

## OpenTide China's Pricing Decision-making Support System 2.0 for Digital Industry in China

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### **Abstract**

*The purpose of this research is to develop a comprehensive pricing decision-making support system that marketers in digital industry can use to set price level and quantity for digital products including mobile phone, TV, computer, mp3 player and monitor. The OpenTide China's pricing Decision-making Support System (OTC's PDSS) consists of the price response function for each product, the promotion response function, the cost function, mixture modeling, Kane's regency modeling and Brian's competitive algorithm. Then we have applied the OTC's PDSS to the digital industry and yielded the profit maximization price point, revenue maximization price point, and the predicted quantity level for each week for each product category.*

**Keywords:** pricing, mixture model, price response function, price decision-making support system

### **1 Introduction**

A consultant is like a doctor. As a doctor examines a patient and suggests a remedy, a consultant examines clients' situation and tries to lead them to a better situation. A doctor and a consultant share in common that they can determine their clients' future. For this reason, a sound consulting should be scientific, systematic, analytic, and strategic because it is concerned with the fate of a company.

OpenTide China has consulted various industries for 10 years in China. The MCG (Management Consulting Group) of this company has developed support systems to help their clients with strategic decision-making. This is the result that OpenTide China strategically made to help their clients' decision-making fundamentally and consistently rather than to help just one-time.

The support system introduced in this paper suggests measurable effects of various alternatives to the client's marketing mix (product, price, promotion, and place), which enables the marketers of the client to achieve specific purposes such as to maintain positioning and maximize profits and sales and protect the brand, etc. OpenTide China has the price-measuring system by product spec for electric home appliances, the advertisement effect measuring system for IT products, the distribution (place) decision-making system for off-line industries, and the pricing decision-making system for IT products. This research introduces the pricing decision-making system developed for digital industry among those systems. The OpenTide China's Pricing Decision-making Support System (OTC's PDSS) is based on the price response function for product lines, the promotion response function by products, and the cost function by each product. In order for these functions to reflect the recent market situation, we calibrated adjustment coefficients by Kane's regency modeling and applied them to PDSS. Also, we integrated Brian's competitive algorithm to reflect the competitiveness of the market. The reservation price, brand preference, and cost structure of the same product are all different from region to region in China, different sale DBs of one product by region should be

made. And different PDSSs should be constructed according those different DBs by region. For this reason, the project database (PDB) by region and product is necessary to construct.

This paper shows the structures and functions of OTC's PDSS to calculate the sales volume and profit by various prices, and it also shows the methods of deriving coefficients. For this purpose, we used 40-inch TVs in Beijing Region.

## 2 System Modeling

### 2.1 Step 1: Price Response Function(PRF)

The relationship between alternative prices and the resulting sales quantity is called the price response function (PRF) (Simon, 1989). The price response function of a product or a brand is a tool to understand the effect of price on sales for a product or a brand. Many researchers have recommended calibrating the price response function for a product or a brand to find the optimal price for the product or the brand based on conjoint analysis (Kucher et al., 1993; Simon, 1989; Yoo, 1991).

There are two approaches to obtaining the price response function. The first approach is to calibrate the price response function with prices and types of promotion as independent variables and with the sales as a dependent variable when there are real sales data. The other approach is to ask customers' purchase intention through consumer research. The conjoint analysis is appropriate for the research on customers' purchase intention to obtain the price response function.

Conjoint analysis has been recommended as an effective tool for determining the value of a product deriving price response functions and optimal prices (Geurts and Whitlark, 1993; Simon, 1989; Weiner, 1994). This conjoint measurement uses individual customer's preference, which also satisfies the condition of setting the prices from the customers' viewpoint.

Therefore OTC's PDSS uses two types of PDB. If the client has already constructed sales DBs, they will be used; if not, we have to construct DBs after collecting customers' purchase intention DBs by separate market researches. Then the price response function will be derived on the basis of those PDBs.

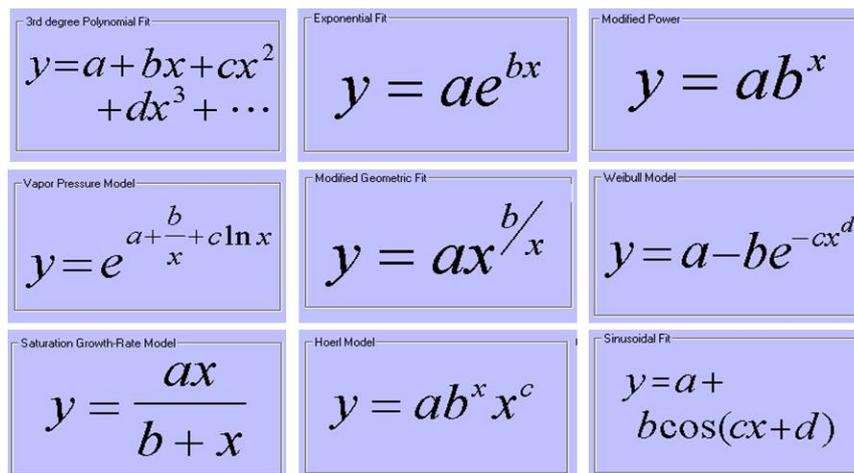


Figure 1. Some of the Price Response Functions in PDSS

Where a, b, c, and d = parameters to be estimated

x = price

y = sales volume

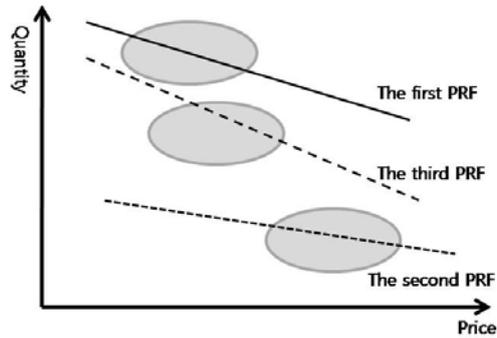


Figure 2. PRF derived from the high-demand and the low-demand seasons

The most systematic way to represent a price response function is by means of a mathematical equation. There are four types of price response function model in OTC's PDSS: linear, multiplicative, attraction, and Gutenberg models. These four basic models are expanded into 21 transformed models. Figure 1 shows some of those expanded models. PSDD applies the 21 expanded models to the PDB and seeks for the function to best explain the price and sale and uses it to predict the future.

## 2.2 Step 2: Dividing PRF into high-demand and low-demand seasons

Generally, on “Guoqingjie” (Chinese National Foundation Day) and “Chunjie” (the Lunar New Year's Day in China), Chinese consumers' purchase behavior is totally different about brands or promotion. So if we construct PDB that is based on the sales DBs of the year and make just one price response function or sales promotion response function on the basis of it, we are likely to neglect the different aspects of dull and active seasons, promotion and non-promotion seasons, normal and abnormal seasons, and high-demand and low demand seasons. To reflect differences in customers' responses to price and promotion in these different seasons, we applied mixture modeling to the price response function.

For example, there were three linear price response functions as for the 40-inch TVs in Beijing. The first price response function explains the price and promotion during the high-demand season of the year, the Lunar New Year's Day, the Labor Day, and the National Foundation Day like Christmas Season in western; the second explains those of the low-demand season; and the third, those of the normal season.

Mixture model is to separate the sample, to identify the segments, and to estimate the parameters of the density function underlying the observed data within each segment. Therefore in the first stage of PDSS, we find the most appropriate price response function. Then in the second stage, we apply the mixture model within the price response function and divide it into several price response functions that explain differences produced by products and regions. Therefore the price response of the first stage can be seen as an aggregated price response function, and that of the second stage, as a disaggregated price response function. General mixture modeling can be found on statistics text. These two steps enable us to understand the sales volumes by prices for subject digital products. Clients can obtain the revenue by prices through multiplying the sale by the price.

## 2.3 Step 3: Promotion Response Function

Marketers try to increase the sales through various types of promotion other than the price. The sales reflect the effects of promotions toward the consumers or the middleman or the local dealer. To reflect it on OTC's PDSS, we inserted dummy variables that reflect promotion when deriving the price response function. As a result we could get differences

by products and regions that affect the sales by each type of promotion. And it enabled the marketers to choose and execute the most effective type of promotion within the budget for marketing.

#### 2.4 Step 4: Cost Function

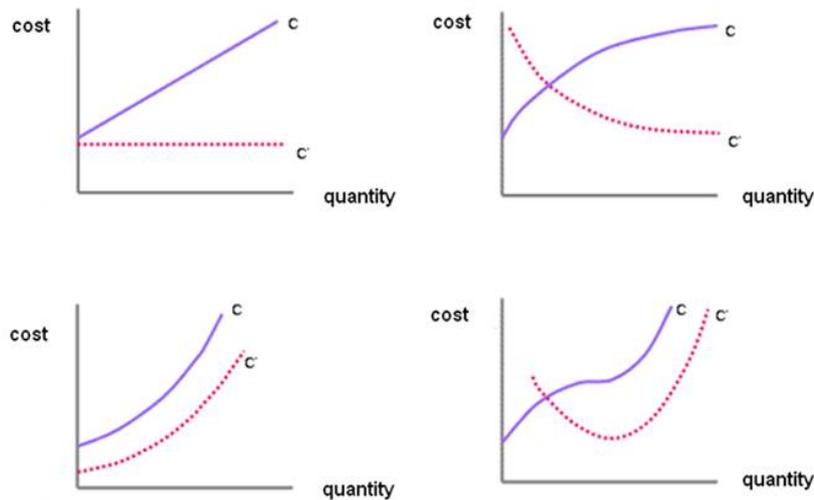


Figure 3. Types of Cost Function

The cost function traces the changes in cost by unit when the sales increase. It is generally known that the cost function has four types shown in Figure 3. Since each industry or company has a different cost function, we have to derive a different cost function when measuring the profits (Yoo, 1991). So the marketers keep the cost function appropriate for their brands, apply it together with the price response function, and achieve the profit function to find the prices that could maximize the profit. OTC's PDSS offers a special pane where clients can choose the cost function and insert it by themselves. This is because the client usually does not want to show its own cost to other companies.

Where  $c$  = unit cost  
 $c'$  = marginal cost

Through this procedure we could get the cost by unit for the sales achieved by prices. In step 3, we could measure the sales volume, the total cost and the profit by prices.

#### 2.5 Step 5: Kane's Regency Model

Since PDB is basically the data of the sales in the past, it could be possible not to be able to reflect the recent sales trend. So we need an adjustment of the sales volume according the situation of the market. To do so, we integrated Kane's Regency Model based on time series model into PDSS.

This model adjusts assumed periods of the price response function and the promotion response function. Based on the moving average model, Kane's Regency Model adjusts periods by which the data of PDB are periodically applied to the price response function. For example, when the marketer uses PDSS, it can be possible that the functions of PDSS cannot reflect the recent situations of the market because of the time lapse. For this reason, Kane's Regency Model adjusts the assumed periods and derive Kane's adjustment

index. This adjustment index changes the values of the price response function and the promotion response function. By this process, we could get the system that reflects the recent situation of the market.

## 2.6 Step 6: Brian's Competitive Algorithm

Steps one to four enable us to predict the sales and profit of our product when we change prices and types of promotion. However, our changes in price and promotion can make changes of our competitors in price and promotion. To reflect this aspect, we applied Brian's Competitive Algorithm to PDSS to derive our price adjustment and sale change in advance.

The Competitive Algorithm suggested by Brian Nam (1999) measures the extents of struggling among the brands in the corresponding positioning. The basic model takes on multinomial logit. The multinomial logit model has also been used to examine various market phenomena such as a price cut effect on a market, market segmentation, choice set change, brand switching, and so on (Bucklin, Gupta and Han, 1995; Bucklin and Lattin, 1991; Hardie, Johnson and Fader, 1993).

There are prices and types of competitors in the utility function used by Brian's Competitive Algorithm. So the cross-elasticity of competitors can be measured. Since PSDS has this algorithm, the marketer can insert the changes in price and the type or degree of promotion of competitors in user interface, and then get the sales by prices and the profits of our new product that reflect the situation.

## 2.7 Step 7: OTC's PDSS

Figure 4 shows the system expressing the modeling that has been discussed.

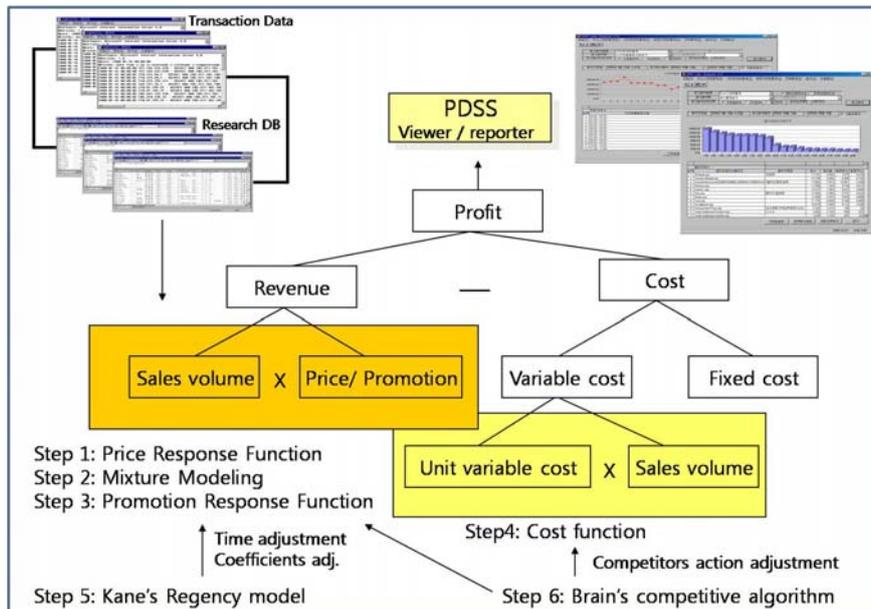


Figure 4. Structure of PDSS

## 3 Application to Digital Industry

### 3.1 Data

The weekly scanner data is used with the period from March 2009 to September 2009 in Beijing in China. Major five brands' weekly price data and Brand A's weekly sales

volume data were collected. Two brands were from South Korea. Two Brands were from Japan. One brand was originated in Mainland China.

### 3.2 Developing price response function

To find the relevant variables for the TV price response function, we investigated the sales pattern and variables for TV a year. Figure 5 shows the flow between the sales volume for each week and price change among two major companies in 40 inch LCD TV market in Tianjin in 2008.

Table 1. PDSS Step-by-Step Algorithm and Its Outputs

Step	Title	Algorithm	Output
1	Aggregate price response function	21 mathematics functions	Sales volume for price points Revenue maximization price point
2	Disaggregated price response function	Mixture modeling	Sales volume for normal periods Sales volume for abnormal periods Revenue maximization price point
3	Promotion response function	21 mathematics functions	Sales volume for promotion types
4	Cost function	4 types	Cost for price point Profit Maximization price point Regency adjustment index
5	Kane's regency model	Time series model	Adjusted Sales volume for normal periods Adjusted Sales volume for abnormal periods Adjusted Revenue maximization price point Adjusted Profit Maximization price point
6	Brian's competitive algorithm	Multinomial Logit formation	Adjusted sales volume, Revenue maximization price point, Profit Maximization price point incorporating competitors' price and promotion action
7	Application to region and product		PDSS for each region and product line

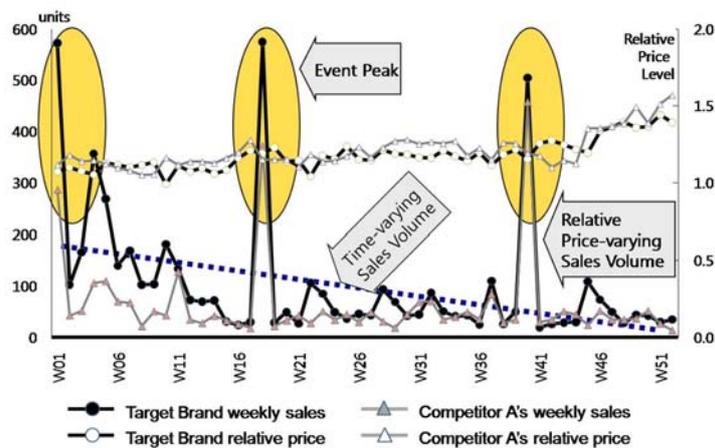


Figure 5. The sale volume and price change for each week in Tianjin in 2008.

First, the sales volume for each week is not stable. The first week a year, Chunjie, Mayday, and Guoqingjie show sales peak. However, the rest week reveals low sales volume. Second, the buyer may postpone purchasing in anticipation of future price or event like Chunjie, Mayday, and Gouqingjie. Third, sales in pre-period influences sales in future. Forth, the time goes by, the sales volume is falling down. Fifth, the relative price to competitors may affect the target brand's sales.

Using this sales pattern a year in TV, we developed the dynamic price response function for the study as follows. The target brand's sales volume for each week is affected by the price level of TV style, the buyers' price expectation, competitive price effect, event effect, and the duration time for waiting event.

## 4 Findings and Future Study

### 4.1 Modeling's capability and predictability

TV PDSS dynamic price response function model is explaining the 96.8 % of variation in weekly sales data in Beijing. That is,  $R^2=0.968$ . The Table 2 shows the gap between the predicted sales volume for Brand A and the real sales volume for each week. After 5 week, modeling produces the one digit gap between predicted sales and real sales. Our modeling for TV PDSS shows stable predicted capability. Because, PDSS modeling can effectively explain the past sales, we can predict the future sales data, systemically. Figure 7 shows the user interface of OTC's TV PDSS for Beijing.

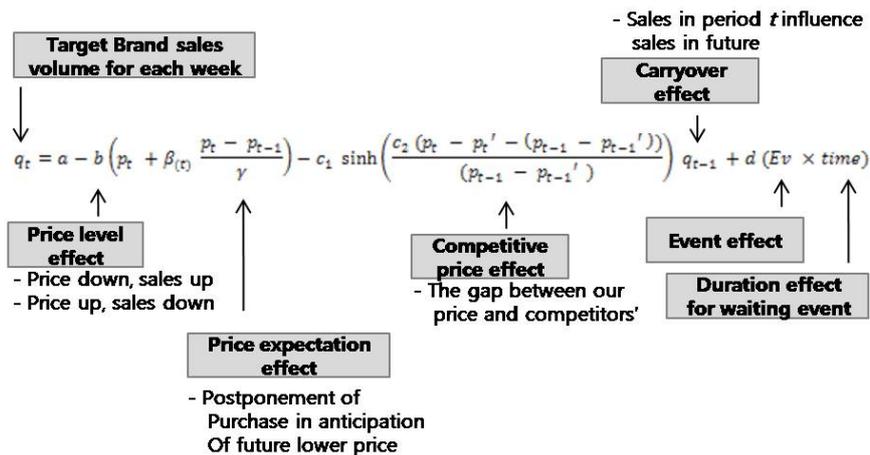


Figure 6. Model for OTC's PDSS

Where a, b, c<sub>1</sub>, c<sub>2</sub>, d = parameters to be estimated

$p_{(t)}$  = price at time t

r = discount rate for time duration

$p_{(t)}$ ' = the average price among competitors

Ev = if the week is holiday such as Chunjie, mayday and

Guoqingjie = 1, otherwise =0

time = inter-event time (weeks)

### 4.2 User interface of PDSS

The OTC's PDSS is designed to three objectives. First, the PDSS shows sales volume forecasting for each week. Figure 7 shows the input window for achieving this objective. Second, the PDSS shows our product's sales volume forecasting whenever competitors' prices change. The PDSS allows inserting competitor's price change scenario to estimate the influence to target brand sales volume as shown at Figure 7. Third, the PDSS

helps to search the profit maximized price level for each week with competitors' price change situation. The outcomes earned by designing this price support system can be summarized as follows. First, different price response functions are derived by different aspects of high-demand and low-demand seasons and active and dull seasons. Marketers can trace the sales changes that appear differently in a low-demand season and in a certain period that all promotion concentrates. Second, different price response functions are derived by regions in China. We apply TV PDSS modeling to other regions such as Shanghai, Guangzhou, and Chengdu. Researchers found that the each city has its own unique price response

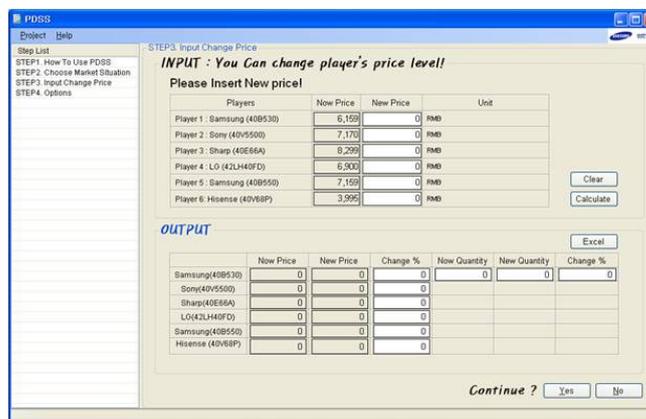
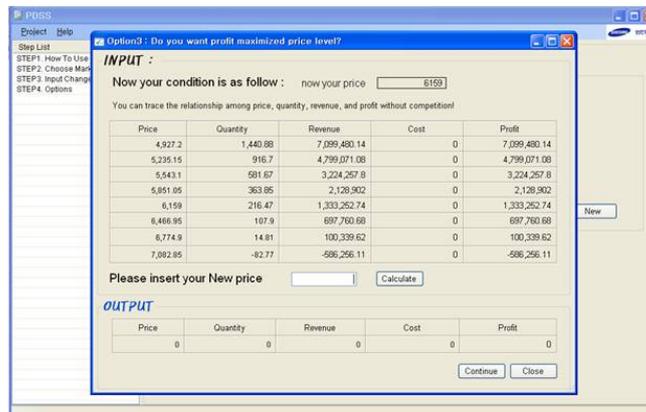
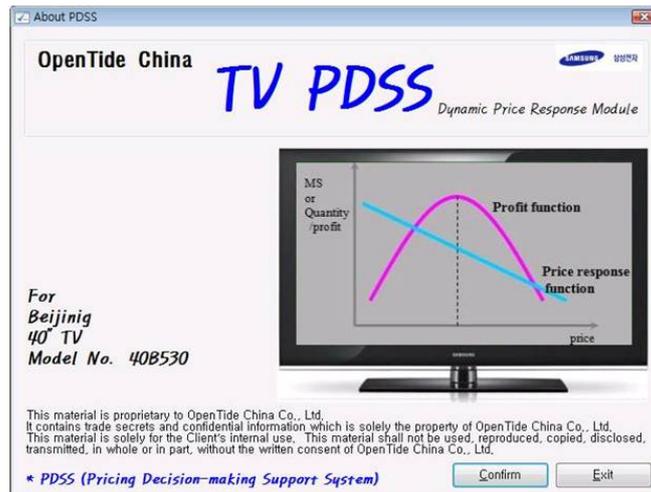


Figure 7. OTC's PDSS interface

Table 2. The predictability of the dynamic price response function

week	Predicted sales	Real sales	Gap between predicted and real sales	gap%	Predicted cumulative sales volume	Real cumulative sales	Gap between predicted cumulative and real sales	gap%
200914	30	53	-23	-42%	30	53	-23	-42.5%
200915	32	43	-11	-27%	62	96	-34	-35.4%
200916	33	46	-13	-29%	95	142	-47	-33.3%
200917	35	86	-51	-59%	130	228	-98	-43.1%
200918	1029	1050	-21	-2%	1,159	1,278	-119	-9.3%
200919	87	34	53	155%	1,245	1,312	-67	-5.1%
200920	3	11	-8	-70%	1,249	1,323	-74	-5.6%
200921	32	26	6	24%	1,281	1,349	-68	-5.0%
200922	278	186	92	49%	1,558	1,535	23	1.5%
200923	34	44	-10	-23%	1,592	1,579	13	0.8%
200924	43	31	12	40%	1,636	1,610	26	1.6%
200925	68	69	-1	-1%	1,704	1,679	25	1.5%
200926	113	112	1	1%	1,817	1,791	26	1.4%
200927	121	116	5	4%	1,938	1,907	31	1.6%
200928	120	117	3	2%	2,057	2,024	33	1.7%
200929	125	76	49	65%	2,183	2,100	83	3.9%
200930	131	90	41	45%	2,313	2,190	123	5.6%
200931	92	121	-29	-24%	2,406	2,311	95	4.1%
200932	92	124	-32	-26%	2,497	2,435	62	2.6%
200933	126	138	-12	-8%	2,624	2,573	51	2.0%
200934	183	179	4	2%	2,807	2,752	55	2.0%
200935	191	276	-85	-31%	2,997	3,028	-31	-1.0%
200936	158	127	31	24%	3,155	3,155	-	0.0%

function. In other countries such as Korea, the sales change by prices is almost consistent. Therefore, PDSS should be made for each region in China.

Third, different price response functions are derived by size and type even in the same group of product. For example, as for the sizes of TV like 32 inches or 40 inches, different degrees of brand loyalty and different price and promotion elasticity are derived in the same market. Therefore, PDSS should be applied to product line as well as product category.

OTC's PDSS is evolutionary. Future version of PDSS will include promotion response to PDSS. In addition to price competition, promotion competition among competitor should be considered to predict the sales volume. The developed PDSS, also, is not including cannibalization effect among Brand A's products.

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