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# Capacity-Driven Pricing Mechanism in Special Service Industries

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**Abstract**

We propose a capacity driven pricing mechanism for several service industries in which the customer behavior, the price demand relationship, and the competition are significantly distinct from other industries. According our observation, we found that the price demand relationship in these industries cannot be modeled by fitted curves; the customers would neither plan in advance nor purchase the service strategically; and the competition would be largely local. We analyze both risk neutral and risk aversion pricing models and conclude the proposed capacity driven model would be the optimal solution under mild assumptions. The resulting pricing mechanism has been implemented at our industrial partner with positive results since 2005.



**Keywords:** Pricing model, Revenue management, Demand curve, Special service industry.

# Capacity Driven Pricing Mechanism in Special Service Industries

## 1 Introduction and Literature Review

Pricing is one of the most important Revenue Management (RM) decisions especially for service industries. The most significant factors that influence pricing decisions are customer behavior, competition, and market demand Gans and Savin (2005). Microeconomics theory suggests that market demand is a function of price. It is a trivial fact that for most industries, whenever a company reduces the price of its products or services, it expects a positive impact on sales. At the same time, a price increase usually negatively impacts the sales. Therefore, the price demand relationship is critical to both academia and practitioners in the field of revenue management and pricing. A common approach is to treat the market demand as the function of price. Based on such functions, a variety of pricing models have been developed on it. King and Topaloglu (2006) provided a pricing model for the fleet management problem. Gupta et al. (2006) and Soysal (2007) are about pricing models for seasonal goods. Their model are primarily based on Markov Decision Process. Cope (2007) introduced the Bayesian model for dynamic pricing in E-commerce. Gans and Savin (2005) integrated the pricing model with the capacity planning.

The price demand relationship on these models are usually established by fitting the historical data points. The fitting process is called norm approximation (see Boyd and Vandenberghe (2004) and references therein). The resulting curve is called the price demand curve or demand curve (DC) which could be either deterministic or stochastic. For example, Nocke and Peitz (2005) and Panda et al. (2006) modeled the market demands by a random vector with transparent distributional information. Instead of using a deterministic DC, a DC with stochastic components is formed by adding random components. There are other alternative approaches to model the price demand relationship. For example, there is a method called "*learning*" method by Bertsimas and Perakis (2006). Basically, the *learning* method is an optimization based heuristic. It works quite well for online shopping activities. When most revenue management and pricing models are built on DC, it gives a perception to the practitioners that the price demand relationship can be *solely* represented by DC.

In addition to the price demand relationship, certain factors such as the pricing decisions by competitors and the customer behavior can greatly affect revenue of a company as well. There are numerous papers that address pricing models under these factors. Anderson and Schneider (2007), Gallego and Hu (2009), Levin et al. (2007) are representative articles for highly specialized pricing models under competition. The basic assumption for these articles is that customers will plan strategically in advance for the perspective price adjustment. Chen and Homem-de-Mello (2009) present a preference based customer behavior model for the airline revenue management. Zhang and Cooper (2005) provide customer behavior analysis when parallel flights are available. Other representative papers are Talluri and van Ryzin (2004), van Ryzin and Vulcano (2006) as comprehensive solutions for network revenue management with customer choice.

Authors of this paper have the luxury of accessing the operational data from an industrial partner. Our industrial partner is a leading real estate management company in the nation. It operates more than $1,000$ local self-storage stores. 90% of customers are residential including college students and small businesses. They rent space for a variety of goods, documents, furniture, seasonal supplies, and recreational vehicles. Customers make their decision based on multiple factors, such as the proximity, appearance and quality of the facilities, reliability of the provider in providing dependable and acceptable service, responsiveness of the provider to the need, assurance that the service will be delivered as expected, and the treatment of the customers by the service provider (see Parasuraman et al. (1988)). According to the company's past 20-year records, the customer behavior, the price demand relationship and the competition are very counter intuitive and different from other industries. Furthermore, none of these observations have been reported from existing literature. Therefore, the company's pricing mechanism should be uniquely designed.

We first present the company's historical data about the price demand relationship. In Figure 1, it shows the sales data from stores in one major U.S. metropolitan area in 2007. The $x$-axis indicates the different price levels and the $y$-axis records the sales generated at corresponding price levels.

Figure 1 about here.

Figure 2 tracks the price and sales over two months from one store in the same region.

Figure 2 about here.

Figure 1 and Figure 2 will yield a poor fitted curve with an extremely low covariance on price and demand.

In Figure 3, we illustrate the 121-week data on both the occupancy levels (upper graph) and the price levels (lower graph). Clearly, both the occupancy levels and the price levels show downward trends. This is counter intuitive because the lower price usually leads to more sales and thereby higher occupancy levels.

Figure 3about here.

After a detailed investigation on the property's performance, we conclude that this was the result of a continuous effort to generate sales from a sequence of price cuts. In order to bring customers into the store, the price level has been in a declining trend in the last 121 weeks. However, the sales number suggests a clear downward trend at the same time. We realized that this property was in a region where the foreclosure rate was far higher than the national average and the real estate prices have plummeted since the last two years. According to this example, even when the company cut the price more aggressively, the number of sales and the occupancy levels would still decline steadily. In this case, we conclude: first, the fitted DC may not be suitable for all the industries; second, cutting pricing will not necessarily bring new market demands in the self-storage industry.

In order to study the impact of price on demand from another perspective, we conduct another pilot pricing experiments. In a Midwest city, we carried out a price in selected stores leaving the price of other stores unchanged for 17 successive weeks in 2006. The result of this action, as illustrated in Figure 4, indicates that a price cut has positive impact in bringing customers in.

Figure 4 about here.

Figure 3 and 4 are sending mixed signals on the effect of price cut and customer demands. From the pilot experiment, lower price will instantly cause higher sales. From Figure 3, however, a lower price failed to yield more sales. The price demand relationship can also show strong randomness in Figures 1 and 2.

Our third observation is called the "jump" effect described in Figure 5 that resulted from a price cut in week 1 at only one store and the price cut was maintained until week 9. The positive effect from the price cut, in this instance, lasted less than 3 weeks.

Figure 5 about here.

We must remark that the observations in Figures 1, 2, 3, 4, and 5 are not coincidences. Similar observations can be obtained at almost all the stores across the nation since the mid 1990s.

Our explanation on these observations is caused by unique customer behavior and local competitions. Prior to introducing our capacity driven pricing mechanism, we first summarize the characteristics of the self-storage industry as the following items.

1. Most often, the customers seek prompt service once their needs emerge. For example, the rental season for properties close to colleges should be from May to September. During the period, college students will rent space for their dormitory belongings. Once their demand disappear, they will move out immediately no matter how much price cut the property may offer.

2. Customer demands usually emerge randomly as the consequence of highly unexpected events, such as divorce, death, relocation, and birth. Under such circumstances, planning in advance is unlikely. Therefore, we can rule out the possibilities of strategical customer, or forward looking customers. As a result, the widely applied game theory based revenue management models may not be used even under competition.

3. The competition only comes from local competitors because of the nature of the service. Customers need to access their units physically within a certain proximity of their residence.

4. In the era of internet, all service providers post their pricing information online to facilitate customers. At the same time, the service price becomes transparent to competitors as well.

5. The available service capacity (ASC) is the number of vacant units and the total service capacity (TSC) is the number of units at the property. Every service provider's ASC is known by other competitors. Within a short term, say a quarter, the service provider's TSC is largely fixed.

6. A price cut will not necessarily generate new market demand. Therefore, whenever a store reduces the price for its service, the positive impact observed is solely contributed by winning active customers, i.e. these seeking the service at that time. Since pricing information is transparent, competitors will match the price cut quickly to eliminate any advantage caused by the price cut.

7. Pricing decision will only affect the decisions of active customers who are shopping for services on the market. Existing customers, once moved in, will not switch their service providers solely due to the factor of service charge.

8. Lastly but most importantly, the service charges are not cost based and the services provided are essentially the same (see Secomandi and Johnson (2007)). Customers can neither determine the physical value of the services nor set their uniform price ranges. Therefore, customers compare the prices from all the local service providers before purchasing. A low price provider will become the favorable choice. We thereby can illustrate customers preference by Figure 6.

   Figure 6 about here.

   Suppose a local store has $m$ competitors, $C_1,\ldots,C_m$, with similar store appearance, reputation, and service protocols. Their price levels are $p_1,\ldots,p_m$ respectively. The low price service provider is always customers' favorite.

Rather than confining our pricing mechanism within the self-storage industry, we identified other service industries which also possess characteristics from 1 to 8. These service industries are the funeral service, the vehicle body shop, the health care lab, and the repair service. In the remaining section of the paper, we call these service industries the special service industry (SSI). For these industries, we propose a capacity driven pricing mechanism. As such, the rest of the paper is organized as follows: in Section 2, we introduce our pricing model by integrating characteristics specific to SSI. In Section 3, we present the resulting pricing mechanism from the model in Section 2. We present the result from business implementation of our industrial partner and conclude the research in Section 4.

## 2 Model

In SSI, companies adjust their prices periodically and within each such a period, prices are fixed. Therefore, we can model the pricing problem on fixed planning horizons. Suppose a company is one of multiple service providers in a certain region. The company's price level is $x$ for certain planning horizon. Due to the uniqueness and the nature of the SSI, we will introduce a set of notations which are different from those in the literature.

- Under the company's price level $x$, the total available service capacities operated by local competitors is $c(x)$.
- Let $\xi$ denote the total market demand during the planning horizon in this region. Unlike other papers, we do not assume the possession of distributional information.
- For certain planning horizon, the company's available service capacity is $b$ which is deterministic and known.
- Under the market demand $\xi$, let $p$ be the price that

$$c(p) + b = \xi.$$

  Since service providers' ASCs are largely fixed during certain planning horizon, $p$ is solely and monotonically determined by $\xi$. Unlike other literature, we use $p$ rather than $\xi$ to incorporate the randomness and $\mathbb{P}(A \leq p \leq B) = 1$. For general purposes, we let $F(\cdot)$ represent the cumulative distribution function of $p$ and $f(\cdot)$ the probability density function. We name $p$ the *market supporting price* (MSP).

- The risk-less profit, or projected revenue is $bx$ when the company's price is $x$ and ASC is $b$.
- When underpricing, i.e. $c(x) + b < \xi$, the company shows conservativeness in pricing. The resulting loss is named as the underpricing loss denoted by $U(x, p) := b(x - p)^-$ where $(x)^- = \max\{-x, 0\}$.
- When overpricing, i.e. $c(x) > \xi$, the company's loss much more severe than the underpricing loss because we may not generate any sale during the planning horizon. We represent the overpricing loss by $O(x, p) := bx\mathbb{I}(p < x)$ where $\mathbb{I}(p < x)$ is 1 if $p < x$ and 0 otherwise.

In the pricing model, the decision variable is the price level $x$ during certain planning horizon. Although the ultimate objective is to maximize the operating revenue, the objective could appear in multiple formats.

- *The risk neutral pricing decision*. This objective is to determine the optimal price $x$ that the expected revenue is maximized.

$$\max_{x \in \mathbb{R}^+} \mathbb{E}_p[bx\mathbb{I}(p > x)] \text{ i.e. } \max_{x \in \mathbb{R}^+} bx\mathbb{P}(p > x) \text{ or } \max_{x \in \mathbb{R}^+} bx[1 - F(x)] \tag{2.1}$$

  where $\mathbb{I}(\cdot)$ is the indicator function of $p > x$.

- *The risk aversion pricing decision*. There are two losses, the underpricing and overpricing. When we compare these two types of losses, we realize that the overpricing may lose all sales during the planning horizon while the underpricing only cause a fraction of revenue. Therefore, the risk aversion pricing should essentially try to avoid the overpricing loss. Let $\alpha$ be the significance level which is usually set at 0.05.

$$\max_{x \in \mathbb{R}^+} bx \text{ subject to: } \mathbb{P}(x < p) \geq 1 - \alpha \tag{2.2}$$

  In our problem, $\alpha$ is the probability of overpricing.

Since the convexity in both model (2.1) and model (2.2) are important, we need to make the following assumption on the distributional information of $p$.

**Assumption 1.** *The probability density of $p$, $f(p)$, is log-concave.*

Since many widely used distributions, such as normal, uniform, logistic, chi-squared, exponential, Laplace, Gamma, and Weibull, are log-concave, our assumption is not restrictive to hurt the generality (see Bagnoli and Bergstrom (1989)).

**Theorem 1.** *The objective of model* (2.1) *is log-concave if $f(x)$ is log-concave density.*

*Proof.* The proof can be divided into two parts. First, if we assume the density of $p$, $f(x)$, is log-concave, Bagnoli and Bergstrom (1989) showed that $(1 - F(x))$ is log-concave. Second, since $x > 0$ is log-concave, then $x(1 - F(x))$ is log-concave. We are done. □

**Theorem 2.** *Model* (2.1) *has the global optimal solution if $x_1^*$ is the optimal solution, we have $1 - F(x_1^*) - x_1^* f(x_1^*)$.*

*Proof.* By theorem 1, then $\log(bx(1 - F(x)))$ is concave. Then

$$\max_{x \in \mathbb{R}^+} \log(bx(1 - F(x))) \tag{2.3}$$

has the same global solution as model (2.1). $x_1^*$ is calculated from the first order optimal condition. □

The risk aversion model (2.2) can be transformed into a convex programming as well. By assumption 1,

$$\min_{x \in \mathbb{R}^+} -bx \text{ Subject to: } \log \alpha - \log[F(x)] \geq 0 \tag{2.4}$$

and its optimal solution $x_2^* = \sup\{x | F(x) = \alpha\}$.

Both optimal solutions from the risk neutral model and the risk aversion model will stay optimal during the planning horizon when competitors' prices remain unchanged. Nevertheless, our observation tells us that any competitor will adjust their prices at any time. Therefore, the commonly interested question on pricing is how to respond to competitors' pricing adjustments. To be specific, the company needs to respond under the following scenarios:

**Scenario A** When our ASC level is low, competitors with large amount of ASC change prices.

**Scenario B** When our ASC level is high, competitors with large amount of ASC change prices.

**Scenario C** When our ASC level is low, competitors with small amount of ASC change prices.

**Scenario D** When our ASC level is high, competitors with small amount of ASC change prices.

The competitors' price change will be modeled by the perturbation on the distribution of $p$. Let $\mathbb{Q}$ be the real probability measure rather than the underlying probability measure $\mathbb{P}$. The real cumulative probability function is $G(x)$ and the real probability density function is $g(x)$. When competitors lift prices, we will have $F(x) \geq G(x), \forall x \in [A,B]$. Likewise, when competitors cut prices, then $F(x) \leq G(x), \forall x \in [A,B]$. The expected MSP will change from $\mathbb{E}_{\mathbb{P}}(p)$ to $\mathbb{E}_{\mathbb{P}}(p)$. In addition, we need the following assumptions.

**Assumption 2.** *$G(x)$ is always log-concave when $F(x)$ is log-concave, and $F(A) = G(A), F(B) = G(B)$.*

**Assumption 3.** *For $x \leq \min\{\mathbb{E}_{\mathbb{P}}(p), \mathbb{E}_{\mathbb{Q}}(p)\}$, $f(x) \leq g(x)$.*

Assumption 2 can be proven as a theorem in Bagnoli and Bergstrom (1989) when the perturbation is modeled by the affine transformations. The purpose of assumption 3 is to guarantee the perturbation is significant enough to differentiate both distributions. We use Figure 7 to show the perturbations on the distribution of $p$. The perturbed cumulative distribution function $G(x)$ is not required to be the shift of $F(x)$, i.e. $F'(x+\delta) \neq F(x), \delta \in \mathbb{R}$. We only require the assumptions 2 and 3.

Figure 7 about here.

**Theorem 3.** *Suppose $y_1^*$ and $y_2^*$ are the optimal solutions of the risk neutral model (2.1) under the distributions $\mathbb{P}$ and $\mathbb{Q}$ respectively. When $F(x) \leq G(x)$, then $y_1^* \geq y_2^*$. Likewise, $y_1^* \leq y_2^*$ in order to make if $F(x) \geq G(x)$.*

*Proof.* Without loss of generality, we assume $F(x) \leq G(x), \forall x \in [A,B]$, i.e. the competitors cut prices. By theorem 2, we have $1 - F(y_1^*) - y_1^* f(y_1^*) = 0$. By assumption 2 and 3, $1 - G(y_1^*) - y_1^* g(y_1^*) \leq 1 - F(y_1^*) - y_1^* f(y_1^*) = 0$. Hence, $y_1^* \geq y_2^*$ by log-concavity of $F(x)$ and $G(x)$. Similarly, we can show that $y_1^* \leq y_2^*$ when competitors lift prices, i.e. $F(x) \geq G(x), \forall x \in [A,B]$. □

**Theorem 4.** *Suppose $y_1^*$ and $y_2^*$ are the optimal solutions of the risk aversion model (2.2) with $\alpha$ under the distributions $\mathbb{P}$ and $\mathbb{Q}$ respectively. When $F(x) \leq G(x)$, then $y_1^* \geq y_2^*$. Likewise, $y_1^* \leq y_2^*$ if $F(x) \geq G(x)$.*

*Proof.* Since $y_1^* = \sup\{y | F(y) = \alpha\}, y_2^* = \sup\{y | G(y) = \alpha\}$. Therefore, when $F(x) \geq G(x), \forall x \in [A,B]$, $y_1^* \geq y_2^*$. Otherwise, $y_1^* \leq y_2^*$ □

By theorems 3 and 4, when competitors cut price and thereby $p$'s distribution shifts to the left, our best response should cut our price to sustain our position in the competition. Similarly, when competitors increase prices and the distribution of $p$ shifts to the right, we can increase our price to avoid the under-pricing loss. That is, the suggestions from both risk neutral model and risk aversion model are consistent with each other. There is only one exception. When 99% units are occupied, the property manager would carry out a significant high price on the remaining ASC. This action can also be justified by theorem 3 and 4. When $b$ is low, the price adjustment will only lead to very limited revenue increase if we follow competitors' adjustments. Under this circumstance, lifting price of remaining ASC to a significantly higher level could gain a large margin with literally no risk. When $b$ is high, however, we should always respond to competitors' pricing adjustments immediately. Such a conclusion from theorems 3 and 4 is consistent with our observation in practice. For a newly opened property, the common strategy is to offer low price to quickly fulfill the vacant units. On the other hand, a 99% occupied property will be reluctant to match competitors' offers.

We must remark both (2.1) and (2.2) are not solved in practice. There are many reasons. First, the SSI is operating in a constantly changing environment and the market demand can not be accurately model by statistical tools. Second, model (2.1) and model (2.2)'s optimal solution can be substantially changed even under a small perturbation (see Ben-Tal and Nemirovski (2000)). In SSI, perturbations on parameters of both models are very likely. Lastly, the optimization model may provide ugly-real solutions which are against some established conventions. In next section, we will develop a pricing mechanism based on both theoretical analysis and simulation study.

## 3 Numerical Study and Business Implementation

In this section, we build a real scale simulation study to justify our pricing mechanism developed. Suppose our store locates in a stable neighborhood with 7 competitors ($m = 7$). To simplify the notation, our store is called "ESS" and seven competitors are named $C_1, \ldots, C_7$ in a sequence in an ascending order by their price levels. The summary for "ESS" and competitors is listed in table 1.

Table 1 about here.

The optimal price is first calculated from the risk neutral model. Afterward, the result is rounded to one of the following

$$\$99, \$105, \$115, \$122.5, \$127.5, \$135, \$145, \$151$$

which are designed to differentiate our price from these seven competitors. For example, when the optimal solution is between 110 and 120, then our price would be $\frac{110+120}{2} = 115$ to simplify the notation and avoid ugly real numbers. Despite providing consistent results with the risk neutral model, the risk aversion model is overly conservative. Therefore, we focus on the risk neutral model in this simulation study.

1. **Large competitor's price adjustment:** A large competitor, $C_4$, adjusts its pricing levels. First, $C_4$ cuts its price from \$125 to \$100. Second $C_4$ increases its price from \$125 to \$150. We put the result with Poisson market demand in figure 8 and the result with uniform market demand in figure 9 respectively.

   Figure 8 about here.

   Figure 9 about here.

   The $x$-axis is our ASC and the $y$-axis is the optimal price. The solid curve represents the optimal price without competitors price changes. The even dotted curve is the optimal price when $C_4$ reduces prices and the uneven dotted curve is the optimal price when $C_4$ increases prices. For all the curves under both distributions, the downward trend is quite significant which means that we should offer low prices when our ASC level is high. The results suggest we should always react to the large competitor's price adjustments. When large competitors increase prices, we should keep our price unchanged or increased. When large competitors cut price, our most likely reaction is to match the price cuts to attract customers.

2. **Small competitor's price adjustment:** This example is to show our most likely pricing decision when a small competitor adjusts price. In this case, there is a small competitor, $C_7$ which has only 6 units available (i.e. $ASC = 6$). We simulate when they cut all these 6 units to \$100 from \$150 and they increase price to \$180 from \$150. The market demand is simulated by both Poisson and uniform distributions. The optimal prices by changing ASC are in figure 10 and figure 11. The simulation results suggest that the small competitor's price cut has far less impact on our pricing decision. Our best reaction is to ignore such changes and focus on the action of large competitors.

   Figure 10 about here.

   Figure 11 about here.

3. **New competitor's emerging:** We create a new competitor, $C_8$ with $ASC = 400$. A new competitor usually emerges on a fast growing market. This competitor could start operating either at \$110 with 400 ASC or at \$180 with 400 ASC. The results are in figure 12 and figure 13.

   Figure 12 about here.

Figure 13 about here.

> The results suggest that a new competitor means a substantial change in the region. When new competitor opening at high price, we should keep our price unchanged (see the corresponding curves in figure 12 and figure 13). However, whenever a new competitor opens at low price, we should match the low price to attract customers regardless our ASC level.

We summarize our mechanism into the following items or *rules* to handle the competition.

1. When a small competitor adjusts price, we tend to keep our current price.

2. When a large competitor adjusts price, we tend to match the adjustment.

3. When a new competitor emerges at high price, we tend to keep our price untouched. However, when a new competitor emerges at low price, we should match the low price to attract new customers.

4. Our ASC is another critical factor on our pricing decision. Whenever our ASC is high, a lower price will help to fill the vacant units. When our ASC is low, we should be conservative on issue price reduction or sales promotions.

Since 2005, this pricing mechanism has been implemented at our industrial partner. Since then, significant improvements on both quarterly occupancy growth (table 2) and the quarterly revenue growth against major competitors (table 3) have been observed. Weighted average occupancy has grown from 81% in the first quarter in 2005 to 87% in the third quarter in 2007. During this time same-store revenue growth has been kept at about 5% after the inflation adjustment.

Table 2 about here.

Table 3 about here.

# 4 Conclusion

In this paper, we discuss the uniqueness of SSI in terms of customer behavior, pricing mechanism and competition. We found that when services provided by different service providers are essentially the same, customers in SSI will put price in front of any other factors. The demands emerge at random and unpredictable. The price reduction will not generate new demands and when the company issues a price cut, the observed positive sales records are solely contributed by attracting active customers. Once customers purchase the service, they will stay with the provider until their needs disappear. The positive effect by price reduction can be canceled within a short period because the competitors will match the price cut.

Based on these observations, we first conclude that the pricing model in SSI should not be built on a fitted price demand curve (DC). Afterward, we presented two pricing models, the risk neutral model and the risk aversion model. Both models suggest match competitors' price adjustments. Another factor is our ASC. When ASC level is high, both models suggest low prices and when ASC is low, the property becomes conservative in price reduction. We also find applying both pricing models directly in practice unrealistic. Instead, we develop a pricing mechanism to substitute both models by theoretical analysis and simulation studies. Comparing with these models, the resulting pricing mechanism is highly operational. We have implemented the model recommendations in our industrial partner since 2005. Our pricing mechanism has outperformed our major competitors and has been recognized as a success in SSI.

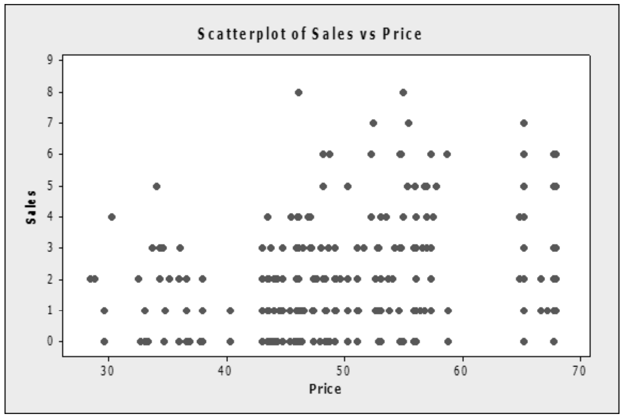


Figure 1: Price vs. Sales in one major U.S. metropolitan area.

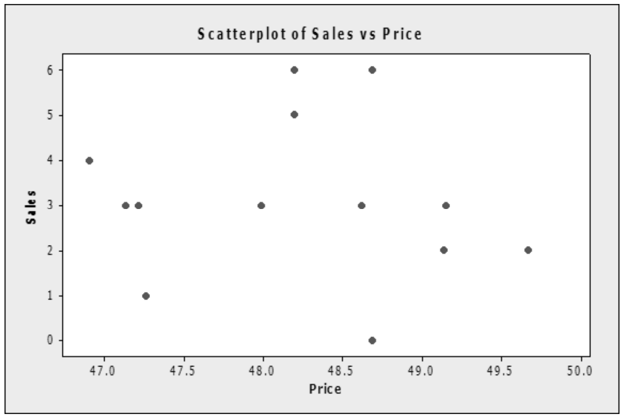


Figure 2: Price vs. Sales from one store in the same metropolitan area of Figure 1.

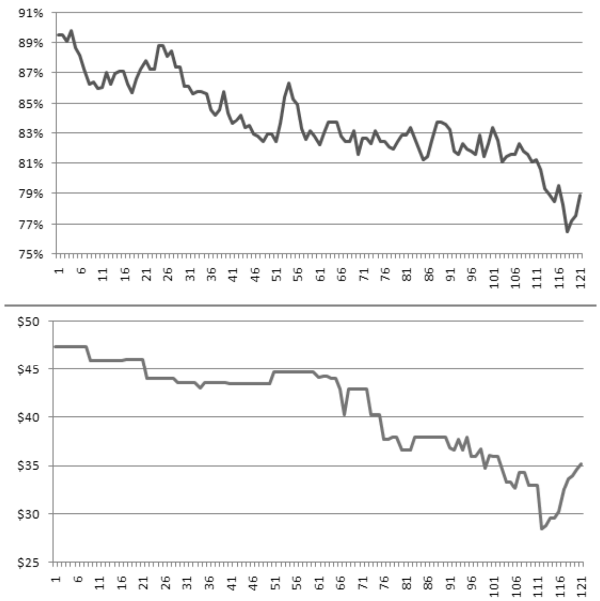


Figure 3: Pricing decision is second to regional, economic factors.

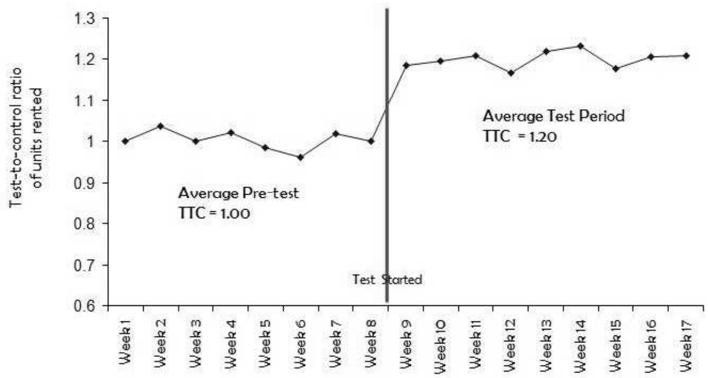


Figure 4: Effect of the price cut on selected stores

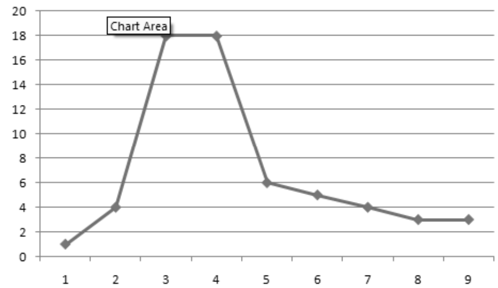


Figure 5: The jump effect of a price cut

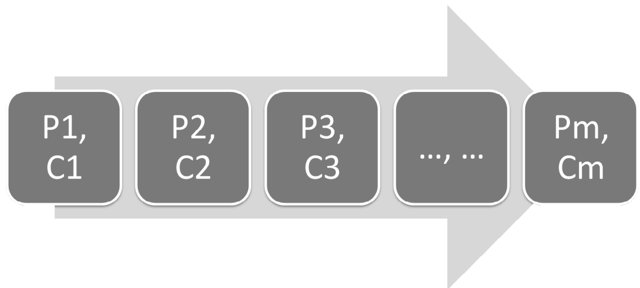


Figure 6: Individual customers' buying preference with $0 \leq p_1 \leq \ldots, \leq p_m$

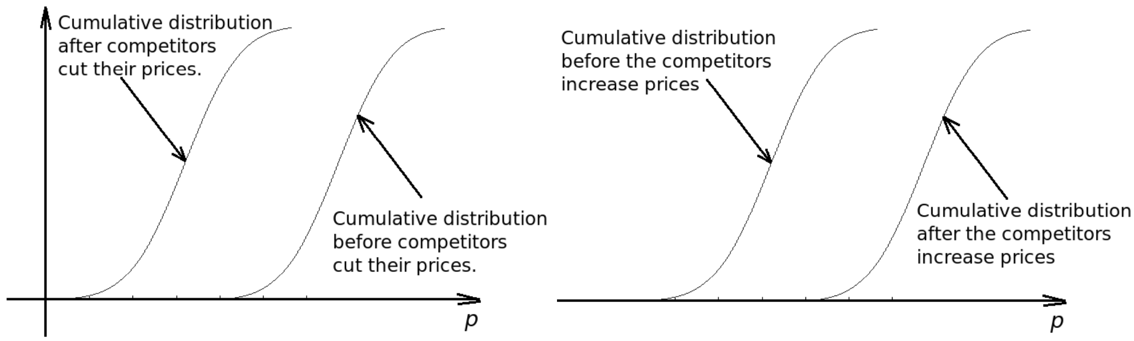


Figure 7: Perturbation caused by competitors' price cuts or price increases

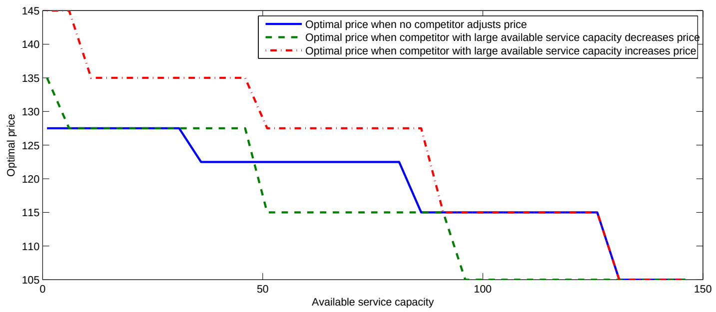


Figure 8: The optimal price when large competitors adjust price (Poisson market demand)

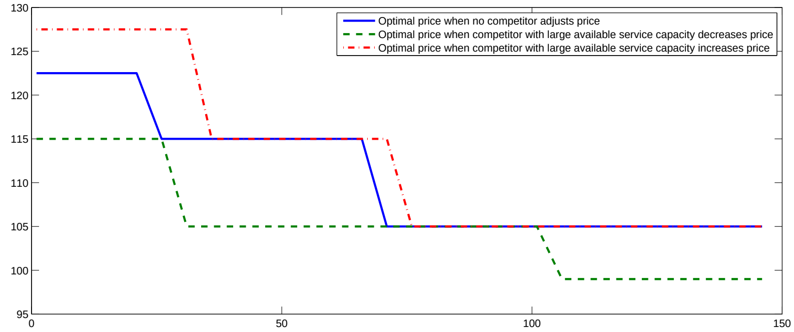


Figure 9: The optimal price when large competitors adjust price (Uniform market demand)

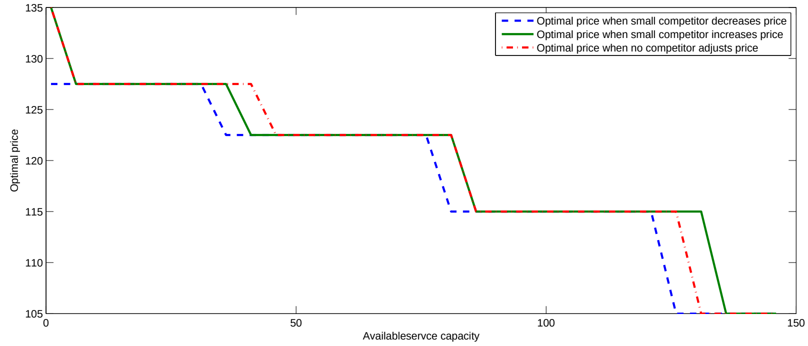


Figure 10: The optimal price when a small competitor adjusts price (Poisson market demand)

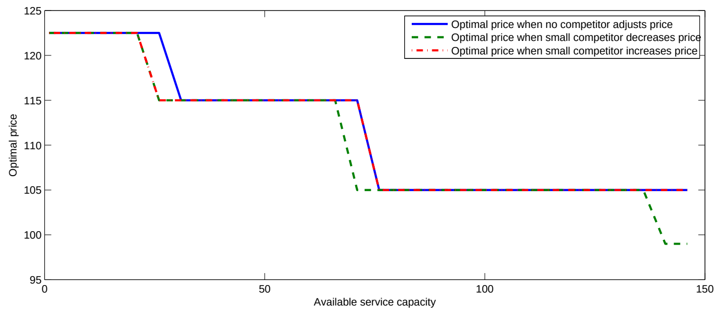


Figure 11: The optimal price when a small competitor adjusts price (Uniform market demand)

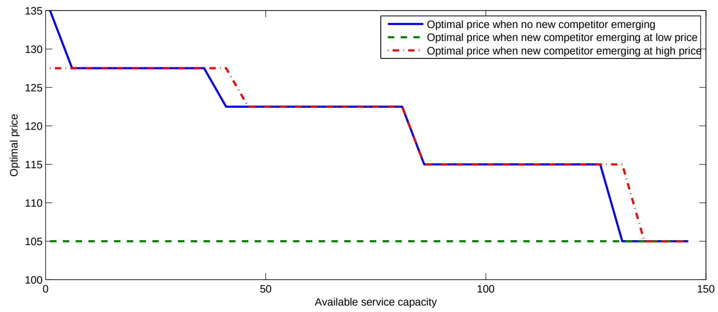


Figure 12: The optimal price when a new competitor emerging (Poisson market demand)

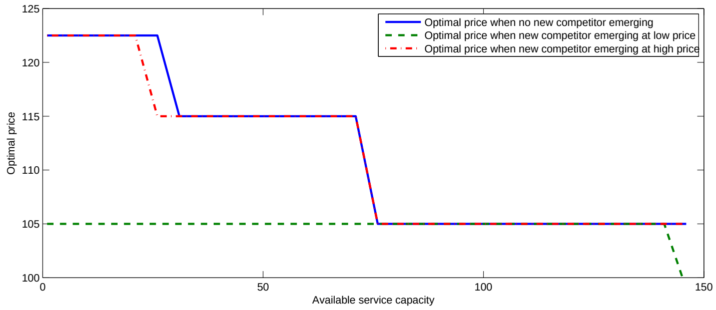


Figure 13: The optimal price when a new competitor emerging (Uniform market demand)

| | ESS | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ |
|---|---|---|---|---|---|---|---|---|
| Price level | $p$ | \$100 | \$110 | \$120 | \$125 | \$130 | \$140 | \$150 |
| Overall capacity | 350 | 260 | 400 | 440 | 300 | 250 | 190 | 150 |
| Occupancy | NA | 75% | 80% | 90% | 86% | 84% | 80% | 96% |
| ASC | $c$ | 65 | 80 | 44 | 42 | 40 | 38 | 6 |

Table 1: Numerical study setting

| Year | 2005 | 2005 | 2005 | 2005 | 2006 | 2006 | 2006 | 2006 | 2007 | 2007 | 2007 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Quarter | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 |
| Sq Ft Occ% | 81% | 83% | 86% | 84% | 83% | 85% | 87% | 85% | 84% | 86% | 87% |
| YTY ΔOcc% | NA | NA | NA | NA | 2.0% | 2.3% | 1.4% | 1.6% | 0.8% | 0.5% | 0.2% |
| YTY Δrevenue | NA | NA | NA | NA | 7.6% | 6.7% | 4.9% | 4.7% | 4.7% | 3.3% | 2.7% |

Table 2: ESS property performance since 2005

| Year | 2006 | 2006 | 2006 | 2006 | 2007 | 2007 | 2007 |
|---|---|---|---|---|---|---|---|
| Quarter | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 |
| Public Storage Δrevenue | 5.1% | 5.7% | 6.1% | 3.4% | 2.9% | 1.7% | 2.1% |
| Sovran Self Storage Δrevenue | 6.8% | 5.8% | 5.8% | 4.0% | 3.5% | 4.0% | 3.5% |
| U-Store-It Δrevenue | 4.2% | 1.7% | 3.8% | 0.8% | 2.2% | -0.8% | 2.3% |
| **Average Peer Group Δrevenue** | **5.4%** | **4.4%** | **5.2%** | **2.7%** | **2.9%** | **1.6%** | **2.6%** |

Table 3: Major competitor's same-store revenue growth since 2006

## References


S. P. Anderson and Y. Schneider. Price competition with revenue management and costly consumer search. Working paper, Department of Economics, University of Virginia, 2007.

M. Bagnoli and T. Bergstrom. Log-concave probability and its applications. Technical report, University of Michigan, 1989.

A. Ben-Tal and A. Nemirovski. Robust solutions of linear programming problems contaminated with uncertain data. *Mathematical Programming*, 88:411–424, 2000.

D. Bertsimas and G. Perakis. Dynamic pricing: A learning approach. In S. Lawphongpanich, D. W. Hearn, and M. J. Smith, editors, *Mathematical and Computational Models for Congestion Charging*. Springer Science and Business Media, Inc., 2006.

S. Boyd and L. Vandenberghe. *Convex Programming*. Cambridge University Press, 2004.

L. Chen and T. Homem-de-Mello. Mathematical programming models for revenue management under customer choice. *European Journal of Operational Research*, 2009. To appear.

E. Cope. Bayesian strategies for dynamic pricing in e-commerce. 54(3):265 – 281, 2007.

G. Gallego and M. Hu. Dynamic pricing of perishable assets under competition. Manuscript, Dept. of IEOR, Columbia University, 2009.

N. Gans and S. Savin. Pricing and capacity rationing in rentals. Working paper, Columbia Business School, 2005.

D. Gupta, A. V. Hill, and T. Bouzdine-Chameeva. A pricing model for clearing end-of-season retail inventory. *European Journal of Operational Research*, 170(2):518–540, 2006.

G. J. King and H. Topaloglu. Incorporating the pricing decisions into the dynamic fleet management problem. To appear in *Journal of the Operational Research Society*, 2006.

T. Levin, Y. Levin, J. McGill, and M. Nediak. Dynamic pricing in the presence of strategic consumers and oligopolistic competition. Working paper, School of Business, Queen's University, 2007.

V. Nocke and M. Peitz. Monopoly pricing under demand uncertainty: The optimality of clearance sales. Working paper, Department of Economics, University of Pennsylvania, 2005.

G. Panda, D. Khan, and U. Ray. A jels stochastic inventory model with random demand. Stochastic Programming E-Print Series, http://www.speps.org, 2006.

A. Parasuraman, V. Zeithami, and L. Berry. A multiple-item scale for measuring customer perceptions of service quality. *Journal of Retailing*, 64:12–40, 1988.

N. Secomandi and J. D. Johnson. Operations management and business pricing. Working paper, Tepper School of Business, Carnegie Mellon University, 2007.

G. P. Soysal. Demand dynamics in the seasonal goods industry: An empirical analysis. Working paper, Kellogg School of Management, Northwestern University, 2007.

K. Talluri and G. van Ryzin. Revenue management under a general discrete choice model of consumer behavior. *Management Science*, 50(1):15–33, 2004.

G. van Ryzin and G. Vulcano. Computing virtual nesting controls for network revenue management under customer choice behavior. *Manufacturing & Service Operations Management*, 10(3):448–467, 2006.

D. Zhang and W. L. Cooper. Revenue management for parallel flights with customer-choice behavior. *Operations Research*, 53:415–431, 2005.