock level, which would lead to a lower-than-average retail price. We summarize this expectation in the following hypothesis.

Hypothesis 2. The retail price of both high-risk and low-risk brands will decrease when the product category is under the manufacturer-managed retail (MMR) than when it is managed under the retailer-managed retail (RMR). The magnitude of the decrease is more significant for high-risk brands than for low-risk brands.

4.2 Game Structure and Sequence of Decisions

Our research goal is to understand the competition behavior difference under two types of retail management, which occur before and after a major policy change in our data. Therefore, we must consider two games, one to model the market structure before the change, and the other for the market after the change. We call them pre- and post-change game, respectively.

4.2.1 Pre-Change Game

We first consider the pre-change game. As we have already discussed in the previous section, before the policy change, the store and the manufacturers behavior in a way we are familiar with – each manufacturer chooses the wholesale price of its own brand, while the retailer chooses the retailer prices of the two brands. Following previous research in channel coordination (e.g., McGuire and staelin 1983), we model the power balance of the channel as Manufacturer-Stackelberg. That is, each manufacturer chooses the wholesale price to maximize its own profit using 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 so as to maximize total profit from both brands given the respective wholesale price.

Sequence. The timing of the game is as follows. First, the two manufacturers each establish its wholesale price. Second, the retailer chooses its profit-maximizing retail prices for the two brands.

Analysis. Backward induction is employed to indentify the equilibrium of this game. Let w_i denote manufacturer *i*'s wholesale price, p_i the retailer's retail price of brand *i*, and *m* the retailer's unit selling cost.

In this setting, the manufacturer *i*'s profit function is given as

$$\Pi_{M_i} = w_i q_i, \qquad i, j = 1, 2 \qquad (4.2)$$

and the retailer's profit is

$$\Pi_R = \sum_{i=1}^{2}(p_i - w_i - m)q_i \qquad (4.3)$$

As in many previous studies, each member of the channel is assumed to seek to maximize its own profit and no cooperation is assumed between the member. Under the assumption of Manufacturer-Stackelberg, the manufacturers' take the retailer's reaction function into consideration for their respective price decisions. The retailer's reaction function given wholesale prices w_1 and w_2 as can be derived from the first-order conditions of Equation (4.3):

$$\frac{\partial \Pi_R}{\partial p_1} = (p_2 - w_2 - m)\gamma + (p_1 - w_1 - m)\lambda_1 + \alpha_1 - \lambda_1 p_1 + \gamma p_2 \qquad (4.3)$$

$$\frac{\partial \Pi_R}{\partial p_2} = (p_1 - w_1 - m)\gamma + (p_2 - w_2 - m)\lambda_2 + \alpha_2 - \lambda_2 p_2 + \gamma p_1 \qquad (4.4)$$

From Equation (4.3) and (4.4), the retailer's reaction function can be derived:

$$p_1 = \frac{(\lambda_1\lambda_2 - \gamma^2)(w_1 + m) + \alpha_1\lambda_2 + \alpha_2\gamma}{2(\lambda_1\lambda_2 - \gamma^2)} \qquad (4.5)$$

$$p_2 = \frac{(\lambda_1\lambda_2 - \gamma^2)(w_2 + m) + \alpha_2\lambda_1 + \alpha_1\gamma}{2(\lambda_1\lambda_2 - \gamma^2)} \qquad (4.6)$$

Under the reaction functions, the manufacturers' Nash equilibrium wholesale prices can be derived from the following first-order conditions of the respective manufacturers' profit maximization problems:

$$\frac{\partial}{\partial w_i}\Pi_{M_i}\left(p_i(w_i), w_j\right) = \frac{1}{2}w_i(\alpha_i - \lambda_1 w_1 - \lambda_1 m + \gamma w_2 + \gamma m) = 0, \quad i,j = 1,2 \;\; i \neq j \qquad (4.7)$$

Solving Equation (4.7) can obtain the wholesale prices. Plug them into Equation (4.5) and (4.6) we can then obtain the corresponding retail prices.

4.2.2 Post-Change Game

Now consider the post-change game, in which the two manufacturers sell their products *directly* to consumers through the store place.

Sequence. The timing of this game is as follows. In the first stage, the retailer establishes a sales revenue sharing percentage between it and the manufacturer. In the second stage, the two manufacturers decide the retail price of their own brand, based on the pre-set revenue sharing percentage.

Analysis. We use the same notations as in the pre-change game, and also employ the backward induction to discuss the process to derive the equilibrium of the game. The game structural changes dramatically from the pre-change game. In this post-change game, the retailer gives control over the retail price decisions to the two manufacturers. Furthermore, the unit selling cost *m* is now carried by the manufacturers. Thus, the manufacturer *i*'s profit function is given as

$$\Pi_{M_i} = d_i p_i q_i - m q_i, \qquad i, j = 1, 2 \qquad (4.8)$$

and the retailer's profit is

$$\Pi_R = \sum_{i=1}^{2} (1 - d_i) p_i q_i \qquad (4.9)$$

where d_i is the revenue percentage manufacturer *i* finally obtains from the sales of its brand, which was decided in Stage 1. For model tractability, we assume that $d_1 = d_2$.

In Stage 2, the manufacturer *i* (*i* = 1, 2) chooses the retail price of its product to maximize its profit from retail sales (Equation 4.8), taking the revenue percentage d_i as given.

Performing the optimization in Equation (4.8) by first-order conditions provides $p_i^*(d_1,d_2)$, the retail price of brand *i*, given the revenue sharing percentage d_1 and d_2:

$$p_1 = \frac{m\lambda_2(2\lambda_1 + \gamma) + d(2\alpha_1\lambda_2 + \alpha_2\gamma)}{d(\lambda_1\lambda_2 - \gamma^2)} \qquad (4.10)$$

$$p_2 = \frac{m\lambda_1(2\lambda_2 + \gamma) + d(2\alpha_2\lambda_1 + \alpha_1\gamma)}{d(\lambda_1\lambda_2 - \gamma^2)} \qquad (4.11)$$

Anticipating the manufacturers' responses to its proposed revenue sharing proposal, the retail chooses d_1 and d_2 to maximize its profit by solving Equation (4.9).

Performing the maximization in Equation (4.9) by first-order conditions would yield d^*. After that, we could substitute d^* into Equation (4.8) to obtain the equilibrium retail prices.

4.3 Some Limitations of Our Model Formulation

We assume that no demand shifts after the management change. It is possible that under the manufacturer-managed retail system, manufacturers have stronger incentive to sell their own products, which results in a demand curve shift. Second, our model assumes deterministic demand function and ignores demand uncertainty. As we have shown in previous sections, however, demand variability plays an important role in our discussion. Indeed, it is the demand variability that causes the bullwhip effect in a supply chain. Thus, a more general complete treatment should include demand uncertainty. Although not explicitly including this factor in our theoretical model, we do generate predictions about the possible impact on brands with different demand variability based on previous research, which we will test using our empirical model.

4.4 The Research Hypotheses

In this section, we analyze three special cases of the general model presented above. The analysis helps us generate research hypotheses for predicted changes, which we will test in my empirical study. Based on our research question, we are mainly interesting in comparing retail price and sales changes in pre-change and post-change game, i.e., as a result of the management change. But we also use numerical simulations to generate implications about the change in manufacturers' and the retailer's profits. We first consider the symmetric case where the base levels of demand as well as price sensitivities of brand 1 and brand 2 are equal. We provide analytically compare the retail price and sales before and after the policy change. After that, we discuss two asymmetric cases, where (1) base levels of demand for the two brands are different; and (2) the price sensitivities of the two brands are different. Because of the intractability of the model in the two asymmetric cases, we take advantage of numerical simulations to generate hypotheses about the retail price and sales change in these two cases.

4.4.1 Symmetric Brands ($\alpha_1 = \alpha_2$, $\lambda_1 = \lambda_2 = 1 > \gamma$)

Analysis of the symmetric brand case results in the following key insights, which is summarized in Hypothesis 3.

Hypothesis 3. The retail price will decrease when the product category is managed under the manufacturer-managed retail (MMR) than when it is managed under the retailer-managed retail (RMR). Sales in the former system are larger than in the latter system.

Proof: See Appendix

Discussion. Hypothesis 3 forms the backbone of our argument. Lower retail prices and greater sales imply more intense competition between competing brands after the management change.

An extensive numerical simulation on manufacturer and retailer profit in this case reveals that (1) the retailer's profits is strictly greater in the post-change game than in the pre-change game; and (2) the profits of both manufacturers are strictly lower in the post-change game than in the pre-change game. Intuitively, the results can be explained as follows: in the post-change game, although the retailer gives control over the retail price variables, that determines its profits to manufacturers in the pre-change game, it also eliminates its inventory holding cost and other selling cost. Furthermore, delegation of the retail price variable to manufacturers has another benefit for the retailer – it restores and intensifies manufacturer competition. The retailer then exploits this competition and enhances its profits.

We are interested in seeing whether the same results hold when the two brands are heterogeneous in terms of either the base level of demand or the price sensitivity. Unfortunately, with these asymmetry assumptions, it is extremely difficult to obtain close form equilibrium solutions for our problem.

Therefore, in what follows, we focus on applying the numerical procedure to derive various hypotheses and implications in the two asymmetric cases.

An important issue when running a numerical procedure is the parameter range selection. Ideally, we need to test all the possible combinations of the parameters. However, the cumbersome numerical computation prevents us from doing that. In our simulation, we decide the parameter ranges to test based on our real data. That is, we first use our data to "guess" the proper range of each parameter in our model, and then run our numerical procedure for the combination of the given ranges.

The data inspection process suggests the following parameters to run our numerical procedure: the base levels of the two brands are 8 and 1.5, respectively (thus the ratio of them are about 5/1). The price sensitivities of the two brands are 3 and 1.5, respectively (thus the ratio of them are about 2/1). The cross price sensitivity is approximately 0.75. The value of *m* (the unit selling cost) is determined by the condition $d < 1$.

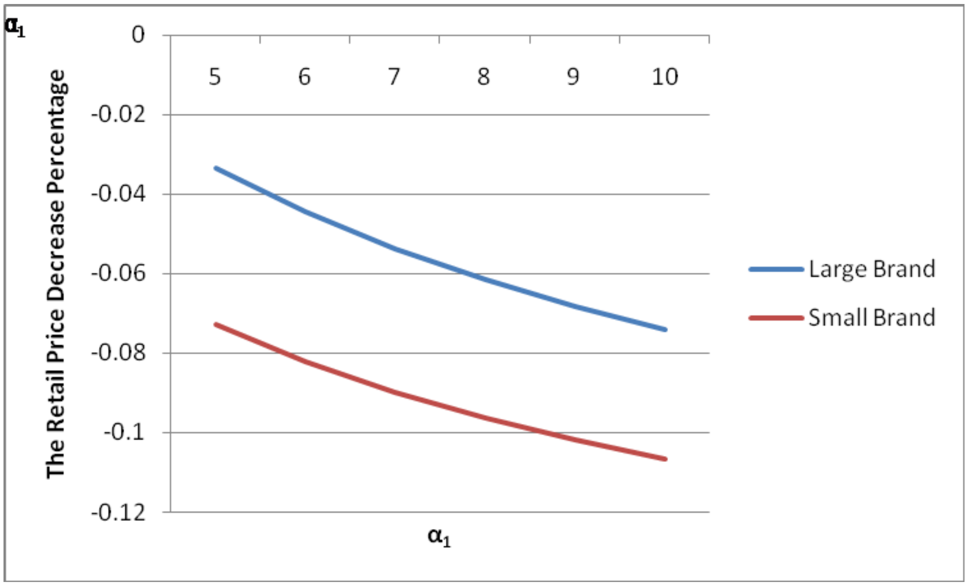
4.4.2 Asymmetric Brands Case 1 ($\alpha_1 > \alpha_2$, $\lambda_1 = \lambda_2 = \lambda > \gamma$)
In this case, we run our numerical procedure for the following parameter ranges: (1) keep the ratio of $\alpha_1/\alpha_2=5/1$, and then allow the values of α_1 and α_2 vary between (5, 10) and (1, 2), respectively; (2) let $\lambda_1 = \lambda_2 = 2$, and $\gamma = 0.75$. For robustness check, we also run the simulations to allow (1) the ratio of α_1/α_2 vary from 10/1 to 2/1 and (2) λ and γ vary between (1.5, 3) and between (0, 1) respectively. Our conclusions hold for all the tested parameter ranges.

Our numerical procedure generates the following hypothesis:

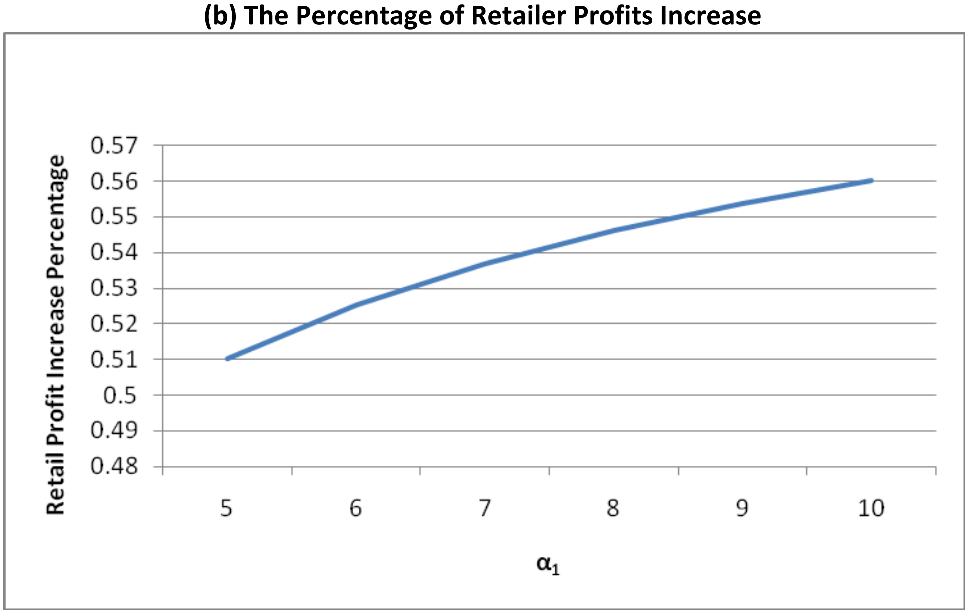
Hypothesis 4. The retail price of both the large brand and the small brand will decrease when the product category is managed under the manufacturer-managed retail (MMR) than when it is under the retailer-managed retail (RMR). The magnitude of the decrease is more significant for the small brand than the large brand. Consequently, the sales of both the large and the small brand will increase when the product category is managed under the former than under the latter.

Discussion. As an illustration, the numerical results of the retail prices when $\alpha_1/\alpha_2 =5$, α_1 varies between 5 to 10, $\lambda_1 = \lambda_2 = 2$, and $\gamma = 0.75$ are graphically summarized in Figure 1 (a). We also run the numerical simulations for retail profits and manufacturers profits on the same parameter ranges. Figure 1(b) and (c) illustrates these results when $\alpha_1/\alpha_2 =5$, α_1 varies between 5 to 10, $\lambda_1 = \lambda_2 = 2$, and $\gamma = 0.75$. Our simulations on retail and manufacturer profits suggest that the retailer profits will increase when the product category is under the manufacturer-managed retail than when it is under the retailer-managed retail, but the profits of both manufacturers profits will decrease when the product category is under the manufacturer-managed retail than when it is under the retailer-managed retail. The profit decrease of the small brand is more significant than the large brand.

(a) The Retail Price Decrease Percentage



(b) The Percentage of Retailer Profits Increase



(c) The Percentage of Manufacturer Profits Decrease

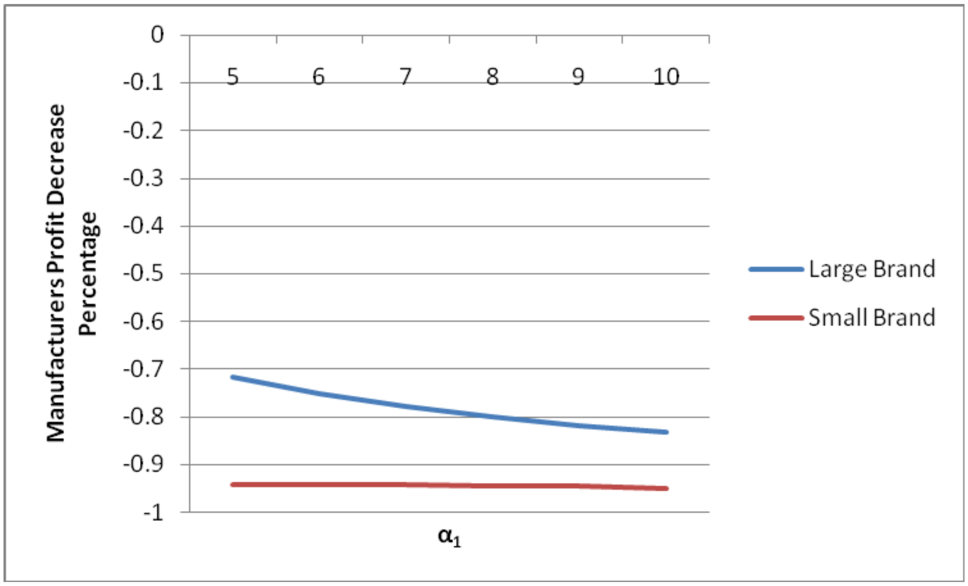


Figure 1
AN ILLUSTRATION OF THE CHANGE IN RETAIL PRICE, RETAILER PROFIT, AND MANUFACTURER PROFIT OF THE POST-CHANGE GAME, AS OPPOSE TO THE PRE-CHANGE GAME

4.4.3 Asymmetric Brands Case 2 ($\alpha_1 = \alpha_2 = \alpha$, $\lambda_2 > \lambda_1 > \gamma$)

In this case, we run our numerical procedure for the following parameter ranges: (1) set $\alpha_1 = \alpha_2 = 6$; (2) keep the ratio of $\lambda_2/\lambda_1 = 2/1$, allow the values of λ_2 and λ_1 vary between (2, 4) and (1, 2), respectively; For robustness check, we also run the simulations to allow (1) the ratio of λ_1/λ_2 vary from 1.5 to 2.5 and (2) α (=$\alpha_1 = \alpha_2$) vary between (1, 10). Our conclusions hold for all the tested parameter ranges.

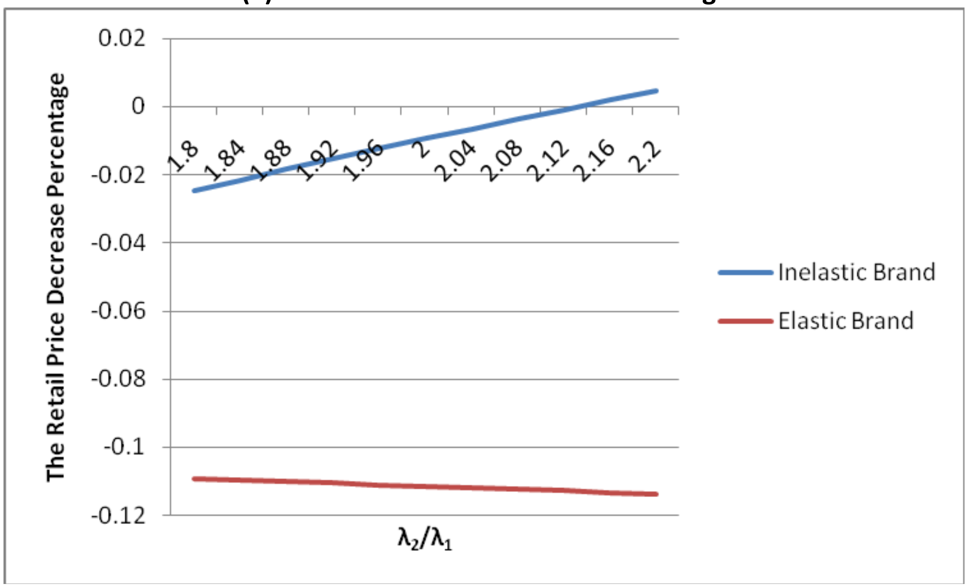
Our numerical procedure reveals the following result:

Hypothesis 5. The retail price of the brand with large price sensitivity will decrease when the product category is managed under the manufacturer-managed retail (MMR) than when it is managed under the retailer-managed retail (RMR). The retail price of the brand with small price sensitivity under MMR could be larger or smaller than under RMR.

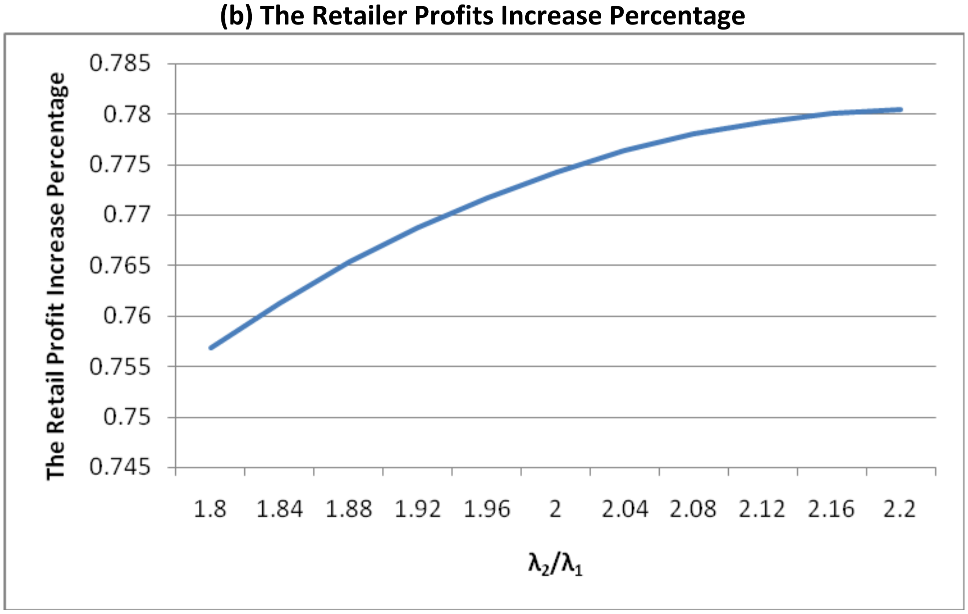
Discussion. As an illustration, the numerical results when $\alpha_1 = \alpha_2 = 6$, $\lambda_1 = 1$, λ_2/λ_1 vary between 1.8 to 2.2, $\gamma = 0.75$, graphically summarized in Figure 2(a). An interesting finding is that the retail price change of the inelastic brand is not determinable. It is plausible that the sign depends on the magnitude of the relative elasticity of the two brands: when the elasticity of the brand with small price sensitivity is sufficiently smaller than the other brand, its retail price will increase under MMR.

We also run the numerical simulations for retail profits and manufacturers profits on the same parameter ranges. Figure 2(b) and (c) illustrates these results when $\alpha_1 = \alpha_2 = 6$, $\lambda_1 = 1$, λ_2/λ_1 vary between 1.8 to 2.2, $\gamma = 0.75$. Our simulations on retail and manufacturer profits reveals a similar conclusion as we obtain in the previous asymmetry case, suggesting that the retailer profits will increase when the product category is managed under the manufacturer-managed retail than when it is under the retailer-managed retail. On the other hand, the manufacturer profits of both of the brands will decrease when the product category is under the manufacturer-managed retail than when it is under the retailer-managed retail. The profit decrease of the price-sensitive brand is more significant than the price-insensitive brand.

(a) The Retail Price Decrease Percentage



(b) The Retailer Profits Increase Percentage



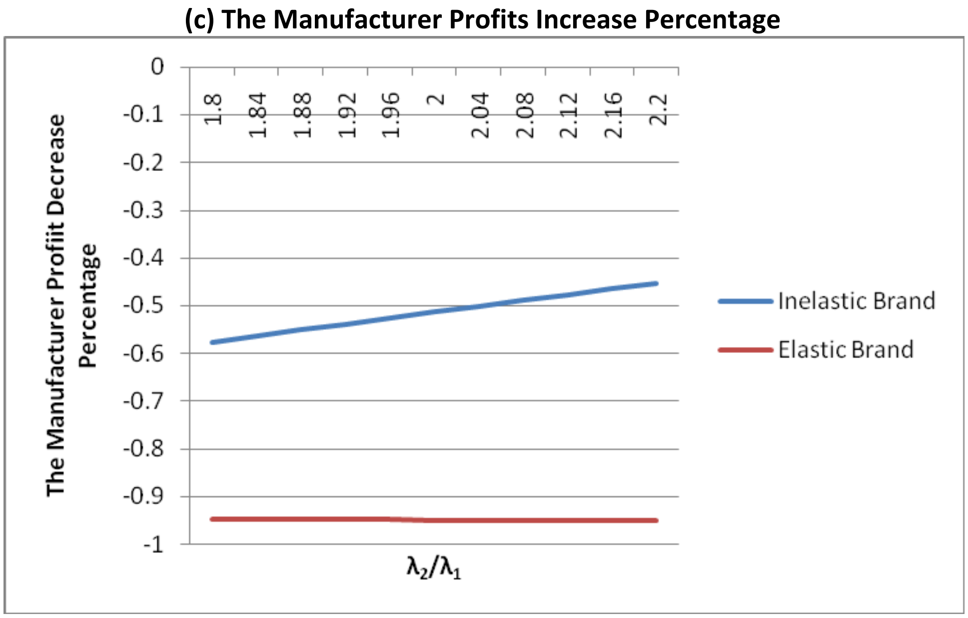


Figure 2
AN ILLUSTRATION OF THE CHANGE IN RETAIL PRICE, RETAILER PROFIT, AND MANUFACTURER PROFIT OF THE POST-CHANGE GAME, AS OPPOSE TO THE PRE-CHANGE GAME

5. THE EMPIRICAL MODEL AND RESULTS

A key implication of our game-theoretic framework is that the switch from RMR (modeled by the pre-change game) to MMR (modeled the post-change game) results in reduced retail price and increased retail sales, which infers to intensified competition between competing brands. In this section, we use the data from the Chinese department store (Section 3) to test whether the observed change in management in real data is consistent with this prediction. We first test this in the entire dataset we select (see Section 5.1 for the data selection process) as a whole. We then attempt to indentify the possible different impacts of the management change on heterogeneous brands, including major versus minor brands, inelastic versus elastic brands, and low-risk versus high-risk brands. We do this for three reasons: First, we note that there is considerable heterogeneity in sales behavior across goods within the product category we investigate. Christen et al. (1997) have shown that when working with arithmetically averaged data, estimation may be sensitive to an aggregation bias when there is heterogeneity in marketing activities. Second, by testing the impacts of the management change on brands with different demand variability, we could further investigate the observational change that is not explained in our game-theoretic framework. Most importantly, testing on heterogeneous brands helps exclude other possible explanations of the observed change in retail price and sales, and affirmatively demonstrate that competition plays a crucial role during the change in management from RMR to MMR.

5.1 Data Selection

Because one of the main purposes of this research is to test whether the management change has significantly different impacts on different brands, our empirical model is built on the brand level. In terms of data time series, our empirical model use weekly data, rather than monthly or quarterly data, for two reasons. First, this provides us with more observations. More importantly, the store's marketing activities, such as promotions and feature advertising, are determined on a weekly basis. Indeed, we also tested our empirical model on the same data but aggregated at the monthly level, but did not obtain meaningful results.

On average, the store sells about 60 brands of the product category. Table 1 shows the number of brands sold in the store in the four years for which we have data.

Table 1
THE NUMBER OF BRANDS SOLD IN THE STORE

Year	Year1	Year2	Year3	Year4
No. Brands	56	65	60	60

Brands sold in the store seem stable across years at first glance. However, this is not the case. A closer look at the data reveals that there are only 13 brands that have consistent presence in the store for the four years. During the time period for which we have data, the Chinese government had a new, much more generous policy on releasing licenses for allowing firms to enter the products category (firms must obtain a license to produce the product in the category). As a result, many new brands appeared. However, most of the new producers were not successful in the market. Typically, a new brand was only available in the store for one or two years, before the manufacturer decided to exit the market, or the store replaced it with a new brand. It is possible that the market fluctuation also has impacts on the brand competition. Therefore, we rule out the brands entering and/or exiting the store during the time period, and focus on the brands with consistent presence in the store. By abstracting from the market entry/exit issue, we can isolate the increased brand competition from the management change from other possible reasons.

Among the 13 brands that were consistently present in the store, we excluded 3 from the data to run our regressions. We do this to further abstract other possible causes from our main focus. Two of them merged in Year 3; the third one was ruled out at the suggestion of the store manager. We were informed that during the time period that we have data, this brand adjusted its brand position and marketing strategy consistently and dramatically.

This data cleaning leaves us with 10 brands, which we name Brand 1 to Brand 10 to maintain confidentiality. Table 2 shows summary statistics for the market shares of the 10 brands, as well as those for the top 4 brands. On average, the 10 brands have a market share of 81.80% of the category sales. That is, by focusing on these 10 brands, we are able to track about 80% of total sales of the category in the store. Therefore, we are confident that the 10 brands are representative of the market condition in the store, and using this data sample to run our regressions is valid. Meanwhile, there is a note that the top 4 brands have an average 61.19% market share, indicating that significant distinction between major brands and minor brands. This also illustrates the high brand heterogeneity in this product category.

Table 2
MARKET SHARE SUMMARY STATISTICS

Market Share	Mean	Median	S.D.	Max	Min
The 10 Brands	81.80%	84.25%	0.050	87.58%	73.71%
The Top 4 Brands	60.19%	61.45%	0.085	70.86%	44.35%

5.2 Brand Classification

To investigate the potentially different impacts on heterogeneous brands from the management change, we use a hierarchical clustering algorithm to classify all the selected brands, then analyze and compare the effects of the management change on the individual brand groups given by the clustering algorithm. In our study, we investigate three types of brand heterogeneity: brand equity, brand elasticity, and brand demand variability.

To apply the clustering algorithm to classify brands, we first run the following regression

$$\ln(q_{it}) = \alpha_i + \tau_t + \beta_i \ln(p_{it}) + \varepsilon_{it} \qquad (5.1)$$

where α_i is the brand fixed effects, τ_t denotes the time trend and seasonality variables, including 4 annual variables and 12 monthly variables (In the estimation we exclude the annual variable for Year 1 and the monthly variable for January), and ε_{it} it the residual. Because the regression is log-log, β_i denotes brand elasticity. We use the estimates of α_i and β_i, and the variance of the estimated residual terms to measure the brand equity, brand elasticity, and brand demand variability, respectively. These estimates were then fed into the clustering algorithm to classify brands.

For each input, the clustering algorithm classifies all the brands into 2 groups: Two groups are classified using the estimated constant terms. These are labeled major and minor brands; the two groups classified based on the estimated price coefficients are named inelastic and elastic brands; finally, the two groups classified based on the variance of the estimated residual terms are called low-risk and high-risk brands. Table 3 summarizes the estimates of α_i, β_i, and ε_{it} for each brand, as well as which group they belong to in terms of the three criterions.

Table 3
BRAND CLASSIFICATION

	α_i	β_i	var(ε_{it})	Major vs. Minor	Inelastic vs. Elastic	Low-Risk vs. High-Risk
Brand 1	2.245	-0.570	0.028	Major	Inelastic	Low-Risk
Brand 2	2.078	-1.027	0.043	Major	Elastic	Low-Risk
Brand 3	1.582	-1.105	0.063	Major	Elastic	Low-Risk
Brand 4	1.566	-0.584	0.040	Major	Inelastic	Low-Risk
Brand 5	0.835	-1.629	0.089	Minor	Elastic	Low-Risk
Brand 6	0.562	-1.016	0.138	Minor	Elastic	High-Risk
Brand 7	0.479	-1.274	0.107	Minor	Elastic	Low-Risk
Brand 8	0.031	-1.126	0.189	Minor	Elastic	High-Risk
Brand 9	-0.074	-1.514	0.144	Minor	Elastic	High-Risk
Brand 10	Reference	-2.149	0.076	Minor	Elastic	Low-Risk

5.3 The Effect of the Management Change on the Retail Price

Our primary interest is to test the effect of the change from retail-managed retail to the manufacturer-managed retail on the price competition between competing brands. We expect that the management change would intensify the brand competition. This means that the retail price is lower and sales are higher after the store was switched from RMR to MMR. In this section, we test the effect of the management change on the retail price. We will test the effect of the management change on sales in the next section.

To reveal the effect on the retail price from the management change, we estimate the following equation for the log of retail price of brand *i* in week *t*:

$$\ln(p_{it}) = \alpha_i + \tau_t + \theta s_{it} + \varepsilon_{it} \qquad (5.2)$$

where p_{it} is the average *final* retail price of brand *i* in week *t*, i.e., the price actually paid by consumers. In the store, the final price paid by consumers is typically lower than the list price for the product category in question, for two reasons: (i) a brand is undergoing a promotion; (ii) salespersons usually have rights to give consumers a discount even if the brand is not on sale. s_t is a binary variable that indicates whether the category is sold under retailer-managed retail (s = 0) or under manufacturer-managed retail (s = 1). α_i is the brand fixed effect, which is used to control for the effect of brand-specific intrinsic aspects on the retail price. We noted that there was apparent time trend or seasonality in the price, and therefore, included time trend and seasonality variables in the regression, which is denoted by τ_t. τ_t

includes 4 annual variables (Year 1 to Year 4) and 12 monthly variables (In the estimation we exclude the annual variable for Year 1 and the monthly dummy for January). There are two things worth mentioning about these time trend and seasonality variables. First, they are not dummy variables equal to either 0 or 1, as typically defined. Instead, because we use weekly-level data, and a week could fall between months or even two years, these variables could take any values between zero and one in our regression. More specifically, the values of these variables are defined to measure the percentage of the days of a week that fall into a particular month or year. In the next section, we will use a similar methodology to define the store's feature advertising variable in our sales regression. Second, a week starts on Monday in our regression, rather than Sunday, as usual. We defined the week in this way to make it consistent to how the store views what a week is. In the store, many promotions end on Sunday, some of which are weekend only promotions available only on Saturdays and Sundays.

In this regression an observation is the weekly average retail price of a brand. Before time *T*, all brands were sold under retailer-managed retail system. After time *T*, however, all brands were *immediately* switched to the manufacturer-managed retail system, so there is no control group of brands sold under RMR at the same time other brands were sold under MMR. Identification of the effect from the management change is therefore primarily due to time series variation in whether or not the manufacturer management is applied. In Section 3, we explained why it is reasonable to consider this kind of variation as exogenous in the price regression. To summarize, we consider this to be an exogenous change for the retail price due to the fact that it was rapid and unanticipated. In addition, the inclusion of the brand and time fixed effects in equation (5.2) controls for time-invariant brand characteristics and brand-invariant time effects, respectively, which also help preclude sources of possible bias. Please note that we don't argue that the management change is an exogenous change for the demand and sales. We will discuss this issue in the following section.

We estimate equation (5.2) for all brands together. We also separately estimate the equation on different brand groups (major versus minor brands, inelastic versus elastic brands, and low-risk versus high-risk brands). Table 4 reports the results from the OLS estimations.

The results are consistent with the predicted changes given by our game-theoretic framework (Hypothesis 1 – Hypothesis 5). The estimated coefficient of the management change dummy for all brands taken as a whole reveals that the change caused the retail price to decrease by an average of 10.7%. Since the average retail price for all brands in our sample is roughly US$ 221, the absolute magnitude of the effect is nearly US$ 22.6. This is a remarkable price drop, considering that the manufacturer's markup could as low as US$ 10 in the market, according to the store management. To further emphasize the magnitude of the effect, this is equal to 0.89 of a standard deviation of the retail price distribution. This result is consistent to the prediction of our theoretical model, and is evidence in favor of the change in management intensifying the price competition of brands.

Table 4

THE EFFECT OF THE MANAGEMENT CHANGE (*s*) ON FINAL RETAIL PRICE

	Regression for	Coefficient	Observations	R^2
All Brands	All (with the brand fixed effect)	-0.107***	2080	0.813
	All (without the brand fixed effect)	-0.107***	2080	0.010
Major vs. Minor Brands	Major	-0.031	832	0.876
	Minor	-0.158***	1248	0.723
Inelastic vs. Elastic Brands	Inelastic	-0.023	416	0.782
	Elastic	-0.128***	1664	0.750
Low-Risk vs. High-Risk Brands	Low-Risk	-0.070***	1456	0.854
	High-Risk	-0.195***	624	0.569

Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

The estimated coefficients of the management change for major versus minor brands show the following: the point estimation of the coefficient for major brands is negative, but it is not statistically significant. However, the estimated effect from the same change on the minor brands is an average decrease in the retail price of 15.8%. Thus, the impact from the change in management was mainly applied to minor brands but not major brands.

This finding is consistent with, and provides empirical evidence to previous marketing research on channel coordination. In their seminal paper, McGuire and Staelin (1983) used a game-theoretic model to show that when products are high substitutable, intermediaries are found to be working as a buffer against intense price competition between manufacturers. A direct inference of their conclusion is that the removal of the previous existing intermediary, as the policy change in our data did, would intensify the brand competition of highly-substitutable products, driving their retail prices down. It is arguable that minor brands in the category usually have higher product substitutability than major brands. Thus, our estimates provide strong empirical evidence to support McGuire and Staelin (1983), and therefore suggest that after the management change, manufacturer competition intensifies especially between highly-substitutable brands.

It is possible that the price decline after the management change could also come from manufacturer cost savings. As we discussed in previous sections, if cost saving is the main driver of the price drop after the change, then we should expect major brands to cut prices more aggressively after the management change. Our estimates show the opposite results, suggesting that it is brand competition rather than the cost saving that is the main driver of the price drop after the management change.

Our estimation for inelastic versus elastic brands shows that the management change had notable impacts on elastic brands, but not on inelastic brands. This is also consistent with the predictions of our theoretical model. As for low-risk versus high-risk brands, the estimated coefficients of the management change are significant for both the low-risk and high-risk brands. However, the difference between them is statistically significant (a simple test of the difference in means between them rejects equality with 99.99 percent confidence). Put in another way, the change in the management drove down the prices of both low-risk brands and high-risk brands, but to different degree. The management change had a more significant impact on brands with more demand variability. As we discussed in previous section, past operation management research shows that high-risk brands benefit more from MMR, compared to low-risk brands. Our results show, however, that high-risk brands also suffer from more intense price competition under MMR. This result suggests that there is a trade-off between the benefits and costs for the manufacturer under the two retail management system.

When estimating the overall effect of the management change, we also estimate an equation without the brand fixed effect. Comparing the results of OLS estimation without fixed effects and the OLS estimation with fixed effects, we find that the estimation results from the two estimations are exactly the same. This supports our argument to consider the change in management as exogenous.

5.3.1 Total Regression

Above, we separately examined the effects on heterogeneous brands from the management change. Notice that there is a large overlap between brands in terms of the heterogeneity (for example, all inelastic brands in our data are major brands), we also estimate the following specification:

$$\ln(p_{tc}) = \alpha_t + \tau_c + \vartheta s_{tc} + \delta_1 s_{tc} MI_{tc} + \delta_2 s_{tc} E_{tc} + \delta_2 s_{tc} HR_{tc} + \varepsilon_{tc} \qquad (5.3)$$

where *MI*, *E*, and *HR* stand for minor brands, elastic brands, and high-risk brands, respectively. The remaining notation is the same as in equation (5.2). In this specification, the coefficient for the management change, ϑ, can be interpreted as the average effect of the change on those brands that are in the intersection of major, inelastic, and low-risk brand groups (we label these brands as major & inelastic & low-risk brands).

Comparing this to equation (5.2), equation (5.3) does a better job indicating the relative magnitudes that different brand heterogeneities contribute to brand competition. Table 5 reports the estimates for the coefficients in equation (5.3). The estimate for the effect of the management change on the major & inelastic & low-risk brands is insignificantly different from zero, although the point estimation is negative. Being the minor brand, the elastic brand, or the high-risk brand individually each significantly changes the effect on the retail price. Among these being the elastic brand has the largest impact, which is almost twice the impact of being the minor brand. This finding strongly supports our contention that competition is a main driver of the price drop after the management change. The negative and significant estimation of being a minor brand shows an inconsistency with the conclusion given by the costing-saving argument.

Table 5
TOTAL REGRESSION: THE EFFECT OF THE MANAGEMENT CHANGE (*s*) ON THE FINAL RETAIL PRICE

	Coefficient
Management Change (*s*)	-0.007
Management Change (*s*) * Minor Brand (*MI*)	-0.064***
Management Change (*s*) * Elastic Brand (*E*)	-0.116***
Management Change (*s*) * High-Risk Brand (*HR*)	-0.103***
Observations	2080
R^2	0.822

Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

Table 6 summarizes the net effect on the final retail price from the management change for each every combination of the types of brand heterogeneity we consider: major versus minor brands, inelastic versus elastic brands, and low-risk versus high-risk brands. To compute, for example, the net effect on the major brands that are elastic and low-risk, sum up the estimated coefficient on Management Change (-0.007) and on Management Change times Elastic Brand (-0.116).

Table 6
THE NET EFFECT OF THE MANAGEMENT CHANGE (*s*) ON THE FINAL RETAIL PRICE

Brand Type	**Net Effect**
Major & Inelastic & Low-Risk Brands	-0.007
Major & Inelastic & High-Risk Brands	-0.110
Major & Elastic & Low-Risk Brands	-0.123
Major & Elastic & High-Risk Brands	-0.223
Minor & Inelastic & Low-Risk Brands	-0.071
Minor & Inelastic & High-Risk Brands	-0.174
Minor & Elastic & Low-Risk Brands	-0.187
Minor & Elastic & High-Risk Brands	-0.290

5.3.2 Lower List Price or More Frequent Promotions or Both?

Our estimation has shown a significant price drop after the management change. One possible reason for price cut is that after the manufacturers are responsible for setting retail prices, they lower the list prices of their brands. If they do so, the final retail price would certainly decrease. However, it is also possible that the manufacturers keep the list price the same as before, but promote their brands more often. This could also lead to a decrease of the final retail prices. In this section, we investigate this question: Are the observed decreases in final price due to the list price cut or more frequent promotion? We present evidence in favor of both of these arguments, from which we conclude that the management change causes a combination of lower lists price and more frequent promotions.

To provide evidence for the first argument, we run another price regression. This regression is exactly same as equation (5.2), except that the dependent variable is the log of the list price of price of brand *i* in week *t*, rather than the brand's final sales price as in equation (5.2).

Table 7
THE EFFECT OF THE MANAGEMENT CHANGE (*s*) ON THE LIST PRICE

	Regression for	Coefficient	Observations	R^2
All Brands	**All (with the brand fixed effect)**	-0.058***	2080	0.806
	All (without the brand fixed effect)	-0.058**	2080	0.059
Major vs. Minor Brands	**Major**	-0.036	832	0.861
	Minor	-0.073***	1248	0.708
Inelastic vs. Elastic Brands	**Inelastic**	-0.045**	416	0.761
	Elastic	-0.061***	1664	0.729
Low-Risk vs. High-Risk Brands	**Low-Risk**	-0.039**	1456	0.841
	High-Risk	-0.103***	624	0.491

Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

Table 7 reports the results from the estimation. We can see that even when we look at the list price alone, that the management change causes a significant price drop. Comparing the results in Table 4 and Table 7, we note that, in general, the magnitude of the effect on the list price from the management change is about half of its impact on the final sales price. For example, for minor brands, the estimated coefficient of the management change dummy is -0.158 and -0.073 in the two tables, respectively. This result can be interpreted as suggesting that half of the price cut induced by the management change comes from the list price decrease.

There is one exception to the above observations. The estimated coefficients show that the management change causes the list price of the inelastic brands to decrease by an average 4.5%, which is statistically significant at the 95 percent confidence level. However, the management change does not exhibit a statistically significant impact on the final price of inelastic brands. This is presumably a spurious correlation, since there is no reason to expect that the management change would cause a larger impact on the list price than on the final price.

We next present evidence that when compared with the store-managed retail system, the manufacturer-managed retail system leads to more frequent promotional activities. To define the promotion frequency, we first compute the difference between the average list price and the average final retail price for each brand in each week. Because in the store, sales representatives have the right to give customers a small discount at any time, the differences are always positive. To identify the promotion frequency, we define a brand as on promotion if the difference is above a certain threshold. The promotion frequency of a brand is then defined as the percentage of weeks in the sample in which the brand is on promotion. The promotion frequency for the category is defined as the average promotion frequency across brands.

Table 8
THE PROMOTION FREQUENCY BEOFRE AND AFTER THE MANAGEMENT CHANGE

	Before the Change in the Management	**After the Change in the Management**
Promotion Frequency	36.6%	70.7%

Table 8 shows the promotion frequency of the category when we choose a threshold of 5%. This shows that the promotion frequency increases significantly, almost doubling, after the product category is changed from RMR to MMR. We also perform this test using different thresholds, and the results are robust. This finding is fairly interesting in itself. Compared to the manufacturer, the store has less incentive to promote. This might be because the store sells all brands in the product category rather than just one brand, and consequently, its profits come from the pool of demands of all the brands. Since a price cut of one brand might have significant impacts on the sales of other brands, the store is hesitant to promote intensively. Under the manufacturer-managed retail system, however, individual manufacturers would promote more aggressively to attract consumers to their own brands. Together with the price cut on the list price, the evidence presented in this section shows that the management change intensifies the manufacturer competition in two dimensions, which drives manufacturers to compete fiercely against each other not only in pricing but also in promotion.

5.4 The Effect of the Management Change on Retail Sales

We expect that the switch to the manufacturer-managed retail leads to more intense brand competition in the sense of lower retail prices and higher sales. In the last section, we have shown that the management change indeed caused a notably retail price drop, in terms of both the list price and the final retail price. In this section, we attempt to document the effect of the change on retail sales.

To analyze the effect of the management change on sales, we estimate the following equation for the log of sales of brand *i* in week *t*:

$$\ln(q_{it}) = \alpha_i + \tau_t + \gamma f_{it} + \delta n_{it} + \eta_1 l_{it}^1 + \eta_2 l_{it}^2 + \theta s_t + \varepsilon_{it} \qquad (5.4)$$

where *s*, α, and τ are the same as in the price regression (equation 5.2). f_{it} is a variable used to measure the store's feature advertising on brand *i* in week *t*. Our data set includes all the store's feature advertising activities on all the brands in the category. f_{it} is defined as the percentage of days during week *t* in which brand *i* is on the store's feature advertising list. Therefore, it takes on a continuum of values between 0 and 1. For example, if brand *i* was featured by the store for a weekend (Saturday and Sunday) only sale, the value of f_{it} is 0.286 (=2/7). The variable n_{it} denotes the number of new models of brand *i* in week *t*. Because we do not have data regarding the exact date when a new model was available in the store, in the regression we use the first date a model was purchased as a proxy of the release date of the model. Caution should be used when interpreting the estimation of n_{it}, because the proxy variable might introduce some upward bias.

l_{it}^1 and l_{it}^2 are two dummies for the category counter location. The counter location of the category within the store was changed twice during the data observation period, one in Week 18 of Year 3, and the other occurred in Week 36 of Year 4. Both of the counter adjustments can be considered exogenous. According to the store manager, the first adjustment occurred because the store decided to renovate the entire floor where the category counter was located, while the second one occurred because the store decided to use the category's current place to build a new facility. However, both location changes had significant impacts on category sales. The first adjustment moved the category counter to a better location, but the second one moved the category counter to a worse location. Therefore, we include them in our sales regression.

The OLS estimates for this specification are reported in Table 9. The estimated coefficient on *s* for all brands implies that the management change from retailer-managed retail to the manufacturer-managed retail increased sales by an average of 24.4%. Together with the estimates from our price regression discussed in the last section, our results present strong empirically evidence that the change in management significantly intensifies brand competition in the category – the change caused the final retail price to decrease by an average of 10.7%, and the sales to increase by an average of 24.4%. As with our estimates on price, estimates for different brand groups suggest that the effect on sales from the management is highly heterogeneous. The change has a significantly greater impact on minor brands, elastic brands, and high-risk brands, than on major brands, inelastic brands, and low-risk brands, respectively.

Table 9
THE EFFECT OF THE MANAGEMENT CHANGE (*s*) ON SALES

Regression for		Coefficient			Observations
		Without Control for Price Effect	Control for Price Effect	Difference	
All Brands		0.244***	0.119***	0.125	2080
Major vs. Minor Brands	Major	0.161***	0.132***	0.029	832
	Minor	0.293***	0.139**	0.154	1248
Inelastic vs. Elastic Brands	Inelastic	0.108**	0.098*	0.010	416
	Elastic	0.272***	0.120***	0.152	1664
Low-Risk vs. High-Risk Brands	Low-Risk	0.191***	0.148***	0.043	1456
	High-Risk	0.357***	0.202**	0.155	624

Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

The estimation from equation (5.4) might suffer from the endogeneity problem. Indeed, according to the store manager, one of the main reasons why the store decided to switch from store-managed retail to manufacturer-managed retail was its concern about declining sales in the product category. The store had a particular concern regarding the sales decline of major brands. However, including the annual variables in equation (5.4) controls for the potential endogeneity of average change due to the change in aggregate demand over time. In addition, our estimates on the annual variables in equation (5.4) reveal that sales of major brands in the store had consistently declined, and the degree of the decline became larger and larger, with an average 24.6% sales drop in Year 4. On the other hand, small brands did not suffer from a significant sales decline in the data (note that this is also consistent with the store administration's concern). Thus, to the extent that one may still be concerned about a possible endogeneity problem in this regression, it is arguable that our sales regression on minor brands should be robust without suffering from this issue.

We also note that the specification in equation (5.4) is subject to an 'overt bias'. This is because, as shown by equation (5.2), the retail price after the management change (s = 1) is different from the retail price before the management change (s = 0). This causes a selection-on-observables issue. To avoid this overt bias and identify the causal effect of the management change on sales, we also estimate the following equation:

$$\ln(q_{it}) = \alpha_i + \tau_t + \beta_{1i}\ln(p_{it}) + \beta_2\ln(cp_{it}) + \gamma f_t + \delta n_{it} + \eta_1 l^1_{it} + \eta_2 l^2_{it} + \theta s_t + \varepsilon_{it} \qquad (5.5)$$

Equation (5.5) is similar to equation (5.4), but has two additional terms. p_{it} denotes the final retail price of brand *i* in week *t*, while cp_{it} denotes the price of brand *i*'s competition in week *t*, which is defined as the average final retail price of the other 9 brands in week *t*. Thus, while we estimate a brand-specific own-elasticity for each brand *i*, we use a common cross-elasticity for all brands.

For the effect of the management change on sales, if the change works only by intensifying the price competition between brands and inducing a price cut, then there would be only a 'sheepskin effect'. That is, after controlling for the pricing effects, we will not see any of the effect of the management change on sales. This relationship is demonstrated by the causal chain in Figure 3.

Figure 3

THE FIRST POSSIBLE CAUSAL CHAIN BETWEEN THE MANAGEMENT CHANGE, RETAIL PRICE, AND SALE

However, it is also possible that the change in the management affects sales *directly* as well as *indirectly* through the retail price change. Perhaps, the store increased the advertising spending on this category , or there were more salespersons after the management change. This relationship is demonstrated by the causal chain in Figure 4:

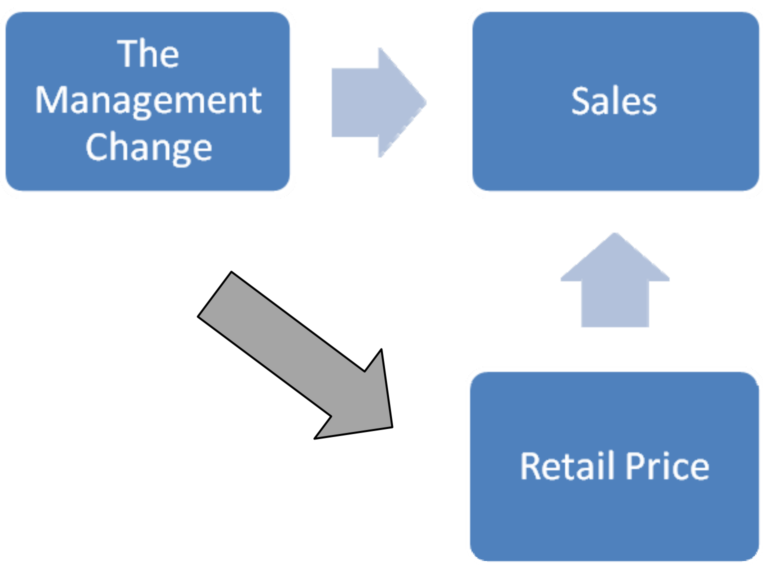


Figure 4

THE SECOND POSSIBLE CAUSAL CHAIN BETWEEN THE MANAGEMENT CHANGE, RETAIL PRICE, AND SALE

In the latter case, controlling for the retail price will show only the *direct* effect of the management change on sales. Specifically, let's rewrite equation (5.2) as

$$\ln(p_{it}) = \alpha_i^1 + \tau_t^1 + \theta_1 s_t + \mu_{it} \qquad (5.6)$$

and equation (5.5) as

$$\ln(q_{it}) = \alpha_i^2 + \tau_t^2 + \beta_1 \ln(p_{it}) + \beta_2 \ln(cp_{it}) + \gamma f_t + \delta n_{it} + \eta_1 l_{it}^1 + \eta_2 l_{it}^2 + \theta_2 s_t + \varepsilon_{it} \qquad (5.7)$$

Substitute equation (5.6) into equation (5.7), we get

$$\ln(q_{it}) = \alpha_i + \tau_t + \beta_2 \ln(cp_{it}) + \gamma f_t + \delta n_{it} + \eta_1 l_{it}^1 + \eta_2 l_{it}^2 + \beta_1 \mu_{it} + (\beta_1 \theta_1 + \theta_2) s_t + \varepsilon_{it} \qquad (5.8)$$

in which $\alpha_i = \alpha_i^1 + \beta_1 \alpha_i^2$, and $\tau_t = \tau_t^1 + \beta_1 \tau_t^2$.

Thus, we have the following effects of the management change on sales:

Total Effect: $\theta_2 + \beta_1\theta_1$

Direct Effect: θ_2

Indirect Effect: $\beta_1\theta_1$

If $\theta_2 = 0$ in the model, then we are back to the case demonstrated in Figure 3. In that case, the total effect equals the indirect effect $\beta_1\theta_1$.

Our sales regression after controlling for the retail price not only solves the 'overt bias' issue, but also helps in precluding some potential sources of endogeneity in equation (5.4). The retail price is highly correlated with the management change, as shown by our price regression. Thus, if the retail price is not correlated with the residual term in equation (5.5), which is plausible, the retail price can be viewed as an instrumental variable. If this is the case, then the assumption in equation (5.5) that the management change is uncorrelated with the residual is valid. In addition, including the store feature advertising as a regressor has the same effect. According to the store manager, the store decided to stop advertising the entire category at approximately the same time that it decided to switch to the manufacturer management.

The estimates for the coefficients in equation (5.5) are also reported in Table 9. All coefficients are highly significant. The estimated effects from the two counter location changes are 0.92 and -0.243 (the results are not reported in a table), respectively. They are consistent with the fact that that the first change moved the category to a better location, while the second one moved the category to a worse location. Moreover, the estimate for the effects of the new models (*n*) and of feature advertising (f) are both significant and within the range of expectations.

Now let us look at the variable of primary interest, the change in the management. The estimated coefficient of 0.119 for all brands taken as a whole suggests that the switch from RMR to MMR increases the sales of the category by 11.9%, even after controlling for the pricing effect. Therefore, the correct causal relationship should be the one in Figure 4, rather than that in Figure 3.

When we look at the estimate difference for different brand groups from the management change, we notice that before controlling for the pricing effect, the difference between major brands (0.161) and minor brands (0.293) is statistically significant (a simple test of the difference in means between them rejects equality with 99.99 percent confidence). After controlling for the pricing effect, however, the difference becomes insignificant. These results reveal that the management change has a greater impact on minor brands than on major brands as a result of the price cut. The remaining factors which also increase sales have similar effects on both major and minor brands. The similar conclusions can be drawn for inelastic versus elastic brands and low-risk versus high-risk brands.

5.4.1 Total Regression

To better understand the relative magnitudes that different brand heterogeneities contribute to the sales increase after the management change, we also estimate the following specification:

$$\ln(q_{it}) = \alpha_i + \tau_t + \beta_{1i}\ln(p_{it}) + \beta_2\ln(cp_{it}) + \gamma f_t + \delta n_{it} + \eta_1 l_{it}^1 + \eta_2 l_{it}^2 + \theta s_t + \rho_1 s_{it} MI_{it} + \rho_2 s_{it} E_{it} + \rho_3 s_{it} HR_{it} + \varepsilon_{it} \qquad (5.9)$$

Table 10

TOTAL REGRESSION: THE EFFECT OF THE MANAGEMENT CHANGE (*s*) ON SALES

	Coefficient
Management Change (*s*)	0.136**
Management Change (*s*) * Minor Brand (*MI*)	0.075
Management Change (*s*) * Elastic Brand (*E*)	0.102
Management Change (*s*) * High-Risk Brand (*HR*)	0.078
Observations	2080
R^2	0.898

Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

The OLS estimates for this specification are reported in Table 10. The results are consistent with our finding in Table 9 – after controlling for the pricing effect, changes in other factors had similar impacts on all brands. This is demonstrated by the insignificance of the estimation for *s***MI*, *s***E*, and *s***HR*.

Since the management change has significant impacts on sales even after controlling for the pricing effect, it is necessary and valuable to examine evidence of whether or to what extent the price decrease is responsible to the sales increase. The column (5) in Table 9 presents the *direct* effect, *indirect* effect, as well as the *total effect* from the management change on sales. As we can see, the price cut incurred by the change is a main reasons for the sales increase, but there exist other factors that also have significant impacts on the sales increase after the management change. In the next section, we attempt to identify some sources of these factors.

5.5 Evidence of Non-Pricing Factors that Might Affect Sales after the Management Change

Above, we showed that the management change causes an average 10.7% decrease in the final retail price and an average 12.5% increase in sales, by which we obtained an affirmative answer to our central question: Does the management change induces more intense brand competition?

However, our regressions also showed that there exist other factors that also increase sales after the management change, and as a result, the increase in sales after the change is caused by a combination of these factors and the change in price. In this section we attempt to identify some of these non-price causes of the sales increase. We discuss the following three factors that could have a potential impact on sales: salesforce, advertising, and the inventory stock level.

Salesforce has potentially large impact on sales. According to the store manager, the change from the retailer-managed retail to the manufacturer-managed retail had a contingent change in terms of both the sales representative number and their salary structure. When the category was managed by the previous system, the sales representatives for the product category were store employees. After the change, manufacturers were responsible to have a sales staff inside the store for their individual brands, According to the store manager, the number of sales representatives increased by about 10% after the change. In addition, unlike store employees, these sales representatives from manufacturers typically received a commission salary, which gave them more incentive to sell. Therefore, the change in the salesforce is indeed an important factor that contributes to the sales increase after the management change.

The level of advertising is another important factor that affects sales. If the store increased its advertising spending on the category after the management change, we would expect sales to increase. However, this is not the case. In fact, the store stopped advertising the category in question after it was switched to MMR. The reason why the store decided to do so is that the category manager of the store believed that this product category had lost consumer attraction. This fact reveals that the more intense brand competition after the management change occurred when there was no feature advertising. It can be expected that the extent of the competition would become even stronger if the store kept advertising under the manufacturer-managed retail. Note that this argument also provides evidence for the higher percentage discount over the list price after the management change.

In addition, under the manufacturer-managed retail, the manufacturer usually uses a centrally managed inventory (e.g., there is a central warehouse in a city). Thereby, it is reasonable to expect that in the store, the product stock-out problem would be mitigated after retail was switched to manufacturer-managed retail. Under MMR, even if a stock-out indeed occurs in the store, the manufacturer can replenish its inventory rapidly. We believe that stock-out mitigation is another factor contributing to the sales increase after the management change.

5.6 Robustness Check

The estimates reported in Tables 4 to Table 9 affirmatively support our argument that the change from the store-managed retail system to the manufacturer-managed retail system increases brand competition. To check the robustness of these estimates, we considered a few variations on the reported regression. First, we run the same regressions in the linear-linear format. There were no significant changes in the estimated effects. We adhere to the use of log-log regressions for the easier result interpretation. Second, to investigate the possibility that the effects on brand competition from the management change are gradual, perhaps even to such an extent that the full effects are not apparent by the end of Year 4, we also estimate the average effects of the change separately for each monthly period after the change (April to December) in Year 4. While not shown in a table, we find that the average effect before August is significantly higher than in the months afterwards, and the effects from September to December are not significantly different from each other. These results suggest that the effects from the management change are realized fairly rapidly. This is further evidence suggesting that the assumption that our regressions do not give rise to an endogeneity problem in the sense of biasing the estimated coefficients is valid. In addition, we run our regressions on the data excluding week 15 – week 18 of Year 4, when the store was in the middle of switching from RMR to MMR. There were no significant changes in the estimated effects.

Another potential issue in our regressions which has not been addressed is that they might be subject to a serial correlation problem. We want to emphasize that the estimates reported in Tables 4 to Table 9 are unbiased and consistent as long as our argument is valid that the regressions are not subject to an endogeneity problem. This conclusion does not hinge on any assumption about serial correlation in the residuals. The consequence of the potential serial correlation problem is that the usual OLS standard errors and test statistics are not valid, even asymptotically. In general, the standard errors from OLS understate the standard deviation of the estimated coefficients, and thus, could jeopardize the model inference conclusion. We applied the approach proposed by Bertrand et al. (2004) to correct the standard errors and to obtain serial correlation–robust inference. Their approach collapses the time series information into a “pre”- and “post”- period and explicitly takes into account the effective sample size. We choose this approach over others because two critical requirements that guarantee that this approach achieves better performance than others both hold in our dataset. The two conditions are (1) “laws are passed at the same time for all states,” and (2) a small numbers of “states.” The result shows that our previous results are robust and our inferences are correct.

To the extent that one may still be concerned about possible bias in our regressions due to serial correlation, we also estimated our regression models using Generalized Least Squares (GLS) to control for AR(1) errors. The results are similar to the estimations obtained using OLS. Table 11 presents the estimated coefficients of final retail price, list price, and sales (without controlling for the pricing effect and with controlling for the pricing effect) using GLS.

Table 11
GLS ESTIMATION: THE EFFECT OF THE MANAGEMENT CHANGE (*s*) ON FINAL RETAIL PRICE, LIST PRICE, AND SALES

Regression for		Prices		Sales	
		Final Retail Price	List Price	w/o Control for Price Effect	w/ Control for Price Effect
All Brands		-0.090***	-0.047**	0.249**	0.134***
Major vs. Minor Brands	Major	-0.014	-0.013	0.164***	0.146***
	Minor	-0.123***	-0.070**	0.298***	0.118**
Inelastic vs. Elastic Brands	Inelastic	-0.015	-0.035	0.097**	0.095***
	Elastic	-0.101***	-0.055**	0.284***	0.135***
Low-Risk vs. High-Risk Brands	Low-Risk	-0.053***	-0.024***	0.193***	0.121***
	High-Risk	-0.158***	-0.081***	0.331***	0.132*

Stars denote significance levels: 99 percent confidence level (***), 95 percent confidence level (**), and 90 percent confidence level (*).

6. CONCLUSION AND DISCUSSION

This study examines the effect of a major policy change in a retailing store on brand competition. We analyze a special data set provided by a top-ranked Chinese department store, covering before and after a rapid policy change in which the retailing of one product category was switched from managed by the store (RMR) to managed by individual manufacturers (MMR). The central finding is that compared to retailer-managed retail, manufacturer-managed retail remarkably intensifies the price competition between competing brands. To establish this, we investigated the retail price and sales change as the result of the management change. We fist showed by a log-log model that overall, the retail price of the product category decreased after the management change. We then applied another log-log model to demonstrate that sales of the entire product category increased after the change.

The finding that the change in retail management induces a change in competition behavior is fairly interesting. Previous literature consistently shows that mechanisms such as channel coordination and reducing the number of intermediaries in a supply chain would benefit the manufacturer. While these benefits may very well accrue to the manufacturer, this study advocates that manufacturer competition, which has been typically ignored when discussing channel coordination, could play a critical role. Our results show that there is a trade-off between the benefits (elimination of double-marginalization, better channel coordination and information sharing, lower inventory holding costs for manufacturers) and costs (higher extent of brand competition) under manufacturer-managed retail, compared to retailer-managed retail. Moreover, the effect is large in magnitude – the estimation of our pricing regression reveals an average 11.9 percent decrease in retail price after the management change. This implies that the management change may hurt the manufacturers at the end, especially those who do not have an advantage in inventory management.

To further justify our conclusion, we also investigated the effect of the management change on three types of brand heterogeneity: major versus minor brands, inelastic versus elastic brands, and low-risk versus high-risk brands. We did this by two approaches: (i) separately examining the effect on individual brand groups, which would clearly show the effect on different brands; and (ii) running a total regression, which does a better job indicating the relative magnitudes that different brand heterogeneities contribute to brand competition. The results from the two approaches are consistent, and reveals that (1) the management change had a significantly impact on manufacturer competition, especially between those whose products are highly substitutable; (2) The impact of the management change on small brands is much more significant than on large brands, and (3) The change in management has a more notable impact on the brands with higher demand variability. The findings (2) and (3) are opposite of the conclusions given by current operations management literature; (2) also helps reject alternative explanation that the price cut after the management change is driven by cost saving.

In addition, we investigated the sources of the price cut and sales increase. After the management change, the retail price was lower could be because of the lower list prices, or could be because the seller (now is the manufacturer) promote more frequently. Our results show that the management change cause a combination of lower list prices and more frequent promotions. Therefore, the management change intensifies the brand competition not only on pricing but also on promotion. As for the sales increase, we showed that the price cut is a major cause but not the only one. Consequently, we provided evidence of other non-price factor that also caused the sales increase after the management change.

From the retailer's viewpoint, this more intense manufacturer competition means larger profits for itself. The same conclusion is shown in our game-theoretic model. Although due to the data limitation, we could not conduct a complete empirical analysis of the policy change on retailer profit, the store's manager confirmed to us that this is indeed the case. According to the store management, the sales of the product category in the store kept decreasing before the management change (which is also verified in our estimation). The store decided to switch to manufacturer-managed retail with a hope to increase sales and the store's profits. The consequence reveals that the intuition of the store administration is correct, which is also consistent to the prediction of our theoretical model. Under manufacturer-managed retail, although the retailer delegate control over two important variables, i.e., retail price and stocking level, that determines their profits to manufacturers under traditional retail-managed retail, it also eliminate its inventory holding cost and other selling cost. Furthermore, delegation of the two decision variables has another benefit for the retailer – it restores and intensifies manufacturer competition. The retailer then exploits this competition and enhances its profit.

A notable phenomenon in industry is that although manufacturer-managed retail provides with the manufacturer many advantages such as better information and lower inventory cost, it is always the retailer who proposes a switch and pushes manufacturers to adopt this new retail system. Our study offers an explanation for this puzzle. Again, more intense competition in manufacturer-managed retail might offset the advantages it brings to manufacturers. Whether or not manufacturers would like to adopt manufacturer-managed retail depends on whether the benefit is larger than the cost incurred by brand competition.

There are many interesting opportunities for future research in this topic. In the current study, we assumed that there is a single retailer. Thus, competition exists only between manufacturers. A more general model might also include competition between two or more retailers. Second, consideration of issues such as retailer and manufacturer marketing efforts would add further richness to the model. Moreover, we illustrate in this study the impact of a policy change in a world wherein the trade-off is between a RMR system and a MMR system. It would be worthwhile to explore the trade-offs between more general contracting policies on channel coordination. Currently, we (Kouvelis, Chan, and Li) are investigating this issue, with a hope to generalize our results further.

Appendix

Proof of Hypothesis 3. We want to show that in the symmetry case, the equilibrium retail price in the post-change game is lower than the equilibrium retail price in the pre-change game. The backward induction is used to solve the equilibrium retail price in both the pre-change game and the post-change game. Please refer to Section 4.3.1 and Section 4.3.2 for a detailed discussion of the procedure to derive the equilibrium. The resulting equilibrium retail prices in the pre-change and post-change game are given by equation (A.1) and (A.2), respectively.

$$p_b = \frac{3\alpha - 2\gamma\alpha + m - \gamma m}{2(2-\gamma)(1-\gamma)} \qquad (A.1)$$

$$p_a = \frac{A}{3\alpha} - \frac{m(m - \gamma m + \gamma\alpha)}{\alpha A} \qquad (A.2)$$

in which

$$A = 3m\left(9m\alpha - 9m\alpha\gamma + \sqrt{3}\left(m(m^3 - 3\gamma m^3 + 3\alpha\gamma m^2 + 3\gamma^2 m^3 - 6\gamma^2 m^2\alpha + 30m\gamma^2\alpha^3 - \gamma^3 m^3 + 3\gamma^3 m^2\alpha - 3\gamma^3 m\alpha^2 + \gamma^3\alpha^3 + 27m\alpha^2 - 54m\alpha^2\gamma)\right)^{1/2}\right)$$

To compare p_b and p_a, we obtain the difference of p_a - p_b as:

$$dp = \frac{4A^2 + 6A^2\gamma - 2A^2\gamma^2 + 12m^2 - 30\gamma m^2 + 24\gamma^2 m^2 - 6\gamma^3 m^2 + 12m\gamma\alpha - 18m\gamma^2\alpha + 6m\gamma^3\alpha + 9\alpha^2 A - 6\alpha^2 A\gamma + 3\alpha A m - 3\alpha A\gamma m}{-6\alpha A(2-\gamma)(1-\gamma)} \qquad (A.3)$$

The denominator of above equation is negative, since A is always positive, and $\gamma \in (0, 1)$. Then the numerator determines the sign of equation (A.3).

Denote the numerator of equation (A.3) as *f*. *f* can be rewritten as:

$$f = 4A^2 + 6m\gamma\alpha^2 + 6\alpha^2 A(1-\gamma) + 3\alpha Am(1-\gamma) + (3\alpha^2 A + 12m\gamma\alpha - 18m\gamma^2\alpha) + 2A^2\gamma(1-\gamma) + 4A^2\gamma + 6m^2\gamma^2(1-\gamma) + (12m^2 - 30\gamma m^2 + 18\gamma^2 m^2) \qquad (A.4)$$

which can be further simplified as:

$$f = 4A^2(1+\gamma) + 6m\gamma\alpha^2 + 6\alpha^2 A(1-\gamma) + 3\alpha Am(1-\gamma) + 2A^2\gamma(1-\gamma) + 6m^2\gamma^2(1-\gamma) + 3\alpha(-6m\gamma^2 + 4m\gamma + \alpha A) + 6m^2(3\gamma^2 - 5\gamma + 2) \qquad (A.5)$$

Note that both $(-6m\gamma^2 + 4m\gamma + \alpha A)$ and $(3\gamma^2 - 5\gamma + 2)$ are positive when *γ* ranges from 0 to 1, then f is positive when $\gamma \in (0, 1)$. Consequently, *dp* is always negative, i.e., p_a, the equilibrium retail price in the post-change game, is always less than p_b, the equilibrium retail price in the pre-change game.

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