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Modeling strategic customers using simulations - with examples from airline revenue management

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Abstract

A condition for airline revenue management is the possibility of identifying and differentiating customer segments (refer to Chiang et al. (2007) for a state of the art). Traditionally, customer differentiation has been realized by the time of request in days before departure as well as by restrictions connected to the tickets sold. Customer segments have been regarded to be fixed over time, based on myopic customer behavior. With the market transparency increased through the Internet as well as the rise of no-frills offers and flat-rates, customer behavior has changed during the last decades. Strategic customer behavior describes a tendency to remember previous buying experiences, adapt expectations and observe the market over longer periods of time before deciding on what (and whether) to buy. The empirical consequences of strategic customer behavior for traditional as well as state-of-the-art revenue management have been little examined. A major reason for this is that measuring the degree of strategic versus myopic tendencies of demand in real customers is difficult and expensive. In this paper, we formulate a mathematical model of strategic customer behavior including parameters defining the propensity to delay buying as well as learning and communicating. We test the empirical consequences of our model using a stochastic simulation, in which customers act as agents deciding whether and when to buy. Thereby, we provide first results on how different ways of strategic behavior affect the success of methods of revenue management, highlighting the possible weaknesses and strengths of approaches when confronted with strategic customers. Of course, strategic customer behavior is not limited to airline revenue management. Useful models of strategic behavior as implemented in the simulation can be applied to analyze a wide range of situations: conditions for this transfer as well as examples are provided as part of the outlook.

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1. Introduction

Revenue Management strives to maximize revenue by segmenting customers and optimizing price and capacity allocation so as to fully use each customer segment's willingness to pay. Ideally, capacity is allocated to the most valuable customer segments, and prices are set to match the maximum willingness to pay. This objective is realized

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based on a demand forecast and a subsequent optimization of availabilities over the time period in which a product is sold.

In the example of airline revenue management, this corresponds to the booking horizon for flight tickets. Traditionally, customer differentiation has been realized by the time of request in days before departure as well as by restrictions connected to the tickets sold. Customer segments have been regarded to be fixed over time. For a thorough introduction to revenue management, please refer to Talluri (2005). For a current state of the art of airline revenue management research, please refer to Chiang et al. (2007).

Many customer models underlying revenue management assume that customers only request to buy a product once within a season, do not request again, have forgotten all about their experiences in the in the next season, and do not communicate with each other. We summarize these behaviors under the term “myopic” and contrast the concept to that of “strategic” customers. Strategic customers plan their buys according to their expectations, current observations, and communication with their peers.

With the market transparency increased through the Internet as well as the rise of no-frills offers and flat-rates, customer behavior has changed during the last decades. The history and consequences of this development have been described in Boyd (2003). One consequence is that customers behave less myopic and more strategic. At the same time, increased competition and a focus on indicators of productivity increase a tendency toward price reductions late in the booking horizon as usually more common in the sale of fashion or electronic goods even in airline revenue management.

In the next section, this paper provides an overview of recent revenue management research with regard to strategic customers, highlighting the specifics of the strategic customer model used in different approaches. Subsequently, we provide an extension of the strategic customer model found by allowing for unsuccessful customers to request again later in the sales horizon, individual learning experiences and including the effects of communication on the amount of strategic customers to be found in a market.

The empirical consequences of strategic customer behavior for traditional as well as state-of-the-art revenue management have been little examined. A major reason for this is that measuring the degree of strategic versus myopic tendencies of demand in real customers is difficult and expensive. Even provided extensive data as gained from laboratory tests or polls, it is impossible to identify the individual customer's actual motives when deciding on how, when and where to book a ticket.

A stochastic simulation offers an approach to analyzing the consequences of customer behavior as well as to incorporating it in the revenue management model. On the one hand, when setting up a simulation, it is possible to consciously decide which qualitative and quantitative aspects of customer behavior to include. On the other hand, customers are transparent in a simulation - any outcome can be fully explained as the interaction of supply and demand. Finally, emergent qualities of complex revenue management systems combined with a non-linear customer model can be observed in detail.

In the second half of this paper, a simulation system for modeling such behavior and its effects in the context of buying products offered at different prices over time is presented. Having implemented a basic stochastic simulation including strategic customer behavior, we provide first results on how different ways of strategic behavior affect the success of methods of revenue management, highlighting the possible weaknesses and strengths of approaches when confronted with strategic customers.

Of course, strategic customer behavior is not limited to the airline industry, nor to revenue management. Useful models of strategic behavior as implemented in the simulation can be applied to analyze a wide range of situations: conditions for this transfer as well as examples are provided as part of the outlook.

2. State of the art

One of the key assumptions of revenue management is that of limited capacity and low cost per unit. As an effect, the findings presented in Coase (1972) cannot be applied to revenue management without further consideration. In addition, a realistic view of the market place as it presents itself in most of the service industries where revenue management can be applied, especially in airline travel, cannot safely disregard the existence of competition. This means that a strict revenue management strategy can be undermined by non-revenue objectives, such as the defense of market shares. When this happens, price discounts late in the sales season can occur not just in fashion-like industries, but also in the airline industry.

The effect of strategic customers in the case of fashion-like seasonal goods given limited capacity is studied in Aviv (2008). The authors consider customer valuations of the product to be variable over the course of the season, assuming that early on, the product is more fashionable and therefore of higher value than late in the season. Given this condition, it seems reasonable to discount pricing as the season progresses – this is realized by splitting the season into two sales periods allowing for a change in pricing in the second period. In this regard, inventory-contingent discount strategies are compared to announced fixed-discount strategies – the first being a common revenue management optimization problem. Customers base their decision to buy on individual valuation thresholds varying with the timing of the decision. The authors find that given strategic customer behavior, pre-commitment to fixed rates of discount can bring a significant advantage to the seller, yielding more than 8% more revenue compared to the inventory-contingent approach. Additionally, the authors conclude that a confrontation of a supply strategy that assumes only myopic behavior with strategic customers can lead to a loss of 20% revenue.

Gallego (2009) consider the fact that over time, customers may learn to anticipate discounts later in the sales season. They reason that therefore, consistent discounts can lead to growing numbers of strategic customers as "training" takes hold. The decision of whether to allow for discounts is shown to be dependent on the degree of knowledge about demand to come available to the seller as well as the share of strategic customers in the market.

In Liu (2008), artificially limiting capacity is proposed as a response to strategic customers when the seller is able to commit to a pre-determined pricing strategy. The underlying assumptions are that customers' actions do not influence one another ("strategic interaction") on reasonably large markets and that customers may be risk-neutral or risk-averse. The authors stress the predominance of strategic customers with regard to durable, infrequently bought goods, as opposed to perishable goods as for example airline tickets. However, with the increasing ease of comparing prices even for perishable goods provided by dedicated websites, this limitation can be regarded as softening.

Two inventory display formats are compared with regard to their effects given the existence of strategic customers in Yin (2009): Customers may be given perfect information on the actual inventory level or be provided information only on the availability of one unit at a time. With regard to the airline industry, this corresponds to the level of information that travel agents can access as opposed to the level of information available when booking flights on websites providing only the lowest fare currently available. The authors suggest that limiting inventory information decreases profit volatility under the existence of strategic customers.

The value of consistent supply strategies and the opportunity of quick response with regard to stocking quantities are pointed out in Cachon (2009). The authors consider a situation where one seller sells a product with uncertain demand over a finite season to three different types of customers. Customers can be myopic (immediately buying the product without a discount), bargain hunters (never buying the product unless it is discounted) or strategic (deciding whether to buy the product now without a discount or to wait for a discount based on their expectations). When capacity is limited, strategic customers have to expect competing for the opportunity to buy first with myopic customers, later with bargain hunters. The seller can mark down inventory at a predetermined point in the season and adjust stocking quantities in response to demand. Customer valuations are allowed to change over the course of the sales season.

Su (2009) stress the value of commitment and availability guarantees when selling to strategic customers, assuming that stock-outs are regarded as costly by the customers. This may be regarded as an alternative to the strategy of artificially limiting capacity, based on the assumption that customers react more favorably to being able to rely on a product being available than to competing for a limited capacity even given the possibility of discounts. According to this logic, sellers that are able to commit to certain stock levels and provide availability guarantees have a competitive advantage in markets with strategic customers.

An example of the consideration of opaque distribution channels as a response to strategic customer behavior is provided by Jerath (2010). In the market considered, two companies sell a substitutable product at different prices over a sales season and have the opportunity of reducing the price of the product at a predetermined point in the season by offering it via an opaque distribution channel. When buying on the opaque channel, customers do not know in advance which company they buy from. In addition to deciding on whether to buy now or later given the comparison of current to expected valuations of the product, customers have assigned brand preferences influencing their product valuation with regard to both sellers. The authors find that in the presence of strategic customers and high demand with limited uncertainty, opaque selling can be preferable as it increases buyer's competition for the product.

3. Extending the strategic customer model

In the following sections, we offer a model describing the segmentation into discrete customer types, the development of the size of these segments as well as overall demand, strategic behavior in terms of expected valuations and delayed purchase, learning from experience and communication. This model is developed consecutively starting from a basic description of demand in terms of quantity of demand and customer segments.

Let D be the overall quantity of demand and K be the capacity available on a market. Let α be a factor describing the amount of demand in terms of capacity. The overall quantity of demand can then be expressed as

$$D = \alpha \cdot K \text{ with } D, K \in \aleph, \alpha \in [0,1] \qquad \text{(Eq. 3.1)}$$

Let the overall quantity of demand be a composite of multiple customer segments $i = 1..I$, so that D_i describes the quantity of demand from customer segment i. Let β_i be a factor describing the share of segments i with regard to the overall demand. The overall quantity of demand can then be expressed as:

$$D = \sum_{i=1}^{I} D_i = \sum_{i=1}^{I} \beta_i \cdot D \text{ with } \beta_i \in [0,1], \sum_{i=1}^{I} \beta_i = 1 \qquad \text{(Eq. 3.2)}$$

Note that the amount of demand to request within different sales periods τ can be expressed in terms of customer segments:

$$D = \sum_{\tau} D_{i,\tau} \text{ with } \tau, D_{i,\tau} \in \aleph \qquad \text{(Eq. 3.3)}$$

3.1. Strategic customers act on expectation

The basic feature of strategic customers is their acting on expectations: Depending on whether they expect the price to decrease in future sales periods and the product to be available in the future, they delay their purchase or decide to buy immediately.

Strategic customers of type i requesting at time τ make their decision of whether to purchase now or later based on their current product valuation $v_{i,\tau}$ as well as the future product valuation $v_{i,\tau+n}$. Note that regardless of customers' expectations with regard to the price and availability of the product in future periods, their valuation of the product may depend on the time of purchase. For example, with fashion goods, a common observation is that fashion items come with a higher customer valuation during early periods as opposed to late periods of the season. On the other hand, with regard to airline tickets, the customer valuation over the course of the sales season might be increasing with growing urgency.

When deciding whether to buy now or later, customers compare their current valuation of the product $v_{i,\tau}$ in relation to the current price p_τ with their future valuation of the product $v_{i,\tau+n}$ in relation to future expected prices $\hat{p}_{i,\tau+n}$ over all future sales periods n. The future part of this comparison is adjusted by the customers' expectation of the product being available in future time periods, $\varphi_{i,\tau+n}$. This expectation may also be described as the customer's degree of optimism: if $\varphi_{i,\tau+n}$ is high, so is the expectation that the product will be available in the future and accordingly the tendency to delay the purchase. Note that both this degree of optimism and the price expected to be offered in future periods depend on the customer type i.

The decision whether or not to delay the purchase can accordingly be expressed as follows: Delay if…

$$v_{i,\tau} - p_\tau \le \sum_n \left(\varphi_{i,\tau+n} \left(v_{i,\tau+n} - \hat{p}_{i,\tau+n} \right) \right) \text{ with } v_{i,\tau}, v_{i,\tau+n}, p_\tau, \hat{p}_{i,\tau+n} \ge 0, \varphi_{i,\tau} \in [0,1] \qquad \text{(Eq. 3.1.1)}$$

When customers do delay their purchase, this leads to an increase in the quantity of customers of this type in the next period.

$$v_{i,\tau} - p_\tau \le \sum_n \left(\varphi_{i,\tau+n} \left(v_{i,\tau+n} - \hat{p}_{i,\tau+n} \right) \right) \longrightarrow D_{i,\tau+1} := D_{i,\tau+1} + 1 \qquad \text{(Eq. 3.1.2)}$$

3.2. Strategic customers learn from experience

As described in Liu (2011), we assume that the expected prices as well as the expected availability of the product, on which strategic customers' decisions to buy or delay are based, are not given, but learned. This can be termed "bounded rationality" – customers cannot expect something they have never experienced.

Customers adjust their expectations with regard to the success of delaying a purchase in season $T+1$ based on their experiences in season T. This is realized by adjusting the level of optimism of season $T+1$ according to the share of successful purchases in season T, $s_{i,\tau}^{T}$ using exponential smoothing. A successful purchase is defined as a delayed purchase at a lower price that was possible due to product availability. Let the parameter γ_i define the weight of new experiences as opposed to current expectations – this may also be termed the speed of learning. Note that all expectations, experiences, and the speed of learning depend on the customer segment i.

The process of adjusting expectations to experiences with regard to product availability can then be described as follows:

$$\varphi_{i,\tau}^{T+1} := (1-\gamma_i)\cdot\varphi_{i,\tau}^{T} + \gamma_i \cdot s_{i,\tau}^{T} \text{ with } \gamma_i, s_{i,\tau}^{T} \in [0,1] \qquad \text{(Eq. 3.2.1)}$$

Customers' expectations with regard to the reduction in price over the course of sales periods are adjusted accordingly, based on the price reductions experienced in the past:

$$\hat{p}_{i,\tau}^{T+1} := (1-\gamma_i)\cdot\hat{p}_{i,\tau}^{T} + \gamma_i \cdot \left(p_{\tau-1}^{T+1} \cdot \frac{p_{\tau}^{T}}{p_{\tau-1}^{T}} \right) \qquad \text{(Eq. 3.2.2)}$$

3.3. Strategic customers communicate

In order to describe the effect of communicating customers, we first need a model describing the development of demand over multiple sales seasons. This includes the overall quantity of demand, D, as well as the demand segmentation described by quantities D_i.

As presented in equation 1.1, demand can be described in terms of capacity using a factor α. In order for the overall quantity of demand to change over time, given that capacity is regarded as constant, α has to change. Let the change of α be defined by a systematic and a random part, weighted by a factor δ. Let the systematic part of the change be defined as a function f, whereas the random part of the change be defined as a normally distributed error term $\varepsilon^{T}{}_{\alpha}$. Given that demand cannot be negative, α can be described for each season T as follows:

$$\alpha^{T} = \max\left(\delta \cdot f\left(\alpha^{T-1}\right) + (1-\delta)\cdot\left(\alpha^{T-1}\cdot\varepsilon_{\alpha}^{T}\right), 0\right) \text{with } \alpha^{T} \in \aleph, \delta \in [0,1], \varepsilon_{\alpha}^{T} \sim N(1,\sigma_{\alpha}^{2}) \qquad \text{(Eq. 3.3.1)}$$

Similarly, the development of the quantity of individual segments of demand as symbolized by D_i can be modeled by describing changes in β_i, the factor presenting the share of D_i in D. In this case, the systematic and the random part are weighted by a factor η. The systematic development of D_i is described by a function g, whereas the random part is described by an error term $\varepsilon^{T}{}_{\beta}$. with triangular distribution. Given that the shares need to add up to 1 in the end, the development can be roughly described as:

$$\beta_i^{T} \approx \eta \cdot g\left(\beta_i^{T-1}\right) + (1-\eta)\cdot\varepsilon_{\beta}^{T} \text{ with } \beta_i^{T}, \varepsilon_{\beta}^{T}, \eta \in [0,1] \qquad \text{(Eq. 3.3.2)}$$

The effect of customer communication can be described in terms of changes in the shares of specific customer segment. The underlying idea is that successful customers will tell others about their strategy and thereby convert them into a part of their customer segment. On the other hand, customers that are not successful with a strategy will look around for better ways of approaching the decision whether to purchase or not and thereby become part of a new customer segment. This can be modeled as the systematic part of the change in β_i, g:

$$g\left(\beta_i^{T-1}\right) = \max\left(\beta_i^{T-1} + \upsilon_i\left(s_i^{T-1} - S_i\right), 0\right) \qquad \text{(Eq. 3.3.3)}$$

In this equation, $s^{T-1}{}_{i}$ describes the share of customers of type i that successfully bought a product at a reduced price. S_i is a parameter defining what the overall group of customers regards as a success worthy of communicating as opposed to a failing strategy. The parameter υ_i defines the efficiency of communication. Both the definition of success and the speed of communication depend on the customer segment i.

In order to ensure that the shares of customer segments add up to *1* in the end and that there is no effect on the overall quantity of demand (unless desired), a small adjustment needs to be made before demand can be calculated.

$$\beta_i^T := \frac{\eta \cdot g\left(\beta_i^{T-1}\right) + (1-\eta) \cdot \varepsilon_\beta^T}{\sum_{i=1}^{I} \left(\eta \cdot g\left(\beta_i^{T-1}\right) + (1-\eta) \cdot \varepsilon_\beta^T\right)} \qquad \text{(Eq.3.3.4)}$$

4. First results

The results presented here are based on an agent-based simulation in which there are three types of customers – myopic, strategic, and bargain hunters. Strategic customers show a request behavior as described in the previous section. The customer segments differ with regard to willingness to pay: Strategic and myopic customers are willing to pay the highest price, whereas bargain hunters will only buy at the lowest reduced price.

Only one seller offers a product over the course of 20 sales seasons, using the opportunity of discounting the price of the product in the final third of the sales season. While most algorithms applied in airline revenue management try not to reduce but rather to increase the price over time before departure, secondary objectives such as market share and productivity can undermine this principle. For this reason, a situation that is common with regard to fashion as well as electronics can also apply in the airline industry.

4.1. The consequence of experience

The first simulation experiments aim to show how the existence of strategic customers affects revenue if the sales strategy does not incorporate strategic customer behavior. As most methods applied in airline revenue management assume that customers do not make their decisions based on previous experiences, this applies in practice.

In the scenario on which the first results have been based, the price of the product has been reduced by 50% in the final third of the sales season, regardless of left-over capacity. Note that strategic customers do not adapt their expectations with regard to price or product availability (optimism) – the speed of learning is 0. The share of strategic customers is also constant, as the degree of communication is 0. Strategic customers do however have a correct initial notion of how far the price will be reduced.

To account for stochastic fluctuations, we included normally distributed error terms for total demand, customer type distribution and distribution of customers over the two periods. The standard deviation for all these error terms is set to 10% of the respective values.

In the following table, the revenue as gained in the twentieth season is presented as compared to what was earned when the share of strategic customers was 0%. Changes in revenue depend on the share of strategic customers as well as on their degree of optimism.

As can be seen from the data shown in the tables 4.1.1, 4.1.2 and 4.1.3, the existence of strategic customers consistently leads to revenue losses. The revenue losses are bounded by 50%, as this is the maximum price reduction: a revenue loss of 50% indicates that all customers wait for the price reduction to buy.

Revenue losses increase with the share of strategic customers found in the market, but not strictly with the level of optimism: This might be due to the fact that many optimistic strategic customers do not get to buy at a reduced fare since they leave a larger share of the product offered at the full price to myopic customers. When the level of optimism is too small, no customer will wait and therefore the existence of strategic customers is not palpable.

Finally, revenue losses are more pronounced when demand is high, since in that case, more of the product could have been sold at the highest fare without the existence of strategic customers. This underlines the intuitive idea that price reductions are helpful only when demand is low.

Table 4.1.1. Scenario 1— α = 2.0

	$\varphi = 0{,}2$	$\varphi = 0{,}4$	$\varphi = 0{,}6$	$\varphi = 0{,}8$
β-strategic : β-myopic = 1 : 3, β-bargain = 0,33	-0,0%	-2,1%	-2,3%	-2,5%
β-strategic : β-myopic = 1 : 1, β-bargain = 0,33	-0,0%	-16,2%	-16,4%	-16,7%
β-strategic : β-myopic = 3 : 1, β-bargain = 0,33	-0,0%	-33,2%	-33,4%	-33,0%
β-strategic : β-myopic = 1 : 0, β-bargain = 0,33	-0,1%	-50,0%	-50,0%	-50,0%

Table 4.1.2. Scenario 2 — α = 1.5

	$\varphi = 0{,}2$	$\varphi = 0{,}4$	$\varphi = 0{,}6$	$\varphi = 0{,}8$
β-strategic : β-myopic = 1 : 3, β-bargain = 0,33	-0,1%	-10,9%	-10,6%	-10,7%
β-strategic : β-myopic = 1 : 1, β-bargain = 0,33	-0,1%	-23,8%	-23,0%	-23,4%
β-strategic : β-myopic = 3 : 1, β-bargain = 0,33	+0,1%	-35,9%	-35,9%	-36,1%
β-strategic : β-myopic = 1 : 0, β-bargain = 0,33	+0,3%	-49,0%	-48,8%	-49,0%

Table 4.1.3. Scenario 3 — α = 1.0

	$\varphi = 0{,}2$	$\varphi = 0{,}4$	$\varphi = 0{,}6$	$\varphi = 0{,}8$
β-strategic : β-myopic = 1 : 3, β-bargain = 0,33	-0,0%	-10,6%	-10,8%	-10,6%
β-strategic : β-myopic = 1 : 1, β-bargain = 0,33	+0,4%	-21,0%	-20,4%	-20,7%
β-strategic : β-myopic = 3 : 1, β-bargain = 0,33	+0,4%	-30,9%	-30,5%	-31,1%
β-strategic : β-myopic = 1 : 0, β-bargain = 0,33	-0,0%	-41,0%	-41,1%	-41,2%

4.2. The consequence of learning

The simulation experiments described here are based on the same seller behavior as presented in section 4.1. In addition to the customer behavior included in the experiments described in the previous section, we have set the speed of learning from 0 to 0.2 for both price and availability expectation (optimism).

As stated earlier, we define learning as the adjustment of expectation to experience: Strategic customers that successfully purchase the product at a reduced price will increase their level of optimism. However, as found in the previous section, if initial optimism is too small, no customers will attempt to wait and thus there are no successful strategic customers. In that case optimism will be decreased even further in each season. No strategic behavior can emerge; learning has no effect on revenue. This is also shown for the case of initial $\varphi = 0{,}2$ in the following table.

When α is smaller or equal to 1.0, strategic behavior will always be successful on the long run. Therefore, learned optimism will tend to 1.0 as long as the initial optimism was high enough (see above). Learning has no effect on revenue in this case.

When α is higher or equal to 2.0, there are enough myopic customers in the first period to sell out the inventory, so independent of strategic customer behavior, the revenue will remain the same.

Disregarding these cases, the following table shows the results for a case in which α is 1.5, with the ratio of strategic to myopic customers being 1:3 and a 33% share of bargain hunters. The table 4.2.1 depicts revenue results after 20 seasons to a situation in which strategic customers do not learn at all, given the same initial discount expected as well as the same initial degree of optimism φ.

In most cases, learning has no significant effect on revenue. In one case though, there is a revenue increase of about 11%. This is surprising since one would expect that “smarter” customers can secure more customer surplus for themselves and thus will reduce revenue for the seller.

Table 4.2.1. Scenario 4 — α = 1,5 with myopic and strategic in proportion 3:1

	φ = 0,2	φ = 0,4	φ = 0,6	φ = 0,8
Initial discount expected = 20%	+0,4%	+11,2%	+0,4%	+0,4%
Initial discount expected = 40%	+0,3%	-0,0%	+0,5%	+0,4%
Initial discount expected = 60%	-0,1%	+0,1%	+0,3%	-0,1%
Initial discount expected = 80%	+0,4%	+0,3%	+0,3%	+0,5%

However, without learning, the optimism parameter acts as a simple threshold. Either all customers are strategic or none. As pointed out above, if none are strategic without learning, then none will be strategic even with learning, because there's never a positive experience of purchasing at a reduced fare. If the optimism parameter is high enough, then without learning, all strategic customers will wait to purchase in the second period, incurring maximum revenue loss on the supplier. With learning, however, the actual success rate will be taken into account, which is lower than 1, since there are more customers in period 2 than leftover capacity.

The optimism parameter will tend to some value φ^* smaller than one. If φ^* is still large enough that strategic customers wait for the second period, then nothing will change. If, however, φ^* gets too small, strategic customers will no longer wait for the second period, thus more customers will buy in the first period, increasing revenue for the seller – this is the first case, where optimism tends all the way down to zero, since there are no more successful strategic customers. This does not contradict the notion that learning customers are smarter and can secure more customer surplus for themselves. When purchasing early to avoid the risk of stock out, strategic customers maximize their own surplus. This does not come at the expense of the seller however, but at the expense of bargain customers in period 2 that will now fail to acquire an item. What's optimal for a subset of customers (here the strategic customers), may not be optimal for all customers as a whole.

When revenue is not reduced at the end of the period and customers learn, all strategic customers are converted into myopic customers after 20 seasons. This is true regardless of the initial level of optimism as well as of the initially expected reduction in price.

4.3. The consequence of communication

The simulation experiments described in this section aim to answer the question how quickly strategic customer behavior spreads when customers communicate. For this purpose, we do not let the price be dependent on a fixed time before departure, but discount the price for a percentage of left-over capacity. This is a common strategy applied in airline revenue management, where discounts may depend on the left-over capacity defined in terms of seat-load factor.

In the table below, the share of the strategic customer segment after 20 seasons is presented for a scenario in which initially, 25% of customers are strategic, 50% are myopic and 25% are bargain customers. The speed of learning is 0.2, with an initial level of optimism of 0.8 and a correct notion of the price reduction to be expected (50%). Strategic customers communicate with varying degrees of efficiency (υ) if more than half have successfully purchased the product at a reduced price ($S=0.5$). Outside of simulations, customers communicate efficiently using travel fare websites such as farecompare.com.

As can be seen in Table 4.3.1, communication does have a significant impact on the share of the strategic customer segment. When the left-over capacity sold at a reduced price makes up a small share of overall capacity (30% or less), the majority of strategic customers tends not to be successful and accordingly, the share of the strategic segment dwindles.

When the left-over capacity sold at a reduced price makes up a large share of overall capacity (40% and more), the majority of strategic customers tends to be successful, and accordingly, the share of the strategic segment grows. The rate of growth depends on the efficiency of communication – after 20 seasons, the share of strategic customers is largest when much capacity is sold at a reduced price and customers communicate efficiently. This finding supports the intuitive understanding of the effect of price reductions.

Table 4.3.1. Scenario 5 — α = 1,0 with initial shares of 25% strategic, 50% myopic and 25% bargain hunters

	υ = 0,0	υ = 0.05	υ = 0.1	υ = 0.2
Reduce 50% of capacity	25,0%	33,0%	35,9%	38,5%
Reduce 40% of capacity	25,0%	13,3%	27,9%	30,5%
Reduce 30% of capacity	25,0%	0,0%	0,8%	11,5%
Reduce 20% of capacity	25,0%	0,0%	0,0%	0,0%
Reduce 10% of capacity	25,0%	0,0%	0,0%	0,0%

5. Outlook

In this paper, we developed a model of strategic customers for revenue management including the concepts of learning and communication. We presented first findings based on a simulation implementing the customer model described. Some of these findings support intuitive ideas on the effects of strategic customer behavior on revenue and markets. Others, such as the effect of learning on overall customer success indicate that strategic customer behavior is not uniformly positive for the overall customer surplus.

The simulation implemented allows for more experiments than the subset presented in this paper. Further experiments might be conducted to explore the sensitivity of varying degrees of learning as well as initial expectations in the context of communication. Additionally, while it became obvious that strategic customer behavior can be eradicated through consistently not reducing the price at the end of the season, the simulation can be used to explore in how far irregular price reductions can be used to sell left-over capacity without letting the segment of strategic customers grow out to a point where revenue is impacted too much.

Counter-intuitive effects with regard to learning and communication might be explored in further detail using game theoretic models. This includes games between customers as well as games between customers and sellers. With regard to the individual customer behavior as well as the possibility of multiple sellers offering comparable products on the same market, evolutionary game theory might be applied to analyze the effects in further detail.

Finally, the customer model presented here may be extended to include customer strategies such as cancel-and-re-book, which can be found in customer segments preferring flexible tickets. The model of communication may be refined further in terms of social networks.

References

Aviv, Y. & Pazgal A. (2008). Optimal Pricing of Seasonal Products in the Presence of Forward-Looking Consumers. *Manufacturing & Service Operations Management*, 10(3).

Boyd, E.A. and Bilegan, I.C. (2003). Revenue management and e-commerce. *Management Science*, 49 (10).

Cachon G.P. & Swinney R. (2009). Purchasing, pricing, and quick response in the presence of strategic consumers. *Management Science*, 55(3).

Coase, R. H. (1972). Durability and monopoly. *Journal of Law and Economics*, 15.

Chiang, W.C., Chen, J.C.H. & Xu, X. (2007). An overview of research on revenue management: Current issues and future research. *International Journal of Revenue Management*, 1 (1).

Cleophas, C., Frank M. & Kliewer, N. (2009). Simulation-based key performance indicators for evaluating the quality of airline demand forecasting. *Journal of Revenue and Pricing Management*, 8 (4).

Gallego, G., Philips, R., Şahin, Ö. (2009) Strategic Management of Distressed Inventory. *Production and Operations Management*, 17(4).

Jerath, K., Netessine, S. & Veeraraghavan, S.K. (2010). Revenue Management with Strategic Customers. *Management Science*, 56(3).

Liu, Q. & van Ryzin, G. (2008). Strategic Capacity Rationing to Induce Early Purchases. *Management Science*, 54(6).

Liu, Q. & van Ryzin, G. (2011). Strategic Capacity Rationing when Customers Learn. *Manufacturing & Service Operations Management*, 13(1)

Su, X. & Zhang, F. (2009). On the Value of Commitment and Availability Guarantees When Selling to Strategic Consumers. *Management Science*, 55(5).

Talluri, K.T. & van Ryzin, G. (2005). *The theory and practice of revenue management*. New York: Springer Science+Business Media Inc.

Yin, R., Aviv, Y., Pazgal, A. & Tang, C.S. (2009). Optimal Markdown Pricing: Implications of Inventory Display Formats in the Presence of Strategic Customers. *Management Science*, 55(8).