

Behavioral Consequences of Overbooking Service Capacity

As a consequence of implementing revenue management systems, many service firms (e.g., airlines, hotels, car rentals) systematically overbook capacity, thus striving to maximize the revenue at one particular point in time (i.e., one flight, one night, and one day). The academic literature has not addressed how customers behaviorally respond to overbooking experiences, such as downgrading, denied service, or upgrading. In this article, the authors use the econometric technique of conditional difference-in-differences analysis to study the effect of such incidences on customer usage patterns in an airline context. They find that customers who experience negative consequences of revenue management significantly reduce the amount of their transactions with the airline, whereas upgraded customers exhibit only weak positive responses. The effects of the negative events are stronger for high-value customer groups, whereas significant effects of positive events can be found only for a low-value customer group. The results suggest the need for a stronger focus on customer reactions to revenue management practices. On a more general level, the study contributes to a more interdisciplinary view of service management by demonstrating the need for a closer interaction between management functions (e.g., marketing and operations) in developing and managing concepts of companywide importance.

Many service companies, especially in the transportation and hospitality sectors, use “revenue management systems” (also referred to as “yield management systems”) to maximize the revenue they generate from a current service offer (e.g., Kimes and Chase 1998; Kimes and Wirtz 2003). For example, airlines sell more tickets than there are seats on the aircraft, and hotels often sell more beds than are available. Companies that use such systems have reported revenue increases of 2%–5% (e.g., Kimes and Wirtz 2003). A current report by the U.S. Department of Transportation (2006) confirms that companies are pursuing overbooking and involuntary denied boarding (i.e., even when compensation is offered) with increasing aggressiveness. In the first nine months of 2006, 1.04 of every 10,000 flight customers were denied boarding, compared with .89 customers in 2005.

The practice of overbooking implies that sometimes the firm may not be able to fulfill all customer demands because of fewer “no-shows” than expected, resulting, for example, in downgrading or denied service. At other times, the firm may be in the position to offer some customers

higher-value services than those originally purchased (e.g., upgrades). Revenue management systems also account for penalties or compensation fees that must be paid to ticket or reservation holders who cannot be served or need to be downgraded. However, they do not yet account for the longer-term behavioral and monetary effects of capacity-driven service experiences, though these have been suspected to be strong and long lasting (e.g., McGill and Van Ryzin 1999). Likewise, the academic literature is restricted to a few studies that theoretically discuss potential customer conflicts, the perceived fairness of different revenue management measures, and the integration of revenue with customer relationship management (CRM) (e.g., Noone, Kimes, and Renaghan 2003; Wirtz, Theng, and Patterson 2003). Thus far, behavioral and/or monetary effects of negative and positive capacity-driven services have not been analyzed empirically. Only one recent article has examined the preference impacts of negative capacity-driven service experiences (Suzuki 2004).

Using data from a major global airline, we shed light on this issue by studying the long-term behavioral and monetary effects of upgrades, downgrades, and denied service. We pay special attention to the question whether the customer status level in the airline’s frequent-flier program affects the strength of those effects. Our study can help service marketing managers who want to convince their revenue management counterparts to adopt a customer perspective and not a product perspective in the design of future revenue management systems. It also contributes to a more interdisciplinary view toward service management by demonstrating the need for a closer interaction between management functions (e.g., marketing and operations) in developing and managing concepts of companywide importance.

The article proceeds as follows: We introduce the topic of revenue management and the practice of overbooking.

Florian v. Wangenheim is Professor of Services and Technology Marketing, TUM Business School, Technische Universität München (e-mail: florian.wangenheim@wi.tum.de). Tomás Bayón is Professor of Marketing, Heilbronn Business School (e-mail: bayon@hn-bs.de). When this article was written, Tomás Bayón was Associate Professor of Marketing, International University in Germany, Bruchsal. The authors thank all partners of the Customer Equity Management research program, participants of the Marketing Science Institute conference on Academic and Practitioner Collaborative Research at Yale University (December 2004), and the four anonymous *JM* reviewers for their helpful comments on previous drafts of this article.

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Next, we discuss the theoretical basis for deriving hypotheses regarding the consequences of upgrading, downgrading, and denied services. We then test our hypotheses using time-series data from a large sample of a major global airline. Finally, we discuss the implications of the results for research and management.

Theoretical Basis

From a customer perspective, denied boarding and downgrading is regarded as the underperformance of a service or as a service failure. Indeed, prior research has already treated such and similar incidents as service failures (e.g., Bejou and Palmer 1998; Hall and Porteus 2000; McColl-Kennedy and Sparks 2003; Taylor and Claxton 1994). In contrast, upgrading can be viewed as the overfulfilment of the service promise; that is, the customer receives more than he or she was promised when the ticket was purchased; to date, this has been discussed in the literature on customer delight or in the context of other service performance that has exceeded expectations (e.g., Finn 2005; Oliver, Rust, and Varki 1997; Rust and Oliver 2000).

A Fairness Theory Approach to Consequences of Overbooking

Wirtz, Theng, and Patterson (2003) suggest treating the consequences of overbooking from a fairness point of view. Fairness theory accommodates cases of both positive and negative inequity, which means that it allows for development of hypotheses for both the negative (downgrading and denied service) and the positive (upgrading) outcomes of interest. Furthermore, by specifically considering not only the output received but also the input of both exchange partners, fairness theory allows for differentiation between status and nonstatus customers in hypothesis development. Given that we aim to explain behavioral rather than attitudinal reactions to over- and underfulfillment and, furthermore, want to analyze differences across usage groups, fairness theory is an appealing framework for this study.

Fairness theory goes back to early work on justice in exchange situations by Adams (1963) and Homans (1961) and has been further developed in both the organizational behavior (e.g., Folger and Skarlicki 1999) and the marketing (e.g., Finn 2005; McColl-Kennedy and Sparks 2003) literature. The terms “fairness” and “equity” are typically used interchangeably.

According to fairness theory, people strive for justice in exchange situations and include both the outcomes obtained in their fairness consideration and the inputs or investments they and the exchange partners make (Homans 1961). For people to feel as if they were treated unfairly, three conditions that correspond to the current application must be fulfilled. First, an unfavorable condition must be present (e.g., a disservice, a downgrade service). Second, the perpetrator must be accountable for the condition (e.g., the firm could have done something to avoid the situation, such as not sell more tickets or rooms than are available). Third, the harmful action (e.g., overbooking) must be viewed as a violation of some moral or ethical code (e.g., the hotel or airline should not make a service promise that it cannot fulfill). In

other words, a service failure is perceived as unfair when the customer believes that the firm could have done something to prevent the situation.

Consequences of Negative Inequity

Empirical studies have confirmed fairness theory in both organizational and marketing research. Employees who believe that they are treated unfairly are more likely to reduce their efforts or terminate their contract than to request that the exchange partner increase its investments (e.g., Campbell and Pritchard 1976; Garner 1986; Schmitt and Maxwell 1972). This notion is in line with the repetitive findings from the service failure literature that dissatisfied customers are more likely to stop buying from a service provider or do nothing than to complain and try to get their problem solved (e.g., Chebat, Davidow, and Codjovi 2005; Stephens and Gwinner 1998). In the marketing literature, perceived negative inequity has been shown to exhibit negative effects on key variables, such as customer satisfaction, intention to rebuy, complaining, and word-of-mouth intentions (e.g., Fisk and Young 1985; Goodwin and Ross 1990; Huppertz, Arenson, and Evans 1978; Maxham and Netemeyer 2002; Shankar, Smith, and Ramaswamy 2003). However, the behavioral consequences of inequity are also unstudied, just as the behavioral consequences of service failures.

Anecdotal evidence confirms that service customers are likely to perceive overbooking as unfair. Recently, an Italian musician who was denied boarding was so enraged that he almost bit an airport worker’s ear off (see Blank 2006). Although firms must comply with government regulations on how bumped service customers are to be compensated, the exchange situation typically engenders feelings of injustice because the service promise was not fulfilled. Given that the most likely reaction to inequity is to decrease inputs/investments into a relationship, customers are expected to lower the amount of business they give to the firm in response to denied service or downgrading incidents. Because customers are sometimes forced to remain with a service provider as a result of high switching barriers in monopolistic situations or because they are members of a loyalty program, they may adjust their investments in the exchange relationship not only by decreasing the number of their transactions but also by trying to take advantage of discount offers or by purchasing lower-level services from the firm. This gives rise to the following hypothesis:

H₁: Service failures arising from overbooking cause customers to decrease their future spending with a service provider.

Consequences of Positive Inequity

Early work on fairness theory shows that positive inequity can trigger feelings of guilt and that people who believe that they are in an advantageous position in an exchange situation sometimes increase their investments or efforts to achieve a balance (Adams 1963; Walster, Berscheid, and Walster 1973). Furthermore, fairness should create customer delight, which in turn should increase satisfaction and loyalty (Oliver 1997). However, empirical evidence

regarding the effect of overfulfilment on future behavior is ambiguous. Early work shows that people who experience positive inequity usually adjust their perceptions of what is a just outcome for them, and thus they do not change their behavior (Adams 1963). For example, Perry (1993) shows that people who are overpaid by their employers psychologically justify this by inflating their evaluations of their own contributions.

In a consumer behavior context, research on customer delight is limited and inconclusive. Although overfulfilment has theoretically and, to a more limited extent, empirically been shown to be a driver of increasing customer purchases and revenues (Bowman and Narayandas 2004; Rust and Oliver 2000), Oliver, Rust, and Varki (1997) find a positive effect of delight on repurchase intention in only one of two studies and conclude that the effect of delight on repurchase intention is service specific. According to Oliver, Rust, and Varki (p. 330), the central issue is “whether consumers can be expected to mentally link a particular delight with more enduring behaviors including intention and loyalty.” In a more recent study, Finn (2005) suspects that Oliver, Rust, and Varki’s results may be due to error modeling and offers alternative explanations for when delight affects behavior. In the current context, there are good arguments both in favor of and against such an effect. On the one hand, customers cannot reasonably expect to be upgraded on a regular basis and therefore may attribute their being upgraded to chance or circumstance. On the other hand, the expectation to be upgraded again in the future may indeed positively influence intention and loyalty. Given the ambiguous evidence in the fairness theory and delight literature with regard to overfulfilment, we formulate alternative hypotheses for positive events.

H_{2a}: Firm-initiated upgrades of services cause customers to increase their spending with a service provider.

H_{2b}: Firm-initiated upgrades of services do not affect customers’ spending with a service provider.

Customer Status as a Determinant of Effect Strength

As we mentioned previously, fairness theory states that customers’ equity considerations depend not only on the received outcomes but also on the investments made. As such, it is likely that customers who have achieved a certain status in their relationship with the provider (e.g., “gold” or “silver” customers) will view their investments into the customer relationship as greater than those of “base” customers, who conduct business with their providers less frequently. Given that firms often communicate to their status customers that they represent an important group for them, these customers also expect a higher level of outcome for themselves and a higher level of investment from their exchange partner. Therefore, a high-status customer would likely perceive the same negative outcome (e.g., a downgrade, a denied service) as more critical and unfair than a base customer. Thus, the negative consequences of downgrading and denying service to the status customers are greater than those for the base customers.

Conversely, the base customer group would likely experience the positive inequity that results from an upgrade more strongly because status customers are more likely to expect an overfulfilment from time to time, given their high level of own investment into the relationship. For base customers, an upgrade is an incentive that they may believe to be more than they deserve because they do not have a history of high spending with the firm. Thus, the positive effects of upgrading should be stronger for the base customers than for the status customers.

H₃: The effects of service failures that arise from overbooking on customer spending are stronger for high-status customers than for low-status customers.

H₄: The effects of service upgrades on customer spending are stronger for low-status customers than for high-status customers.

Data Set and Methodology

Data

To test our hypotheses, we analyzed the customer database of a large global airline. The database contains detailed individual information regarding the transactions and revenues, covering the period from January 2001 to December 2004. It includes the booking class (economy versus business), the route (continental versus intercontinental), and whether the booking address is a business or a private address. Information on basic demographics (e.g., age, gender), the duration of the customer relationship, the miles obtained in the frequent-flier program, and the status level in the loyalty program (gold, silver, or bronze) is also included. Regarding the key variables of interest, the occurrence (whether or not) and the exact dates of three events—namely, involuntary denied boarding, involuntary downgrading (from business class to economy), and upgrading (from economy to business)—are available at the individual customer level.

We also obtained information from the airline about how customers are selected for downgrades, denied boardings, and upgrades. When it becomes clear that there are definitely not enough seats on the aircraft, the airline first considers the customer status in its loyalty program (gold, silver, or bronze), then the amount of points collected in the loyalty program, and finally the price paid for the current flight to prioritize high-value customers for positive treatment and low-value customers for negative treatment. This information is important to be able to account for this selection mechanism.

We first obtained a random sample from the customer base of approximately 330,000 customers. Furthermore, we obtained data from all customers who had experienced at least one of the three service events involuntarily over the first six months of 2002; that is, we excluded customers who had volunteered for denied boarding or downgrades from the data set. This enabled us to analyze and compare transaction behavior before and after upgrading, downgrading, and denied boarding for a substantial period and on a detailed level. In summary, we obtained data from 556

downgraded, 836 boarding-denied, and 2283 upgraded customers.

Method

From a methodological point of view, three events of upgrading, downgrading, and denied boarding can be viewed as “treatments” that some customers receive, and we are interested in studying their “treatment effects” on customer transaction behavior and revenues. Although airlines do not voluntarily bump or downgrade individual customers, it is clear that the likelihood that an individual customer will hold a ticket for an over- or underbooked aircraft increases the more often the customer flies. The airline uses the rules we mentioned previously (which are similar across the industry) for selecting customers to be bumped, downgraded, or upgraded. The resultant selection effects appear in Table 1, which, in the columns to the left of the variables, shows basic descriptive statistics for this study. In both the first six months of 2002 (the comparison period) and the full year before that (2001), all treatment groups exhibited usage patterns that were substantially different from those of the typical customer. Women are underrepresented in all groups, given their lower average number of flights, and age is not related to the reception of any of the treatments.

The analysis of endogenous treatment effects in a non-experimental setting has been an important concern in the econometric literature for the past three decades (e.g., Diaz and Handa 2004; Heckman, Ichimura, and Todd 1997; Rosenbaum and Rubin 1984; Rubin 1973). Recently, simulation studies have shown that propensity score matching (PSM) leads to the best results when the selection mecha-

nism is well known (Heckmann, Ichimura, and Todd 1997). The PSM technique is used to analyze treatment effects, and it attempts to answer the counterfactual question (Heckman 1997; Rosenbaum and Rubin 1984; Rubin 1973, 1977) of how the flying behavior of someone who has received one of the treatments would have developed had he or she not received the treatment. The PSM method solves this problem by artificially creating a control group in which each treatment recipient is matched to one “similar” nonrecipient. When a good-fitting control group has been created, differences between treatment receivers and nonreceivers can be analyzed by comparing the two groups.

The PSM technique has been shown to provide the best results of all matching techniques under two conditions. First, the predictors of the treatment must be well known and measured for both treatment and nontreatment cases. As we discussed previously, the selection rules were made available to us. Second, PSM is especially effective when longitudinal data are available, which is also the case for the current application.

Figure 1 graphically displays the four-stage PSM procedure we use herein. First, we obtain a propensity score for all recipients and nonrecipients using logistic regression. We formulate a binomial logit model for each of the three treatments, in which the treatment (e.g., downgrading) represents the dependent variable and the number of flights, the accrued miles, and the sociodemographic variables (to account for unobserved heterogeneity) are the independent variables. In addition, we added square miles collected to the equations for predicting negative events, following the rationale that customers who have collected more miles are

TABLE 1
Group Means Before and After Matching and Percentage Reduction in Bias (PRB)

Before Matching			After Matching		
Control	Downgrading	Downgrading (N = 952) ^a	Control	Downgrading	PRB
6.61	15.84	All high-value flights (Months 1–6 in 2002)	12.63	13.34	92.3%
25.0%	61.7%	% Gold and silver status	59.3%	61.7%	93.5%
713.10	4623.89	Revenue in 2001	3964.70	3753.39	94.6%
24,337.50	71,270.63	Miles in 2001	64134.45	63867.39	99.4%
28.5%	10.9%	% Female customers	15.1%	10.1%	71.6%
Control	Denied Boarding	Denied Boarding (N = 1566) ^b	Control	Denied Boarding	PRB
6.61	15.59	All flights (Months 1–6 in 2002)	12.30	12.44	98.4%
25.0%	50.1%	% Gold and silver status	47.4%	46.2%	95.2%
713.10	4019.23	Revenue in 2001	3547.02	3392.96	93.2%
24,337.50	55,262.70	Miles in 2001	56076.32	54525.56	95.0%
28.5%	19.7%	% Female customers	20.3%	21.2%	89.8%
Control	Upgrading	Upgrading (N = 1720) ^c	Control	Upgrading	PRB
6.61	16.00	All flights (Months 1–6 in 2002)	8.71	8.69	99.8%
25.0%	59.2%	% Gold and silver status	38.0%	41.5%	89.8%
713.10	4232.90	Revenue in 2001	2240.01	2201.08	98.6%
24,337.50	63,400.03	Miles in 2001	34155.62	34153.48	100.0%
28.5%	18.9%	% Female customers	21.9%	24.5%	72.9%

^a93.8% of original cases matched.

^b85.6% of original cases matched.

^c75.3% of original cases matched.

privileged when it comes to downgrading and denied-boarding decisions. Furthermore, in the downgrading model, we used the number of high-value bookings (i.e., business-class bookings) and not the number of flights as a predictor, because a customer can get downgraded only from a high-value booking class. The probability of the event occurring as given by the binary logistic regression model is the propensity score, which we subsequently used for matching, as we describe next. The results of the logit regression appear in Table 2.

The information we received from the airline about what drives the likelihood of receiving a treatment is correct. The number of flights in the respective period is the strongest predictor for all three treatments. The square miles collected in the loyalty program are an additional predictor for the negative treatments, whereas the (nonsquare) miles collected in the loyalty program are a predictor of upgrading. Again, the rationale is that airlines try to refrain

from bumping or downgrading high-value customers, preferring instead to give them upgrades. Note that the purpose of the logistic regression model here is only to obtain parameter estimates to compute propensity scores for each individual and perform the matching.

Second, we match participants to nonparticipants with a matching algorithm. There are various techniques to accomplish this (Diaz and Handa 2004). In general, simulation studies (Barabas 2004; Heckman et al. 1998) report that the various available matching techniques all yield comparable results. Nearest-neighbor matching, which is an algorithm that is well known from procedures such as cluster analysis, in which the treatment case is matched with the nontreatment case closest to its propensity score, is the basic idea underlying all variants. Formally, let $P(X_i)$ be individual i 's propensity score. The treated individual i is matched to the nontreated individual j , where j is $\min ||P(X_i) - P(X_j)||$.

FIGURE 1
PSM Procedure

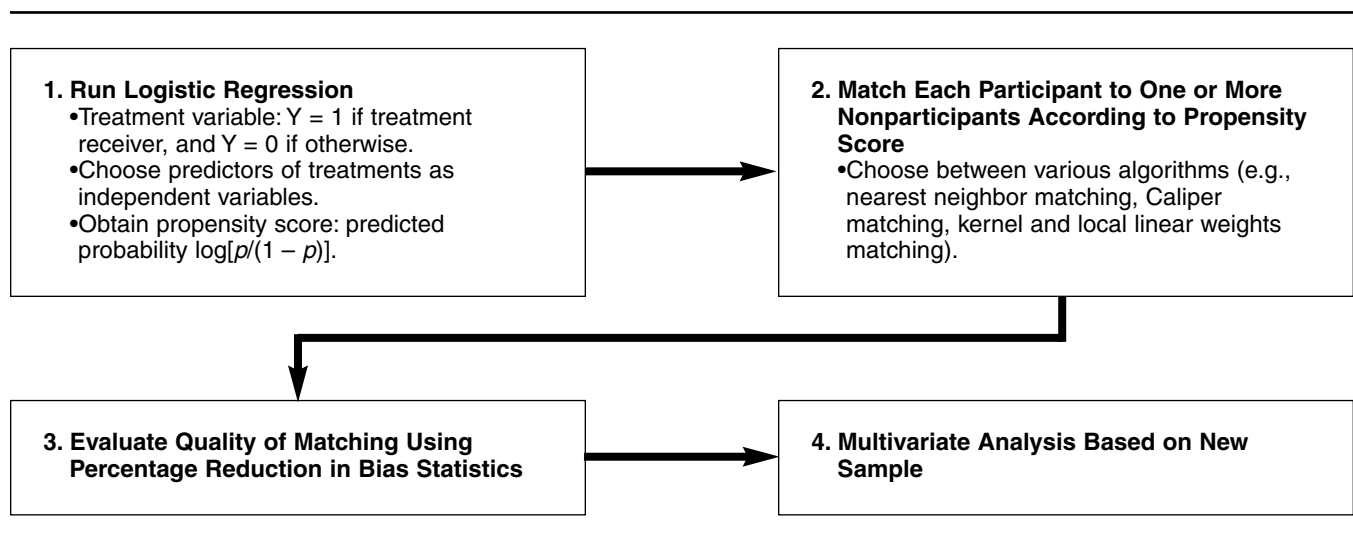


TABLE 2
Results of Logistic Regression Analysis

Independent Variables	Downgrading		Denied Boarding		Upgrading	
Constant	4.66	(.16)*	-4.11	(.12)*	-2.00	(.06)*
All high-value flights (Months 1–6 in 2002)	.32	(.03)*	—		—	
All flights (Months 1–6 in 2002)	—		.53	(.02)*	.63	(.01)*
Status (bronze)						
Status (silver)	-.04	(.14)	-.15	(.10)	.52	(.05)*
Status (gold)	-1.00	(.16)*	-.74	(.12)*	1.50	(.06)*
Miles 2001	-.05	(.01)*	-.05	(.01)*	271.05	(32.82)*
Revenue 2001	-.88	(.13)*	.31	(.11)**	.05	(.01)*
Gender (1 = female)	-7417.84	(1298.03)*	-1045.68	(685.61)	.40	(.06)*
Age	-1.30	(5.77)	-2.51	(2.90)	-.01	(2.73)
Log-likelihood	-1894.46		-6978.06		-14,003.94	

* $p < .01$.

Notes: The parameter for Status (bronze) is set to zero. The coefficients for "All high-value flights" and "All flights" are divided by 10. The coefficients for "Miles," "Revenue," "Gender," and "Age" are divided by 10,000.

Although this technique is intuitive, it may be difficult to find good matches for some people. We overcome this problem with caliper matching (Cochran and Rubin 1973), in which a so-called common-support region is specified (i.e., a tolerance zone for the difference in the propensity score between matches and nonmatches). Then, the nearest neighbor is matched to the treatment case only if $||P(X_i) - P(X_j)|| < \epsilon$, where ϵ is the specified tolerance zone. Potential disadvantages of this procedure are that there are often treatment cases for which no appropriate matching partner can be found in the data set. Besides, subjectivity in choosing the tolerance zone may be a further disadvantage. There is some controversy about using either the Silverman (1986) rule or subjective judgment for determining the size of the tolerance zone. We began with the Silverman rule, which states that the tolerance zone should equal 1.06 times the standard deviation of the propensity score divided by the fifth root of the sample size, which resulted in values of .00038 for downgrading, .00041 for denied boarding, and .00054 for upgrading. However, given our unusually large control group, we were able to impose a far stricter rule for the caliper matching, which finally resulted in a .0000001 rule for all models. Applying this rigid rule ensures that the control and the treatment groups are indeed similar to each other. Even with this strict rule, we were able to match 85.6% of all denied boarding cases, 93.8% of all downgrading cases, and 75.3% of all upgrading cases to a nontreatment case, which are good quotas. Thus, the typical disadvantages of caliper matching are not particularly relevant in this case, and the method represents a suitable solution for our application.

We validated our approach by splitting the control group data set into three subsamples of approximately 110,000 customers each, and we conducted the matching with each of the three control groups in turn. The resultant parameter estimates were similar for each of the subsamples, and all hypotheses tests corresponded to the results we present subsequently. This increases confidence in the reliability and validity of the results because we obtain the same results regardless of the control group.

Third, we evaluate the quality of the matching by computing the percentage reduction in bias (PRB) (Rosenbaum and Rubin 1984) according to the following formula:

$$(1) \quad PRB_n = 1 - \frac{|\bar{x}_{i,n}^A - \bar{x}_{j,n}^A|}{|\bar{x}_{i,n}^B - \bar{x}_{j,n}^B|},$$

where

- PRB_n = the percentage reduction in bias for the n th predictor variable,
- $\bar{x}_{i,n}^A$ = the mean of the n th predictor variable for the treatment group after matching,
- $\bar{x}_{j,n}^A$ = the mean of the n th predictor variable for the nontreatment group after matching,
- $\bar{x}_{i,n}^B$ = the mean of the n th predictor variable for the treatment group before matching,
- $\bar{x}_{j,n}^B$ = the mean of the n th predictor variable for the nontreatment group before matching, and
- N = the number of predictor variables.

The matching produced a nontreatment group that was similar to the treatment group with regard to the time before 2002. This also becomes clear in the right-hand columns of Table 1, which show the means for the treatment group and the control group we obtained from the caliper matching. The treatment group is similar to the control group in all predictor variables, and the PRB indicates a strong reduction of bias for all included predictors.

Fourth, after substantially reducing our sample size and obtaining three pairs of similar treatment and control groups, we determine the treatment effect by conditional difference-in-differences by applying the following equation:

$$(2) \quad \hat{\beta} = \frac{1}{n} \left[\sum_{i \in I_1 \cap S_p} (Y_{1ti} - Y_{0t'i}) - \sum_{j \in I_1 \cap S_p} (Y_{0tj} - Y_{0t'j}) \right],$$

where $\hat{\beta}$ is the estimated treatment effect, n is the total number of treatment cases, $Y_{1ti} - Y_{0t'i}$ is the before-and-after difference of the treatment cases, $Y_{0tj} - Y_{0t'j}$ is the before-and-after difference of the control cases, and S_p is the defined common support region. This is simply an application of the general linear model

$$(3) \quad (Y_t - Y_t) = \alpha + \beta D + \epsilon$$

on all matched cases. In other words, the before-and-after difference of the outcome variable is written as a function of treatment D (where 1 = treatment case, and 0 = control case) with its parameter $\hat{\beta}$, which is an estimator of the treatment effect that controls for the a priori difference between the treatment and the nontreatment cases. The combination of PSM with a difference-in-differences technique (also called the “conditional difference-in-differences technique”) has been found to be less sensitive to bias than all other known methods for evaluating treatment effects in a nonexperimental setting (Heckman, Ichimura, and Todd 1997). The model can be extended to capture the effects of covariates to control for the bias that could not be removed by the matching.

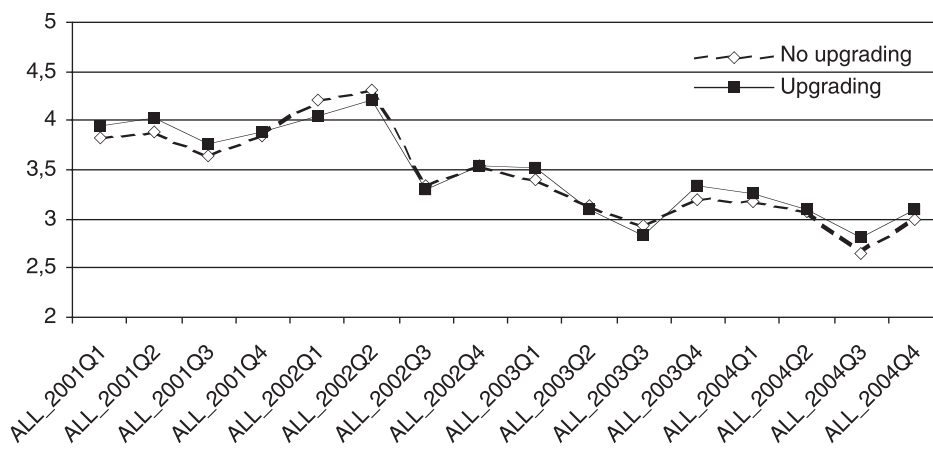
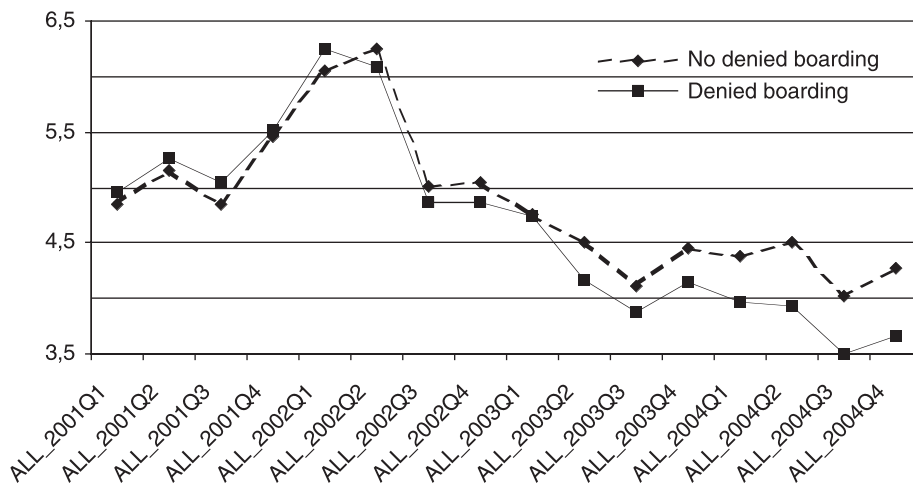
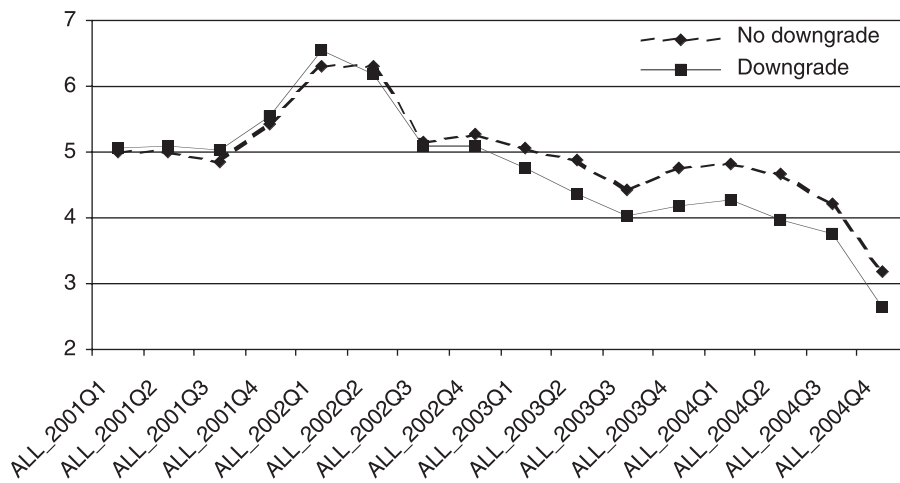
Results

All Customers

The central question underlying this research is whether a treatment effect of the negative (denied boarding and downgrading) and positive (upgrading) events can be observed. A first impression can be obtained from Figure 2, in which we display the time series of the number of transactions for all three treatment and their respective control groups.

As Table 1 shows, we were able to remove the original bias on the observed variables by conducting the caliper matching procedure for the time before the treatment (i.e., until June 2002). Until then, both the treatment and the control groups exhibited similar usage patterns. Furthermore, Figure 2 shows that after the treatment reception, there is a negative effect of the denied-boarding treatment (the control group flies more often than the nontreatment group). There seems to be an even stronger effect of downgrading.

FIGURE 2
Number-of-Flights Comparison of Treatment and Control Group for Downgrading, Denied Boarding, and Upgrading



For upgrading, there is only a small difference between treatment receivers and nonreceivers.

For obtaining estimates of the treatment effect, $\hat{\beta}$, for the various treatments, we estimated the general linear model (Equation 3). As dependent variables, we used the before-and-after differences for (1) the number of transactions and (2) the revenues. Given that we estimated the treatment effect for the number of flights for ten quarters (2002q3–2004q4), ten observations per customer are available for the dependent variable “number of flights.” For revenue data, which is available only on a yearly basis, we had two observations (2003 and 2004). Thus, for our two dependent variables, we obtained a panel structure with ten and two measurement points for number of flights and revenue, respectively. This sums to six models (three matched samples and two dependent variables). Hausman tests (Greene 2003) indicate that for each of the six models, a random-effects, rather than a fixed-effects, model should be preferred. This is not surprising, because the Hausman test rejects the assumption of equal effects across individuals, whereas in H_3 , we already assumed that effects should vary across loyalty status groups. For both dependent variables, we estimated the random-effects model

$$(4) \quad y_{it} = \beta x_{it} + u_i + e_{it},$$

where y_{it} is the dependent variable (the difference-in-differences in the number of transactions and the difference-in-differences in revenues, respectively); β is the treatment effect; u_i is a customer-specific, time-invariant disturbance, where $E[u_i] = 0$ and $\text{Var}[u_i] = \sigma_u^2$; and e_{it} is the “classical” disturbance, where $E[e_{it}] = 0$, $\text{Var}[e_{it}] = \sigma_e^2$, and $\text{Cov}[e_{it}, u_i] = 0$.

To test for a potential effect of differences between the control and the treatment groups that had not been removed by the matching procedure, we also included the variables from the logit model in the estimation of the treatment effect. Given that the matching produced similar groups, however, it is not surprising that none of the additional covariates exhibited statistically significant effects on transaction behavior, and thus Table 3 displays only the results for the treatment effects.

The treatment variables downgrading and denied boarding exhibit statistically significant effects on both the number of flights and the revenues obtained. For example, Table 3 can be interpreted such that customers who were denied

boarding conduct .1352 flights less than those who have not been denied boarding. For confidentiality reasons, the airline asked us to display only indexed values for the yearly revenue effects. We scaled the strongest negative effect (downgrading) to represent a value of exactly 100, and we rescaled all other parameter estimates to reflect the correct effect relative to this value. In other words, the downgrading effect is more than seven times higher than the effect of denied boarding.¹

In summary, the results in Table 4 lend substantial support to H_1 , in that there is a strong negative effect of downgrading and denied boarding on customer transactions and revenues. In contrast, none of the upgrading effects—neither on the number of flights nor on revenues—are statistically significant. In other words, customers do not react positively to upgrading, or at least, the effect is weak. Thus, H_{2a} is rejected, and the alternative hypothesis, H_{2b} , is supported.

We further tested for potential differences between the treatments and additional variables that we suspected might moderate the exhibited effects. In particular, we added an interaction effect between the variable “passenger type” (business versus private) and the treatments to the model and an interaction effect between the variable “flight length” (continental versus intercontinental) and the treatments. None of the interactions exhibited a statistically significant effect in any of the models. We conclude that effects do not vary systematically between business and private travelers, as might be suspected. Furthermore, there is no evidence that the effects are more severe for longer than shorter flights. We conclude that the difference in the amount of compensation paid to downgraded or denied-boarding customers between continental and intercontinental flights is more or less adequate (though the absolute sum is not).

Customer Segments

Given that H_3 and H_4 suggest segment-specific differences, we repeated the previously mentioned matching procedure on a segment level; that is, we matched the treatment receivers of the three groups (i.e., gold, silver, and bronze customers) only with nontreatment receivers of the same

¹In light of the difference in the number of flights, the resultant monetary effects are much higher than the displayed parameters.

TABLE 3
Effects of Treatments on Number of Flights (Quarterly) and on Revenues (Yearly)

Treatment Effects	Sample Size	Dependent Variable: Difference-in-Differences for Number of Flights (2002q3–2004q4)	Dependent Variable: Difference-in-Differences for Revenues (2003–2004)
Denied boarding	1566	−.14 (.05)**	13.43 (5.86)*
Downgrading	952	−.54 (.06)**	−100.00 (200.93)**
Upgrading	3440	.05 (.05)	.03 (8.10)

* $p < .05$.

** $p < .01$.

Notes: Coefficients for revenue effects are distorted for confidentiality reasons, but values reflect correct relative differences and significance levels.

TABLE 4
Effects of Treatments for Different Status Groups

Treatment Effects	Sample Size	Difference-in-Differences for Number of Flights (2002q3–2004q4)	Difference-in-Differences for Revenues (2003–2004)
Denied Boarding			
Bronze	448	-.10 (.14)	-.30 (11.49)
Silver	221	-.47 (.10)**	-52.40 (26.34)*
Gold	158	-1.49 (.19)**	-93.04 (45.13)*
Downgrading			
Bronze	92	-.28 (.17)	-12.10 (98.92)
Silver	162	-.88 (.13)**	-46.71 (10.64)**
Gold	218	-1.73 (.32)**	-170.32 (40.21)**
Upgrading			
Bronze	924	.21 (.04)**	2.62 (2.58)
Silver	741	.27 (.34)	10.93 (10.34)
Gold	53	.24 (.30)	18.02 (11.54)
		Likelihood Ratio Tests for Group Equivalence	Likelihood Ratio Tests for Group Equivalence
		Denied boarding: $\chi^2_{2d.f.} = 115.73, p < .001$	Denied boarding: $\chi^2_{2d.f.} = 88.02, p < .001$
		Downgrading: $\chi^2_{2d.f.} = 332.81, p < .001$	Downgrading: $\chi^2_{2d.f.} = 401.24, p < .001$
		Upgrading: $\chi^2_{2d.f.} = 41.46, p < .001$	Upgrading: $\chi^2_{2d.f.} = 71.47, p < .001$

* $p < .05$.

** $p < .01$.

Notes: Coefficients are distorted for confidentiality reasons, but values reflect correct relative differences and significance levels.

status group and conducted the same analysis again. Instead of simply using the matched data sets that we obtained for testing H_1 and H_2 and including dummy variables for the different customer status groups, this procedure ensures the highest possible level of comparability on the individual treatment level and, in general, is recommended in the matching literature (e.g., Heckman, Ichimura, and Todd 1997).²

Again, caliper matching produced comparable groups with regard to their transaction and spending patterns before the treatment. As Table 4 shows, the difference-in-differences results show substantial variation in the parameter estimates in the expected direction. The strongest negative effects can be observed for both downgrading and denied boarding for the gold customers, whereas there is hardly any effect for the bronze groups. Conversely, only the bronze customers react (mildly) positively to courtesy upgrades. In summary, negative incidents negatively affect high-value customers, and positive incidents only affect low-value customers.

To provide a formal test of H_3 and H_4 , we conducted likelihood ratio specification tests for our models (e.g., Greene 2003). In other words, we compared a restricted model, in which treatment coefficients are restricted to be equal across customer value groups, with an unrestricted

model, in which parameter estimates are allowed to vary across groups. If we let $\log L_u$ be the log-likelihood of the unrestricted model and $\log L_r$ be the log-likelihood of the restricted model, then $2 \times (\log L_u - \log L_r)$ follows a chi-square distribution with $(G - 1) \times K$ degrees of freedom, where G is the number of groups (in our case three) and K is the number of parameters (in our case, one for each treatment, respectively). Given the large differences in the parameters across groups, it is not surprising that we obtain statistical significance of the chi-square test for all six models (see Table 4). Because the group differences are in the expected direction, H_3 and H_4 are supported.

Discussion

The results of this study show, for the first time, the behavioral and monetary consequences of positive and negative treatments (denied boarding, downgrading, and upgrading) that arise from overbooking. We find that the negative events exhibit strong and lasting negative effects on usage levels and revenues, whereas the positive events show only mild effects on low-value customers. Our discussion addresses theoretical and practical implications simultaneously and is divided into three sections.

Application of Fairness Theory

In the empirical study, we did not test our theoretical explanation that the consequences of overbooking on subsequent

²However, using the data set, we obtain the same substantial results and only marginal differences in the parameter estimates.

customer behavior can be explained by fairness theory. To understand whether being downgraded or denied boarding is really perceived as unfair and reduces the intention to fly again with the same airline, we conducted a role-play scenario experiment in which 620 undergraduate students from three different German universities participated. The design was a 3 (upgrading, denied boarding, and downgrading) \times 3 (gold, silver, and bronze customers) \times 2 (private and business travel) treatment. Of the participants, 102 were non-German students, providing an international perspective as well. In general, the results confirmed our theoretical model and field study results; that is, downgrading and denied boarding were perceived as highly unfair and negatively affected repurchase intentions. Downgrading and denied boarding were perceived as more unfair in the high-value customer groups than in the low-value customer group. Upgrading had a significant effect on fairness perceptions only for the low-value customer group, and even for this group, there was no effect on repurchase intentions. There were no differences between business and private travel. Furthermore, German and non-German students did not differ, essentially suggesting that the effects are not nationally or culturally bound. (Further details regarding the design, analysis, and results of the experiment are available on request.) In summary, the results of this experiment confirm that customers perceive the practice of overbooking as unfair.

Prior research has encouraged a stronger focus on theory development in future studies in the area of customer metrics and lifetime value (e.g., Bolton, Lemon, and Verhoef 2004). We could confirm hypotheses grounded in fairness theory that high-value customers react most strongly to negative events whereas low-value customers react most strongly to positive events. Although we did not specifically design the current research (a field study) to test fairness theory, the empirical results, combined with the experimental study, encourage the customer lifetime value/customer equity literature to integrate this theory into its analysis framework. It seems that fairness theory could provide the basis for a wide array of research propositions and hypotheses that examine differences among various customer value groups.

In this context, an area for managerial action is compensation. Thus far, the customer equity literature has developed several suggestions for prioritizing high-value customers, but it has been silent on the issue of compensation for service failures. Following the argumentation from fairness theory and the empirical results we obtained, it would make sense for firms to offer higher compensation to bumped or downgraded high-status customers than is legally required. In other words, differential treatment between high- and low-value customers is all the more important when something goes wrong than when everything goes well.

A Customer-Centric View on Revenue Management

Our study provides an illustrative example of a situation in which a customer-centric view has implications that vary

dramatically from the product-centric view typically encountered in yield management applications (i.e., revenues from origin–destination networks are maximized). Rust, Lemon, and Zeithaml (2004) argue convincingly in favor of the superiority of a customer-centric, and thus customer lifetime value–maximizing, view. As they point out, by using customer-centric measures as a target metric, the return on marketing can be accurately measured. Although a customer-centric view has been favored for decades, especially in the marketing literature, neither the literature nor management practice in revenue management has taken this view into account.

In building models for revenue management, the results from the current study could be taken into account by integrating the average treatment effect of denied boarding and downgrading into maximization algorithms. The resultant model would add these costs to the calculated compensation costs that must be paid to any downgraded or bumped customer, so that the model would reflect not only the legal but also the behavioral consequences of such events. However, there is also a more sophisticated, though more difficult, long-term alternative to react to the results.

For the past 15 years, service providers have invested heavily in enhancing customer databases. Today's databases are important tools for all kinds of CRM activities, and they are typically in the domain of firms' marketing departments. In contrast, booking systems are often managed by "service production" or "network planning" departments and, because of their technical nature, are information technology driven rather than customer driven. The practical management literature has recently highlighted the importance of integrating such data sources for effective CRM (e.g., Wind, Mahajan, and Gunther 2002), and this study demonstrates the usefulness of such a convergence. If the airline is able to control not only the proportion of overbookings on a flight but also the proportion of overbookings per customer status, the system could, for example, check the proportion of gold-status customers who are booked on the flight, and because this group is overrepresented compared with an average flight, the overbooking ratio could be decreased. As such, the firm would decrease the likelihood that a high-value customer experiences a negative event and, in return, could take a greater chance on a flight with more low-value customers. This would require firms to educate their customers to indicate their frequent-flier identification when they book their flight. However, this does not seem unrealistic, given that the firms can communicate to their high-value customers that indicating the frequent-flier status early in the booking process can only be advantageous for them.

Asymmetric Effects of Positive and Negative Events

We do not find strong effects for positive treatments. Thus, although it is clear that negative treatment effects are strong and lasting, positive effects are, if at all, small. This confirms the findings from the customer satisfaction literature on the asymmetric effects of positive and negative events on customer satisfaction (e.g., Inman, Dyer, and Jia 1997;

Rust, Zahorik, and Keiningham 1995). Whereas decreased attribute-level satisfaction can affect overall satisfaction severely, increases in attribute-level satisfaction do not have a strong effect on overall satisfaction (e.g., Mittal, Ross, and Baldasare 1998). Theoretically, this can be explained by prospect theory (Kahneman and Tversky 1979), which suggests that losses (or negative disconfirmation) are valued more than gains (or positive disconfirmation).

However, note also that for lower-value customer groups, the behavioral difference between positive and negative treatments is much smaller than it is for higher-value groups. Thus, it appears that losses (gains) have especially negative (positive) consequences when the customer's own investment into the relationship is perceived as high (low). Our experimental study also confirmed this; the positive events were rated far less positive than the negative events were rated negative.

The results indicate that excluding customers from a service (i.e., denied boarding) is less harmful to both the number of transactions and the revenues from customers than serving customers less than they expect (i.e., downgrading). However, this may be explained by the notion that, often, airlines are able to find fairly "good" solutions for denied boarding passengers (i.e., booking them on alternative flights). Customers may then believe that the airline has done its best to solve the problem, whereas downgraded customers are simply disappointed by getting less than they expected (and deserved). Moreover, customers who book in high-value classes are mostly gold and silver customers and, as such, react more strongly to service failures, as fairness theory suggests. In this sense, a downgraded customer

is a more severe threat for the firm than a bumped customer. Thus, firms should be particularly careful in overbooking their high-value classes. Indeed, because the effects of overbooking on the lower-value classes are not as severe, the segmented approach to overbooking and compensation we described previously seems to make even more sense.

Conclusion

This article shows that ignoring the long-term behavioral consequences of overbooking may lead to severe consequences for service providers. For extensions of this research, it would be insightful to conduct qualitative depth interviews with bumped, downgraded, and upgraded customers to understand better the motives for their reactions to overbooking. Furthermore, as is often the case when firm-specific data are used, it would be worthwhile to compare the results across airlines and industries. Finally, we caution that the actual negative effects may be even more dramatic than those computed because of a high likelihood of negative word of mouth by bumped and downgraded customers.

On a more general level, this study emphasizes the importance of cross-functional integration of management functions, especially in service firms. Studying customer-related consequences of a practice that is traditionally performed by operations management departments leads to new insights for customer management. Therefore, we encourage future work that uses customer-related metrics as outcome variables of traditionally nonmarketing related issues.

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