<table>
<thead>
<tr>
<th>Page</th>
<th>Title</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Editorial</td>
<td>Jason C.H. Chen and Wen-Chyuan Chiang</td>
</tr>
<tr>
<td>5</td>
<td>Keynote paper: Large-scale entry deterrence of a low-cost competitor: an early success of airline revenue management</td>
<td>Frederick H.deB. Harris</td>
</tr>
<tr>
<td>28</td>
<td>Revenue management for broadcasting commercials: the channel’s problem of selecting and scheduling the advertisements to be aired</td>
<td>Alf Kimms and Michael Müller-Bungart</td>
</tr>
<tr>
<td>45</td>
<td>Bundling of information goods: a value driver for new mobile TV services</td>
<td>Tarja Rautio, Mai Anttila and Matti Tuominen</td>
</tr>
<tr>
<td>65</td>
<td>The optimal ratio between advertising and sales income</td>
<td>Andrea Mangani</td>
</tr>
<tr>
<td>79</td>
<td>Effects of experiential elements on experiential satisfaction and loyalty intentions: a case study of the super basketball league in Taiwan</td>
<td>Yie-Fang Kao, Li-Shia Huang and Ming-Hsien Yang</td>
</tr>
<tr>
<td>97</td>
<td>An overview of research on revenue management: current issues and future research</td>
<td>Wen-Chyuan Chiang, Jason C.H. Chen and Xiaojing Xu</td>
</tr>
</tbody>
</table>
Editorial

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Wen-Chyuan Chiang is a Professor of Operations Management at the College of Business Administration, The University of Tulsa. He received his PhD in Operations Management and his MBA from the University of Texas at Austin and his BA from the National Taiwan Normal University. His research interests include revenue management, supply chain management, distribution and logistics, manufacturing operations and AI applications to operations management problems. His research appears in Management Science, IIE Transactions, Decision Sciences, Int. J. Production Research, European Journal of Operational Research, Annals of Operations Research, Journal of the Operational Research Society and INFORMS Journal on Computing, among others. He is the recipient of the Mayo Excellence in Research Award for six times. He is the Editor of Int. J. Revenue Management and a senior editor of Production and Operations Management.
1 Introduction

It is our pleasure to welcome all of you to the inaugural issue of the International Journal of Revenue Management (IJRM). The IJRM is an interdisciplinary and refereed journal that provides authoritative sources of reference and an international forum in the field of revenue management. The objective of the journal is to establish an effective channel of communication among business decision-makers, policy makers, government agencies, academic and research institutions and persons concerned with the complex role of revenue management. Specifically, the IJRM aims to promote creative, innovative concepts, strategies, theories and methodologies in the area of revenue management. The IJRM publishes well-written and academically rigorous manuscripts.

Though the IJRM is devoted to the main area of revenue management, it also expands its scope to broadly cover any issues overlapping or related to revenue management. The subject of coverage includes:

- Revenue or yield management
- Customer relationship management
- Knowledge management and value creation
- Cluster analysis
- Consumer behaviour
- Branding, segmentation and channel management
- E-commerce/e-business
- Strategy
- Supply chain and demand management
- Enterprise resource planning
- Production and operations management
- Business processes and management
- Forecasting
- Pricing/dynamic pricing/option pricing
- Database/data warehouse management
- Data mining and business intelligence
- Information technology/resource management and outsourcing
- Computerisation
- Decision support systems
- Software development
- Economics of revenue management
- Healthcare management
2 Inside this issue

This inaugural issue of the *IJRM* contains five papers that cover revenue management issues in different industries and one paper that reviews the most recent literature.

The first paper, ‘Large scale entry deterrence of a low-cost competitor: an early success of airline revenue management’ by Harris, analyses how Piedmont Airlines, a large regional incumbent, had deterred People Express, a low-cost discounter, in city-pair airline markets during 1984–1987. From the analysis, he argues that People Express chose the right strategy but for the wrong entry game and proposes that the best reply responses of incumbents should be determined by customer sorting in response to stockouts. The implemented real-time inventory management optimisation tools in Piedmont are proved to be crucial to Piedmont’s success of deterrence.

The second paper, ‘Revenue management for broadcasting commercials: the channel’s problem of selecting and scheduling ads to be aired’ by Kimms and Muller-Bungart, addresses a broadcasting company’s planning problem of maximising revenues by choosing orders and scheduling spots from accepted orders. The authors use a mathematical model to represent the problem, and implement five heuristics – two general MIP-based heuristics (Dive-and-Fix and Relax-and-Fix), two heuristics based on the LP relaxation of the model and a greedy heuristic - to find the solution for the problem.

In the third paper, ‘Bundling of information goods: a value driver for new mobile TV services’, Rautio, Anttila and Tuominen present a conceptual model to show how many different characteristics of information goods support or limit the selection of bundling as a pricing strategy. Then the authors propose 14 hypotheses and test them with conjoint analysis in the context of a mobile TV service, which is expected to be launched in 2006. The results of this study suggest that bundling increases the demand in all cases and consumers strongly prefer two-part pricing and flat access rates.

The fourth paper, ‘The optimal ratio between advertising and sales income’ by Mangâni, presents a simple model to derive the optimal ratio between advertising and sales revenues for a publisher to maximise its profits. Furthermore, the author uses the same analytical framework to explore the optimal relationship between investments in quality, advertising revenues, and sales income. The authors’ findings confirm previous empirical studies and stylised facts of the media industry.

In the fifth paper, ‘Effects of experimental elements on experiential satisfaction and loyalty intentions: a case study of the super basketball league in Taiwan’ by Kao, Huang and Yang, makes an empirical study on basketball games to investigate the relationships among experiential elements, mediating constructs and loyalty intentions. The authors
J.C.H. Chen and W-C. Chiang propose 9 hypotheses and use quota sampling to collect the data so as to test these hypotheses. From the research, they observe that sports industry should focus on consumers’ experiential processes, enhance positive experiential stimulus in the game, and make the games more interactive and unique.

The last paper, ‘An overview of research on revenue management: Current issues and future research’, Chiang, Chen and Xu provide an overview of literature on revenue management. The overview focuses on recent progress of revenue management in different industries. The research of major revenue management issues, including capacity control, overbooking, pricing, forecasting, economics, implementation, performance evaluation and OR techniques are reviewed in this article. Based on the review, the authors present several promising areas for future research.

Acknowledgements

The Editor-in-Chief and Editor would like to express their sincere gratitude to the contributing authors and to all the distinguished Editorial Board members for agreeing to serve on the board of the IJRM and reviewing the papers for this inaugural issue. We would like to take this opportunity to thank Dr. Mohammed A. Dorgham, Mr. Jim Corlett and Ms. Sue O’Mara of Inderscience Publishers for their support throughout the launching of this journal. Finally, to our readers around the world, we thank you very much for using this journal as your source of information and hope you find it helpful in your research endeavours.
Keynote paper: Large-scale entry deterrence of a low-cost competitor: an early success of airline revenue management

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Abstract: In both entry deterrence theory and practice, customer sorting in response to stockouts determines the best reply responses of incumbents threatened by entry. People Express (PE) chose the right strategy but for the wrong entry game and ended up being deterred in the Southeast region by the incumbent Piedmont Airlines (PI). Piedmont had recently developed the second earliest full-scale implementation of a real-time inventory management optimisation tool. By employing optimal capacity controls in segmented fare classes, Piedmont was able to increase the service quality to its higher-yield loyal business customers on the congested flights precipitated by the price war with PE. When prices returned to substantially higher cost-covering target price levels, Piedmont’s revenue tripled while PE’s revenue actually declined. Soon thereafter, it became clear that Piedmont had successfully deterred a low-cost discounter.

Keywords: airlines; entry deterrence; revenue management.

Reference to this paper should be made as follows: Harris, F.H.deB. (2007) ‘Large-scale entry deterrence of a low-cost competitor: an early success of airline revenue management’, Int. J. Revenue Management, Vol. 1, No. 1, pp.5–27.

Biographical notes: Frederick Harris is the John B. McKinnon Professor of Managerial Economics and Finance at the Babcock Graduate School of Management, Wake Forest University. He specialises in pricing tactics and capacity planning. From 1988 to 1993, he served on the Board of Associate Editors of the Journal of Industrial Economics. His management research benchmarks capacity-constrained pricing, order processing and capital planning of large companies against state-of-the-art techniques in revenue management. He is the co-author of Managerial Economics: Applications, Strategy, and Tactics, 10th edition. He earned a BA from Dartmouth College and a PhD from the University of Virginia in 1981.
1 Introduction

Sequential games of entry deterrence and accommodation have uncovered a rich variety of strategic incumbent behaviour in response to entry or potential entry including credible price discount threats (Milgrom and Roberts, 1982; Fudenberg and Tirole, 1986) advertising campaigns (Bernheim, 1984), excess capacity pre-commitments (Dixit, 1989) and demand management rationing schemes based on customer loyalty (Deneckere, Dan and Lee, 1992) or advance purchase requirements (Sherman and Visscher, 1982). The rational business decisions of incumbents in these game-theoretic models vary from the relatively passive acquisition of enough excess capacity to absorb the demand stimulated by discounters to the very aggressive incumbent who engages in legal predation.1 This state of theory knowledge presents something of an embarrassment of riches in the industrial economics of entry deterrence.

Moreover, some of the most important results of entry deterrence and accommodation games are not robust but instead depend upon carefully specified restrictions. Davidson and Deneckere (1986) show that altering the rule by which customers sort across capacity-constrained suppliers can easily reverse the incumbent’s decision to undertake excess capacity investments to deter entry. Fudenberg and Tirole (1984) and Gal-Or (1985) demonstrate that the deterrent effect of incumbent capacity or advertising investments depends upon whether the subsequent competition is in prices (Bertrand competitive assumptions) or quantities (Cournot competitive assumptions), and whether the incumbent can secure first-mover vs. second-mover advantage. Given this pivotal nature of customer sorting rules, the structure of competition and the decision timing, many leading graduate texts like Tirole (1988) and Rasmussen (2001) as well as the Handbook of Industrial Organisation (Shapiro, 1989) argue that industry studies must be intertwined with game-theoretic analysis of entry deterrence and accommodation to discriminate among the myriad alternative hypotheses.2

The present paper analyses a two-stage entry deterrence/accommodation game in city-pair airline markets. Specifically, we analyse a Southwest-like new entrant People Express (PE) and the strategy and tactics employed by a large regional incumbent (Piedmont Airlines) to deter entry into the very profitable Southeast regional markets during 1984–1987.3 Piedmont employed a surprisingly sophisticated revenue management system to optimise their tactically motivated differential pricing and capacity controls in a very highly segmented market environment. Very detailed cost and price data are publicly available in DOT reports. With 20 years distance from the actual events, we also secured access to proprietary realised revenue data that allow a formal analysis of each airlines’ capacity, pricing and service quality choices. This actual data on firm-specific tactics in a particular city-pair allow us to distinguish several pricing and capacity choice implications predicted by sequential game theory and lend support to the pivotal importance of revenue management practices in entry deterrence. At the same time, the analysis illustrates the need to combine game-theoretic reasoning with a careful study of market-specific customer-sorting rules in order to assess public policy issues such as predatory intent.

1.1 Policy implications

Taking business from a rival now and in the future through aggressive pricing below cost directly benefits consumers. Predatory pricing rules therefore tread a fine line between
Large-scale entry deterrence of a low-cost competitor

protecting competition, which is a well-established purpose of antitrust policy, and protecting individual competitors, which is not. As the US Supreme Court declared in *Spectrum Sports, Inc., et al. v. Shirley McQuillan, 113 US. 884 (1993)* and *Brooke Group Ltd. v. Brown and Williamson Tobacco Corporation 113 US. 2578 (1993)*, a specific intent to harm competitors by pricing below cost is not enough to convict an incumbent firm of predatory pricing. Instead, a finding of illegal predation also requires a reasonable probability of recouping the losses from predatory pricing with later excess profit. Dominant hub market shares like Northwest at Minneapolis (84%) and Detroit (80%) or US Airways at Pittsburgh (81%) and Charlotte (93%) appear necessary today for a finding of predatory intent. Berry (1992) studies the equilibrium entry decision at both hubs and non-hubs with heterogeneous firms, whose networks and cost structures are better suited to some city-pair markets than to others.

Of course, under perfectly contestable market conditions of open entry, low switching costs and slow incumbent response, hit-and-run entry prevents any such recoupment from one period to another. Hence, temporary price-cutting below cost in fully contestable markets simply reduces stockholder wealth permanently. In city-pair airline markets, however, easy entry and low customer switching costs are often combined with lightning fast incumbent response. In such markets, William Baumol argued in *Continental Airlines, Inc. v. American Airlines, Inc., 824 F. Supp. 689 (1993)* that deep-discount fares served a different, entirely legitimate business purpose – namely, multi-product price discrimination and yield (revenue) management. Indeed, airline price discrimination implemented through travel restrictions and optimal stop sales mechanisms in lower yield segments is more extensive in the especially competitive city-pair markets with lower market concentration (Stavins, 2001). Distinguishing carefully between yield management-based pricing strategy in highly competitive markets and predatory pricing tactics in hub-dominant markets is required today by a predation doctrine that no longer relies upon cost-based evidence alone to disprove specific intent.6

1.2 An overview of the model and results

We employ a modification of Gelman and Salop’s (1983) two-stage entry deterrence and accommodation game as a representation of differentiated product oligopoly. PE’s 1981–1983 entry strategy at the Newark North terminal combined very low operating cost with frequent departures and unbundled services to produce a high-productivity operation with a uniform low fare. In peripheral Middle Atlantic city-pairs, PE managed to achieve accommodative pricing responses from incumbent carriers. As a post-entry growth strategy in 1984–1985, the same universal discounting and high service frequency accompanied by large-scale region-wide entry proved unsuccessful in the Southeast regional market. An analysis of these events as a two-stage entry deterrence/accommodation game provides insights as to why PE’s entry strategy failed as a growth strategy, why PE chose a large-scale rather than a small-scale entry into the Southeastern region and why PE never tried to induce accommodation by reducing capacity. In addition, the model predicts Piedmont Airlines’ decision to match PE’s rock bottom fares on select inventory, in particular customer segments, and not do so in others. In fact, this early application of revenue management decision support systems proved pivotal to Piedmont’s eventual success in deterring PE’s entry.

In the Southeast during the first six months of 1985, Piedmont matched PE’s very low penetration pricing (e.g. $29/19 for a peak/off-peak Greensboro–Newark round-trip),
while expanding capacity and further segmenting the market (See Table 1). To enhance the brand loyalty of repeat purchase business travellers in the affected city-pairs, Piedmont increased both its delivery reliability (with fewer cancellations, better on-time departure/arrivals and almost no stockouts at departure) and its change order responsiveness (with fewer change order denials on a well-functioning reservation system). In stark contrast, PE continued to operate without reservations. Most importantly, Piedmont employed one of the earliest tactical applications of new yield management decision support tools to allocate seats optimally between full and discount fare classes and thereby control the revenue dilution and prevent displacement of higher yield business customers. Indeed, corporate travel desks were guaranteed that open seats available anywhere on the Piedmont planes would be assigned adjacent to the company’s traveller. Two of Piedmont’s best corporate customers in the Greensboro–New York market were offered and agreed to price premiums to secure this additional service. By June 1985, the price war was over. Fares did not return to their pre-entry levels (e.g. $139 for Greensboro–Newark) but did raise to $79/49, and PE announced plans to discontinue all services to its remaining Southeastern cities.

Table 1  Lowest published fares for point-to-point service, Greensboro to Newark

<table>
<thead>
<tr>
<th>Month/Year</th>
<th>Piedmont Peak/Off Peak ($)</th>
<th>People Express Peak/Off Peak ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>October 1984</td>
<td>139</td>
<td>n.a.</td>
</tr>
<tr>
<td>December 1984</td>
<td>79/49</td>
<td>n.a.</td>
</tr>
<tr>
<td>January 1985</td>
<td>49/35</td>
<td>49/35</td>
</tr>
<tr>
<td>February 1985</td>
<td>39/29</td>
<td>39/29</td>
</tr>
<tr>
<td>April 1985</td>
<td>29/19</td>
<td>29/19</td>
</tr>
<tr>
<td>June 1985</td>
<td>79/49</td>
<td>79/49</td>
</tr>
</tbody>
</table>

*Source:* Greensboro News and Record.

The paper proceeds as follows. First, an extensive form model of two-stage entry deterrence and accommodation games and their strategic equilibria are applied to actual data from the PE–Piedmont competition. A detailed analysis of the cost structures of the two carriers highlights their differences on a representative fleet inventory. The sequence of prices and capacity choices from early December 1984 to June 1985 is then analysed and found inconsistent with game-theoretic predictions under some customer-sorting rules, but consistent with others.

Briefly, the author argues that PE chose the right strategy but for the wrong entry game and ended up being deterred. Rather than recognising the proportional rationing of a major regional airlines’ target customers at differential prices and the loyalty to the incumbent of those same target customers at matching prices, PE presumed the inverse intensity rationing typical of its earlier experience in the Middle Atlantic peripheral routes served by Mohawk, Allegheny and other predecessors of US Airways. In contrast, Piedmont identified more than a dozen target customer segments of PE, conducted extensive competitor surveillance on each, matched prices on select capacity in several of the leisure segments and yet positioned its own upgraded product to target several growing and highly profitable business travel segments. As PE’s deep discount fares returned to full cost-covering levels, Piedmont’s traffic grew while PE’s declined, and PE was forced to withdraw.
Analysis of these events provides new insights when seen through the game-theoretic glass of alternative customer-sorting rules in a two-stage entry deterrence-accommodation game. Faced with differential prices, the way customers sort across alternative suppliers in response to a planned stockout of low-priced capacity proves pivotal to the success of alternative incumbent strategies for confronting discounters. A key ingredient in these strategies is the capability of the incumbent’s revenue management system to implement optimal capacity controls in real-time across differentially priced segments.

2 Theoretical framework

We modify the two-stage entry deterrence and accommodation game of Gelman and Salop (1983) and Herk (1993) to analyse the Piedmont–PE competition. Bertrand pricing of airfares combined with capacity constraints makes for Cournot-like competition in this industry (Kreps and Scheinkman, 1983). The entrant PE is presented with an irrevocable capacity choice and price announcement in Stage 1 followed by a pricing choice of the PI in Stage 2. Figure 1 represents these decisions as an extensive form of sequential game tree for the Greensboro–Newark city-pair that proved representative of this entry threat across the Southeast region. Let us call the capacities ‘Large’ and ‘Small’ and the incumbent’s pricing actions ‘Accommodate’, ‘Match’ and ‘Undercut’. Legally, predating by undercutting the new entrant’s cost-covering price while remaining above one’s own cost is also possible but only when the incumbent enjoys a cost advantage. In this instance, analysis of the Piedmont and PE cost data (displayed in Table 2) reveals a lower-cost PE entrant at $13.63 vs. Piedmont’s $16.69 for a 443 revenue passenger mile point-to-point flight.7

Ideally in such accommodation and entry games, the common information set known to both firms includes rival prices, share-of-the-market demand, own costs and the rationing rules by which customers sort across firms in response to discounts and stockouts. The entry game is initiated by marketing research revealing the target pricing of the new entrant and by an excess capacity pre-commitment on the part of the incumbent. Thereafter, the sequence of the play we analyse begins with an entrant capacity choice (and penetration pricing announcement) followed by an incumbent price response and then customers sort across suppliers, and the demand is realised. In Figure 1, a pre-entry incumbent price of $79 and a new entrant target price of $49 reflect the actual fare data in the Greensboro–Newark city-pair. Incremental variable costs per seat are set very low for both firms (consistent with proprietary data detailed later), and linear pricing as opposed to a non-linear price discrimination scheme is assumed to simplify the game tree. To illustrate the mechanics of the game, we employ representative flight data to analyse the projected payoffs assuming (provisionally) an intensity rationing customer-sorting rule. Later, we address two other rationing rules by which customers sort across differentially priced capacity in many revenue management environments today.

Intensity rationing occurs when the highest willingness to pay customers of all competitors seek out and attempts to secure the scarce capacity of the low-price firm (Rasmussen, 2001). Specifying an incumbent share-of-the-market demand that closely approximates the actual passenger seat demand per flight in the Greensboro–Newark market as \[300 - 2.124\ \text{Price}\], we find PI prefers a $79 accommodating price in the top row of Figure 1 as long as the lower-price potential entrant PE invests in small seat
capacity. The small capacity choice of the entrant entails offering 30 seats consistent with a DeHaviland 128 commuter aircraft assigned to the route. With this small capacity choice by PE, accommodating the entrant (under an intensity rationing customer-sorting rule) implies that the high-price incumbent’s potential demand of 132 seats is eroded to 102, which at Piedmont’s gross margins of $62.31 yields total contributions of \((79 - 16.69) \times 102\), i.e. a payoff of $6,356 per flight for PI.

Table 2 Piedmont Airlines and People Express cost structures

<table>
<thead>
<tr>
<th>Aircraft performance and operating characteristics</th>
<th>People Express</th>
<th>Piedmont 737-200</th>
<th>Piedmont 727-200</th>
<th>Folker-28</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity utilisation (revenue hours per aircraft per day)</td>
<td>9.01</td>
<td>737-200</td>
<td>737-200</td>
<td>6.84</td>
</tr>
<tr>
<td>Capacity (average available seats per aircraft mile)</td>
<td>120</td>
<td>112</td>
<td>162</td>
<td>65</td>
</tr>
<tr>
<td>Gallons of fuel consumed per block hour</td>
<td>740</td>
<td>817</td>
<td>1329</td>
<td>603</td>
</tr>
<tr>
<td>Average revenue passengers per aircraft mile</td>
<td>82.30</td>
<td>58.70</td>
<td>85.6</td>
<td>81.7</td>
</tr>
<tr>
<td>Seat load factor</td>
<td>68.90%</td>
<td>52.40%</td>
<td>52.90%</td>
<td>48.80%</td>
</tr>
</tbody>
</table>

Aircraft operating expenses

**Flying operations expense** (in dollars per block hour)

| Crew | 105.32 | 350.10 | 418.55 | 165.59 |
| Fuel and oil | 609.74 | 698.25 | 1,135.15 | 520.35 |
| Insurance | 7.99 | 9.85 | 7.74 | 10.19 |
| Other | 53.56 | 1.36 | 0.44 | 0.61 |
| Total flying operations | $776.61 | $1,059.56 | $1,561.88 | $696.74 |

**Maintenance expense** (in dollars per block hour)

| Direct maintenance airframe and other | 185.77 | 82.60 | 114.93 | 94.22 |
| Direct maintenance engine | 54.40 | 72.37 | 123.75 | 76.88 |
| Maintenance burden | 53.39 | 56.87 | 102.8 | 54.31 |
| Total maintenance | $293.56 | $211.94 | $341.48 | $225.41 |

**Total operating costs** (in dollars per block hour)

| Air miles GSO-EWR | 443.00 | 443.00 | 443.00 | 443.00 |
| Block hours | 1.52 | 1.49 | 1.31 | 1.58 |
| Total variable costs per GSO-EWR flight | $1,635.60 | $1,896.16 | $2,502.04 | $1,453.78 |
| Variable cost per seat | $13.63 | $16.31 | $15.44 | $22.37 |

*Weighted average variable cost per seat (GSO-EWR flight inventory)*

| | $13.63 | $16.69 |
**Figure 1** Matching price response with intensity rationing

<table>
<thead>
<tr>
<th>Entrant capacity decision</th>
<th>Incumbent PI pricing decision</th>
<th>Original demand</th>
<th>Demand incumbent</th>
<th>Sales of entrant</th>
<th>Profit (incumbent)</th>
<th>Profit (entrant)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small capacity 30</td>
<td><strong>Accommodate incumbent's price:</strong> $79</td>
<td>132</td>
<td>102</td>
<td>30</td>
<td>$6,356</td>
<td>$969</td>
</tr>
<tr>
<td></td>
<td><strong>Match incumbent's price:</strong> $49</td>
<td>196</td>
<td>166 (64 new in market)</td>
<td>30</td>
<td>$5,368</td>
<td>$969</td>
</tr>
<tr>
<td>PE entry decision</td>
<td><strong>Accommodate incumbent's price:</strong> $79</td>
<td>132</td>
<td>12</td>
<td>120</td>
<td>$748</td>
<td>$3,877</td>
</tr>
<tr>
<td></td>
<td><strong>Match incumbent's price:</strong> $49</td>
<td>196</td>
<td>132 (64 new in market)</td>
<td>64</td>
<td>$4,263</td>
<td>$2,068</td>
</tr>
</tbody>
</table>
The alternative is at best a substantially lower $5,368 payoff for PI from matching the entrant’s price cut to $49, shown in the second row of Figure 1. When either firm or both reduce prices to $49, 64 additional customers are attracted into the market but again only 30 can find the capacity available at the new entrant who remains small. Even assuming that all these price-stimulated demanders prefer the established carrier’s offering at identical $49 prices and therefore that the unit sales of the incumbent swell from 102 to 166 for a \((49 - 16.69) \times 166 = 5,368\) payoff, PI still prefers to accommodate when PE enters small. That is, the $6,356 payoff from serving each of the 102 customers willing to pay $79 remains the incumbent’s best reply response. Consequently, in this subgame defined by small PE capacity, PE can project a \((49 - 16.69) \times 30 = 969\) payoff per flight from the reliably predictive $79 accommodative price response of Piedmont.

However, quite the reverse is true of a PE large capacity entry strategy. Under the accommodating price response in the third row of Figure 1, the ‘Large’ capacity choice generates \((49 - 16.69) \times 120 = 3,877\) for the entrant. Certainly under intensity rationing of the low-price seats, all the high willingness-to-pay customers of the incumbent seek out PE, so the incumbent’s demand at $79 falls to just 12 seats with operating profit of just $748. That is, a 120 seat 737 flown several times a day by the new entrant is sufficient to serve essentially the entire market. Anticipating such a huge decline in their passenger demand and load factor, PI would clearly prefer to deter rather than accommodate by announcing matching prices ex ante (in the fourth row of Figure 1), thereby obtaining a payoff of \((49 - 16.69) \times 132 = 4,265\). This matching best reply response by PI leaves only the 64 new customers attracted into the market by the discounting, but therefrom a sizeable \((49 - 16.69) \times 64 = 2,068\) payoff is earned.

Examining then the subgame perfect equilibrium in Figure 1, the incumbent prefers to match in the large capacity end-game and to accommodate in the small capacity end-game. This is the main contribution of the classic paper on two-stage entry deterrence by Gelman and Salop (1983) – a basic insight of ‘judo economics’ that when large capacity entry attracts matching price retaliation, small capacity entry may well induce the accommodation. Even knowing this, given the intensity rationing customer sorting rule, the entrant prefers nevertheless to select the large-scale entry because of higher payoffs, i.e. \(2,068\) in the bottom row of Figure 1 vs. \(969\) in the top row. The equilibrium strategy pair \{Large, Match\} follows from the 64 new customers attracted into the market by the entrant’s discounting, who decide to transact with that firm despite the incumbent’s offer to match the new entrant’s low $49 price. In short, \{Large, Match\} is a dominant strategy pair in that PE’s payoff is higher with a large scale of entry decision regardless of the best reply pricing response of the Piedmont incumbent, given intensity rationing.

Gelman and Salop (1983) obtain the opposite strategic equilibrium result – \{Small, Accommodate\} – by sorting no customers to the new entrant under matching prices. In their model as long as costs are equal or incumbents enjoy a cost advantage, large-scale entry with matching prices has smaller payoffs for the new entrant than small-scale entry with accommodating price differentials. Whether or not the firms involved will choose the \{Large, Match\} equilibrium strategy pair in Figure 1 or the \{Small, Accommodate\} equilibrium strategy pair in Gelman and Salop (1982) depends on the rationing rule for sorting customers across capacity-constrained suppliers. This is the point in the analysis at which industry-specific and even market-specific fact-finding must come into play.

The intensity rationing customer-sorting rule in Figure 1 characterises some oligopolistic rivalries (e.g. discounting between Avis and Hertz) but fails to reflect the
marketing strategy and, in particular, the target customer of PE. Recall that under \textit{intensity rationing}, the highest willingness to pay customers secure the capacity of the low-price firm. In contrast, PE’s prototypical target customer was a low willingness to pay and low ability to pay business traveller – e.g. a manufacturer’s trade representative who often needs to travel on short notice but is seldom fully reimbursed by a company expense account. Thus, \textit{intensity rationing} does not capture the competitive reality of the entry threat posed by companies like PE and Southwest Airlines.

2.1 Alternative customer-sorting rules

Several alternative customer-sorting rules are available to model PE demand (Rasmussen, 2001). Probably the simplest is \textit{brand loyalty to incumbents}. In this case, even in the face of differentially higher prices, prior customers of the incumbent reject the new entrant’s offered capacity and instead back order and re-schedule when denied service at the incumbent. Inexorable competitive pressure from imitators normally erodes this degree of brand loyalty, but Microsoft might be an example of the exceptions. At the other extreme, \textit{intensity rationing} (or sometimes \textit{efficient rationing}) allocates the fixed-priced capacity of new entrant discounters in a manner that achieves maximum consumer surplus. As we saw in Section 2, this implies that those customers with the highest willingness to pay secure the low-priced capacity. Of course, the obvious qualification is that such customers are also most likely to have the highest opportunity cost of their time, and therefore would be least likely to exert the effort, time and inconvenience to seek out, queue up and order early to secure low-priced capacity.

A third alternative is \textit{proportional rationing} of the low-priced capacity. Under proportional rationing, all customers willing to pay the low prices – i.e. both regular customers of the incumbent and the new customers attracted into the market by the entrant’s discounting, – have an equal chance of transacting at low prices. Of course, capacity constraints prevent the low-price entrant from displacing the incumbent and satisfying the entire market (Tirole, 1988). For example, if 70 customers were present in the market at the incumbent’s original high price and 30 additional customers appear in response to the discounts, the probability of any customer not being served by a low-price entrant with 40 seats of capacity is \(1 - \left[\frac{100 - 40}{100}\right] = 0.6\), and the incumbent’s expected demand therefore falls from 70 seats to \(70 \times 0.6 = 42\).

Finally, a less-threatening customer-sorting pattern posed by new low-priced capacity in a segmented market is \textit{inverse intensity rationing}. In this instance, the lowest willingness to pay customers quickly absorb all the capacity of the low-priced entrant. Starting with that new-to-the-market customer just willing to pay the entrant’s low price, the entrant proceeds up the demand curve serving customers until it stocks out (Rasmussen, 2001). Under this \textit{inverse intensity rationing}, the demand of the incumbent may be largely unaffected if the discounter’s capacity remains relatively small. As we shall see, the segmented market associated with \textit{inverse intensity rationing} most closely resembles PE’s original entry into peripheral Middle Atlantic markets while \textit{proportional rationing} most closely characterised the Southeastern business travel markets developed by Piedmont.
3 People Express entry and growth strategy

During early 1981, PE became the first new entry into the deregulated airline industry. PE’s entry strategy was to offer a uniform low-price, no frills, high-frequency region-wide service to 13 peripheral Middle Atlantic cities by using a hub and spoke system out of Newark, NJ. PE achieved a 31% reduction relative to the industry average in average indirect fixed costs per flight (e.g. scheduled maintenance) and a 25% reduction in average variable costs per flight (i.e. fuel, crew) by unbundling all services, adopting 15 and 20 min turnaround times, working longer crew shifts, and converting all first class and galley space into additional coach class seats. Having secured the lowest operating cost structure in the industry, PE set out to attract customers who saw regional air travel as a commodity. PE believed that at low enough fares such customers would occasionally fly rather than drive 350–500 miles. As one example, PE flew Newark to Pittsburgh for $39 (weekday)/$19 (weekend) when the competing lowest cost flight was $128. A loyal clientele of weekenders and business travellers without expense accounts soon developed.

As to service frequency, PE anticipated that if it entered a trunk airline market dominated by the major carriers or a peripheral market with less than the number of flights a regional airline offered, the incumbent airlines would likely respond with increased flight frequency, more convenient departures and numerous additional services. Consequently, PE decided to provide very high frequency service on only 13 peripheral routes in their Middle Atlantic hub and spoke network out of Newark. A critical success factor for this entry strategy was to avoid retaliation by the major carriers or the large regional airlines.

Figure 2 depicts the two-stage entry deterrence/accommodation game PE encountered on these peripheral Middle Atlantic routes. With inverse intensity rationing, low willingness to pay customers, attracted into the market by the discounter’s price announcement, did business with PE and quickly filled its capacity. This meant that even in the case of large capacity entry (in the bottom two rows of Figure 2), the effect on incumbent demand was much less severe than would have been the case if high willingness to pay customers had been the new entrant’s target market. With the inverse intensity rationing depicted in Figure 2, accommodating the large capacity entrant by maintaining a $79–49 price differential resulted in a decline of incumbent demand from 132 to 76 seats, whereas with the intensity rationing (depicted in Figure 1) the decline would have been from 132 to 12 seats.

In essence, PE had created a new segment of the Middle Atlantic market not previously served by the much more expensive and infrequent Mohawk and Allegheny and USAir flights. Consequently, the subgame perfect equilibrium strategy was for PE to enter Newark with large scale and for incumbents to accommodate (i.e. $4,736 preferred to $4,265). This {Large, Accommodate} strategic equilibrium was repeated again and again in People’s initial 13 city-pair markets (i.e. Newark to Syracuse, Albany, Buffalo, Norfolk, Columbus, etc.)
<table>
<thead>
<tr>
<th>Starting price</th>
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<tbody>
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<td>132</td>
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<td>Large capacity</td>
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<tr>
<td>Variable costs</td>
<td>$16.69</td>
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<tr>
<td>Demand at pent</td>
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</tr>
</tbody>
</table>

**Figure 2**
Accommodative price response with inverse intensity rationing

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<tr>
<th>Incumbent PI pricing decision</th>
<th>Original demand</th>
<th>Demand incumbent</th>
<th>Sales of entrant</th>
<th>Profit (incumbent)</th>
<th>Profit (entrant)</th>
</tr>
</thead>
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<td>166</td>
<td>30</td>
<td>$5,368</td>
<td>$969</td>
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</table>

**PE entry decision**

<table>
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<tr>
<th>Incumbent PI pricing decision</th>
<th>Original demand</th>
<th>Demand incumbent</th>
<th>Sales of entrant</th>
<th>Profit (incumbent)</th>
<th>Profit (entrant)</th>
</tr>
</thead>
<tbody>
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<td>120</td>
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<td>$3,877</td>
</tr>
<tr>
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<td>196</td>
<td>132</td>
<td>64</td>
<td>$4,265</td>
<td>$2,068</td>
</tr>
</tbody>
</table>
By 1984, PE faced a decision whether to expand its fleet by purchasing 38 additional used 737s at very attractive prices. Senior management recommended against the expansion but Donald Burr insisted that the airline must grow. In early 1984, PE began flying from Newark to Chicago and Minneapolis, the hubs of United and Northwest, respectively. Both these routes were very profitable feeder spokes into hubs where the majors enjoyed large economies of scale in passenger transfers and baggage handling. United, Northwest and American all immediately matched PE’s price rather than accommodate its entry into these new submarkets. In part because of this lack of success on the trunk routes to Chicago and Minneapolis, in December 1984 PE announced the inception of service from Newark into a major Piedmont market at Greensboro, North Carolina.

PE’s pre-entry advertising highlighted a fare of $49, a 45% reduction off Piedmont’s $79 fare. In the Middle Atlantic markets, PE had discovered that by pre-announcing a deep discount, a matching price response became less attractive and an accommodating price response became more attractive to any and all incumbents. That is, if the $4,736 incumbent payoff in Figure 2 from accommodating large-scale PE entry with differentially high incumbent prices looked like it would prove indistinguishable or better to the incumbents than the $4,265 payoff from matching price, People simply lowered its fares. At $39, for example, the matching price response would yield $(39 - 16.69) \times 132 = $2,945 to the incumbent and $(39 - 16.69) \times 85 = $1,896 to PE, whereas the accommodation price response would yield $(79 - 16.69) \times (132 - 120) - 85 = $6,044 to the incumbent and $(39 - 16.69) \times 120 = $2,677 to PE. As long as price remained above variable cost per seat, PE found that it was better off and incumbents were more likely to accommodate at lower fares.

### 3.1 Cost structure of People Express and Piedmont

Variable costs per seat at PE, which the author estimates as $13.63 for the Newark-Greensboro flight, were substantially below those at United, Northwest and American and somewhat below Piedmont’s $16.69. These numbers are astounding low because they represent only direct costs associated with these flights and because the cost structure of any airline is very capital-intensive with typical margins of 70–80%. Comparing 1986 data in Table 2 for the 737-200s flown by both carriers, it is clear that PE’s lower crew costs per block hour were responsible for their cost advantage. Lower wear-and-tear depreciation on PE’s older airframes and engines was offset by higher required maintenance costs. In sum, PE’s $202 cost savings per block hour ($1,070 vs. $1,272) translated into a 25% cost advantage (3 vs. 4 cents per available seat mile). PE had more flying hours per day per plane (9.01 vs. 6.84) and much higher load factors (68.9% vs. 52.4%) than Piedmont. Thus, the 25% cost advantage per available seat mile grew to a 45% cost advantage per revenue passenger mile (5 vs. 9 cents).

Combining the airline-specific operating expense data for flying operations and direct maintenance with block-to-block speed and seat capacity data, one can calculate the incremental variable cost of a seat on the Greensboro–Newark route. The one-way 443 mile trip at very similar block-to-block speeds had crew, fuel, flight insurance, cabin service, airframe maintenance, engine maintenance and parts cost per seat on 737-200s of $13.63 at PE and $16.93 at Piedmont. Some of Piedmont’s planes operated at slightly higher and others operated at considerably higher expense – i.e. the Folker-28s at $22.37. Taking a weighted average over the entire Piedmont flight inventory during the 6-month
period, January–June 1985 (See Table AI in the Appendix), the incumbent’s variable cost during the price war was $16.69 per seat. In conclusion, PE enjoyed an incremental cost advantage of 18% against Piedmont. The cost savings arose from lower crew salaries spread across more flying hours and from cabins equipped with 120 rather than 112 seats. Against its initial competitors flying 90 seat 737 aircraft in the Middle Atlantic region, PE’s incremental cost advantage had been substantially larger.

4 Pricing against a low-cost competitor under proportional rationing

Piedmont Airlines was the second fastest-growing and among the most profitable airlines in the immediate post-deregulation era. By serving small- and medium-sized cities largely ignored by the major airlines and by connecting through hubs with little or no competition, Piedmont retained 95% of its passengers on connecting flights (Air Transport World, January 1985). This hub and spoke system performance set the industry standard and proved very profitable. This attracted the interest of several potential entrants from American Airlines at RDU to USAir at Charlotte. In November 1984, Piedmont learned that PE would initiate service into Greensboro and to Raleigh-Durham, Dayton and Charlotte, all very profitable Piedmont city-pairs. By this point, PE operated 55 planes (mostly 737s), employed 4,000 people and carried more than a million passengers a month to 39 cities.

4.1 Piedmont Airlines–People Express competition

In the Greensboro market, Piedmont seized the first-mover advantage against PE and in December 1984 pre-emptively announced a reduction of its $139 point-to-point fare to Newark to $79 peak, $49 off-peak. This off-peak fare represented Piedmont’s analysis of PE’s fully allocated cost for a similar route from Newark to Columbus and was approximately 300% of Piedmont’s incremental variable cost of $16.69. Table 1 illustrates the monthly sequence of price changes that Piedmont and PE announced in the Newark–Greensboro market thereafter. In each month, Piedmont waited to respond to PE’s fares and then matched the low-cost entrant’s price promotions. From $79/$49 in December, the fares spiralled downward to $29/$19 in April, off-peak just 15% above Piedmont’s incremental variable costs.

Piedmont’s decision to match the price of the low-cost new entrant required careful analysis of the order of play, rival options, customer-sorting rules and predicted end-game outcomes. From the earliest days of the Piedmont–PE rivalry, Piedmont managers perceived the value of tracking their tactical success by competitor surveillance at the individual departure level. Piedmont counted and categorised every passenger on and off every flight that PE flew into Piedmont cities. Piedmont found that Greensboro–Newark customers sorted randomly to the low-price supplier when substantial price differentials were present, and that loyalty to the incumbent prevailed when prices were identical. This brand preference for the incumbent was almost universal at $79 prices, but remained strong even with the new lower willingness to pay customers attracted into the Southeastern airline markets by PE discounts of $49, $39, $29 and even $19.
Figure 3
Accommodative price response with proportional rationing

<table>
<thead>
<tr>
<th>Starting price</th>
<th>79</th>
<th>Small capacity</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>New price</td>
<td>49</td>
<td>Large capacity</td>
<td>120</td>
</tr>
<tr>
<td>Demand at starting price</td>
<td>132</td>
<td>Variable costs</td>
<td>$16.69</td>
</tr>
<tr>
<td>Capacity of incumbent</td>
<td>300</td>
<td>Demand at pent</td>
<td>196</td>
</tr>
</tbody>
</table>

**Entrant capacity decision**

<table>
<thead>
<tr>
<th>Incumbent PI pricing decision</th>
<th>Original demand</th>
<th>Demand incumbent</th>
<th>Sales of entrant</th>
<th>Profit (incumbent)</th>
<th>Profit (entrant)</th>
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<tr>
<td>Accommodate incumbent's price:</td>
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<td>112</td>
<td>30</td>
<td>$6,979</td>
<td>$1,061</td>
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<td>Small capacity 30</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Match incumbent's price:</td>
<td>196</td>
<td>166</td>
<td>0 - 30</td>
<td>$5,365</td>
<td>0 to $1,061</td>
</tr>
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**PE entry decision**

<table>
<thead>
<tr>
<th>Incumbent PI pricing decision</th>
<th>Original demand</th>
<th>Demand incumbent</th>
<th>Sales of entrant</th>
<th>Profit (incumbent)</th>
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<tbody>
<tr>
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<td>120</td>
<td>$3,178</td>
<td>$4,244</td>
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<tr>
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<td></td>
<td></td>
</tr>
<tr>
<td>Match incumbent's price:</td>
<td>196</td>
<td>132</td>
<td>0 - 64</td>
<td>$4,265</td>
<td>0 to $2,264</td>
</tr>
</tbody>
</table>
The two-stage entry deterrence and accommodation game with proportional rationing is depicted in Figure 3. With differential $79 and $49 prices, every customer willing to pay at least $49 has an equal probability of securing service at the low-price entrant. For small-scale entry, this means 30 seats would be rationed among 196 demanders, so each of the 132 customers willing to pay the incumbent’s $79 accommodating price faces a \((1 - (196 - 30)/196)\) chance – i.e. a 0.1531 chance – of being served and a 0.8469 chance of being denied service at the low-price entrant. Therefore, the expected demand at Piedmont was 0.8469 \times 132 = 112\) seats and expected operating profit was $6,979. Similarly, for the large-scale entry and accommodating prices (in the third row of Figure 3), 132 \times (196 - 120)/196 = 51\) seats was the incumbent’s expected demand, and $3,178 was Piedmont’s resulting operating profit.

Matching prices generated lower operating profits for Piedmont in the face of small-scale entry by PE (i.e. $6,330 < $6,979) but higher profits in the face of large-scale entry ($6,330 > $3,178). Again, competitor surveillance and very accurate target customer tracking allowed Piedmont to conclude that with matching prices PE would at most garner the 64 new customers per flight attracted into the market by the rampant discounting. At best, with matching prices PE would attract no customers. Using my estimates of the lower incremental variable cost of $13.63 for PE, the new entrant’s large capacity would have generated \((49 - 13.63) \times 120 = $4,244\) if Piedmont had accommodated and $2,264 or possibly $0 if Piedmont matched. In the case of small capacity entry, PE’s predictable payoff per flight was $1,061, emergent from a prospective Piedmont decision to accommodate.

End-game analysis of Figure 3 suggests and former Piedmont executives recall that the incumbent clearly preferred to accommodate in the face of small-scale entry. However, everyone at Piedmont anticipated that PE’s entry was likely to be very large scale indeed. One reason was their sense that large capacity entry had proven to be a dominant strategy in PE’s prior experiences with Middle Atlantic markets. And of course, PE had just acquired 38 additional planes tripling the previous capacity of its fleet.

Even if PE only attracted the 64 new customers in the low-price segment of the market (from $49 to $79), the Piedmont payoff from matching ($4,265) still exceeded its payoff from accommodating ($3,178). Indeed, for any magnitude of loyal customer sorting to the incumbent between 196 and 99 (i.e. at anything between 100% and 51% share of the market), the matching price strategy remained preferable to the incumbent. Could PE really have anticipated reaching a break-in market share greater than 49%? Only in that case did large capacity entry make sense. Otherwise, the subgame perfect strategic equilibrium was \{Small, Accommodate\}, and large capacity entry was a strategic mistake.

Actual data on passenger loads during this $49 price period indicate that at the height of PE’s success, Piedmont and PE split the market 58 to 42%, respectively. Piedmont secured customer loyalty with heavily advertised service quality enhancements including scheduling convenience, delivery reliability, amenities and change order responsiveness. The following non-price competitive tactics were adopted in Greensboro and in each of the other PE entry markets:

- Piedmont offered more flights than PE and aggressively marketed their service frequency advantage.
Piedmont lowered prices in cities that were within driving distance of Greensboro to stabilize load factors in those nearby cities and prevent drive-in demand. This ensured desired service quality could be maintained at Greensboro.

Piedmont offered all seats at one price on certain flights from Greensboro to New York and had detailed real-time capacity controls to sustain higher yields for inelastic business demand on other flights and in other cities (e.g. Charlotte and Raleigh-Durham.)

Piedmont used comparative advertising to belittle PE’s lack of amenities, especially the lack of meal service and baggage handling.

When $49 proved unsuccessful in promoting accommodation, Table 1 shows that PE initiated a 6-month sequence of ever deepening price cuts to attempt to make accommodation more attractive. This tactic replicated PE’s experience in the Middle Atlantic markets where, as we saw earlier in analysing Figure 2, inverse intensity rationing lead incumbents to be more accommodative as PE’s prices dropped. The $39, $29 peak and $19 off-peak fares were well below break-even levels and nearing both firms’ incremental cost. Especially in this period, Piedmont was careful to follow PE’s price moves rather than risk having to prove they had not engaged in predatory pricing below cost.

Eventually at $19 prices in April, May and June, both firms were operating cattle car air travel with load factors of 95–103%. The first four rows of Table 3 depict PE’s and Piedmont’s passenger counts and actual realised revenue. PE had seized more than 50% of the market, and accommodation for the first time offered Piedmont higher profits than continuing their matching price policy. For example, at $19 or $29 in the first four rows, Piedmont’s contribution margins were only ($19.00 – 16.69)/$19 = 12.2% or ($29.00 – 16.69)/$29 = 42.4%. Therefore, there were only $2,832 × 12.2% = $345 or at best $3910× 42.4% = $1,658 operating profits available to the incumbent from continuing to match prices. A unilateral move by Piedmont to $79 accommodating prices must have then begun to look very attractive. However, Piedmont had identified a matching price route to tactical success. From counting passengers in more than a dozen target customer segments, Piedmont knew that if and when PE raised fares to begin covering its allocated costs, PE’s load factors would drop faster than those of Piedmont.

Table 3 illustrates 8 days in June 1985. For example, in day 2 of week 1 the fare from GSO to Newark was $29 and in week 2 the fare was increased to $79 on day 2. Both firms lost substantial business. Piedmont saw its load factors drop from 96.79% to 73.19% but was able to retain up to 51 more passengers per flight departure than PE whose load factors dropped from oversales at 103.24% to 43.82%.10 As the price of PE flights increased, customers who encountered matching Piedmont fares were no longer willing to be a part of the ‘PE experience’. Passenger complaints increased to 20 times those of Piedmont and 5 times the industry average – i.e. 10.3 per 10,000 passengers relative to Piedmont’s 0.5, American’s 1.93 and United’s 2.06 (Wall Street Journal, May 19, 1986, p.A1).
Table 3

Piedmont and People Express cost and revenue per flight (Greensboro-Newark)

<table>
<thead>
<tr>
<th>Week</th>
<th>Day</th>
<th>Y-Class fare ($)</th>
<th>Marginal cost ($)</th>
<th>Contribution margin</th>
<th>Marginal cost ($)</th>
<th>Contribution margin</th>
<th>Flight demand*</th>
<th>Load Factor</th>
<th>Passenger revenue**</th>
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<tr>
<td>1</td>
<td>1</td>
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<tr>
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<td>49.00</td>
<td>13.63</td>
<td>35.37</td>
<td>16.69</td>
<td>32.31</td>
<td>101</td>
<td>141</td>
<td>4,574.00</td>
</tr>
</tbody>
</table>

*Exact figures on actual seat demand are disguised but proportions (correct market shares and load factors) are maintained.

**Revenue is actual revenue passenger receipts, not average flight demand times the Y-class fare shown in column 2.

†Involuntary boarding denials occurred at these price levels.

Source: Company Data.
Piedmont’s competitor surveillance had detected several very different segments of PE demand. The highly price-elastic occasional air travellers were flying PE while price-inelastic, yet service quality elastic Piedmont business customers were flying the incumbent. Sales representatives with sample cases, no checked luggage and formal business shoes were flying the new entrant. Business travellers with briefcases, casual shoes and checked luggage were flying the incumbent. AT&T, a large corporate travel customer from the Greensboro regional office to Newark headquarters, even offered Piedmont a price premium of $79 near the start of the price war to secure the high delivery reliability and change order responsive service. Stop sales mechanisms derived as in the Belobaba (1989) model were used to protect their seats, and these nascent yield management techniques paid off (Cross, 1988; Kimes, 1989; Harris, 1995a,b).

For example in Table 3, comparing the first four to the second four rows, as day 2 fares rose from $19 to $79, PE revenues per flight rose by 76% from $3,030 to $5,326. However, with the same price increase, Piedmont revenues per flight on day 2 more than tripled from $2,881 to $9,114. Similarly, as day 4 fares increased from $29 in week 1 to the full-cost covering level of $49 in week 2, PE revenues per flight remained flat ($4,586 to $4,574) whereas Piedmont revenues per flight rose by 64% from $3,910 to $6,415. This relative and absolute decline in flight revenues during PE’s weekday and weekend business, as prices rose sufficiently to cover allocated costs, doomed their entry to failure and forced an eventual withdrawal.

Shutdown was not immediate and indeed extended over more than a year to September 1986. PE operations in the Greensboro–Newark market continued to make positive contributions towards covering allocated cost at any fare above $13.63. Recall that Table 2 documents PE was operating with a 5 cent per RPM operating cost. This figure compares with approximately 9 cents per RPM at Piedmont, and 10 cents at United, American and Delta. Consequently, discount flight operations continued for an extended period despite the losses against fully allocated cost. Comparably low cost structures at Jet Blue today have led to similar discounting by these current low-cost competitors.

5 Conclusion

Since Piedmont Airline’s matching price response was a predictable subgame perfect equilibrium strategy, one is tempted to conclude that PE misread the customer-sorting rule applicable to Newark–Greensboro and other similar Piedmont markets. Rather than recognising customer loyalty to the incumbent at matching prices and proportional rationing at differential prices, PE appears to have assumed the inverse intensity rationing typical of PE’s initial peripheral Middle Atlantic routes. If this customer sorting had described Piedmont’s regular customers, large-scale entry would have resulted in accommodative prices. {Large, Accommodate} is the subgame perfect equilibrium of the PE entry deterrence game with inverse intensity rationing (in Figure 2). Instead, with proportional rationing and customer loyalty to incumbents at matching prices in the Southeastern regional business travel markets, only small-scale entry could have induced differential accommodating prices and sustained $1061 payoffs for PE on the Newark–Greensboro route.

Clearly, a small-scale entry approach would have violated PE’s highly successful entry strategy of swamping a peripheral city-pair market with high frequency service on
Large-scale entry deterrence of a low-cost competitor

737s at one low uniform price. However, these were not peripheral routes with PE attracting new business customers and weekenders out of cars and off buses. Rather, they were established business travel markets of a major regional airline whose otherwise loyal customers at matching prices sought out and randomly managed to secure the discount PE seats at accommodative differential prices. Therefore, aggressive matching rather than accommodative differential pricing by the incumbent was predictable, was signalled pre-emptively by Piedmont, and should have been anticipated by PE.

When their large-scale entry proved unsuccessful, PE never appears to have considered changing the scale of operations in Piedmont’s markets. The trunk airlines were successfully deterring PE’s entry into Chicago and Minneapolis. Yet, Don Burr had taken on 38 additional 737 aircraft as a debt-financed capital equipment purchase. The purchase price was right, which meant that the market for resale was lousy. Although capital disinvestment was not a viable option, the new planes could have been redeployed elsewhere. For example, some industry analysts have speculated that in 1986–1987, PE’s Newark hub and spoke system might well have been replicated in Phoenix, Arizona. Later, of course, Phoenix did become the hub of a successful low-cost airline, America West.

5.1 Assessing predatory intent

McGahhee v. Northern Propane Gas Co., 858 F2d 1487, 1501 (11th Cir. 1988, Brooke Group 113 US. 2578 (1993) and Spectrum Sport 113 US. 884 (1993) make clear that capacity choices, market share and barriers to both entry and exit are all components of a two-pronged test in predatory pricing cases. A finding of illegal predation requires both cost-based and other evidence of intent to harm competition and the reasonable probability of tactical and/or strategic success. As a powerful tool for analysing oligopolistic rivalry and therefore potential predatory intent, game-theoretic models of capacity and pricing strategy should play a significant role in identifying what outcomes of specific actions are reasonably probable in these cases. Specifically, entry deterrence and accommodation games can discriminate among alternative strategies as equilibrium strategies vs. strategies ‘off the equilibrium path’ with no real chance of success, and thereby game-theoretic reasoning can refute some claims of predatory intent.

The lessons for predation policy of the Piedmont-PE rivalry may now be identified. The capacity and pricing choices of both the new entrant and the incumbent were rational and reasonable in light of the entry deterrence/accommodation games each player perceived. PE’s capacity strategy appears to reflect the entry accommodation game with inverse intensity rationing in which it had engaged in the Middle Atlantic region. Piedmont, on the other hand, expanded capacity to meet anticipated demand and to maintain high delivery reliability and change order responsiveness for premium-priced business travellers. Ex post analysis of the actual revenue and cost data for a representative city-pair in the Southeast reveals that during the height of the price war both carriers operated near their expanded capacities.

As to predatory pricing, Piedmont’s price change initiatives from $139 to $79 to $49 exceeded by a wide margin the conditions of the Areeda-Turner cost-based defence, and thereafter the incumbent simply met the competition. PE initiated several lower price points descending from average total cost (about $49) down to $39, $29 and $19. This lowest price was still 39% above PE’s incremental variable cost, which the author has estimated as $13.63. Under Matushita, PE’s pricing might be questioned given the near
50% market share PE at times achieved. Nevertheless, our entry game with inverse intensity rationing (in Figure 2) strongly suggests that by this pricing strategy PE sought to achieve accommodation, not predation.

6 Summary

In sum, PE chose the right strategy but for the wrong entry game and ended up being deterred. In the interim, customers benefited with massive price reductions, and in the long run fares were reduced from $139 to $79. The game-theoretic analysis of these events suggests that an expansion of the Areeda–Turner cost-based test to include such analyses can help ensure a well-designed predatory pricing policy. Although the customer-sorting rules here are more complicated, Gelman and Salop’s (1982) basic insight of judo economics applies. The subgame perfect strategic equilibrium in which Piedmont decided to match PE’s deep discount fares hinged on the large-scale entry of PE. A small-scale entry would likely have been accommodated with differentially higher Piedmont pricing. In both entry deterrence theory and practice, customer sorting in response to stockouts determines the best reply responses of incumbents threatened by entry.

Once Piedmont decided to match the new entrant’s penetration prices, it proved critical that the incumbent had recently developed the second earliest implementation of real-time inventory management optimisation tools. By employing optimal capacity controls in segmented fare classes, Piedmont was actually able to increase the service quality to its higher-yield loyal business customers. Without the capability to stop advance sales at appropriate levels, Piedmont would not have been able to build regular customer loyalty on the congested flights precipitated by the price war with PE. Because it could do so, when prices returned (in a predictable life cycle sense) to cost-covering substantially higher target price levels, Piedmont’s revenue tripled while PE’s revenue actually declined. Soon thereafter, it became clear that Piedmont had successfully deterred a low-cost discounter.

Acknowledgements

I wish to acknowledge insightful comments and perceptive advice from Tad Hutcheson, Anne Winklemann, Rocky Wiggins, Pete Van Nort and Rob Emrich, as well as many enjoyable conversations about these matters with Dan Brock Jr., former Senior Vice President, Marketing, Piedmont Airlines, and more recently, former Vice President, Marketing Services, US. Airways. Tony Luce provided exceptional research assistance in the preparation of a related case study.

References


Table A1  Fleet planning and flight capacity of the incumbent and entrant starting in October 1984, two months prior to entry, and continuing throughout the 6 months of deep discounting in 1985.

<table>
<thead>
<tr>
<th>Flight Segment</th>
<th>Airline</th>
<th>Flights</th>
<th>Equipment</th>
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</thead>
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<tr>
<td>October 1984</td>
<td>EWR to GSO PI</td>
<td>3</td>
<td>737-200 (3)</td>
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<tr>
<td></td>
<td>GSO to EWR PI</td>
<td>2</td>
<td>727-200 (2)</td>
</tr>
<tr>
<td>December 1984</td>
<td>EWR to GSO PI</td>
<td>3</td>
<td>737-200 (2), 727-200 (1)</td>
</tr>
<tr>
<td></td>
<td>GSO to EWR PI</td>
<td>2</td>
<td>727-200 (2)</td>
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<tr>
<td></td>
<td></td>
<td>1</td>
<td>737-200 – Weekend flight</td>
</tr>
<tr>
<td>January 1985</td>
<td>EWR to GSO PI</td>
<td>6</td>
<td>F-28 (1), 737-200 (4), 727-200 (1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>737-200 – Weekend flight</td>
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<tr>
<td></td>
<td>PE</td>
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<td>737-(5)</td>
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<td></td>
<td>GSO to EWR PI</td>
<td>5</td>
<td>727-200 (2), 737-200 (3)</td>
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<td>Source:</td>
<td>Company Data.</td>
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</table>

Notes

1. Legal predation entails lowering price below your opponent’s incremental variable cost when your cost is lower still. In addition, some higher cost incumbents are rationally motivated to secure reputations indistinguishable from ‘crazies’ who price below their own incremental variable cost despite no prospect of later recouping the loss. See Milgrom and Roberts (1982) and Rasmussen (2001).

2. This approach differs markedly, of course, from the empirical entry models of Reiss and Spiller (1989) and Berry (1992) where richness of the strategic decision environment is traded off for empirical tractability.

3. In a companion paper (Harris and Emrich, 2005), Robert Emrich and I develop a theoretical analysis and employ a structural equations empirical model to estimate the effect of capacity allocation, flight frequency and the probability of stockout on optimal airline price-cost margins in
this same time period of unfettered competition between the early low-cost discounters and one of the major incumbents, American Airlines.


The Areeda–Turner (1975) rule set forth in Matsuhita Electric Industries Co. v. Zenith Radio Corp., 475 U.S. 574, 585 (1986) explained that a firm’s temporarily low demand might necessitate reducing price below full cost in order to avoid larger losses, but argued that no rational firm would continue to operate with price below incremental variable cost. Evidence to the contrary would indicate an intention to injure competition through predation, and prices above incremental variable cost would constitute an affirmative defense. However, Transamerica Computer v. International Business Machines, 698 F. 2d 1377, 1387 (9th Cir. 1983), cert. denied , 464 U.S. 955 (1983) specifically questioned the precision of the Areeda–Turner cost-based defence, and only two federal circuits (i.e. the 1st and 2nd) continue to apply it as determinative.

Nevertheless, airline executives correctly perceive that reports of the demise of the cost-based test for predatory pricing conduct have been greatly exaggerated. As a result, most tactical initiatives involving deep price discounting in the airline industry stay at least 10–15% above the Areeda–Turner incremental variable cost standard, as did both firms in the Piedmont–People Express price war described herein.

Inverse intensity rationing describes the customer sorting that takes place at differential prices when discounters have created a new target customer segment at the low prices introduced by virtue of the discounter’s entry. These new especially price-sensitive customers seek out and exhaust the discounted seats.

Higher cost incumbents are restrained by the Areeda–Turner predation rule from initiating price cuts below competitor prices and understand they must instead rely upon decision timing that ‘meets the competition’. Consequently, consistent with actual events in the People Express–Piedmont price war, Figure 1 addresses only accommodating and matching price responses by the incumbent Piedmont.

Alternatively, one could conceive of this capacity choice as 30 point-to-point seats on a Boeing 737 with through passengers occupying the remaining capacity.

The data are scaled to disguise the actual seat demand, but proportions (correct market shares and load factors) are maintained.
Revenue management for broadcasting commercials: the channel’s problem of selecting and scheduling the advertisements to be aired

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Abstract: We describe a planning problem at a broadcasting company (e.g. a TV or radio channel): Advertisers place orders for commercials. Typically, each order consists of multiple spots, and the airdates of the spots are not fixed by the advertiser. Therefore, the channel has to decide simultaneously which orders to accept or to reject and when spots from accepted orders should be scheduled. We formally describe this problem in a mathematical model, present five heuristics, develop a rigorous method to generate a test bed and evaluate the performance of the heuristics on over 10,000 instances of various sizes.

Keywords: advertising; broadcasting; flexible products; order acceptance; revenue management; scheduling.

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1 Introduction

1.1 The process of ordering and scheduling commercials

The process of ordering and scheduling commercials can roughly be described as follows: An advertiser sends an order to a TV or radio channel. The advertiser may be the company whose products are described in the advertisements or an intermediary such as an advertising agency. The order defines the number of spots to be broadcasted and when these spots should be aired. It is very common that the advertiser does not precisely define the airdates of its spots, but defines only some rather general rules. For example, the advertiser may request that all spots should be aired within the next 30 days, where 20% of which should be aired on weekdays in the morning and 80% should be aired on weekends in the afternoon. The price the advertiser has to pay for the order, however, is fixed and known to both parties before the spots are actually scheduled by the channel.

Advertisers may cancel the scheduled spots according to certain rules. The broadcaster may or may not charge a cancellation fee (penalty), and the advertiser may be fully, in part or not at all refunded, in case he has already paid. Naturally, there are no ‘No Shows’ in this application: cancellations close to the planned airdate (48 hours in advance, say) are not allowed, i.e. if the advertiser has not cancelled his order until that time, he will be charged the full price and the spot will be aired.

1.2 Literature review

The scheduling of advertisements on web pages is related to the problem at hand, albeit not identical. Frequently discussed problems in this area are how the so-called advertising banners of varying sizes should be placed on the screen, and how the banners should change over time (e.g. Aggarwal, Wolf and Yu, 1998; Adler, Gibbons and Matias, 2002; Dean and Goemans, 2003; Dawande, Kumar and Sriskandarajah, 2003, 2005; Freund and Naor, 2004). Other areas of research related to internet advertising include how the impact of online commercials can be evaluated (e.g. Cao, 1999), how banners on web pages can be inserted depending on the actual, individual visitor (e.g. Yager, 1997) or how individualised advertisings by e-mail (not spam) can be designed (e.g. Ansari and Mela, 2003). Messages tailored to individual customers (or groups of customers) are also discussed in the area of mobile telephony (e.g. Barwise and Strong, 2002; deReyck and Degraeve, 2003) and digital TV (e.g. Thomas 2000; Lekakos, Papakiriakopoulos and Chorianopoulos, 2001).

A comprehensive overview on radio business is presented by Czygan (2003), for instance. Numerous authors investigate the impact of radio advertising. Geer and Geer
(2003), for example, analyse the effect of political advertisements in election campaigns; Verhoef, Hoekstra and van Aalst (2000) focus on radio commercials intended to provoke an immediate reaction of the listener (e.g. a telephone call); and Verhoef and Donkers (2005) compare advertisements by mail, internet, radio and TV. However, Lambert (1983) and Marx and Bouvard (1990) seem to be the only references directly related to the scheduling of radio spots.

General information and statistics on TV advertising are regularly published, for example by the German Association of the Advertising Industry in Germany (Zentralverband der deutschen Werbewirtschaft, 2004). Text books on media economics also cover TV, of course, see e.g. Heinrich (1999) or Altmeppen and Karmasin (2004). Köcher (2000, 2002, 2004) discusses a controlling scheme for advertisement-sponsored companies. Köcher (2002), in particular, describes on a conceptual level how a system for accepting and rejecting orders to maximise revenues could be designed. Therefore, Köcher’s work stresses the importance of our approach. The contribution of this paper with respect to these references is to present (for the first time) an operational model combining the interdependent decisions of accepting/rejecting orders and the scheduling of spots.

Quite a large sum of the literature deals with designing TV timetables that attract many viewers (e.g. Horen, 1980; Eechambadi, 1989; Cancian, Bills and Bergstrom, 1995; Reddy, Aronson and Stam, 1998). Webster (1985) models audience behaviours and analyses whether a spectator watching a certain show will also watch the following programme. Although we assume throughout the paper that the TV timetable has already been defined, this research is relevant because the timetable determines the attractiveness of the programme for viewers and hence influences the decision of advertisers to place orders and choose time windows for spots.

The scheduling of TV spots (which is one part of the problem we will cover in this paper) has been dealt with in only quite a few papers. Brown (1969) describes the situation at the TV channel ‘Thames Television’ and demonstrates various difficulties in scheduling spots manually. Furthermore, he outlines an algorithm for the systematic exchange of spots of different lengths between breaks to gain room for additional spots. Balachandra (1977) presents a simulation study concerned with the impact of spots depending on the advertising schedule. Hägele, Dünlaing and Riis (2000) prove that the problem as defined by Brown is NP-complete. Bollapragada et al. (2002) describe the situation at National Broadcasting Company (NBC). Bollapragada, Busseck and Malik (2004) refer to the problem at NBC and develop an algorithm to schedule spots that should be aired more than once such that all transmissions of the spot are distributed as uniformly over time as possible. Bollapragada and Garbiras (2004) again refer to NBC and describe the scheduling problem by using some of the restrictions that we will also use in this paper. In that respect the work of Bollapragada and Garbiras (2004), which deals with the problem of scheduling but not with the problem of order acceptance/rejection, is very similar to a crucial part of our problem. An important distinction between both papers is, though, that Bollapragada and Garbiras (2004) allow for the violation of some constraints (at a penalty cost) where our approach strictly enforces all constraints (to be described later), which makes finding a feasible schedule for a given set of orders much more thorny in our problem.

Summing up, a review of the literature reveals that the research dealing with problems of accepting orders and scheduling of advertisements at the same time does not yet exist. In this paper, we therefore describe an approach to these interdependent
problems, aiming at solving them simultaneously. After introducing some notation in this section, we present a mathematical decision model in Section 2. We develop heuristics to solve the problem in Section 3 and test them on a systematically generated test bed in Section 4. We conclude the paper with a summary of our results, and point out some future research opportunities.

2 A mathematical model

2.1 Formalising the supply side

The timetable (TV or radio programme) that has been published by the channel is the base for all advertising contracts. This timetable remains fixed over the planning horizon. The timetable defines a number of time slots for commercial breaks. Denote the set of all breaks in the planning horizon by $B$. For each $b \in B$, let $0 \leq d_b^{\min} \leq d_b^{\max}$ be the minimum and maximum duration, respectively, of break $b$. We chose to model the length of a commercial break like this, because it seems unrealistic that the length of $b$ is known and fixed before the actual schedule of spots is determined. However, if this should be the case for some break $b$, we can easily represent this by letting $d_b^{\min} = d_b^{\max}$. For a practical instance we can safely assume $d_b^{\min} = 0$, though the TV or radio channel can fill any break to the desired length with spots advertising its own programme.

2.2 Formalising the demand side

Let $O$ be the set of orders sent to the channel by advertisers. With each order $o \in O$, there is associated a revenue (price) of $v_o > 0$. An order $o \in O$ consists of a non-empty set of spots $S_o$. For the convenience of notation we assume that the total number of spots is $S$ and that the set of all spots is $\{1, \ldots, S\}$, so that $S_o \subseteq \{1, \ldots, S\}$, $o \in O$. Naturally, we require $\bigcup_{o \in O} S_o = \{1, \ldots, S\}$ and $S_o \cap S_p = \emptyset$ for all $o, p \in O, o \neq p$.

For each spot $s = 1, \ldots, S$, a set of breaks $\emptyset \neq B_s \subseteq B$ where $s$ could be scheduled is given. Note that the advertiser may precisely define the commercial break where $s$ will be aired by letting $|B_s| = 1$. An order $o \in O$ must either be accepted in its entirety (i.e. all spots $s \in S_o$ have to be feasibly scheduled) or fully rejected. The length of $s = 1, \ldots, S$ is denoted by $0 < l_s \leq \min_{b \in B_s} \{d_b^{\max}\}$. Denote the set of all spots (regardless of the order to which they belong) that can be scheduled in break $b \in B$ by $S(b) \subseteq \{1, \ldots, S\}$. $S(b)$ can formally be defined as follows:

$$S(b) = \{s = 1, \ldots, S \mid b \in B_s\}$$

we require $\sum_{s \in S(b)} l_s \geq d_b^{\min}$, $b \in B$.

It is common to assure that the advertisements for two competing products (e.g. BMW and Daimler-Chrysler cars) are not aired in the same break. We model these conflicts as follows: Let $C \subseteq 2^{\{1, \ldots, S\}}$. $C \in C$ implies that all spots $s \in C$ are in conflict and cannot be scheduled in the same break.
In addition to specifying a set of breaks where a spot \( s \) can be scheduled, the advertiser may define whether \( s \) should be the first spot, the last spot or in an arbitrary position (including the first or the last) in a break. Of course, we have to make sure that there is at most one spot at that position in each break. We model this fact as follows: For each break \( b \), add a conflict set to \( C \) for each position that is explicitly booked.

For the convenience of the reader, we have summarised the notation in the Appendix.

2.3 The model

We use the following decision variables:

\[ y_o = \begin{cases} 
1 & \text{if order } o \text{ is accepted} \\
0 & \text{otherwise} 
\end{cases} \quad o \in O \]

\[ x_{sb} = \begin{cases} 
1 & \text{if spot } s \text{ is scheduled in break } b \\
0 & \text{otherwise} 
\end{cases} \quad s = 1, \ldots, S, b \in B_s \]

Note that the binary decision variable \( x_{sb} \) is absolutely sufficient to represent a feasible schedule although the position of \( s \) in \( b \) is not precisely determined: The exact sequence of spots that have been scheduled in break \( b \) is irrelevant in our setting.

For notational convenience, define

\[ BC = \{(b, C) \in B \times C \mid |S(b) \cap C| \geq 2\} \]

The objective is to maximise revenues obtained from accepted orders. The complete model is as follows:

\[
\max \sum_{o \in O} v_o y_o \quad (1)
\]

Steps:

\[
\sum_{b \in B_s} x_{sb} = y_o \quad o \in O, s \in S_o \quad (2)
\]

\[
d_{b}^{\min} \leq \sum_{s \in S(b)} l_s x_{sb} \leq d_{b}^{\max} \quad b \in B \quad (3)
\]

\[
\sum_{s \in C \cap S(b)} x_{sb} \leq 1 \quad (b, C) \in BC \quad (4)
\]

\[
x_{sb} \in \{0, 1\} \quad s \in \{1, \ldots, S\}, b \in B_s \quad (5)
\]

\[
0 \leq y_o \leq 1 \quad o \in O \quad (6)
\]

By Equation (2), revenue \( v_o \) can be obtained if and only if all spots of order \( o \) are scheduled. Equation (3) restricts the length of all breaks \( b \in B \) to the given minimal and maximal lengths. By Equation (4), no conflicting spots are scheduled in the same break. Restrictions in Equation (5) define the decision variables \( x_{sb} \) as stated verbally before. Finally, it is sufficient to require \( y_o \in [0, 1] \) in Equation (6): Since the \( x_{sb} \) are binary, \( y_o \) will be integer by Equation (2).
Equations (1)–(6) are a straightforward way to state the problem at hand in a linear model with binary variables. Though there is admittedly a large body of literature on scheduling problems in general, this is the first attempt of a model that addresses the scheduling and revenue management problem of accepting/rejecting orders at the same time.

3 Heuristics

In general, it is not easy to find a feasible solution for a given instance: Restriction in Equation (3) requires a minimum number of spots to be scheduled in each break. If the number of conflicts in $C$ is large, it may be necessary to enumerate all candidate solutions to prove that no feasible solution exists. So in the following, we assume that $d_{bh}^{\min} = 0$. In this case, a trivial feasible solution exists ($y_b = x_{sb} = 0$). This is not a critical assumption for two reasons: Since we want to maximise revenues by accepting orders and scheduling all spots in each accepted order, we can expect that most breaks will be ‘nearly full’ in an optimal solution of a typical instance. However, if a break still happens to violate the minimum duration constraint, the broadcasting company will fill this break up with spots advertising its own TV or radio programme in practice.

Using AMPL/CPLEX, we implemented two general MIP-based heuristics, Dive-and-Fix and Relax-and-Fix along the lines of Wolsey (1998), two heuristics based on the LP relaxation of the model and a Greedy heuristic.

Note that in Sections 3 and 4, all computational times mentioned are ‘wall clock’ times (measured in seconds), not CPU seconds.

3.1 MIP-based heuristics

The idea of the Dive-and-Fix heuristic is to solve the LP relaxation, fix a variable that is ‘almost binary’ (but has a fractional value) to 0 or 1 and resolve the resulting LP. It consists of the following steps:

1. Solve the LP relaxation of the problem.
2. Let $x_{sb}^*, s \in \{1, \ldots, S\}, b \in B_s$ be the optimal values of the $x$ variables. Let $F = \{(s, b) : x_{sb}^* \not\in \{0, 1\}\}$ be the set of $x$ variables that are fractional.
3. If $F = \emptyset$, a feasible solution has been found, so STOP. Otherwise let $(s^*, b^*) = \min_{(s, b) \in F} \left\{ \min \{x_{sb}^*, 1-x_{sb}^*\} \right\}$ be the index of the variable closest to integer (but fractional).
4. If $x_{s^*b^*}^* < 0.5$, fix $x_{s^*b^*} = 0$, otherwise fix $x_{s^*b^*} = 1$. Resolve the resulting LP. If it is infeasible, the heuristic has failed, so STOP. Otherwise go to 2.

The Relax-and-Fix heuristic processes the orders sequentially in a Greedy fashion. If order $o$ is processed, the integrality restriction in Equation (5) is enforced for all $s \in S_o$, $b \in B_s$ and relaxed for all other variables. If a feasible solution is found, the values of $x_{sb}$, $s \in S_o, b \in B_s$ are fixed and the next order is processed. A detailed description follows:
1 For the ease of exposition, let the orders be indexed such that \( v_1 \geq \ldots \geq v_{|O|} \).
Let \( o^* = 1 \).

2 Consider the relaxed problem:

\[
\max \sum_{o \in O} v_o y_o
\]

Steps (2), (3), (4), (6) and

\[
x_{sb} \in \{0, 1\} \quad s \in S_{o^*}^+, b \in B_s
\]

\[
0 \leq x_{sb} \leq 1 \quad s \in \{1, \ldots, S\} - S_{o^*}^+, b \in B_s
\]

Try to find an optimal solution to that problem using CPLEX while imposing a time limit of 2 sec on the computation.

3 If an optimal (or at least a feasible) solution was found, fix \( y_{o^*} \) and \( x_{sb} \), \( s \in S_{o^*}^+, b \in B_s \) to the values returned by CPLEX. Otherwise, fix \( y_{o^*} \) and \( x_{sb} \), \( s \in S_{o^*}^+, b \in B_s \) to 0.

4 Let \( o^* = o^* + 1 \). If \( o^* \leq |O| \) go to 2.

In contrast to Dive-and-Fix, Relax-and-Fix will always return a feasible solution, because we can always fix variables to 0 in Step 3 to ensure the feasibility.

### 3.2 LP-based heuristics

While Dive-and-Fix and Relax-and-Fix solve LPs (or MIPs, respectively) in an iterative fashion, the heuristics to be described in this section have a simpler structure: only one LP is solved and after that a single IP is solved. Therefore, we can expect these heuristics to be much faster. In the first heuristic, called ForceOnes, we solve the LP relaxation of the problem, fix all variables \( y_o, x_{sb} \) with an optimal LP value of 1 to that value and try to find an optimal (or at least feasible) solution for the remaining IP in 5 sec using CPLEX. ForceZeroes works analogously: Variables with an optimal LP value of 0 are fixed to that value and the remaining IP is solved using CPLEX, again with a time limit of 5 sec. Note that ForceZeroes will always return a feasible solution, where ForceOnes may fail to find one though the (integer) feasible region of the original problem is non-empty by construction.

### 3.3 Greedy heuristic

Like Relax-and-Fix, Greedy processes the orders sequentially according to their prices. If order \( o \) is processed, we try to find a feasible solution such that \( y_o = 1 \). If that succeeds, the values of \( y_o \) and \( x_{sb} \), \( s \in S_o, b \in B_s \) are fixed and the next order is processed. Otherwise, we fix \( y_o \) and \( x_{sb} \), \( s \in S_o, b \in B_s \) to 0. Summing up, Greedy consists of the following steps:

1 For the ease of exposition, let the orders again be indexed such that \( v_1 \geq \ldots \geq v_{|O|} \).
Let \( o^* = 1 \). Solve the LP relaxation of the problem.
2 If $y_o = 1$ and $x_{sb} \in \{0, 1\}$, $s \in S_o$, $b \in B_s$, an integer feasible schedule for $o^*$ has been found; so fix these variables and go to 5.

3 Otherwise consider the modified problem:

$$
\max \sum_{o \in O} v_o y_o
$$

Steps (2), (3), (4), (6) and

$x_{sb} \in \{0, 1\}$ $s \in S_o$, $b \in B_s$

$0 \leq x_{sb} \leq 1$ $s \in \{1, \ldots, S\} - S_o$, $b \in B_s$

$y_o = 1$

Try to find an optimal solution to that problem using CPLEX, imposing a time limit of 2 sec on the computation.

4 If an optimal (or at least a feasible) solution was found, fix $y_o = 1$ and $x_{sb}$, $s \in S_o$, $b \in B_s$ to the values returned by CPLEX. Otherwise, fix $y_o$ and $x_{sb}$, $s \in S_o$, $b \in B_s$ to 0 and solve the LP relaxation of the resulting problem.

5 Let $o^* = o^* + 1$. If $o^* \leq |O|$ go to 2.

Since we fix variables to 0 in Step 4 if no feasible schedule for an order was found, Greedy always generates a feasible solution in our instances.

Note that Greedy will, in general, not produce the same solution as Relax-and-Fix: For some $o \in O$, the latter may find that $y_o = 0$ is an optimal solution to the relaxed problem in Step 2. Thus $y_o$ is fixed to 0. Greedy, on the other hand, may find that a feasible solution with $y_o = 1$ exists, so $y_o$ is fixed to 1.

4 Computational study

To the best of our knowledge, no systematic test-bed is available from the literature. Bollapragada and Garbiras (2004) briefly summarise the data of their example, a practical instance from NBC; it contained 4,500 spots and 900 breaks. They also mention that their instance had 662 conflicts. However, only 516 conflicts can feasibly be resolved. Note that Bollapragada and Garbiras (2004) assume that all spots have to be scheduled. Unresolved conflicts incur a penalty cost. In contrast, our model does not allow for any conflicts, but not all spots have to be scheduled.

We closely refer to the planning situation in Spanish TV, RTVE and RTVV, in the following. RTVE is the market-leading Spanish broadcasting company. In 2003, it earned ca. 700 million euros from advertising, that is almost 80% of its total earnings. RTVV is a regional channel, covering the area of Valencia, Castellon and Alicante. RTVV is also a market-leading company (with respect to its regional scope). It earned 40 million euros from advertising in 2003. Both companies run various TV and radio channels.
Therefore, our test-bed is based on strong practical evidence. As was mentioned earlier, Bollapragada and Garbiras (2004) describe a similar situation for NBC. So we do strongly believe that the setting we describe in the following is a representative for many broadcasting companies.

4.1 Preliminary considerations: length of breaks and spots

In all of our instances, we let $d_{b}^{\text{min}} = 0$. In this case, a trivial feasible solution exists ($y_{a} = x_{ab} = 0$).

It seems to be reasonable that all breaks have the same length, so we set $d_{b}^{\text{max}} = 360$ (6 minutes) for all $b \in B$. In Spanish TV, for instance, the standard length of a spot is 20 sec, so we should have 18 spots in a break on average. The minimum length of a (regular) spot is 10 sec, and the length of a spot hardly exceeds 120 sec. Therefore, we choose $l$, at random where the distribution $p_{l}$ is given by the following table:

<table>
<thead>
<tr>
<th>$l$</th>
<th>$p_{l}$</th>
<th>$l \times p_{l}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>0.395</td>
<td>3.95</td>
</tr>
<tr>
<td>20</td>
<td>0.450</td>
<td>9.00</td>
</tr>
<tr>
<td>30</td>
<td>0.070</td>
<td>2.10</td>
</tr>
<tr>
<td>45</td>
<td>0.050</td>
<td>2.25</td>
</tr>
<tr>
<td>60</td>
<td>0.020</td>
<td>1.20</td>
</tr>
<tr>
<td>90</td>
<td>0.010</td>
<td>0.90</td>
</tr>
<tr>
<td>120</td>
<td>0.005</td>
<td>0.60</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td>1</td>
<td>20</td>
</tr>
</tbody>
</table>

4.2 Size of the instances and prices

It remains to be defined how we determine the number of breaks (i.e. the set $B$), the overall number of spots ($S$), the number of orders ($O$), the distribution of spots among orders ($S_{o}$) and breaks ($B_{o}$) and the conflicts ($C$).

We let the number of breaks be $|B| \in \{10, 15, 20, 50, 100\}$. Given $|B|$, we let $S = NLF \times |B|$, where $NLF \in \{15, 18, 20, 25, 30, 35\}$. The reasoning behind this is as follows: In revenue management problems, it is common to define the relation between demand and available resource capacity (See Kimms and Müller-Bungart (2006) for a discussion). This relation is called the nominal load factor. In all our instances, we can schedule on average 18 spots per break. So if $NLF \leq 18$, the number of spots that we can schedule is mostly limited by the conflicts, hence it should be possible to accept (almost) all orders. As the nominal load factor grows, the revenue management problem becomes c.p. more important since more and more orders will have to be rejected.

We assume that the spots are evenly distributed among the breaks – a reasonable assumption; otherwise it won’t make sense to have breaks of (roughly) the same length in practice – so for each $s \in \{1, \ldots, S\}$ we let $|B_{s}| = \lfloor \alpha \times |B| \rfloor$ where $\alpha \in \{0.1, 0.2\}$. Then, we uniformly choose $|B_{s}|$ breaks from $B$ for each $s = 1, \ldots, S$. 
To determine the number of orders \(|O|\) and the distribution of spots to orders (i.e. the sets \(S_o\)), we use the following procedure: Let \(q \in \{1, 5, 10, 20, 50, 100\} \) and then define \(|O|\) and \(S_o\) as follows: Let \(|O| = \lfloor S/q \rfloor\). If \(S/q\) is integer, we assign the first \(q\) spots to \(S_1\), the second \(q\) spots to \(S_2\) and so forth, i.e. \(|S_o| = q, o \in O\). Otherwise, we raise \(q\) by redefining \(q = \lfloor S/|O| \rfloor\). If \(S/|O|\) is integer, we assign the first \(q\) spots to \(S_1\), the second \(q\) spots to \(S_2\) and so forth, i.e. \(|S_o| = q, o \in O\). Otherwise, the sets \(S_o, o \in O\) are assigned \(q + 1\) spots each and the rest of all orders are assigned \(q\) spots each.

Given the \(B_o\), we can compute the sets \(S(b)\). We will use these sets to define conflicts as follows: Denote the number of conflicts per break by \(c \in \{0, 1, 5\}\). Each \(C \in C\) has the same size \(|C| \in \{2, 3\}\). So for each break \(b \in B\) we create \(c\) conflicts by selecting \(|C|\) spots at random from \(S(b)\) each time.

For the prices \(v_o\), we compute the total length of all spots in \(o\) by \(l_o = \sum_{t \in S_o} l_t\). Then, we let \(v_o = l_o \cdot u_o\), where \(u_o \sim U(25, 500)\). This means that a second costs between 25 and 500 Euros; that is the usual price charged in Spanish TV.

Summing up, we have varied the parameters as follows:

\[
\begin{align*}
|B| & \in \{10, 15, 20, 50, 100\} \\
NLF & \in \{15, 18, 20, 25, 30, 35\} \\
\alpha & \in \{0.1, 0.2\} \\
q & \in \{1, 5, 10, 20, 50, 100\} \\
c & \in \{0, 1, 5\} \\
|C| & \in \{2, 3\}\quad (if \ c > 0)
\end{align*}
\]  

Therefore, we had \(5 \cdot 6 \cdot 2 \cdot 6 = 360\) combinations of \(|C|, NLF, \alpha, q\). So there were 360 parameter combinations with no conflicts, and \(360 \cdot 2 \cdot 2 = 1,440\) instances with conflicts, that is \(1,800\) combinations altogether. For each combination we generated ten instances, totalling up to \(18,000\) instances.

### 4.3 Optimal solutions

First of all, we tried to find out optimal solutions with AMPL/CPLEX on a Pentium 4 computer at 3.06 GHz. For all 3,600 instances with \(|B| = 10\), we obtained optimal solutions within 60 sec. For instances with 15 or more breaks, it turned out to be practically impossible to obtain optimal solutions within a reasonable amount of time, so we restrict ourselves in the following discussion of optimal solutions to the instances with \(|B| = 10\).

On average, an optimal solution for an instance with ten breaks could be obtained in 3.35 sec (with a standard deviation of 9.55 sec). Table 1 reveals that almost 80% of all instances could be solved in a second or less. On the other hand, 138 instances took more than 30 sec.

Not surprisingly, the average computational time increases with NLF and \(\alpha\) and decreases with \(q\). The effect of the number of conflicts per break and the number of conflicting spots, \(c\) and \(|C|\), is less clear though (see Table 2): On one hand, the computational times are higher for \(c = 5\). On the other hand, if there are more conflicts,
the feasible region gets smaller and a branch-and-bound procedure may converge faster, so instances with \( c = 1 \) have been solved faster (on average) than instances with \( c = 0 \).  

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Optimal solution times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time (sec)</td>
<td>Instances (abs.)</td>
</tr>
<tr>
<td>up to 1 sec</td>
<td>2,873</td>
</tr>
<tr>
<td>1 to 5</td>
<td>243</td>
</tr>
<tr>
<td>5 to 10</td>
<td>115</td>
</tr>
<tr>
<td>10 to 30</td>
<td>231</td>
</tr>
<tr>
<td>30 to 60</td>
<td>138</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Effect of conflicts on computational times</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c )</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>–</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
</tr>
</tbody>
</table>

4.4 Heuristic performance on instances with ten breaks

We are now going to evaluate the performance of our heuristics. We start with instances with \( |B| = 10 \) where we can compare the heuristic LBs with the known optimal revenues. We start with reviewing the computational times and the number of feasible solutions found for each heuristic in Table 3. Relax-and-Fix, Greedy and ForceZeroes were guaranteed to find feasible solutions for all 3,600 instances. ForceOnes and Dive-and-Fix found feasible solutions in approximately 80% of all cases.  

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Feasible solutions and computational times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heuristic</td>
<td>Feasible solution</td>
</tr>
<tr>
<td>Found (%)</td>
<td>Not found (%)</td>
</tr>
<tr>
<td>Dive-and-Fix</td>
<td>2,991</td>
</tr>
<tr>
<td>Relax-and-Fix</td>
<td>3,600</td>
</tr>
<tr>
<td>ForceOnes</td>
<td>2,764</td>
</tr>
<tr>
<td>ForceZeroes</td>
<td>3,600</td>
</tr>
<tr>
<td>Greedy</td>
<td>3,600</td>
</tr>
</tbody>
</table>

Before we summarise the computational times, note that the average and maximal times given in Table 3 refer to all 3,600 instances, i.e. the cases where ForceOnes and Dive-and-Fix have not found a feasible solution are included.

For small instances here (with \( |B| = 10 \)), ForceOnes and ForceZeroes were very fast and never reached their time limit of 5 sec. Dive-and-Fix and Relax-and-Fix performed...
well on average. The Greedy heuristic was a bit slower. Also note that the time limit of 2 sec for each order used by Relax-and-Fix and Greedy was (on average) not restrictive.

An optimal revenue of 0 is found in 425 instances, and all heuristics found this optimal solution in all cases. Table 4 assesses the quality of the lower bounds for the remaining 3,175 instances using the percentage gap between lower bound and optimum, which is defined as follows:

\[
\text{Gap} = \frac{\text{Optimal revenue} - \text{lower bound}}{\text{Optimal revenue}} \in [0, 1]
\]

(7)

<table>
<thead>
<tr>
<th>Heuristic</th>
<th>Instances</th>
<th>Gap as defined by (7)</th>
<th>Optimum found</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(%)</td>
<td>Avg. (%)</td>
<td>SD (%)</td>
</tr>
<tr>
<td>Dive-and-Fix</td>
<td>2,566</td>
<td>80.8</td>
<td>87.0</td>
</tr>
<tr>
<td>Relax-and-Fix</td>
<td>3,175</td>
<td>100.0</td>
<td>2.9</td>
</tr>
<tr>
<td>ForceOnes</td>
<td>2,339</td>
<td>73.7</td>
<td>1.4</td>
</tr>
<tr>
<td>ForceZeroes</td>
<td>3,175</td>
<td>100.0</td>
<td>4.0</td>
</tr>
<tr>
<td>Greedy</td>
<td>3,175</td>
<td>100.0</td>
<td>4.8</td>
</tr>
</tbody>
</table>

The very bad performance of Dive-and-Fix is due to the fact that it produced a lower bound of 0 in 2,210 of the 2,566 instances (ca. 86%), though the optimal revenue was non-zero. These instances have a gap of 100%. The average gap for the remaining 356 instances is only 6.4%, with a standard deviation of 8.8% and a maximum of 71.9%. Nevertheless, the performance of Dive-and-Fix is unsatisfactory.

ForceOnes produced the best gaps. On the other hand, it failed to produce a lower bound at all for over 25% of all instances with non-zero optimal revenue. This also largely explains why the number of optimal solutions found is relatively small: ForceOnes indeed found optimal solutions in only 35% of the 3,175 instances, but in over 48% of the instances it found a feasible solution.

Relax-and-Fix is outperformed by ForceOnes with respect to gaps. On the other hand, Relax-and-Fix is guaranteed to find a feasible solution (in our instances) where ForceOnes is not, and it finds the most optimal solutions. Its gaps are better than ForceZeroes' (which will also find a feasible solution for sure), but the latter is faster. Greedy performs slightly worse than ForceZeroes on average, but the deviation of the gaps is smaller.

4.5 Instances with a large number of breaks

For the larger instances with \(|\mathcal{B}| \in \{15, 20, 50, 100\}\) we could not obtain optimal solutions within satisfactory computational times, so in this section we will compare the heuristics among each other.

Table 5a shows that it got clearly more difficult for Dive-and-Fix and ForceOnes to find feasible solutions for medium-sized instances with \(|\mathcal{B}| \in \{15, 20\}\).

For instances with 50 and 100 breaks we had to impose an overall time limit of 60 seconds on Dive-and-Fix, Relax-and-Fix and Greedy to finish the computational study within a reasonable amount of time. Thus, Relax-and-Fix and Greedy may now fail to
find a feasible solution due to the time limit. Table 5b shows that indeed for the majority of instances with 100 breaks, both did not finish within 60 sec.

Table 5a  Number of instances where feasible solutions were found

<table>
<thead>
<tr>
<th>Heuristic</th>
<th>15 Breaks: feasible solution</th>
<th>20 Breaks: feasible solution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Found (%)</td>
<td>Not found (%)</td>
</tr>
<tr>
<td></td>
<td>Found (%)</td>
<td>Not found (%)</td>
</tr>
<tr>
<td>Dive-and-Fix</td>
<td>2,298</td>
<td>63.8</td>
</tr>
<tr>
<td>ForceOnes</td>
<td>2,585</td>
<td>71.8</td>
</tr>
</tbody>
</table>

Table 5b  Number of instances where feasible solutions were found

<table>
<thead>
<tr>
<th>Heuristic</th>
<th>50 Breaks: feasible solution</th>
<th>100 Breaks: feasible solution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Found (%)</td>
<td>Not found (%)</td>
</tr>
<tr>
<td></td>
<td>Found (%)</td>
<td>Not found (%)</td>
</tr>
<tr>
<td>Dive-and-Fix</td>
<td>571</td>
<td>15.9</td>
</tr>
<tr>
<td>Relax-and-Fix</td>
<td>3,047</td>
<td>84.6</td>
</tr>
<tr>
<td>ForceOnes</td>
<td>1,127</td>
<td>31.3</td>
</tr>
<tr>
<td>Greedy</td>
<td>2,903</td>
<td>80.6</td>
</tr>
</tbody>
</table>

Except for Dive-and-Fix, the relationship of computational times given by Table 6 is similar to the small instances with $|B| = 10$ ForceOnes and ForceZeroes were very fast. Both have reached their time limits of 5 sec now (marked by ‘*’ in the table). However, their typical performance is clearly not affected by the time limit. To obtain a meaningful average time for Dive-and-Fix, Relax-and-Fix and Greedy, we have excluded the instances where the time limit of 60 sec (marked by ‘***’ in the tables) has been reached. Relax-and-Fix and Greedy performs satisfactory on a typical instance. Both do in general not seem to be restricted by the maximum processing time of 2 sec per order. The computational time of Dive-and-Fix is less favourable, though.

Table 6  Wall clock times in seconds

<table>
<thead>
<tr>
<th>Heuristic</th>
<th>15 Breaks</th>
<th>20 Breaks</th>
<th>50 Breaks</th>
<th>100 Breaks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dive-and-Fix</td>
<td>3.75</td>
<td>25.00</td>
<td>9.60</td>
<td>41.00</td>
</tr>
<tr>
<td>Relax-and-Fix</td>
<td>1.10</td>
<td>11.00</td>
<td>2.52</td>
<td>21.00</td>
</tr>
<tr>
<td>ForceOnes</td>
<td>0.07</td>
<td>*</td>
<td>0.13</td>
<td>*</td>
</tr>
<tr>
<td>ForceZeroes</td>
<td>0.07</td>
<td>1.28</td>
<td>0.13</td>
<td>0.73</td>
</tr>
<tr>
<td>Greedy</td>
<td>3.65</td>
<td>52.00</td>
<td>5.94</td>
<td>76.00</td>
</tr>
</tbody>
</table>

* and *** indicate that the time limit of 5 and 60 sec, respectively, was reached

For $|B| = 10$, there were 283 instances where the best lower bound found was 0. All these instances were feasibly solved by all heuristics. The remaining 14,117 instances were again compared using a percentage gap defined as follows:

$$\text{Gap} = \frac{\text{Best lower bound} - \text{lower bound}}{\text{Best lower bound}} \in [0, 1]$$  \hspace{1cm} (8)
For $|B| = \{15, 20\}$, \textit{Dive-and-Fix} suffers again from the fact that it delivers a lower bound of 0 though the best bound is strictly greater. However, the effect is smaller: Only 755 (37.5\%) and 19 (1.9\%) instances (out of all instances where \textit{Dive-and-Fix} found a feasible solutions) are affected, respectively.

Table 7 summarises the statistics on the gaps as defined by Equation (8). For $|B| = 15$, the results are pretty similar to the previous case: \textit{ForceOnes} is best, but fails to find a bound on many instances. \textit{Relax-and-Fix} is (slightly) better than \textit{ForceZeroes} on average. The former finds the best bound more often, but the latter is much faster. \textit{Greedy} performs slightly worse than both, but is very robust in the sense that the deviation of the gaps is small.

For $|B| = 20$, the performance of \textit{Dive-and-Fix} was again unsatisfactory. \textit{ForceZeroes} retained its position. \textit{Relax-and-Fix} was clearly best, but \textit{Greedy} competes well showing again a very small deviation of the gaps. Surprisingly, \textit{ForceOnes} was outperformed by both \textit{Relax-and-Fix} and \textit{Greedy}.

For the very large instances with $|B| \in \{50, 100\}$, all heuristics have a similar performance with respect to the gaps, only \textit{ForceZeroes} is slightly behind. However, \textit{ForceZeroes} is very successful in delivering the best bound for $|B| = 100$, albeit this observation can largely be attributed to the fact that all other heuristics fail to produce a bound at all on more than two thirds of the instances.

\begin{table}[h]
\centering
\caption{Gaps for instances with $|B| \in \{15, 20, 50, 100\}$}
\begin{tabular}{lcccccc}
\hline
\textbf{Heuristic} & \textbf{Instances} & \textbf{Gap as defined by Equation (8)} & \textbf{Best LB found} \\
 & (% ) & Avg. (%) & SD (%) & Max. (%) & (\%) \\
\hline
\multirow{2}{*}{$|B|=15$} & \textit{Dive-and-Fix} & 2,015 & 60.7 & 43.0 & 45.8 & 100.0 & 432 & 13.0 \\
 & \textit{Relax-and-Fix} & 3,317 & 100.0 & 3.3 & 12.4 & 100.0 & 2,195 & 66.2 \\
 & \textit{ForceOnes} & 2,302 & 69.4 & 0.9 & 2.0 & 22.7 & 1,241 & 37.4 \\
 & \textit{ForceZeroes} & 3,317 & 100.0 & 3.6 & 9.0 & 100.0 & 1,424 & 42.9 \\
 & \textit{Greedy} & 3,317 & 100.0 & 4.6 & 7.4 & 61.7 & 1,438 & 43.4 \\
 & \textit{Dive-and-Fix} & 1,022 & 28.4 & 8.2 & 19.4 & 100.0 & 468 & 13.0 \\
 & \textit{Relax-and-Fix} & 3,600 & 100.0 & 0.5 & 2.0 & 33.0 & 2,918 & 81.1 \\
 & \textit{ForceOnes} & 1,358 & 37.7 & 16.6 & 1.9 & 12.5 & 416 & 11.6 \\
 & \textit{ForceZeroes} & 3,600 & 100.0 & 4.5 & 7.1 & 35.6 & 361 & 10.0 \\
 & \textit{Greedy} & 3,600 & 100.0 & 1.9 & 2.9 & 13.3 & 1,877 & 52.1 \\
 & \textit{Dive-and-Fix} & 571 & 15.9 & 0.0 & 0.0 & 0.5 & 561 & 15.6 \\
 & \textit{Relax-and-Fix} & 3,047 & 84.6 & 0.3 & 1.1 & 13.1 & 2,338 & 64.9 \\
 & \textit{ForceOnes} & 1,127 & 31.3 & 0.7 & 1.0 & 5.6 & 557 & 15.5 \\
 & \textit{ForceZeroes} & 3,600 & 100.0 & 4.1 & 4.0 & 20.7 & 453 & 12.6 \\
 & \textit{Greedy} & 2,903 & 80.6 & 1.0 & 1.7 & 13.1 & 1,601 & 44.5 \\
 & \textit{Dive-and-Fix} & 155 & 4.3 & 0.0 & 0.1 & 0.6 & 153 & 4.3 \\
 & \textit{Relax-and-Fix} & 1,022 & 28.4 & 0.2 & 0.8 & 6.3 & 802 & 22.3 \\
 & \textit{ForceOnes} & 1,087 & 30.2 & 0.4 & 0.7 & 3.8 & 633 & 17.6 \\
 & \textit{ForceZeroes} & 3,600 & 100.0 & 1.9 & 3.3 & 15.1 & 2,286 & 63.5 \\
 & \textit{Greedy} & 1,203 & 33.4 & 0.2 & 0.8 & 6.4 & 1,063 & 29.5 \\
\hline
\end{tabular}
\end{table}
5 Conclusion and future research opportunities

In this paper, we rigorously described a broadcasting company’s problem of selecting orders and scheduling spots from accepted orders at the same time. Five heuristics for that problem have been proposed and tested. We developed a systematic procedure to generate test instances for the problem at hand based on the situation in Spain. Since this situation is similar to previous descriptions in the literature, it seems to be able to generate representative test problems.

We restricted ourselves to heuristic solutions of the problem. Finding exact solutions to the problems, e.g. using branch-and-bound or branch-and-cut schemes will be a fruitful area of future research. Since all heuristics we presented in this paper (except Dive-and-Fix) performed well with respect to gaps and running times, they can be used as the ‘core’ of a DSS to support the actual managerial decisions in practice. All the heuristics are easy to understand and implement, so the missing part to put our approach into practice is basically a user interface.

We assumed that the set of orders $O$ and the associated data like prices $v_o$, etc. are known. This precisely describes the situation when orders are placed over time and the channel decides about acceptance or rejection at a fixed due date after which no orders are accepted. This assumption is also justified if the values and characteristics of future orders can be forecasted with sufficient accuracy. If the channel has to decide about orders shortly after they are placed and before knowing about potential future orders, a dynamic, stochastic model would be more appropriate. In such a model, however, given an order with known characteristics, it has to be decided whether it can be feasibly scheduled and whether it is profitable to accept it. At least for the first question, a problem very similar to the one presented here has to be solved. In that respect, this paper is a cornerstone for future research on dynamic and stochastic approaches to the problem.

Acknowledgements

We thank Alejandro Belloch Egea for collecting information on the Spanish TV channels, RTVE and RTVV. The constructive comments of two anonymous referees are also gratefully acknowledged.

References


A. Kimms and M. Müller-Bungart


**Appendix: Notation**

**Parameters**

- $s$: Number of spots
- $l_s$: Length of spot
- $O$: Set of orders
- $v_o$: Revenue of order $o$
- $S_o$: Spots of order $o$
- $B$: Set of breaks
- $d_b^{\min}, d_b^{\max}$: Minimum and maximum duration of break $b$
- $B_s$: Set of breaks admissible for spot $s$
- $C$: Set of conflict sets. If $C \in C$, all spots $s \in C \subseteq \{1, \ldots, S\}$ cannot be scheduled in the same break.

**Decision variables**

- $y_o$: =1, if order $o$ is accepted (0 otherwise)
- $x_{sb}$: =1, if spot $s$ is scheduled in break $b$ (0 otherwise)
Bundling of information goods: a value driver for new mobile TV services

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Abstract: Information goods have several characteristics that make their pricing especially challenging. From the point of view of revenue management, bundling has many advantages that seem to match the challenges of pricing information goods. Because bundling is a value-based pricing strategy, segmentation has a significant role in supporting and increasing efficiency of bundling. In this context, we develop a conceptual model showing how many characteristics of information goods support or limit the selection of bundling as a pricing strategy. The conceptual model developed and the hypotheses stated are tested with conjoint analysis in the context of a new mobile TV service bundle. The mobile TV is a new innovation, and the service is expected to be launched in Finland in 2006. Totally 164 respondents gave answers to our internet survey. In this study, bundling increased the demand in all cases. However, consumers strongly preferred two-part pricing and flat access rates of new mobile TV services. Actually, our research findings give support to segmentation on the basis of bundling.

Keywords: conjoint analysis; information goods; mobile TV; price bundling; revenue management; segmentation; value-based pricing.


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1 Introduction

Information goods have several special characteristics that make their pricing especially challenging. Regarding costs, information goods have high fixed costs compared to the near-zero marginal costs. Therefore, cost-based pricing is not appropriate for information goods. On the other hand, although marginal costs are near zero, producing the first copy of information goods can be extremely expensive and the product life cycles are typically short. In this kind of context, pricing decisions are critical for the company’s success and profitability.

Value-based pricing of information goods has its challenges also. According to the theory of value-based pricing, the price should be based on the value that the selected target consumers place to the product instead of its costs (Knox and Maklan, 1999; Nagle and Holden, 2002). The value of information goods is a cumbersome concept due to many factors. There is still a lack of consensus in the conceptualisation of information value and its components (Lopes, 2002). The value is often influenced by both positive and negative network externalities. Furthermore, customer valuations for information goods vary widely and involve high uncertainty.

Bundling is a value-based pricing method (Guiltimean, 1987). Two-part pricing is also one form of bundling and is widely used for information goods. Bundling has many advantages that seem to match the challenges of pricing information goods. Segmentation can often significantly increase the efficiency of bundling. Because the efficiency of bundling strongly depends on its ability to reduce variation in consumer valuations, identifying customer segments that differ regarding valuations and applying segmented pricing is critical for profitably applying bundling. Some variables that could explain the variation in the valuations of information goods are consumer heterogeneity regarding usage, expertise and adoption (Danaher, 2002; Essagaier et al., 2002; Jain and Kannan, 2002).

This study applies the generic and behavioural pricing theory to a special pricing decision situation in which information goods are bundled. A conceptual framework model is developed for analysing bundling of information goods. The empirical part used the framework model to test whether bundling is an appropriate pricing strategy for mobile TV services. A quantitative internet survey (N = 164) was conducted. The key research methodology used was conjoint analysis.
2 Theoretical frame of reference

Digital goods are goods or services that are digitised, i.e. presented as a series of bits (Turban et al., 2002). Choi et al. (1997) classify digital products into three groups: information and entertainment products; symbols, tokens and concepts; and processes and services. In this study, information goods refer to digitally distributed digital information and entertainment goods. The consumption of digital information goods always requires a complementary device. Compared with other goods and services, information goods resemble services more than physical goods. They are immaterial and as services, they are characterised by intangibility, inseparability and perishability (Zeithaml et al., 1985). Lopes (2002) adds two more things on how information goods resemble services: acquisition occurs through multiple interactions with the vendor and the final control of the product remains with the provider. Like services, information goods are also very flexible by nature. On the other hand, information goods differ both from services and physical goods in two major ways. The first important difference is the cost structure, i.e. high fixed costs compared to almost zero marginal costs. The second difference is that information goods do not suffer from heterogeneity due to the digitalisation.

The mobile TV is an example of information goods. It is also an example of the ongoing digital convergence. The mobile TV will bring TV-like broadcasting services to mobile phones. At the product level, it combines two existing products: a mobile telephone and a television. At the industry level it will converge two existing industries: the telecommunication and the broadcasting industry. Because the mobile TV combines strengths of both networks, a whole set of new services can be invented. From consumer’s point of view, the mobile TV is still just another new service for the mobile phone. Regarding customer expectations, there has already been one large research project in Finland that evaluated the mobile TV from consumers’ point of view (MobTV, 2003). The service is estimated to be launched in Finland in 2006. Mobile TV has still a lot of challenges in the future: terminals are not yet commercially available, and standardisation and regulation works have just begun.

2.1 Challenges in pricing of information goods

Information goods have several special characteristics that make their pricing challenging. These characteristics are shown on the left side of Figure 1. Cost-based strategies are not appropriate for information goods due to the cost structure where the relevant costs for pricing, i.e. incremental and avoidable costs of digitally distributed information goods are almost zero. On the other hand, value-based pricing has its challenges too (Nagle and Holden, 2002). The customer valuations of information goods are characterised by high uncertainty and the valuations vary widely between people (Shapiro and Varian, 1999). There is a lack of consensus in the conceptualisation of the information value and its components, and the conceptualisation can be complex, which explains partly the high uncertainty and high variations in customer valuations (Lopes, 2002). In addition, the same information goods may have different valuations at different times (Bakos and Brynjolfsson, 1999). The value of information goods is also highly dependent on the context (Martyn and Flowerdew, 1983). For example, mobile devices reach consumers at the moment when their demand for a certain piece of information is at its highest, which should also increase its perceived value.
Still, probably the most important factor influencing customer valuations of information goods are network externalities. All three types of network externalities are present: negative, positive direct and positive indirect network externalities (Gupta et al., 1999; Essegaier et al., 2002; Jain and Kannan, 2002; Lee and O’Connor, 2003). Positive network externalities are important in new product industries. Depending on the company objectives, the presence of network externalities changes the optimal pricing strategies for product’s launch phase (Stremersch and Tellis, 2002; Lee and O’Connor, 2003). Also, indirect network externalities involve a difficult coordination problem, since service providers and hardware manufacturers are normally independent companies (Gupta et al., 1999). When the network externalities are present, the demand curve looks a bit like Shy’s inverse aggregate demand function (Shy, 2001) for telecommunication services. One impacting variable is missing from Shy’s model: Earlier adopters usually have different valuations than late adopters. This could affect the shape of the demand curve. Also, budget constraints influence the demand of information goods (Bakos and Brynjolfsson, 1999). In practice, demand for information goods (Jain and Kannan, 2002) and telecommunication services (Danaher, 2002) seem to be quite inelastic.

The competitive environment in information industries varies widely. Therefore, one has to be very careful when generalising any pricing-related results from one industry to another. Network externalities, scarce resources and intellectual property rights are factors that help explain the different competitive outcomes in information industries. Regarding the product, the level of differentiation, very short product life cycles and high switching costs of information goods influence pricing (Grunenwald and Vernon, 1988). Regarding product differentiation, Lopes (2002) provides an interesting division of information goods into viewpoint-based and fact-based goods. Fact-based information is more commodity-like information and, when the reliability of the fact-based information providers is high, the competition is driven towards pricing. Promotions are not very useful in information industries, because they do not impose inconvenience to customers and, therefore, they do not cause the price-sensitive consumers to identify themselves (Shapiro and Varian, 1999).

### 2.2 Bundling of information goods

Bundling is the practice of selling two or more products and/or services in a single package (Guilliman, 1987). Both price bundling and product bundling can be used for information goods (Stremersch and Tellis, 2002). Bundling is a value-based pricing method, or more precisely one form of differential pricing and versioning (Shapiro and Varian, 1999; Nagle and Holden, 2002). The basic economic rationale behind bundling is the transfer of consumer surplus from one product to another (Guilliman, 1987), but there are several other advantages possibly gained from bundling. These advantages seem to map very well to the challenges in pricing information goods. The advantages and the risks involved in bundling are shown at the right side of Figure 1. In contrast to third-degree price discrimination (Chen and Iyer, 2002) bundling operates on a ‘one-size-fits-all’ principle, and the seller does not have to enforce any resale restrictions.

The cost structure of information goods favours bundling. Bundling reveals major advantages when fixed costs are high compared to marginal costs, when fixed costs can be shared with the bundled products, when demand fluctuates or when items have high set-up costs. Marginal costs have an especially critical role. Bundling a larger number of goods becomes quickly unprofitable for goods with substantial marginal costs (Bakos and
Bundling of information goods

Bundling reduces both average and fixed costs. Average costs are reduced by the demand increase and by shared fixed costs. Bundling can also directly reduce fixed costs by helping in planning and by increasing the efficiency of the company’s operations (Bakos and Brynjolfsson, 1999).

Regarding customers and demand, bundling increases loyalty, decreases price sensitivity, increases demand and reduces variation and uncertainty in it (Eppen et al., 1991; Soman and Gourville, 2001). Bundling requires that consumers differ in their valuations (Shy, 2001). Especially when more than two products are involved, the larger the dispersion and the higher the uncertainty in customer valuations, the bigger the gains are from bundling (Shapiro and Varian, 1999). The dispersion in valuations could be one of the main reasons why bundling seems so suitable for services and immaterial goods. The demand is also increased simply due to the consumer surplus transfer (Guiltinan, 1987). The demand also increases due to the possibility to optimise the price of the whole bundle. A company can direct the consumption towards the products with higher margins and plan its discount policies better (Eppen et al., 1991).

For information goods, the demand-related gains from bundling are most significant. Information has always been sold in bundles due to the considerable variation in users’ willingness-to-pay. Although other reasons to bundle like economies of scale in printing, binding, shipping and marketing might vanish with digitalisation, it still pays to sell information bundles (Chuang and Sirbu, 1997). Bakos and Brynjolfsson (1999) write about a multiproduct monopolist bundling of a large number of information goods. They argue that under a wide variety of conditions bundling any number of goods with zero marginal costs increases the seller’s profits. The basic rationale is the law of large numbers, which makes it easier to predict consumers’ valuations. The larger the number of goods bundled, the greater the reduction in the variance. The reduction in buyer diversity then helps sellers extract higher profits (Schlamensee, 1984). Their results do not extend to most physical goods due to marginal costs.

There are two major advantages from bundling related to the product. Firstly, bundling increases possibilities to differentiate the product. There are more possibilities simply because there are more products and features, but there are also possibilities that are not available to producers of individual products. Secondly, bundling can significantly reduce the product’s time-to-market, because a company can use its established branding, markets and distribution channels created for another product. Finally, bundling can change the whole competitive structure of the industry.

2.3 Methods of bundling

There are two basic methods of bundling: pure and mixed bundling (Guiltinan, 1987). In pure bundling the products are sold only bundled. In the mixed bundling the buyer can either buy the bundle or included products separately. Further, there are two modes of mixed bundling: mixed-leader bundling and mixed-joint bundling. For information goods, a major share of the bundling literature discusses two-part pricing, which is a special case of mixed-leader bundling. Guiltinan (1987) provides a framework for analysing conditions under which each mixed bundling method is an effective marketing tool (McAfee and McMillan, 1989). He writes about bundling of two services. He notes that before and after bundling there are four basic segments:
those who buy both services
those that buy only Service A
those that buy only Service B and
non-customers.

Guiltinan separates two different cases depending on whether the company’s objective is to cross-sell services or to acquire new customers. The optimal selection of the mixed bundling method and the selection of the leader product will be dependent on unbundled demand levels, relative margins, consumer surplus and complementary relationship among products. Two basic rules are that mixed leader bundling is applicable when the other product (leader) has a substantially larger demand but lower profit margins and mixed joint bundling is most appropriate when demands and margins are approximately equal.

Several studies have shown that the allocation of the profit margin in mixed bundling is a fairly complex issue (Janiszewski and da Cunha, 2002). Simply partitioning the prices in a bundle can influence the attractiveness of the bundle. There is evidence that an equivalent price reduction to the overall bundle, one of the individual products in the bundle or distributed among the individual products can alter the perceived attractiveness of the bundle. (Mazumdar and Jun, 1993; Yadav and Monroe, 1993; Heath et al., 1995; Kaicker et al., 1995; Yadav 1995; Johnson et al., 1999). The more detailed discussion regarding the distribution of profit margin is not tested in this study.

Two-part pricing for information goods usually means that a company chooses a pricing structure that is some kind of a combination of a flat access price and a usage price. Pure flat fees can be thought as one form of pure bundling. The choice of pricing structure in various information industries varies (Essegaier et al., 2002). Pricing structures vary even across firms and over time in the same industry as firms frequently experiment with different pricing schemes. Some of the existing literature advocates two-part pricing instead of pure flat rates (e.g. Oi, 1971; Rochet and Stole, 1999). Usage-based pricing can be used to charge high-value users with higher prices, and it can even price discriminate them more efficiently. In fact, the dispersion in consumer valuations is only a problem if a company is forced to use flat prices (Shapiro and Varian, 1999).

Using flat rates or assigning a major share of the price to the access fee brings many advantages. Firstly, a high access price or a flat fee reduces risks in many ways (Zehle, 2001). Secondly, customers strongly prefer flat rates to per-use pricing for psychological reasons as the overestimation of usage and the avoidance of worrying about occasional large bills or whether each usage is common (Fishburn and Odlyzko, 1999). High uncertainty in consumer valuations increases the consumer preference for flat rates (John et al., 1999). Thirdly, strong positive network externalities favour flat rates per-usage pricing, because flat rates encourage usage by existing customers (John et al., 1999). On the other hand, flat rates are not always applicable. When negative network externalities are present, usage prices help to avoid the excessive usage of network resources (Essegaier et al., 2002). In theory, flat rate pricing also increases the risk of price wars (Fishburn and Odlyzko, 1999). In practice, the competitive situations in various markets are fairly stable. The selection of the pricing structure also depends on the company’s objectives, because the access price and the usage price have a totally different impact on consumer behaviour (Danaher, 2002). Consumers seem to be more price-sensitive to
access fees than to usage fees (e.g. Bewley and Fiebig, 1988; Hackl and Westlund, 1996; Danaher, 2002).

2.4 Supporting bundling with segmentation

The efficiency of bundling depends on its ability to reduce variation in consumer valuations. In some cases, simple bundling does not decrease the variation. It can even increase differences and decrease the profitability. The first case is when goods with high variance in valuations are added to a bundle (Bakos and Brynjolfsson, 1999). The second case is when different customer segments differ systematically in their valuations, and the valuations of goods are correlated to one or more underlying variables characterising the segments. In that case, a company should use segmentation and third-degree price discrimination to support bundling. It should create different bundles for segments or offer discounts to the lower valuation segment (Bakos and Brynjolfsson, 1999). When there are other reasons for segmentation than systematic differences in valuations, a company is better off by targeting one bundle for a large aggregate market combining several segments and higher priced special bundles to unusual customer segments (Eppen et al., 1991).

Some variables that could explain the variation in the valuation of information goods are consumer heterogeneity regarding usage, expertise and adoption (Danaher, 2002; Essagaier et al., 2002; Jain and Kannan, 2002). The same variables can be used to segment the information goods market. The information goods customers can be divided to heavy and light users (Jain et al., 1999; Danaher, 2002; Essegaier et al., 2002), to novice and expert users (Alba and Hutchinson, 1987; Mitchell and Dacin, 1996; Mittal and Kumar, 1999; Jain and Kannan, 2002) and to early and late adopters (von Hippel, 1988; Cabral et al., 1997; Shapiro and Varian, 1999). The importance of usage for bundling is quite straightforward, and its meaning to bundle has also been shown in other industries like performing arts (Venkatesh and Mahajan, 1993). Franz and Wolkinger (2003) write that lead users differ from other users regarding the priced bundles of information services.

2.5 Conceptual model and hypotheses

This section presents the theoretical framework model for analysing bundling in the context of information goods. The framework model is shown in Figure 1.

Figure 1 Theoretical framework: building of information goods
### Table 1  
Research hypotheses and results

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Briefly stated</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>What advantages and risks do bundling involve especially in the context of information goods?</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H1</td>
<td>Bundling decreases price sensitivity.</td>
<td>Rejected</td>
</tr>
<tr>
<td>H2</td>
<td>Bundling increases demand measured by purchase likelihood.</td>
<td>Accepted</td>
</tr>
<tr>
<td>H3</td>
<td>Bundling reduces the dispersion of consumer valuations.</td>
<td>Accepted</td>
</tr>
<tr>
<td><strong>What bundling methods are there, and how can a company select the most appropriate one? How should a company distribute the profit margin among the bundled products?</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H4</td>
<td>Mixed-leader bundling increases revenue when the demand for the leader is much higher, but its reservation price is lower than the follower’s price.</td>
<td>Accepted</td>
</tr>
<tr>
<td>H5</td>
<td>Mixed-joint bundling increases revenue when the demands and reservation prices for both products are approximately equal.</td>
<td>Not able to test</td>
</tr>
<tr>
<td>H6</td>
<td>Simple partitioning of the prices in a bundle influences the demand of a bundle.</td>
<td>Accepted</td>
</tr>
<tr>
<td>H7</td>
<td>Consumers prefer flat rates significantly to two-part pricing.</td>
<td>Accepted</td>
</tr>
<tr>
<td>H8</td>
<td>Consumers are more price-sensitive to access fees than to usage fees</td>
<td>Accepted</td>
</tr>
<tr>
<td><strong>Can segmentation increase the efficiency of bundling?</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H9</td>
<td>Usage-based segmentation can increase the efficiency of bundling.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Bundling decreases price-sensitivity of heavy users more than light users.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>• There exists differences in consumer valuations between heavy users and light users that can be utilised in bundling.</td>
<td>Accepted</td>
</tr>
<tr>
<td>H10</td>
<td>Usage-based segmentation affects the selection between two-part pricing and flat fees.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Heavy users prefer more flat rates than light users.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>• Heavy users are more price-sensitive to access than light users.</td>
<td>Accepted</td>
</tr>
<tr>
<td>H11</td>
<td>Expertise-based segmentation can increase the efficiency of bundling.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Bundling decreases price-sensitivity of expert users more than novice users.</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td>• There exists differences in consumer valuations between expert users and novice users that can be utilised in bundling.</td>
<td>Accepted</td>
</tr>
<tr>
<td>H12</td>
<td>Expertise-based segmentation influences the selection between two-part pricing and flat fees.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Expert users prefer more flat rates than novice users.</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td>• Expert users are more price-sensitive to access fees than novice users.</td>
<td>Rejected</td>
</tr>
<tr>
<td>H13</td>
<td>Adoption-based segmentation can increase the efficiency of bundling.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Bundling decreases price-sensitivity of early adopters more than late adopters.</td>
<td>Rejected</td>
</tr>
<tr>
<td></td>
<td>• There exists differences in consumer valuations between early adopters and late adopters that can be utilised in bundling.</td>
<td>Accepted</td>
</tr>
<tr>
<td>H14</td>
<td>Adoption-based segmentation affects the selection between two-part pricing and flat fees.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Early adopters prefer more flat rates than late adopters.</td>
<td>Accepted</td>
</tr>
<tr>
<td></td>
<td>• Early adopters are more price-sensitive to access fees than late adopters.</td>
<td>Accepted</td>
</tr>
</tbody>
</table>
The left side of Figure 1 shows the challenges in pricing information goods, and the right side of Figure 1 displays the advantages and risks involved in bundling. The items to be measured are marked bold. The framework model can be used to measure the change in these items before and after the bundling, to analyse their impact in the efficiency of bundling or their role in the selection of a bundling method. The efficiency of bundling means here the increase in the revenue compared to the unbundling situation. Regarding costs nothing is measured, because all information goods share the same cost structure. The most important measurements are made about customers and demand.

On the left side of Figure 1, demand, price sensitivity and factors explaining the variation in valuations are measured. Usage, expertise and adoption were identified as potential variables explaining the variation. The right side of Figure 1 measures the efficiency of bundling. Basically, only two variables need to be measured: demand and dispersion in valuations after bundling. These measurements are then used to test the hypotheses regarding bundling, which are summarised in Table 1.

### 3 Research methodology

A cross-sectional web-based survey was executed by the company DIGITA during January 2003 in Finland. No pre-selection of the 164 respondents was made, i.e. the survey was an internet survey using the convenience sampling method. Therefore, the results are only tentative. The website used for the research is an information portal for digital TV consumers in Finland (www-digitv-fi). The sample shared many characteristics of consumers who have adopted similar services like digital TV or broadband internet in Finland. Age groups 25–39 (58%), higher educational (44%) and household income levels (68%, over 40,000 euro per year) and men (86%) were over representative in the sample. Still, the commercial launch of mobile TV services requires a large-scale quantitative statistical analysis. Before the internet survey the questionnaire was pre-tested with respondents.

The key method used was conjoint analysis. Other statistical analyses used for analysing the data were cross tabulation and Analysis Of Variance (ANOVA) with the help of SPSS software package version 1997 (Malhotra and Briks, 2003). ANOVA was used for examining the differences among means for two or more populations. The null hypothesis in ANOVA is that all means are equal. The ANOVA method was used in this study to analyse which of the differences in part utilities and attribute importances derived with conjoint analysis between each two groups were statistically significant.

#### 3.1 Conjoint analysis

The key research method used in this study was conjoint analysis. It is a very popular programme based on the optimising method used to measure consumers’ trade-offs when they are choosing between different products and services. The aim of conducting conjoint analysis is to decompose customer evaluation of products and services and to find out which parts of the evaluations, i.e. which product attributes and their levels, are the most important to the customer. Conjoint analysis estimates the structure of consumer preferences (such as part utilities and importance weights) towards overall product evaluations in terms of levels of different product attributes (Green and Srinivasan, 1990). Mathematically, conjoint analysis can be used for situations where multiple
independent variables are interdependent and affect the ordering of a dependent variable. For example, one attribute could be product price expressed in terms of a few relevant price levels. Other attributes could be product quality attributes and their relevant levels. Conjoint analysis forces respondents to trade-off competing values for each other, thereby uncovering purchase motivations of individual consumers realistically (McCullough, 2002). Conjoint analysis is especially helpful at the early stage of product development, when designers decide about the price and quality characteristics of the product. It can be applied to study customer price sensitivity, possibility of segmentation and marketing prospects.

The most common type of conjoint analysis application is the full profile approach, and it was used in this study. The service alternatives and their prices to be evaluated by the consumers were pre-specified and included into the questionnaire. Thus they affected the questionnaire design essentially.

3.2 Key operational measures and data requirements

The hypotheses contain several theoretical concepts that need to be transferred into operational concepts before they can be utilised in the questionnaire. Also, the basis for selecting the services included in the study is explained.

The first set of hypotheses concerned the advantages and risks involved in bundling. It contains the following theoretical concepts: price, price sensitivity, demand and consumer valuation. A price is defined theoretically as an information cue. In this study it is defined as the amount of euros assigned for a product and displayed in the questionnaire (the list price for a product or a service). The price part utility vector derived with conjoint analysis for each consumer served as an operational concept for price sensitivity. Demand was measured by consumers’ purchase intentions. Consumer valuations are measured in this study behaviourally with a subjective reservation price. Although they do not directly measure the reference price or reservation price, the part utility of each channel or bundle was used as a measure for the relative reservation prices. This is a very simplified approach for measuring reservation prices (Jedidi and Zhang, 2002).

The third set of hypotheses is about enhancing the efficiency of bundling with segmentation. This section contains several difficult concepts like a heavy user, a light user, an expert user, a novice user, an early adopter and a late adopter. Because the mobile TV is a totally new innovation, there are no direct measurements for usage, expertise or adoption of the service. Similar services like mobile phone, pay-TV or internet services could be used to form indirect measurements. This study is a consumer behavioural research. Because mobile TV is just another mobile phone service from the customer’s point of view, the existing mobile phone services seemed the most promising candidate. It could be expected that consumers, who use their mobile phones a lot, use many services and adopt new mobile services quickly, could behave similarly with the mobile TV. Although this is a risky assumption, the mobile market looks still the closest counterpart to the future mobile TV markets.

Three mobile TV services were used to test the hypotheses. DIGITA was interested in getting interest information for a wide range of services. It would have been impractical to evaluate the pricing and bundling hypotheses for all these services. The services selected were a news channel, a financial news channel and a games channel. These services were selected for two main reasons. Firstly, most consumers understand these
services easily. Secondly, they were assumed to be suitable for testing the mixed bundling hypothesis due to their expected demands and reservation prices. The research showed that some of these assumptions were not true.

3.3 Design of the questionnaire

The size of the questionnaire was limited to 20 questions. Firstly, the research topic was introduced. Secondly, there were ten questions regarding respondent’s usage, expertise and adoption of other electronic services. Thirdly, to clarify the topic further there were two orientating questions about the possible mobile TV terminals and mobile TV services. DIGITA also requested this information. The latter question regarding services was also used to check the internal consistency of the results. Fourthly, the two bundling questions formed the core of this research. The first conjoint analysis focused on the two-part pricing of a single channel. In the second conjoint analysis, two channels were bundled using either mixed-leader or mixed-joint bundling. Only flat rates were used in the second conjoint analysis. The results of the two conjoint analyses were made comparable by applying simulation to the results of the first conjoint analysis.

The first set of pricing questions was concerned about two-part pricing. Four attributes were included: the channel, the price structure, the monthly access fee and the usage price. Because conjoint analysis is sensitive for a different amount of attribute levels, three levels were used for each attribute. The attributes and their possible levels are shown in Table 2.

Table 2  Two-part pricing: attributes and levels for conjoint analysis

<table>
<thead>
<tr>
<th>Content</th>
<th>Pricing mode</th>
<th>Access fee per month (euros)</th>
<th>Usage price per transaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>News</td>
<td>Flat fee</td>
<td>3</td>
<td>50 cents</td>
</tr>
<tr>
<td>Financial news</td>
<td>Two-part pricing including 20 transactions</td>
<td>6</td>
<td>1 euro</td>
</tr>
<tr>
<td>Games</td>
<td>Two-part pricing including 5 transactions</td>
<td>9</td>
<td>2 euros</td>
</tr>
</tbody>
</table>

The first set of pricing questions in Table 2 concerned three fixed pricing alternatives: a pure flat fee with no usage restrictions, a flat fee plus a usage fee with 20 sessions included and a flat fee plus a usage fee with five sessions included. The usage levels were suggested by DIGITA. The monthly fee was set at 3, 6 or 9 euros per month level and the usage fee at 50 cents, 1 euro or 2 euros per use level. DIGITA expected that the total amount a customer would be willing to pay for this kind of services could be between 15 and 20 euros per month, and the highest price for pay TV bundles per channels is around 7 euros per channel. The second set of pricing questions concerned the bundling of two services in order to measure how mixed-leader or mixed-joint bundling of two channels affects the demand and price sensitivity of those channels.

Four attributes were included: three 2-service bundles, the monthly access fee for the bundle, the share of the price assigned to the leader product and the discount in the mixed-joint bundling. Again, because conjoint analysis is sensitive to a different amount of levels for the attributes, three levels were used for each attribute. The attributes and selected levels are shown in Table 3.
Table 3  Mixed bundling: attributes and levels for conjoint analysis

<table>
<thead>
<tr>
<th>Bundle</th>
<th>Flat fee per channel per month (euros)</th>
<th>Share of the price assigned to the leader (%)</th>
<th>Discount on mixed joint (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixed leader: news (leader) and games</td>
<td>3</td>
<td>40</td>
<td>10</td>
</tr>
<tr>
<td>Mixed leader: games (leader) and financial news</td>
<td>6</td>
<td>60</td>
<td>25</td>
</tr>
<tr>
<td>Mixed joint: news and financial news</td>
<td>9</td>
<td>80</td>
<td>40</td>
</tr>
</tbody>
</table>

Respondents’ purchase intentions were asked using forced choice approach with five-point scales. Both conjoint analysis and simulation were done using the SPSS categories conjoint package (Malhotra and Briks, 2003). The full profile approach with fractional factorial conjoint analysis design was used, and the decision rule for combining different attributes was the linear model. Four attributes and three levels of each attribute were included into the conjoint analysis (see Tables 2 and 3).

4  Research findings

Upon the completion of the data collection, the sample consisted of 164 respondents, which is an adequate number to run conjoint analysis. The summary of part utilities in conjunction with the two conjoint analyses are reported in Appendix 1. In both analyses, the scale was such that the highest purchase intention had the lowest value (1 = would surely buy). Therefore, the lower the utility, the more it increases the consumer’s intention to purchase. The research covered other topics also, but only the pricing-related findings will be discussed. From the point of view of our hypotheses test, Table 1 summarises the results.

The advantages of bundling were not very strongly supported. The reason could be that the research design was too simple. This could also explain why bundling did not reduce price sensitivity (see Appendix 1, H1 rejected). Pricing information was basically the only information cue in addition to the core benefit (the content) available to respondents. Bundling increased the demand in all evaluated cases, but the increase was fairly small (H2 accepted).

The results somewhat supported Hypothesis 3 claiming that bundling reduces the dispersion in customer valuations tested. To test the hypothesis, descriptive statistics were run (see Appendix 2). The test was simply that if the standard deviation for the reservation prices of the bundle is lower than for its parts, dispersion is reduced. For seven cases out of nine the standard deviation for the bundle was smaller. The reduction was largest for the games and financial news bundle at the highest price levels. The reason for this reduction is not very useful and cannot be found from the columns, minimum, maximum and mean. The reason is simply that consumers in the second conjoint analysis are more concentrated on the lowest purchase intention figures (3–5). On the other hand, the dispersion slightly increased for two cases. The cases were the news and games bundle and the news and financial news bundle at the lowest price level, i.e. 3 euros per channel (H3 accepted).

The misbehaving factor, i.e. the discount in mixed-joint bundling disturbed the analysis to some extent. Probably, a more realistic research design with a wider set of
information cues and price ranges would support the expected advantages of bundling much more strongly. The analysis of mixed bundling was complicated by the fact that the original assumptions regarding price elasticity and reservation prices for the services proved to be false. Still, the conditions indicated by Guiltinan (1987) seemed to increase the efficiency of bundling. In addition, this part provided three useful results. Firstly, in mixed-joint bundling too large discounts easily offset the advantages of the increase in demand. Secondly, in all cases the company would have achieved the highest revenues at the highest price levels. Thirdly, the simple partitioning of the price clearly affects the attractiveness of the bundle. How the discount should be exactly assigned was not analysed.

The results regarding two-part pricing are probably the clearest, and they confirm the theory (H6 accepted). As expected, consumers strongly preferred flat rates (H7 accepted). This was true for all consumer groups regardless of their usage, expertise or adoption of electronic services. There were some differences in how strongly the flat rates were preferred and how price-sensitive the consumers were towards flat fees and usage prices. The only contradicting result was that novice users prefer flat rates more than expert users although they were less price-sensitive towards access fees. Flat rates reduce customer uncertainty, which could explain the preference of novice users for them. Another result was that the pricing mode was found to be an important factor. It was found to be more important than price levels, and sometimes even more important than the content. This might indicate that the preference for flat rates was not simply due to the higher estimated individual total usage cost (Morwitz et al., 1998). There could be at least three explanations for this. Firstly, it could be that consumers really do dislike usage prices. Secondly, it could be a methodology problem related to conjoint analysis. In conjoint analysis, the selection of attribute levels affects the relative importance of these attributes. Thirdly, it could be that the simple research design directs the respondent’s attention to the pricing mode.

Regarding usage, expertise or adoption of electronic services, usage seems to be the best indicator of consumer’s pricing behaviour. There were clear differences between heavy users and light users in all pricing-related issues. As mentioned earlier, the pricing-related differences between expert users and novice users could probably be explained with consumer uncertainty. On the other hand, adoption of electronic services does not seem to provide much additional information to pricing. The most significant differences between early adopters and late adopters were related to their interest in various services. Using mobile market as an indicator for usage and expertise seems, however, a somewhat risky assumption in this study. Additional concepts for usage, expertise and adoption should be tested with a representative sample.

5 Conclusion

The research findings of this study supported the conceptual model developed showing how many characteristics of information goods support or limit the selection of bundling as a pricing strategy for new mobile TV services. Hypotheses derived on the basis of the conceptual model were tested with conjoint analysis in the context of a new mobile TV service bundle. Two basic methods of bundling, pure and mixed bundling, were analysed. Also the possibility of two-part pricing for information goods as a combination of a flat access price and a usage price was analysed.
The research findings gave tentative support to the claim that bundling is a useful pricing strategy for information goods. It showed to some extent that many advantages could be achieved by bundling. Second, it gave some guidelines for selecting a bundling method, and for assigning the profit margin among the bundled products. It also showed that segmentation could increase the efficiency of bundling, especially between heavy and light users of new mobile TV services.

The advantages of bundling were not very strongly supported. The limitation of this conjoint analysis research design was that it was too simple. More information cues are needed. Pricing information was basically the only information cue in addition to the core benefit (the content) of new mobile TV services to the respondents. More complicated and more realistic research design should be used in future studies.

For marketing management, this study provides some indications what the future price structure and the price level could be. Also, there seems to be different consumer segments that are interested in different service bundles. The segments also differ regarding pricing, which can provide some ideas for price discrimination. This study suggests that the pricing structure for future mobile TV services could resemble the pricing structures in cable TV more than the typical two-part pricing used in mobile industries. There are three main reasons why flat rate pricing is recommended for TV-like services in mobile TV. Firstly, there are no negative network externalities present. Secondly, consumers seem to strongly advocate flat access rate pricing. Thirdly, flat rate pricing encourages usage, which can support creating positive network effects. Before the commercial launch, a new quantitative consumer research with a representative sample is highly recommended.

References


Appendix 1: Summary of part utilities and ANOVA results in conjoint analyses

Conjoint analysis 1: two-part pricing

![Summary utilities charts](image-url)
The $F$ tests should be used only for descriptive purpose because the clusters have been chosen to maximise the difference among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.
Conjoint analysis 2: mixed bundling

Summary utilities

Utility

Mleader: games as leader + news
Mjoint: news and finance
Mleader: news as leader + game

Summary utilities

Utility

Monthly rate (€/mo)

6 12 18

Summary utilities

Utility

Discount on Mleader (%) 25 40 60

Summary utilities

Utility

Discount on Mjoint (%) 10 25 40
### ANOVA

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Square</td>
</tr>
<tr>
<td>3 euro permonth</td>
<td>2.383</td>
</tr>
<tr>
<td>6 euro permonth</td>
<td>0.611</td>
</tr>
<tr>
<td>9 euro permonth</td>
<td>0.614</td>
</tr>
<tr>
<td>20%</td>
<td>0.606</td>
</tr>
<tr>
<td>40%</td>
<td>5.242</td>
</tr>
<tr>
<td>60%</td>
<td>2.288</td>
</tr>
<tr>
<td>Mleader: games as leader + news</td>
<td>2.282</td>
</tr>
<tr>
<td>Mjoint: news and finance</td>
<td>10.374</td>
</tr>
<tr>
<td>Mleader: news as leader + games</td>
<td>20.795</td>
</tr>
<tr>
<td>10%</td>
<td>5.273</td>
</tr>
<tr>
<td>25%</td>
<td>0.781</td>
</tr>
<tr>
<td>40%</td>
<td>2.02</td>
</tr>
</tbody>
</table>

The $F$ tests should be used only for descriptive purpose because the clusters have been chosen to maximise the difference among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

### Appendix 2: Dispersion of customer valuations

#### Descriptive statistics

<table>
<thead>
<tr>
<th>Channel/bundle</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>SD</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>News 3 euros</td>
<td>1</td>
<td>5</td>
<td>2.4677</td>
<td>1.15776</td>
<td>1.34</td>
</tr>
<tr>
<td>Financial 3 euros (simulated)</td>
<td>0.67</td>
<td>5.33</td>
<td>2.9704</td>
<td>1.1318</td>
<td>1.281</td>
</tr>
<tr>
<td>Games 3 euros (simulated)</td>
<td>–0.33</td>
<td>6</td>
<td>2.8683</td>
<td>1.14513</td>
<td>1.311</td>
</tr>
<tr>
<td>News 6 euros (simulated)</td>
<td>0.67</td>
<td>5.33</td>
<td>2.9731</td>
<td>1.0171</td>
<td>1.035</td>
</tr>
<tr>
<td>Financial 6 euros</td>
<td>1</td>
<td>5</td>
<td>3.4758</td>
<td>1.08298</td>
<td>1.173</td>
</tr>
<tr>
<td>Games 6 euros (simulated)</td>
<td>–0.33</td>
<td>5.67</td>
<td>3.3737</td>
<td>1.03558</td>
<td>1.072</td>
</tr>
<tr>
<td>News 9 euros (simulated)</td>
<td>0.67</td>
<td>5</td>
<td>3.0269</td>
<td>1.00459</td>
<td>1.009</td>
</tr>
<tr>
<td>Financial 9 euros (simulated)</td>
<td>0.67</td>
<td>5</td>
<td>3.5296</td>
<td>0.93416</td>
<td>0.873</td>
</tr>
<tr>
<td>Games 9 euros</td>
<td>1</td>
<td>5</td>
<td>3.4274</td>
<td>1.13223</td>
<td>1.282</td>
</tr>
<tr>
<td>Mixed Leader: News (Leader) + Games, 6 euros</td>
<td>1</td>
<td>5</td>
<td>3.52</td>
<td>1.233</td>
<td>1.52</td>
</tr>
<tr>
<td>Mixed Joint: News + Finance, 6 euros</td>
<td>1</td>
<td>5</td>
<td>3.19</td>
<td>1.34</td>
<td>1.795</td>
</tr>
<tr>
<td>Mixed Leader: Games (Leader) + Finance, 6 euros</td>
<td>1</td>
<td>5</td>
<td>4.18</td>
<td>0.937</td>
<td>0.879</td>
</tr>
<tr>
<td>Mixed Leader: News (Leader) + Games, 12 euros</td>
<td>1</td>
<td>5</td>
<td>4.24</td>
<td>0.82</td>
<td>0.673</td>
</tr>
<tr>
<td>Mixed Joint: News + Finance, 12 euros</td>
<td>2</td>
<td>5</td>
<td>4.09</td>
<td>0.937</td>
<td>0.878</td>
</tr>
<tr>
<td>Mixed Leader: Games (Leader) + Finance, 12 euros</td>
<td>3</td>
<td>5</td>
<td>4.40</td>
<td>0.673</td>
<td>0.452</td>
</tr>
<tr>
<td>Mixed Leader: News (Leader) + Games, 18 euros</td>
<td>1</td>
<td>5</td>
<td>4.31</td>
<td>0.876</td>
<td>0.767</td>
</tr>
<tr>
<td>Mixed Joint: News + Finance, 18 euros</td>
<td>2</td>
<td>5</td>
<td>4.39</td>
<td>0.783</td>
<td>0.613</td>
</tr>
<tr>
<td>Mixed Leader: Games (Leader) + Finance, 18 euros</td>
<td>3</td>
<td>5</td>
<td>4.56</td>
<td>0.559</td>
<td>0.313</td>
</tr>
</tbody>
</table>

Valid N (listwise)
The optimal ratio between advertising and sales income

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Abstract: We derive the optimal ratio between advertising and sales income when a publisher maximises its profits with respect to advertising space and product price. If consumers are more adverse towards advertising than towards price, the ratio is higher. The same theoretical framework is used to examine the relationship between the structure of media revenues and product quality. The findings of the model confirm empirical observations and some stylised facts of the media industry. In addition, we discuss some possible extensions of the model in order to include the evolution of business methods in media markets, and describe the managerial implications.

Keywords: advertising; Media markets; Pricing; revenue management.

Reference to this paper should be made as follows: Mangâni, A. (2007) ‘The optimal ratio between advertising and sales income’, Int. J. Revenue Management, Vol. 1, No. 1, pp.65–78.

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1 Introduction: theoretical models and empirical observations

Many media derive their revenues from both sales to consumers and sales of advertising space to advertisers. This is a characteristic of newspapers, magazines, pay-TV and internet service providers. In all these cases revenue management is complex, because the publishers participate in what is called a ‘dual-product market’: the revenues due to direct sales (hereafter, sales income) are related to advertising revenues, and the other way round. In addition, the objectives of publishing firms are sometimes misinterpreted by public opinion: although it seems quite reasonable to assume that a publisher, as well as any other private firm, wants to maximise total profits, many observers describe the activities of publishers as driven by the maximisation of circulation (in the case of newspapers), audience (TV) or accesses (internet). But, in general, what is the optimal ratio between advertising revenue and sales income?
Although several authors have put forward theoretical models that analyse the characteristics of media markets and firms’ behaviour, the question of the optimal advertising/sales ratio has never been addressed directly. A crucial assumption in the theoretical models of media markets regards the attitude of consumers (readers, viewers, etc.) towards advertisements contained in the media. In particular, there is a debate in the literature as to whether consumers increase or decrease their consumption of media products when the space devoted to advertising is higher, that is, if they are ‘ad-lovers’ or ‘ad-adverse’. In the case of newspapers and magazines, empirical research suggests that the attitude towards advertising is country-specific, because it is deeply rooted in cultural habits. While American readers are apparently ad-loving (see, among others, Bogart, 1989; Rosse, 1980), European studies indicate that a significant percentage of the European press readership is ad-averse (see Sonnac, 2000 and references therein). Under the hypothesis of ad-loving, there is a circulation effect between the quantity of advertising and the size of the readership, giving rise to the so-called circulation spiral (Gustafsson, 1978).

According to this theory “the larger of two competing newspapers is favoured by a process of mutual reinforcement between circulation and advertising, as a larger circulation attracts advertisements, which in turn attracts more advertising and again more readers. In contrast, the smaller of two competing newspapers is caught in a vicious circle, its circulation has less appeal for the advertisers, and it loses readers if the newspaper does not contain attractive advertising. A decreasing circulation again aggravates the problems of selling advertising space, so that finally the smaller newspaper will have to close down” (Gustafsson, 1978).

The difference between the ‘American’ and ‘European’ approach is also reflected in the theoretical studies of newspaper industry. Blair and Romano (1993) analysed the pricing decisions of a newspaper publisher, assuming that the circulation demand rises with increases in the quantity of advertising. Sonnac (2000) examined the implications of assuming readers’ advertising aversion on the main variables determined in a monopolistic press industry, namely, the price and circulation, advertising price and volume of newspapers, from a theoretical viewpoint. Her most important finding was that the circulation spiral assumption holds even when readers are ad-averse.

A study (reported in Sonnac, 2000) examined ad-avoidance for six media in five different European countries (France, Spain, Italy, the UK and Germany). The study found that ad-avoidance crucially affects each of these countries and each of the media, although this avoidance does not manifest itself in the same manner and in the same proportion across European countries. Table 1 refers to the number of persons among the five countries represented in the panel who said ‘yes’ to the following question: “When you read a newspaper and/or a magazine, do you avoid the advertising pages?”

Table 1 might suggest that the aversion towards advertising is higher in the UK than in other countries. However, if we look at Table 2 regarding the breakdown of newspapers’ revenues between advertising and sales, the share of revenues due to advertising is relatively high in the UK. The same table shows that the proportion of advertising revenues varies significantly in the countries under review. Of course, Table 2 reports average values, and these have to be interpreted carefully. However, it might be useful to elaborate a model to explain such differences in the source of revenues, a model that is not driven only by a higher or lower aversion of consumers towards advertising.
The optimal ratio between advertising and sales income

Table 1    Comparing ‘ad-avoiders’ in newspapers and magazines

<table>
<thead>
<tr>
<th>Country</th>
<th>Newspapers (%)</th>
<th>Magazines (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>France</td>
<td>51</td>
<td>50</td>
</tr>
<tr>
<td>Italy</td>
<td>51</td>
<td>46</td>
</tr>
<tr>
<td>Spain</td>
<td>48</td>
<td>53</td>
</tr>
<tr>
<td>Germany</td>
<td>54</td>
<td>43</td>
</tr>
<tr>
<td>UK</td>
<td>62</td>
<td>53</td>
</tr>
</tbody>
</table>

Note: Reported from Sonnac (2000).

Table 2    Newspapers’ advertising and sales revenues (2002)

<table>
<thead>
<tr>
<th>Country</th>
<th>Advertising (%)</th>
<th>Sales (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>France</td>
<td>47</td>
<td>53</td>
</tr>
<tr>
<td>Spain</td>
<td>56</td>
<td>44</td>
</tr>
<tr>
<td>Germany</td>
<td>57</td>
<td>43</td>
</tr>
<tr>
<td>Netherlands</td>
<td>52</td>
<td>48</td>
</tr>
<tr>
<td>UK</td>
<td>65</td>
<td>35</td>
</tr>
</tbody>
</table>


In this paper we derive the optimal ratio between advertising and sales revenues, in order to generalise and simplify an intuition of Masson et al. (1990). The model fits magazines and newspapers particularly well, but might be applicable to other types of media (for example, internet content providers and pay-TV). We assume a monopoly market, because the study of oligopoly is affected by too specific assumptions regarding consumer preferences (demand), a firm’s costs and the structure of the ‘game’. We do not make any assumptions about the functional form of each variable, thus the analysis should acquire a greater generality.\(^1\)

Section 2 introduces the ‘basic’ model and describes some ‘stylised facts’ that, together with theoretical and empirical findings of other authors, confirm the robustness of its results. Section 3 presents a numerical example, which may be useful for the application of analytical tools of the model. Section 4 discusses the main results of the model, which is modified through the introduction of the newspaper’s ‘quality’ among the choice variables of the publisher. Other extensions regard the oligopolistic competition of newspapers, product differentiation and the rise of free media products. Section 5 sums up, suggests the limitations of the model and highlights its relevance in revenue management.

2 A simple model

Assume that there is a newspaper monopolist who sells the product to readers (hereafter, consumers) with a price \(p\), and advertising space \(a\) to firms at a fee \(t\), with \(p, a, t > 0\). Let the number of newspapers sold \(n\) be a function of the advertising space \(a\) and price \(p\). Therefore \(n = n(a, p)\), with \(\partial n/\partial a < 0\), that is we are assuming ‘ad-adverse consumers’ and \(\partial n/\partial p < 0\). On the other hand, assume that the fee \(t\) is positively correlated to the
number of newspapers sold, that is it depends on the number of readers. Thus \( t = \alpha(n(a, p)) \), with \( \partial t/\partial n > 0 \). These are standard assumptions made in previous media markets models and are quite realistic: the publisher simply ‘produces’ readers both for direct sales and for the sale of advertising space.

Of course, advertising rates depend not only on the number of readers who ‘access’ the advertisements (i.e. circulation) but also on their social and cultural characteristics. However, ‘audience’ size is normally seen as the most important factor affecting the price of advertisements (see, among others, Picard, 2002).

The profit function is thus given by

\[
\Pi = pn(a, p) + at(n(a, p)) - C(n(a, p))
\] (1)

where \( C(n(a, p)) \) is the cost of production of \( n \). Suppose that \( \Pi \) is strictly concave in \( a \) and \( p \) and twice continuously differentiable, and assume that the monopolist chooses \( a \) and \( p \) to maximise \( \Pi \). The first-order conditions are

\[
\frac{\partial n}{\partial a} \left[ p + \alpha \frac{\partial a}{\partial n} - \frac{\partial C}{\partial n} \right] = -t
\] (2)

\[
\frac{\partial n}{\partial p} \left[ p + \alpha \frac{\partial a}{\partial n} - \frac{\partial C}{\partial n} \right] = -n
\] (3)

Dividing Equation (2) by Equation (3) we obtain

\[
\frac{\frac{\partial n}{\partial a}}{\frac{\partial n}{\partial p}} = \frac{t}{n}
\] (4)

Multiplying both terms by \( a/p \) and the first term by \( n/n \) yields

\[
\frac{ta}{pn} = \frac{\eta_{n,a}}{\eta_{n,p}}
\] (5)

where \( \eta_{n,a} = (\partial n/\partial a)/(\partial n/\partial a) \) and \( \eta_{n,p} = (\partial n/\partial p)/(\partial n/\partial p) \). The optimal advertising–sales ratio is equal, in the optimum, to the ratio between the elasticity of demand with respect to advertising space and the elasticity of demand to product price. In other words, when the aversion of readers towards advertising is higher than their aversion towards price, the newspaper will derive most revenues from advertising. This surprising result may explain some inconsistencies observed in the first section.

The model presented in this section assumes that consumers are averse to advertisements. Indeed, some economists suggest that a part of readers like advertisements in the print media, because advertising provides information that may be useful for purchases (informative advertising). For this reason, a higher quantity of advertising in the paper increases the consumption of the media by some readers. Even accepting the possibility of ‘ad-lover’ consumers, the result obtained in this section is still valid, at least when it is applied to the traditional newspaper market. In this context, it is not important where the majority of consumers’ attitude lie, or ‘how many’ consumers are ‘ad-adverse’ or ‘ad-lovers’. What is important is the effect of advertising on total circulation: if the advertising aversion effect prevails, an increase in advertising quantity...
The optimal ratio between advertising and sales income

will determine, anyhow, a reduction in circulation; thus the assumption $\frac{\Delta n}{\Delta t} < 0$ may be maintained. In fact in the case of newspapers and magazines, the product offered is the same for all readers, and it is impossible to verify whether a buyer is an ‘ad-lover’ or ‘ad-adverse’. This prevents market segmentation, unless an editor is publishing different titles.

An application of the model presented is the newspaper industry in the UK, described by Doyle (2002) as follows: “The UK national newspaper market can be subdivided into at least two broad segments: up-market or ‘quality’ titles and mass-market or ‘popular’ titles. … so-called quality newspapers aimed at wealthier socio-economic sections of the population tend to derive a higher proportion of their income from advertising than their more popular tabloid rivals”. These figures are reported in Table 3. The data do not show that British readers of quality titles ‘love’ advertising, rather that, given a level of advertising aversion (which we may assume to be constant across different segments of readers), a lower price elasticity of a group of readers causes a higher share of advertising revenues, according to the outcome of the simple model presented in this paper.

In other words, a group of consumers with homogeneous socio-cultural characteristics may reveal themselves to be particularly adverse to advertising messages. However, the ‘economic’ characteristics of the group are likely to affect the price elasticity of demand. In such cases, the optimal ratio between advertising and sales revenues may be higher than one that goes against what might be expected if only the readers’ attitude towards advertising was considered.

Table 3  Revenues of UK national newspapers (2003)

<table>
<thead>
<tr>
<th>Type of publication</th>
<th>Advertising (%)</th>
<th>Sales (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>National quality dailies (e.g. The Telegraph)</td>
<td>64</td>
<td>36</td>
</tr>
<tr>
<td>National popular dailies (e.g. The Sun)</td>
<td>46</td>
<td>54</td>
</tr>
<tr>
<td>National quality Sundays (e.g. Sunday Times)</td>
<td>65</td>
<td>35</td>
</tr>
<tr>
<td>National popular Sundays (e.g. Mail on Sunday)</td>
<td>46</td>
<td>54</td>
</tr>
</tbody>
</table>

Source: Advertising Association (http://www.adassoc.org.uk)

The analytical result confirms some empirical observations and general intuitions concerning the structure of revenues of media firms. It is usually suggested that advertisers are attracted by those media which are accessed by wealthier segments of population, when they are readers, viewers, listeners and so on (Narasimhan, 1984; Kalita and Ducoffe, 1995). The willingness-to-pay of these sections of consumers is high and thus, for a given effectiveness of advertising (though difficult to estimate), their expenses will be greater and advertisers will earn larger revenues. In particular, it is suggested that publications that target high-income readers tend to have smaller circulation but earn more per-copy revenue. For example, Koschat and Putsis (2002) found that publications whose readers are concentrated in the age range of 29–39 years earn a premium, as do the publications with a higher-income readership. On the other hand, Kalita and Ducoffe (1995) found that increased advertising revenue compensate for decreased circulation revenue in the case of expensive magazines. Indeed, a consumer with higher education and income exhibits a high willingness-to-pay for all goods including the media product, and thus the price elasticity of demand in Equation (5) will be low. This explains why newspapers targeted to individuals that earn high income and characterised by broad education derive most revenues from advertising. This result applies also to magazines.
The magazine market has recently been explored by several theoretical and empirical studies (among others, Kalita and Ducoff, 1995; Koschat and Putsis, 2002; Hakfoort and Weigand, 2003; Depken, 2004; Depken and Wilson, 2004). In actual fact, advertising is by far the more important source of revenues of the business or professional magazines. On the contrary, those magazines that present, for example, leisure and travel contents (‘consumer’ titles) derive the majority of their income from cover sales.

In conclusion, the attention devoted to consumers’ preferences regarding advertising, both in theoretical and empirical studies, has probably been exaggerated and driven by the desire to explain some stylised facts. We have shown that preferences towards advertising may offer only partial support for revenue management: in two separate countries or markets, when the aversion towards advertising is the same but the price elasticity is different, the optimal advertising/sales ratio should vary across the two samples. These considerations are important for editors that operate in distinct media markets.

### 3 From theory to practice

How can the model be ‘translated’ to practical implications for the revenue management of media firms? First, it is useful to show how the variations of the cover price and the quantity of advertising may modify the share of advertising revenues. In fact, one should object that this share is not easily manageable by the publisher, given the complexity of the ‘dual product markets’. For example, let us suppose that the publisher wants a higher share of advertising revenues. It is not clear if it should increase the quantity of advertising or cut the cover price of the newspaper. In fact, more pages devoted to advertising would decrease circulation \( n \) and thus also the fee \( t \) charged to advertisers. Hence, the total effect on the ratio between advertising revenues and sales income is unclear.

In reality, it is sufficient to assume that the advertising fee is proportional to the number of readers, that is \( t(n) = kn(a, p) \), to obtain the following result: an increase in the advertising quantity and/or a decrease in the newspaper’s price lead to a growth of the advertising revenues/sales income ratio, and the other way around\(^3\). However, the two actions have different effects on circulation: if advertising rises, the circulation decreases; if the price is cut, the circulation is higher. This difference is important when different ‘types’ of publications want to increase the share of advertising revenues: a ‘generalist’ title will probably prefer to cut the cover price, while ‘specialised’ publications will tend to vary the quantity of advertising.

Given that the choice variable is known by the publisher, how can it verify if the advertising revenues/sales income ratio is optimal? For example, if \( \eta_{a} = 1 \) and \( \eta_{p} = 0.5 \), the revenues deriving from advertising should be two times the income deriving from copy sales. Let us assume that because of the massive theoretical and empirical work on the theme, the price elasticity of demand may be estimated. Much more complicated is to estimate the elasticity of circulation with respect to the quantity of advertising in a newspaper, since few studies have directly addressed this topic.

A first option is to analyse the historical data of newspapers’ circulation and advertising and conduct a standard econometric analysis. However, the circulation of newspapers is affected by several factors (quantity of advertising, cover prices, newspapers’ contents, nature of competition, personal habits, etc.). It is a complex
exercise to set out the effect of each variable on circulation by looking at the available data. Probably, an approach based on specific surveys is more useful. However, a ‘direct’ investigation is not adequate. For example, it is difficult to obtain relevant information using questions such as “If the quantity of advertising in your newspaper increases by 10%, how much will you reduce your annual consumption?” On one hand, the readers would find the question too complex; on the other hand, a reader tends to purchase, in the medium-short run, the same title, and he/she substitutes it for another when, for example, its contents are no longer satisfying or the advertising is excessive.

For these reasons, it is better to adopt an indirect approach. For example, a survey as the one reported in Section 1, when adequately modified and refined, may provide an estimation of the attitude of readers towards print advertising. A possible question may be “When you read a newspaper and/or a magazine, how much advertising do you avoid?”, with multiple choices such as 100%, 75%, 50% and so on. The survey reported in Section 1 showed only the share of readers who were ‘absolutely’ adverse to advertising. Actually, many readers read only a part of the advertising messages. In order to transform this information in elasticity of circulation with respect to advertising, we interpret \( n \) in the model as the number of pages ‘read’ rather than as the number of readers or copies sold. The following numerical example illustrates this approach.

Let us assume a newspaper with \( N = 1000 \) readers. Each copy of the newspaper has ten pages of information and ten pages of advertising. A survey is conducted among the newspaper’s readers. The survey shows that 500 readers avoid the advertising pages completely, while the other 500 read only half of the advertising pages (for the sake of simplicity, we consider only these two cases). Denote with \( n \) the total (information and advertising) pages of the newspaper effectively ‘read’. Hence, we have \( n_0 = (500 \times 10) + 500 \times (10 + 5) = 12,500 \). Which is the effect on \( n \) if the quantity of advertising increases by 10%, that is when it covers 11 pages instead of 10 (with the total newspaper’s pages being constant)? We have that \( n_1 = (500 \times 9) + 500 \times (9 + 5.5) = 11,750 \). Therefore, the number of pages read decreases by 6%. In this case, the elasticity of circulation to advertising is equal to \(-0.6(-6%/10%)\). Assume that the elasticity of circulation to price is \(-0.3\); the optimal ratio between advertising revenue and sales income is 2. Of course, a survey may be much more accurate than this example: for instance, there will be readers who read a third of advertising pages, others who read all the advertising pages. The only objective of this example is to show how the analytical results of the model may be implemented for practical applications in media revenue management.

### 4 Extensions and discussion

In this section we extend and discuss the results obtained in the previous section. This will be done by introducing quality issues and interpreting the result with respect to different media, on account of the rapid evolution of the media system.

#### 4.1 Newspaper quality

A possible objection to the model presented is that readers usually decide to purchase a newspaper taking into account its contents, and not only its price and the proportion of the newspaper’s surface devoted to advertising. In other words, the circulation depends
also on the degree of product differentiation of a newspaper. Economists usually
distinguish the differentiation based on quality (vertical product differentiation) from the
differentiation based on variety (horizontal product differentiation). Although the latter
has sense within an oligopolistic environment, the choice of product quality may have
some effects in a monopoly market. Let us examine if the inclusion of quality issues in
the model tends to modify the main result and/or provide additional information for
revenue management4.

The quality of a newspaper depends, for example, on the professional skills and
expertise of journalists, the number of reporters and editors, the depth of coverage, as
well as on physical characteristics of the paper such as the possibility to publish full-
colour photos and so on. Of course, it is difficult to measure the quality of a newspaper.
However, let us assume that a publisher invests an amount $s$ in the quality of its
newspaper; thus $s$ is another component of total costs. In addition, let us suppose that the
quality of the newspaper is expressed by $s$, in the sense that higher investments determine
higher quality. Finally, we assume that the number of readers $n$ (circulation) is increasing
in the quality of the newspapers. The profit function of the editor is thus

$$\Pi = pn(a, p, s) + at[n(a, p, s)] - C[n(a, p, s)] - s$$

(6)

We maintain the assumptions made in the previous section; in addition, we assume that
$\varphi_n/\varphi_s > 0$. The publisher maximises Equation (6) with respect to $a$, $p$ and $s$. Under the
usual assumptions for profit maximisation, the first-order conditions are

$$\frac{\partial n}{\partial a} \left[ p + a \frac{\partial t}{\partial n} - \frac{\partial C}{\partial n} \right] = -t$$

(7)

$$\frac{\partial n}{\partial p} \left[ p + a \frac{\partial t}{\partial n} - \frac{\partial C}{\partial n} \right] = -n$$

(8)

$$\frac{\partial n}{\partial s} \left[ p + a \frac{\partial t}{\partial n} - \frac{\partial C}{\partial n} \right] = 1$$

(9)

It is possible to verify that condition in Equation (5) still holds. Moreover, the first-order
conditions yield other expressions with high informative content. For example, dividing
Equation (9) by Equation (8) we obtain

$$\frac{\left( \frac{\partial n}{\partial s} \right)}{\left( \frac{\partial n}{\partial p} \right)} = \frac{1}{n}$$

(10)

Multiplying both terms by $n/p$ and $s/n$ yields

$$\frac{s}{pn} = \frac{\eta_{n,s}}{\eta_{n,p}}$$

(11)

where $\eta_{n,s} = (\varphi_n/\varphi_s)/(\varphi_s/\varphi_s)$. The result described in Equation (11) is quite reasonable and
intuitive. The optimal ratio between investments in quality and sales income is directly
proportional to the elasticity of circulation with respect to quality, and inversely
proportional to the elasticity of circulation to copy price. This result confirms that the
The optimal ratio between advertising and sales income

quality of a newspaper is high when readers are characterised by high income, that is when \( \eta_{kn} \) is low. In addition, note that dividing Equation (9) by Equation (7) we have

\[
\frac{\partial n}{\partial s} = -\frac{1}{t}
\]

Multiplying both terms by \( n/a \) and by \( s/n \) yields

\[
\frac{s}{at} = \frac{\eta_{ns}}{\eta_{n,a}}
\]

Hence, the quality-investments/advertising-revenues ratio is directly proportional to the preference for quality, and inversely proportional to the advertising aversion. The lower is the readers’ aversion towards advertising, the higher the investments in quality will be. This result shows analytically the process of circulation spiral described in Section 1: a newspaper may exploit its advertising income to offer contents with greater quality, enlarge circulation and then increase advertising revenues. The more rapid is this virtuous circle, the less-averse readers are to advertising. The results expressed by Equation (11) and Equation (13) are more intuitive than the formula expressed by Equation (5), but all results are derived from the same analytical framework. This reasserts the robustness of the analysis. In addition, all findings reflect the actual functioning of newspaper and magazine markets. A limitation of these results is that higher investments not always produce changes that are perceived as quality enhancements by readers.

4.2 Oligopoly markets and price competition

The model that we put forward assumes a monopoly market, mainly for methodological reasons. Of course, a pure monopoly market is rare in real industries. When a newspaper faces the competition of other titles, the price elasticity of circulation in Equation (5) will increase, because the value of \( \eta_{kn} \) depends on the availability of substitutes. In other words, price competition between newspapers may vary the own price elasticity (indeed, the own price elasticity resumes the information regarding the price cross-elasticity, which is very difficult to estimate), and thus also the advertising/sales ratio may change. Let us assume, for the sake of simplicity, that \( \eta_{n,a} \) is constant; other available titles thus reduce the optimal advertising/sales ratio. This explains why, in the market of ‘popular’ newspapers and magazines characterised in all countries by many competitors and fiercer price competition, the proportion of revenues deriving from advertising is lower, as opposed to ‘quality’ markets that which normally present a quite high level of concentration.

The higher concentration in the quality markets is probably due to the nature of competition between firms. When these tend to compete by adopting strategies of vertical product differentiation (differentiation defined by ‘quality’), a well-established result in the literature of industrial organization is that the level of concentration has a lower bound. Indeed, firms implement strategies of vertical product differentiation just for relaxing price competition and segmenting the market (see the seminal work of Shaked and Sutton, 1983). This reduces both the cross and own price elasticity of demand.
Nevertheless, a strong price competition is possible among quality newspapers. A textbook example is given by the price war in the UK newspaper industry during the 1990s. The war began when the Rupert Murdoch’s News International started a series of price reductions in 1993, after a long period of price stability. The cover price of *The Times* was reduced from 45 p to 30 p. Other titles were soon forced to cut their cover prices. The price war continued until 2000, and it caused an incredible increase in the circulation of *The Times*. Doyle (2000) shows that such an aggressive price strategy increased the price elasticity of newspaper circulation, which was equal to 0.58 in June 1993 and 1.68 after 7 years. According to Equation (5), this should have determined a reduction of the share of advertising revenues. Indeed, Doyle (2000) asserts that “by June 2000, sales income was well in excess of pre-price war levels”. However, the quantity of advertising being constant, a greater circulation increases the willingness-to-pay of advertisers, thus it is possible that also the fee $t$ increases. Hence, depending on the functional form of $t(n)$ with respect to $n(a, p)$, we have contrasting effects on the advertising/sales ratio. This point is accurately illustrated by Hoskins et al. (2004) by means of graphical analysis.

Newspapers also compete with other media. The elasticity of substitution of different media (for both consumers and advertisers) is a long-debated issue, especially for the interest of advertisers and brand companies in the optimal media mix for their marketing activities. However, it is complex to include this aspect of media markets in the model presented, because the same individual often purchases and accesses different media at the same time. In reality, Silk et al. (2002) show that interdependencies among market demands for seven of the eight major US mass advertising media are rather weak.

However, in recent years several observers have highlighted that internet represents a serious threat for the newspaper industry. Given its highly informative content, the internet is perceived by population as quite similar to traditional print media. In particular, the websites that provide news and information online represent the media which may be considered as a close substitute of traditional newspapers. On the contrary, the different nature and depth of magazines’ and TV’s contents should permit them to resist more than newspapers. Today, all newspaper editors have created online versions of their traditional titles: readers may find (free of charge or paying a fee) all or a part of the news contained in the paper version. This evolution may determine a ‘cannibalisation’ of traditional newspapers’ revenues, since some readers quit purchasing the paper version to access the editorial content online although these are offered with lower quantity and quality. In other words, the consumption of online newspapers may increase the own price elasticity of traditional newspapers. If the aversion towards advertising is constant, we will have a reduction of circulation as well as advertising revenues. However, these effects may be associated to the increase in the newspaper cover price.

In fact, condition in Equation (5) may be expressed as

$$p = \frac{\tan \eta_{n,p}}{\eta_{n,a}}$$

(14)

If $\eta_{n,p}$ and $\eta_{n,a}$ are constant, a lower circulation $n$ will make the optimal price $p$ to increase. Once more, the effect on the advertising/sales optimal ratio is uncertain: advertising revenues decrease (lower circulation affects the fee $t$) but sales income may
The optimal ratio between advertising and sales income

be higher or lower. The characteristics of readers determines which effect will prevail, which is often related to national habits in media consumption.

An example is the Italian newspaper industry. The first online journals appeared in 1999. Between 2000 and 2002 the accesses to online versions of national newspapers have been constantly increasing, determining a reduction in the circulation of traditional newspapers by 4% (Filistrucchi, 2004). The advertising revenues of newspapers decreased from 1640 to 1406 million euros between 2000 and 2002, while in the same period the sales income grew from 1187 to 1326 million euros. The breakdown in total revenues between advertising and sales in the industry decreased from 58% to 51.5%. Therefore, the increase in newspapers’ price compensated the reduction of circulation, which reduced the advertising revenue. A similar phenomenon was observed in the UK magazine market. Between 1986 and 1999 the revenues deriving from cover sales have been constantly increasing. Doyle (2000), reporting these data, suggests that this was caused by an increase in the cover price of more specialised magazines, whose diffusion grew up as opposed to a decline in the market share of ‘generalist’ titles. Therefore, the price elasticity of magazine circulation is quite low: the price increase did not determine a fall in circulation. Thus advertising revenues being constant, sales income increased.

4.3 Free press

The relationship between the quality of informative content and the sources of revenue may be also explored with respect to free dailies. Free newspapers in many countries have experienced a steady increase in numbers, circulation and advertising revenues in recent years. Penetration has increased in a majority of countries for which data are available in the past few years (see, for example, the data reported in the website of the World Association of Newspapers, http://www.wan-press.org/). In some countries free papers are responsible for a substantial part of the total daily circulation in metropolitan areas. Free dailies are normally distributed in the public transport system, and also in office buildings, shopping malls, hospitals and university campuses. The first ‘modern’ free daily, Metro, was founded in Stockholm in 1995; editions in other countries soon followed. In these markets the assumption of a monopoly market fits particularly well: often, in each distribution point there is only one title available. Since a free daily derives its revenues solely from advertising, the free press market is very similar to commercial broadcasting (commercial television and radio stations). The profit function of the publisher is thus

$$\Pi = at[n(a, s)] - C[n(a, s)] - s$$

(15)

It is easy to show that condition in Equation (13) holds. Once more the circulation spiral is at work. This is evident if we express Equation (13) as follows:

$$s = at \frac{\eta_{a,s}}{\eta_{n,s}}$$

(16)

In other words, the investments in the quality of the publisher are proportional to advertising revenues (and the other way around).
5 Conclusions

Many newspapers and magazines derive the bulk of their revenues from advertising. In this paper we have shown that, given the peculiarities of media markets, this is possible even when readers are averse to commercial advertisements. In fact, given some assumptions, we have obtained the surprising result that advertising revenues actually exceed product revenues when the elasticity of demand (circulation) with respect to advertising space is higher than the elasticity of demand (circulation) to product price. All other things being equal, when consumers’ aversion towards advertising rises, the share of advertising revenues rises as well.

Using the same analytical framework, we have also shown what is the optimal relationship between investments in quality, advertising revenues and sales income. All these results seem to be confirmed by some stylised facts regarding media markets. Finally, we have discussed some implications of the model and considered some extensions to include the possibility of price competition and product differentiation.

It would be interesting to extend this analysis to an oligopoly market in order to check the robustness of the results, but this would imply specific assumptions regarding the demand functions and the structure of the ‘game’. These ‘analytical’ limitations are clear in recent studies that put forward theoretical models of media markets, for example, Gabszewicz et al. (2005), Cunningham and Alexander (2004) and Gabszewicz et al. (2002). Such limitations are reflected in the (scarce) ability of the models to be used in revenue management. There are several methodological reasons to assume a monopoly market (see, for example, Shugan, 2002). In addition, the assumption of a monopolist publisher may fit many local markets of several advanced countries (see, for example, Picard, 2004, who asserted that “the newspapers industry in the United States is characterised by monopoly and its attendant market power, with 98% of newspapers existing as the only daily paper published within their markets”).

The result obtained in this paper may shed some light about the debate on the attitude of readers towards print advertising. Economic scholars assert that American readers are ad-lovers; apart from the difficulty of verifying such a phenomenon, this assumption is used to justify that the advertising/sales ratio is higher in the USA than in Europe. In reality, what is important is the relationship between the elasticities defined in this paper: although readers are ad-verse, a low price elasticity can explain why newspapers derive most revenues from advertising. Actually, also those who accept the assumption that some readers are ad-lovers, admit that the (virtuous) circulation spiral presents an ‘upper bound’ for which any increase in the advertising space is perceived negatively by the readership (on this point, see Sonnac, 2000). From an empirical point of view, it would be interesting to find out where the majority of consumers’ attitude towards advertising lie although this would not modify the main results of the model presented. This analysis may be developed in future research, since it is beyond the scope of this paper.

The findings of this paper are relevant for practitioners in two respects:

1 The model is applicable to newspapers, magazines, pay-TV, internet service providers and to all firms that may derive their revenues from both advertising and sales; in relation with pay-TV and internet service providers, the model may be modified in order to take into account the technological evolution that permits a segmentation of readers–consumer by offering distinct media products.
The optimal ratio between advertising and sales income

2 The general outcome holds even if one assumes a specific form of the function, which links ‘circulation’ to the quantity of advertising; this is important when a publisher has detailed empirical information about the consumers’ response function to advertising, for example, in the case of internet publishing. On the web it is easier to observe how consumers behave and respond to different advertising configurations, as well as to follow the readers’ ‘actions’ on banners and other formats of advertising.

The management of the revenues of media firms presents specific characteristics, which differentiate it from the revenue management of most other firms. For this reason, it is important to develop *ad hoc* theoretical and empirical tools. These will permit operations in markets that are continuously evolving, under the impulse of technological innovation and increasing competitive pressure.

References


**Notes**

1Baye and Morgan (2000) put forward an explanation of the ratio between advertising revenues and subscription revenues. The results, however, are difficult to interpret through standard empirical tools possessed by practitioners.

2However, there are some media that permit to differentiate the product according to the characteristics of consumers, such as the internet service providers. The study of Prasad et al. (2003) is particularly interesting in this context. These authors suggest that, with contemporary electronic media, media providers can inexpensively design and offer several price-advertisement choices to consumers, and the managerial decision (related to balancing the revenue from advertising and subscription) is not restricted to setting a single price and advertising level. In relation to the newspaper market, the diffusion of online versions among readers–consumers and the enhancement of the interactive relationship between the publisher and readers offer the opportunity to provide personalised media products, effectively segment the demand, adopt price discrimination and thus vary the optimal advertising/sales ratio, depending on the characteristics of each segment of readers.

3The proof, although straightforward, is available from by the author upon request.

4If we introduce a quality dimension in the model, this does not mean that the newspaper will necessarily be a ‘high quality’ publication, but only that the publisher decides to devote an amount of money to reach a given level of quality.

5Saying that condition in Equation (13) holds also for free media products does not mean that the ‘values’ of the formula are the same for free and paid products: we are considering two distinct markets, hence the value of elasticities may be different and thus quality investments and advertising revenue may vary.
Effects of experiential elements on experiential satisfaction and loyalty intentions: a case study of the super basketball league in Taiwan

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Abstract: As the change of economical environment, customers consume sometimes merely for fun, joy and pleasure instead of problems solving or specific product function. For consumers, sports performance means more than competition, but the entertainment, excitement and wonderful memories. For most sport leagues, attracting customers to watch the live games can contribute a lot to revenues. The spectators of sport games are motivated by entertainment, thus sport leagues can focus on the experiential elements to maintain satisfied and loyal customers to increase revenues. In consequence, the purpose of this study is to explore the influence of experiential elements, such as surprise, participation and immersion on experiential satisfaction and loyalty intentions, and propose a model to depict the structural relationship among the experiential processes. This study collected 452 samples on basketball games, and the model reached an adequate fit. Managerial implications and future research directions are also provided.

Keywords: experiential element; experiential marketing; experiential satisfaction; loyalty intention; revenue management; sports performance industry.

1 Introduction

Consumers nowadays purchase a product not only for problem solving or product functions, but also for fun and enjoyment as the development and changes of economies (Holbrook and Hirschman, 1982). Buying behaviour is no longer simply rational for consumers. In late 1970s, some researchers began to question the information processing perspective and identified that some important consumption phenomena were neglected (Olshavsky and Grabois, 1979; Sheth, 1979). The ignored phenomena include various playful leisure activities, esthetic enjoyment and emotional responses. The research of consumer behaviour has changed from the traditional view of rational choice to emotional or affective needs. The experiential perspective regards consumption as a subjective state of consciousness with a variety of symbolic meanings, hedonic responses and esthetic criteria (Holbrook and Hirschman, 1982).

Pine II and Gilmore (1999) identified that the economic value has progressed from commodities, goods and services to experiences. Distinct experience can differentiate itself from competitors and charge the price at a premium. In other words, it is no longer enough to offer good product or service in the competitive environment. Schmitt (1999) identified that marketing has progressed into a new stage, which focuses on experiences rather than functions or packages. Moreover, the concept of experiential marketing is helpful for marketers to find market niches instead of involving in price wars or product function competition.

The research of experiential consumption is getting noticed recently. For example, Schmitt (1999) proposed the experiential modules, which include sense, feel, think, act and relate (Schmitt, 1999). Nevertheless, the effect of experiential marketing on consumer behaviour still needs to be explored. Some researches pointed out the importance of experiential marketing in arts (Petkus, 2004), tourism (Hannam, 2004) and sports (Stenhouse, 2003). However, instead of verifying the concepts from empirical data these researches focused on introducing the concepts. This research takes basketball shows as an example and collects empirical data to explore the experiential elements and experiential process of consumers, so as to provide better evidence regarding the potential impact of experiential marketing on revenues.
The spending of sports is approximately US$200 billion globally (Carter and Rovell, 2003), implying the fast growth in sport industry. The development of sport industry is an important policy in many countries. The formation and development of professional sport industry is helpful for the growth of other industries and thus helpful for economic prosperity. Thus, the sport industry is important in many highly developed countries. Sport managers always strive to generate more revenues to offset the rising costs of maintaining sport teams. Since gate receipts and media revenues are two major source of income for most professional sports (Leonard, 1997), increasing ticket sales is a very important task for sport leagues. Thus, understanding the reasons that lead consumers to watch live games in stadiums or even become loyal to watching the games is imperative for increasing revenues.

According to the database of Eastern Integrated Consumer Profile (E-ICP) (2003), baseball, basketball and snooker are three major sport shows watched by the audience in Taiwan. Since basketball is one of the most popular sports in Taiwan, Super Basketball League (SBL) was formed in November, 2003. There are seven teams and 84 routine games in SBL, which is the largest basketball league in Taiwan. Therefore, this research takes the basketball games of SBL as an empirical example to discuss the experiential process.

Though many people play or watch basketball games in Taiwan, few people go to the gymnasia to watch the live shows. Most people prefer to watch the games on TV. Why do some consumers still prefer to watch the show on site? What element or characteristic of the game arouses the affect or feeling of these consumers? The nature of a basketball game is not only competition, but also enjoyment, impressive memories and entertainment. Lots of researches tried to find personal motives for sport consumption (Trail and James, 2001). The major motives include achievement, acquisition of knowledge, aesthetics, drama, escape, family, physical attraction, physical skill and social interaction. Many studies suggested that entertainment, drama and escape are major motives for sport consumption (James and Riding, 2002; James and Ross, 2004). These researches implied that experiential elements are important for sport consumption.

Holbrook and Hirschman (1982) proposed that consumers may make purchase decisions by rational or logical thinking, but consumers’ decisions may also be driven by affects. For example, consumers often have the emotions of fantasies, feeling, and fun, pursuing excitements or sensory pleasures. Experience is usually motivated by extrinsic stimuli, thus, marketers should provide experiential stimuli to consumers (Schmitt, 1999). In addition, if professional sport leagues want to maintain a large number of loyal fans, they should provide the fans with unforgettable entertainment experiences (Carter and Rovell, 2003). According to the definition of experiential marketing, the content of a performance includes all detailed processes that are related to consumer experiences, such as the service provided by workers, the programmes performed by the actors, and the on-site atmosphere. A basketball show is also a performance art. The act (game) played by the actors (sportsmen) is one of the experiential components, which includes the complete entertaining activities.

Therefore, it is necessary to analyse the experiential processes during consumption and fully understand the changes of consumer mental processes and loyalty intentions after purchase. Thus, this research tries to explore the effect of experiential elements on loyalty intentions and their mediating processes, and propose a conceptual model to portray the processes.
2 Literature review

2.1 Experience economy and experiential marketing

Pine II and Gilmore (1999) suggest that marketers should provide great value to customers, such as customisation and unforgettable experiences. Experiences are important to consumers. When businesses take services as the stage and the products as props, and involve consumers in the process, experiences occur.

In the experience economy, experiential activities can segment markets and charge premium prices. Commodities are fungible, goods are tangible, services are intangible and experiences are memorable. Consumers are enjoying the experiences provided by businesses when purchasing experiences.

In the stage of experience economy, every business plans various experiences, and thus it is easier to emphasise uniqueness and charge prices based on the unique value instead of competitive market prices. Therefore, in the highly growing economy, consumers’ needs are getting various and personalised, and traditional services and marketing practices cannot satisfy their needs. Thus, experience is becoming the best way to satisfy consumer needs.

Businesses create experiences by using products and services as props and stages, producing memorable and impressive activities to consumers (Pine II and Gilmore, 1999). Experiences are inherent in the minds of everybody, and are the results of involving in physical, emotional and cognitive activities. Experiences come from the interaction of personal minds and events, and thus no one experiences the same with the other person (Schmitt, 1999).

McGregor (1974) identified that in the generally neglected experiential view, the criteria for successful consumption are essentially esthetic in nature and hinge on an appreciation of the product for its own sake, apart from any utilitarian function that it may or may not perform (Holbrook and Hirschman, 1982). Thus, the processes of experiential consumption are like the appreciation of art, emphasising the nature of the product or service without regard to its functional utility. Consequently, the major difference between experiential marketing and traditional marketing, which emphasises promoting product functions, is that the former takes customer as affective decision makers who consume for excitement and joy.

2.2 Experiential elements

Holbrook (2000) proposed that more and more consumers love happy adventures and joyful processes of using products, suggesting that experience orientation is becoming the mainstream. Schmitt (1999) suggested five strategic experiential modes – sense, feel, think, act and relate – as the basis of experiential marketing. However, many sensory variables may also influence consumption intentions.

This research explores variables that affects consumers during experiential activities, and finds that surprise, participation and immersion are three essential components in sport shows. The three experiential elements are discussed as follows.
2.2.1 **Surprise**

Holbrook and Hirschman (1982) identified that consumer experiences come from the pursuit of fantasies, feelings and fun. The experiences enhance many sensory stimuli (Pine II and Gilmore, 1999). Schmitt (1999) proposed that consumer senses, feelings, minds, and behaviours will continuously interact with the environments, and consumers acquire unique feelings and experiences from these interactions. Special, unique or even extraordinary experiences surprise consumers, making the experiences vivid in memory. Therefore, marketers should provide stable quality service and creative content service to induce participants to generate good experiences.

Thus, this research defines surprise as the feeling of freshness, uniqueness and distinctiveness in the processes of consuming products or services.

2.2.2 **Participation**

Holbrook and Hirschman (1982) suggested that experiences often relate to emotions, feelings and other subconscious levels. Schmitt (1999) proposed that experiences often come from indirect appreciation or direct participation.

Pine II and Gilmore (1999) identified that exhibiting experiences is to make customers involve in the activities, rather than just to entertain customers. This research takes participation as an important variable in testing the experiential consumption processes. Participation is not just the inputs of consumer spirits, energies or time during leisure activities. This research defines participation as the degree of interaction among consumers and products, services or environments during consumption.

2.2.3 **Immersion**

Csikszentmihalyi (1975) proposed the flow theory and identified that consumers enter into the status of immersion when involving thoroughly in activities, paying attention to the activities and filtering out all unrelated perceptions. Immersion is a temporal and subject experience and it helps to explain the reasons of loyal behaviours (Webster, Trevino and Ryan, 1993). Consumers have the desires of pursuing fun and achievement. When consumers interest in some activities, they will fully involve in the activities and forget the surrounding environments.

From the experiential perspective, Pine II and Gilmore (1999) identified that immersion is the integration of consumers and experiences. Specifically, the players or the audience immerse and focus on the games, isolating themselves from the reality. The tension and uncertainty of games attract the participants. The games can also generate imagination and creativity, which detach the participant from the reality. For example, when the audiences watch basketball games in the gymnasium or performance arts in the theatre, the scenes, surprises, stimuli, music and the interaction between actors and the audiences can all influence the experiential processes of consumers.

Thus, this research defines immersion as the involvement of consumers when enjoying the consumption and to forget the passing of time. Immersion makes consumers emphasise consumption processes instead of results.
2.3 Emotional experiences

Havlena and Holbrook (1986) identified that the most important factors in experiential consumption are emotional factors, which are personal perception of emotions (Russell and Snodgrass, 1987). The environment can affect perceptions and human affective responses, and the environmental factors felt by personal senses include visual stimulus and non-visual stimulus such as the senses of touch, smell, taste and hearing (Ulrich, 1983). Any environment, including that of a retail store, will produce an emotional state in an individual that can be characterised in terms of the three PAD (pleasure-arousal-dominance) dimensions (Mehrabian and Russell, 1974; Donovan and Rossiter, 1982). Pleasure refers to the degree to which the person feels good, joyful, happy or satisfied in the situation; arousal refers to the degree to which a person feels excited, stimulated, alert or active in the situation; and dominance refers to the extent to which the individual feels in control of the situation. Moreover, the positive emotions of pleasure and arousal would positively influence consumers’ buying behaviours (Donovan and Rossiter, 1982).

Since emotional experiences are important in the experience processes based on the experiential perspective, this research takes emotional experience as a mediator in the experience process model and puts emphasis on the emotional pleasure and arousal under specific situation. Thus, this research defines emotional experience as consumer subjective positive feelings aroused by external stimuli, such as pleasure and arousal.

The three experiential elements – surprise, participation and immersion – are subjective feelings aroused by the play or games, and these elements can thus positively generate emotional experiences. Thus, the following three hypotheses are proposed:

**Hypotheses 1.** There is a positive relationship between surprise and consumers’ emotional experiences.

**Hypotheses 2.** There is a positive relationship between participation and consumers’ emotional experiences.

**Hypotheses 3.** There is a positive relationship between immersion and consumers’ emotional experiences.

2.4 Experiential attitudes

Attitude is the enduring and consistent behavioral tendency toward an object, such as a person, a brand, or an event. Attitude can change after direct or indirect learning. Attitude differs from opinion or belief. Attitude focuses on affect or feelings, but opinion or belief focuses on cognition. Attitude is also an important variable to predict behaviours. Therefore, in this research attitude is used as a mediator in the experiential process.

Overall, from the experiential perspective, experiential attitude is defined as consumers’ positive or negative behavioural tendency towards experienced stimuli during consumption processes.

Therefore, positive emotions aroused by external stimuli would generate positive feelings towards the stimuli and thus positively affect experiential attitude. That is, emotional experiences will positively affect experiential attitudes.

**Hypotheses 4.** There is a positive relationship between emotional experiences and consumers’ experiential attitudes.
2.5 Experiential satisfactions

2.5.1 Product and service satisfaction

Customer satisfaction has a positive impact on increasing revenues (Anderson, Fornell and Lehmann, 1994; Fornell, Ittner and Larcker, 1995). Satisfaction is the assessment of all previous relationship quality between buyers and sellers, and forms as the expectation of future quality (Crosby, Evans and Cowels, 1990). Anderson and Narus (1990) proposed that satisfaction is the overall evaluation of the relationship between buyers and sellers. Satisfaction of channel members is often defined as one firm’s comprehensive evaluation of relationship on another firm, and thus forming a positive feeling towards the firm (Garbarino and Johnson, 1999). Ganesan (1994) defined satisfaction as the positive feelings formed by the overall evaluation when retailers negotiate with the suppliers.

Satisfaction judgment is often used to compare the performance or quality of products or services (Anderson et al., 1994). Generally, the measurement of satisfaction is defined as the disconfirmation beliefs between consumer expectation before purchase and perceived actual performance of the product or service. This definition is often used as the criteria for assessing satisfaction (Oliver, 1980; Westbrook, 1980; Bearden and Teel, 1983). Other assessment criteria are also discussed in the literature, such as the performance need or the results level (Westbrook and Reilly, 1983), and performance equity or results (Oliver and Swan, 1989).

2.5.2 Experiential satisfaction

Previous literature regarding satisfaction often focused on satisfaction of products or services. In fact, satisfaction is also an important variable in experiences (Oliver, 1980; Westbrook and Oliver, 1991). Customer satisfaction of a specific transaction is the immediate evaluation after purchase, or the positive feeling towards recent transaction experiences (Oliver, 1993). Customers use personal experiences to form cognitive and effective evaluation about service relationship and thus form the degree of satisfaction (Storbacka, Standvik and Grönnroos, 1994). Anderson et al. (1994) proposed that satisfaction is the overall evaluation of the purchased products or services based on previous experiences. Mano and Oliver (1993) suggested that in the post consumption experience, product-elicited affect is highly correlated with satisfaction.

The experiential satisfaction discussed in this research is extended from the concept of service satisfaction, which explores service satisfaction and consumers’ affects in specific situation. Although experiential satisfaction is extended from the concept of service satisfaction, experiential satisfaction focuses on consumers’ overall evaluation of experiences after consumption. Thus, from the experiential perspective, experiential satisfaction is the satisfaction experienced from the service content under a specific transaction. Consumers will compare the experience with prior expectation after consumption, and generate cognitive consistency or cognitive dissonance. The emotional responses based on cognitive consistency or dissonance form the results of satisfaction or dissatisfaction. Therefore, this research tries to propose the concept of experiential satisfaction based on experiential perspective, and defines experiential satisfaction as the results of consumers’ evaluation on the contents presented by service providers.
The positive emotional experiences rose from external stimuli would generate positive feelings that lead to experiential satisfaction. Thus, the following hypothesis is proposed.

**Hypotheses 5.** There is a positive relationship between emotional experiences and consumers’ experiential satisfactions.

Experiential attitude involves the positive or negative effect towards products or services. Positive effect is highly correlated with satisfaction. Thus, experiential attitude is positively related to experiential satisfaction, and the following hypothesis is proposed.

**Hypotheses 6.** There is a positive relationship between experiential attitudes and consumers’ experiential satisfactions.

### 2.6 Loyalty intentions

#### 2.6.1 Loyalty and revenues

Customer satisfaction and loyalty intentions have been widely identified as important indications of profitability, especially for service firms (Anderson et al., 1994; Edvardsson et al., 2000). Firms usually incur costs on acquiring customers, such as awareness advertising and prospecting costs. However, firms often receive revenues from satisfied or loyal customers. The revenue growth comes from the cross-selling of additional products or services and an increase in purchase volume or customer referrals. Many researches suggested that customer satisfaction and loyalty have positive impact on increasing revenues and financial performance (Fornell et al., 1995; Smith and Wright, 2004). Thus, increasing satisfied spectators or loyal fans is an important way for sport leagues to increase revenues.

Loyalty is the willingness of making investment or sacrifice of one person in order to enhance one relationship. Earlier studies took repeat purchase or repurchase intentions as an index of brand or service loyalty (Heskett et al., 1994). Recent studies such as Rust, Zahorik and Keiningham (1995), Zeithaml, Berry and Parasurman (1996) tended to use consumer preferences of businesses, word-of-mouth, and praises as the criteria for measuring loyalty intentions. Reinartz and Kumar (2002) suggested that the costs of serving loyal customers are low and loyal customers are willing to spend more money than disloyal customers. Besides, loyal customers can also serve as powerful marketers for promoting products.

According to literatures, this research selects repurchase intentions and recommendation intentions as the measurement of loyalty intentions.

#### 2.6.2 Repurchase intention

Usually, loyal customers buy more products or services from the same company than disloyal customers (Verhoef, Franses and Hoekstra, 2002). Generally, as customer satisfaction increases, the perceived benefits of switching to another service provider decrease, and thus repurchase intention increases (Anderson and Sullivan, 1993). Most researches support the correlation between satisfaction and customer retention (Oliver and Swan, 1989; Fornell, 1992; Taylor and Baker, 1994).

Thus, in this research, repurchase intention is consumers’ willingness to maintain transaction relationship with service providers after experiential consumption.
2.6.3 Recommendation intention

Jones and Sasser (1995) found that satisfied customers exhibit not only repurchase behaviour but also word-of-mouth communication and public recommendation. When customers are loyal to one service provider, they are pleased to recommend the service to other customers, such as friends, family members, or colleagues (Verhoef, Franses and Hoekstra, 2002). Thus, customers’ willingness to recommend is a powerful indication of loyalty (Reichheld, 2003). In addition, when customers act as warrantors, they usually do not get economic benefits from the firms. They put their personal credit at stakes. Therefore, customers risk their credits only when they are strongly loyal to the company (Reichheld, 2003).

Thus, in this research, recommendation intention is consumers’ willingness to recommend other people to deal with the service provider after experiential consumption. Most research of consumer post-purchase behaviour focuses on the issue of customer satisfaction. Consumers form expectation on products or retailers before purchase, and feel satisfied or even loyal to the products or retailers when the perceived performance exceeds expectation (Blackwell, Miniard and Engel, 2001). Satisfied customers communicate their learning of previous experiences. Thus, satisfaction can explain some important post-purchase behaviour, such as complaint and word-of-mouth communication (Howard, 1989). Moreover, overall satisfaction can affect consumers’ repurchase intentions (Fornell, 1992).

Prus and Brandt (1995) identified that customer satisfaction drives customer loyalty. Customer loyalty refers to the commitment of maintaining a long-term relationship with a brand or firm, and exhibits the behaviours of repurchasing the same brand or purchasing the firm’s other products and recommending the brand to other persons.

Therefore, when consumers are more satisfied with an experience, they are more likely to repurchase the product or service and recommend the experience to other people. Besides, when consumers are willing to repurchase the product or service in the future, they also tend to recommend the experience to other people. Thus, the following hypotheses are proposed.

**Hypotheses 7.** There is a positive relationship between experiential satisfactions and consumers’ repurchase intentions.

**Hypotheses 8.** There is a positive relationship between experiential satisfactions and consumers’ recommendation intentions.

**Hypotheses 9.** There is a positive relationship between repurchase intention and consumers’ recommendation intentions.

2.7 Research structure

All the hypotheses and the research structure are depicted in Figure 1. The three experiential elements will affect loyalty intentions through emotional experience, experiential attitude and satisfaction.
3 Research method

3.1 Measures

The scales used to measure the latent constructs are provided in Table 1. All constructs were assessed using five-point Likert rating scales, with 1 representing strongly disagree and 5 representing strongly agree.

Surprise, participation and immersion are the three experiential elements discussed in this research. Surprise is defined as the freshness, specialty, and uniqueness, which are perceived by consumers when using a product or during a service. This research focuses on basketball games, so the definition is modified as the uniqueness and surprising experience during the games. Three items were measured. Participation is defined as the interaction between consumers and product or service. This research focuses on consumer participation in programmes or shows provided by the host. Two items were measured. Immersion is the involvement of consumers during consumption, leading consumers to forgetting time and putting emphasis on consumption processes instead of consumption results. This research focuses on the involvement during basketball games. Four items were collected by five-point Likert scales.

Emotional experience, experiential attitude and experiential satisfaction are the three mediating constructs discussed in this research. Emotional experience is defined as the subjective positive feelings perceived by consumers during consumption, such as excitement and happiness. This research focuses on the feelings experienced during the games and measures by four items. Experiential attitude is consumers’ positive or negative evaluations towards consumption experiences. This research put emphasis on consumers’ subjective evaluation of the games according to their experiences. Three statements were measured. Experiential satisfaction is defined as the integrated evaluations of the consumptions and the contentment to the whole consumption process. This research focuses on the overall evaluations of the basketball games and measures by four items.

Repurchase intention and recommendation intention are the two loyalty intentions discussed in this research. Repurchase intention is the willingness to keep a transaction relationship with service providers after one purchase. This research modifies the definition as the willingness to come back to watch the games in future. Two items were collected. Recommendation intention is the willingness to suggest other people to
Effects of experiential elements

transact with the service provider. This research modifies the definition as the willingness to suggest others to watch the show after this game. Three items were measured.

Table 1  Scale items and measurement properties

<table>
<thead>
<tr>
<th>Construct</th>
<th>Item</th>
<th>Item Reliability (IR)</th>
<th>Scale Reliability (SR)</th>
<th>Variance Extracted (VE)</th>
<th>Cronbach’s α</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surprise</td>
<td>I can see some surprising, wonderful actions.</td>
<td>0.53</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I can see the scenes that cannot be substituted by TV broadcasting.</td>
<td>0.57</td>
<td>0.78</td>
<td>0.75</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>I can see some unexpected program.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Participation</td>
<td>I join the games provided by the host.</td>
<td>0.74</td>
<td>0.91</td>
<td>0.69</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>I interact with the host.</td>
<td>0.93</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Immersion</td>
<td>I forget the time running by.</td>
<td>0.51</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I feel comfortable for watching this game.</td>
<td>0.79</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I enjoy the process of this game.</td>
<td>0.84</td>
<td>0.91</td>
<td>0.85</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>I involve in this game.</td>
<td>0.73</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emotional experience</td>
<td>The game is cliff-hanging.</td>
<td>0.61</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>The game is marvelous.</td>
<td>0.66</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I feel joyful by the atmosphere on the scene.</td>
<td>0.82</td>
<td>0.91</td>
<td>0.82</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>I am happy about the experience tonight.</td>
<td>0.77</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experiential attitude</td>
<td>The program is good.</td>
<td>0.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I think the host is thoughtful.</td>
<td>0.72</td>
<td>0.88</td>
<td>0.76</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>I like the atmosphere of this game.</td>
<td>0.72</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experiential satisfaction</td>
<td>I am satisfied by this game.</td>
<td>0.73</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I am satisfied by the light and music of this site.</td>
<td>0.55</td>
<td>0.89</td>
<td>0.78</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>It is worthwhile to watch the game tonight.</td>
<td>0.72</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I am satisfied by the whole program.</td>
<td>0.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Repurchase intention</td>
<td>I will come back to watch the game in the future.</td>
<td>0.92</td>
<td>0.96</td>
<td>0.67</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>I will come to feel the atmosphere again.</td>
<td>0.93</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recommendation intention</td>
<td>I will recommend this game to my friends.</td>
<td>0.80</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>I will tell my friends about the positive experience of watching this game.</td>
<td>0.70</td>
<td>0.89</td>
<td>0.73</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>I will say the name of this game when someone asks me about my leisure activities.</td>
<td>0.72</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

†For each construct, the item reliability (IR), scale reliability (SR) variance extracted (VE), and Cronbach’s α are provided.
3.2 Sampling

Quota sampling was used to collect the data. According to E-ICP (Eastern Integrated Consumer Profile), one marketing research agency in Taiwan, basketball game is one of the most popular sports in Taiwan. However, only 4.5% of people will go to see the games on average. This research takes SBL as an example, and collects the data from two popular games in Taipei Physical Education College Gymnasium on two weekends during March 2004. The population was stratified as five groups based on ages, and the sampling percentage was calculated according to census data and the database of E-ICP. The calculation is shown in Table 2. Five hundred questionnaires were delivered and 452 effective samples were collected. Effective sample rate is 90.4%. The percentage of the male is 51 sample. The actual sampling structure is not significantly different from that of E-ICP ($\chi^2 = 4.608, df = 4, p > 0.05$), implying that the sampling result is adequate.

<table>
<thead>
<tr>
<th>Table 2 Sampling structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Population (census data)</td>
</tr>
<tr>
<td>The percentage of people that will go to see the games (E-ICP)</td>
</tr>
<tr>
<td>People that will go to see the game (=A $\times$ B)</td>
</tr>
<tr>
<td>Sampling percentage ($Ci/\Sigma Ci$)</td>
</tr>
<tr>
<td>Expected number of samples ($500 \times Di$)</td>
</tr>
<tr>
<td>Actual number of samples (total 452)</td>
</tr>
<tr>
<td>Actual sampling percentage ($Fi/\Sigma Fi$)</td>
</tr>
</tbody>
</table>

4 Analysis and results

4.1 Measurement properties of the scales

The scales used to measure the latent constructs in the model are provided in Table 1. Item reliability, construct reliability, variance extracted and Cronbach’s $\alpha$ are shown. The assessment of the measurement properties of all eight scales indicated that the factor loadings (lambdas) were high and significant ($p < 0.001$), which satisfies the criteria for convergent validity. Fornell and Larcker (1981) suggest that discriminant validity can be assessed by determining whether the variance extracted estimates for two constructs are greater than the square of the parameter estimate between them. The largest squares of correlations is 0.618, which is smaller than the lowest variances extracted (0.67). Therefore, the data passes the discriminant validity criterion of Fornell and Larcker. Fornell and Larcker (1981) also stress the importance of examining composite reliability and variance extracted. Bagozzi and Yi (1988) suggest two criteria: composite reliability
should be ≥0.60, and variance extracted should be ≥0.50. All eight composite reliabilities were >0.78 and all eight variance extracted were >0.67 (see Table 1). Finally, all of the Cronbach’s αs are above 0.70, suggesting good measurement reliability.

4.2 Model fit

The causal model was specified as shown in Figure 1. The PSI, TD and TE matrices were diagonal and free. The lambda matrices (both X and Y) were full and fixed. Then the individual items associated with the exogenous and endogenous constructs were freed. However, one of the lambdas for each construct was set to 1.0 to properly define the measurement (Jöreskog and Sörbom, 1989).

The overall fit of the structural model was determined initially by examining $\chi^2$ statistics, which was significant. A significant $\chi^2$ statistics could indicate an inadequate fit, but this statistics is sensitive to sample size and model complexity; therefore, based on this evidence alone rejection of a model is inappropriate (Bagozzi and Yi, 1988). Accordingly, other measures of fit compensating for sample size also were applied: GFI was 0.84, AGFI was 0.80, CFI was 0.91, NFI was 0.89, and NNFI was 0.90. All of these indices showed an adequate fit (see Table 3).

Table 3  Testing the model relationships

<table>
<thead>
<tr>
<th>From</th>
<th>To</th>
<th>Sign</th>
<th>Standardized estimate</th>
<th>t-value†</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1 surprise</td>
<td>→ emotional experience</td>
<td>+</td>
<td>0.15</td>
<td>2.34</td>
</tr>
<tr>
<td>H2 participation</td>
<td>→ emotional experience</td>
<td>+</td>
<td>0.10</td>
<td>2.97</td>
</tr>
<tr>
<td>H3 immersion</td>
<td>→ emotional experience</td>
<td>+</td>
<td>0.71</td>
<td>9.77</td>
</tr>
<tr>
<td>H4 emotional experience</td>
<td>→ experiential attitude</td>
<td>+</td>
<td>0.82</td>
<td>15.85</td>
</tr>
<tr>
<td>H5 emotional experience</td>
<td>→ experiential satisfaction</td>
<td>+</td>
<td>0.51</td>
<td>9.44</td>
</tr>
<tr>
<td>H6 experiential attitude</td>
<td>→ experiential satisfaction</td>
<td>+</td>
<td>0.50</td>
<td>9.33</td>
</tr>
<tr>
<td>H7 experiential satisfaction</td>
<td>→ repurchase intention</td>
<td>+</td>
<td>0.72</td>
<td>17.04</td>
</tr>
<tr>
<td>H8 experiential satisfaction</td>
<td>→ recommendation intention</td>
<td>+</td>
<td>0.50</td>
<td>9.97</td>
</tr>
<tr>
<td>H9 repurchase intention</td>
<td>→ recommendation intention</td>
<td>+</td>
<td>0.41</td>
<td>8.57</td>
</tr>
</tbody>
</table>

Goodness-of-fit statistics

Chi-Square (df) = 1097.11 (263), GFI = 0.84, AGFI = 0.80, CFI = 0.91, NFI = 0.89, NNFI = 0.90, RMR = 0.057

†Significant at $p < 0.01$ (one-tailed).

4.3 Hypotheses tests

The standardised estimates for the various model paths and the associated t-values are provided in Table 3. All hypotheses were supported. Surprise, participation and immersion are the three important experiential elements that are positively related to emotional experiences. Specifically, when consumers perceive unique or special experiences during consumption processes, interact closely with the product or service, or highly involve in the consumption activities, higher emotional experience will be aroused (H1–H3). The effects of three experiential elements on loyalty intentions are mediated by
three constructs – emotional experience, experiential attitude and experiential satisfaction. The results suggest that higher emotional experiences will lead to higher experiential attitude and experiential satisfaction (H4, H5). Experiential attitude is also positively related to experiential satisfaction (H6). When consumers are more satisfied with the experiences, they are more likely to exhibit higher loyalty intentions (H7, H8), which are expressed by repurchase and recommendation intentions. The results are in accordance with Anderson and Sullivan (1993) and Jones and Sasser (1995). In addition, higher repurchase intention also leads to higher recommendation intention (H9).

5 Discussion

This research discusses the effects of experiential elements on loyalty intentions. Three important experiential elements – surprise, participation and immersion – are selected according to the characteristics of sport games. The effects of these three experiential elements on loyalty intentions are mediated by three constructs – emotional experience, experiential attitude and experiential satisfaction. These intermediary constructs are important to clarify the experiential processes during consumption. The empirical results support all structural paths and exhibit adequate model fit. This structural model is helpful for understanding the detailed process of experiential marketing.

5.1 Managerial implications

Experiential elements are important factors to determine successful and profitable sports games. Traditional sports industry should be repositioned to focus on consumers’ experiential processes so as to increase revenues. The competition could be reorganized as a program, including some entertainment activities and shows, and thus attract more people to watch the games. This research suggests that surprise, participation, and immersion are three important experiential elements for satisfactions and loyalty intentions, implying that basketball leagues could enhance positive experiential stimulus in the show. Besides coordinating the on-site atmosphere, the leagues could design the programmes as more interactive and unique.

5.1.1 Surprise

The performance of players and team records are important for the element of surprise. Thus, unchanged mix of players and competition between teams disparity in competence are by no means surprising to the audience. In other words, if consumers would easily predict the results of games before competition, it is harmful for the leagues. The managers of basketball teams and leagues should establish a good system to recruit new players and rearrange the players sometimes to strengthen the element of surprise, and thus keep the show interesting and unexpectable.

5.1.2 Participation

To increase the element of participation, the leagues could design more activities to interact with the audience. For example, the host or the cheerleader could design some
interactive activities with the audience. Thus, the spectators could participate in the cheering actions and exclaim slogans loudly, instead of watching the game passively.

5.1.3 Immersion

From the empirical result of this research, immersion is the most influential element to emotional experience. Thus, enhancing the element of immersion will lead to great improvement in emotional experience. The leagues should watch out for the physical facilities and the progress of the games. Every detail component of the game, such as the light, music, activities and the pace of the competition, is important for the audience to get fully involved in the game.

5.2 Limitations and avenues for future research

This research takes basketball game as an example to verify the relationship between experiential elements and loyalty intentions. The results are helpful for other sports industries. However, as experiential marketing is getting more and more important in service industries, participation and involvement of consumers are important in industries such as tourism or on-line games. The experiential elements and experiential processes of these and other industries can be explored in future studies.

The experiential processes may be diverse for consumers differed in demographics or psychographics. This research proposes a structure for simplicity. Future studies can provide different models based on various segments. For example, age, gender, lifestyles and involvement may have moderating effects on the structure. The determinant experiential elements may also differ for different segments, and managers should stress different experiential contents for different segments. The comparison of experiential processes across different cultures can also be discussed in the future.

Acknowledgement

The authors are grateful for the constructive comments from the editor, Jason C.H. Chen, and two anonymous reviewers of Int. J. Revenue Management. The authors are also grateful to Yu-Lin Li for his assistance in collecting data used in this study.

References


Effects of experiential elements


An overview of research on revenue management: current issues and future research

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Abstract: The paper provides a comprehensive review of the recent development of revenue management in different industries. We discuss research on different revenue management strategies including pricing, auctions, capacity control, overbooking and forecasting. Related issues such as economic concerns, customer perception, competition and consolidation, implementation, performance evaluation, and common techniques and approaches used for solving revenue management problems are also discussed. Finally, we give our suggestion on some important areas that warrant further research.

Keywords: revenue management; yield management.


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1 Introduction

Revenue management, or yield management, is concerned with creating and managing service packages to maximize revenue. By thoroughly understanding customers’ value functions and behavior, a firm can design service packages for different market segments using appropriate combinations of attributes such as price, amenities, purchase restrictions, and distribution channels. Chase and Charles (1999) and Kimes (2000b) present a brief introduction on revenue management and its related issues.

The research on revenue management can be traced back 40 years, when American Airlines implemented a computer reservations system (SABRE) in 1966, which had the capability of controlling reservations inventory. But the prevalence of revenue management came after the Airline Deregulation Act of 1978. This act loosened control of airline prices and led to a rapid change and a rash of innovation in the industry. Since then, airline revenue management systems have developed significantly from single-leg inventory control through segment control to origin-destination control. New information technologies play a critical role in the development of revenue management. Each advance in information technology has led to more sophisticated revenue management capabilities. Today revenue management systems and related information technologies have become crucial factors of business success for airlines, hotels, car rentals and many
An overview of research on revenue management

other industries. Revenue management has been credited with US$500 and $300 million of increased revenue and earnings by US Airlines and Delta Airlines, respectively (Boyd, 1998). Cross (1997) reports that revenue management helps Marriott Hotel to gain US$100 million additional annual revenue. Elliott (2003) presents how revenue management can contribute substantially to cost savings and revenue maximisation while helping maintain quality.

The objective of this paper is to review the most recent literature on revenue management to give readers a general overview of the types of revenue management problems that have been addressed in a variety of industries. The majority of our study covers published articles in recent years. We also include several working papers, conference proceedings and case studies that we believe are valuable in this study. Overall, we have examined 221 articles.

Several review papers have provided an overview of research on revenue management. We provide a list of these papers in Table 1. In order to differentiate from these survey papers, we will focus on the progress of revenue management in recent years, especially after 1999.

Table 1 Revenue management overview

<table>
<thead>
<tr>
<th>Reference</th>
<th>Abstracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weatherford and Bodily (1992)</td>
<td>This paper reviews over 40 articles, proposes a 14-element taxonomy for revenue management, and classifies the published work using this taxonomy.</td>
</tr>
<tr>
<td>McGill and van Ryzin (1999)</td>
<td>This paper reviews the history of research on transportation revenue management, especially airline revenue management, and the development in forecasting, overbooking, and seat inventory control. This paper also includes a glossary of revenue management terminology and a bibliography of over 190 references.</td>
</tr>
<tr>
<td>Pak and Piersma (2002)</td>
<td>This paper presents a review of the variety of OR techniques for airline revenue management problems from over 30 articles.</td>
</tr>
<tr>
<td>Bitran and Caldentey (2003)</td>
<td>This paper reviews 88 papers that primarily focus on the research and results of dynamic pricing policies and their relation to revenue management.</td>
</tr>
<tr>
<td>Kimes (2003)</td>
<td>This paper reviews her research in revenue management, including 11 articles published in Cornell Hotel and Restaurant Administration Quarterly and discusses areas for future research.</td>
</tr>
<tr>
<td>Boyd and Bilegan (2003)</td>
<td>This paper references over 110 articles to review the history of revenue management to illustrate a successful e-commerce model of dynamic, automated sales enabled by central reservation and revenue management systems.</td>
</tr>
<tr>
<td>Elmaghraby and Keskinocak (2003)</td>
<td>This paper reviews over 80 articles and current practices in dynamic pricing in the presence of inventory considerations.</td>
</tr>
</tbody>
</table>

In addition, several books have been published in recent years that focus on the issue of revenue management. Revenue Management: Hard-core Tactics for Market Domination (1997) written by Robert G. Cross addresses fundamental questions about revenue management such as how revenue management can be applied to a range of businesses.
and what kind of techniques can be used in revenue management. Anthony Ingold, Una McMahon-Beattie and Ian Yeoman’s *Yield Management: Strategies for the Service Industries* (2000) focuses on theoretical foundations, knowledge and applications of revenue management. Ian Yeoman and Una McMahon-Beattie’s *Revenue Management and Pricing: Case Studies and Applications* (2004) is an extension of their previous *Yield Management*. This case study book views revenue management and pricing as a practical subject; it helps readers to understand what can be done by revenue management, how practitioners face the related issues, and how they work with problems. Kalyan Talluri and Garrett van Ryzin’s *The Theory and Practice of Revenue Management* (2004b) provides a thorough introduction of concepts of revenue management. This book includes three primary sections: quantity-based revenue management, price-based revenue management and other related elements of revenue management. Robert Philips’ *Pricing and Revenue Optimization* (2005) is another book that provides a comprehensive introduction of pricing and revenue management. This book covers basic price optimization, price differentiation, pricing with constrained supply, revenue management, capacity allocation, network management, overbooking, markdown management, customized pricing, and customer acceptance.

The remainder of this paper is organized in the following sections. In Section 2, we discuss the application of revenue management in different industries. Section 3 provides a thorough discussion of primary revenue management problems. We give some important areas for future research in Section 4 and conclude our review in Section 5.

2 The applications of revenue management

Gallego and Phillips (2004) introduce the concept of flexible products for revenue management. They define a flexible product as a ‘menu’ of two or more alternative, typically substitute, products offered by a constrained supplier using a sales or booking process. In this context, products include not only physical products but also service offerings. Researchers have applied revenue management models in a wide variety of industries where suppliers offer flexible products.

Airlines, hotels and rental car industries represent three major traditional applications of revenue management. These industries share some similar characteristics. All of their products are perishable, the demand for their products vary significantly over time, and they have large fixed costs while variable costs are small in the short run.

Because of revenue management’s success in these industries, researchers and practitioners have begun trying to adopt it in a wide range of miscellaneous industries such as restaurants, casinos, cargo, Internet services and apartment renting. These industries share some similar characteristics with the traditional industries. Some of these practices have acquired great success. In fact, all service providers can take advantage of revenue management theory. Just as Berman (2005) says, revenue management is an effective mechanism to allocate a service provider’s relatively fixed capacity and to provide discounts on a much broader scale. Table 2 shows the publications of revenue management addressing airlines, hotels and rental car industries, and Table 3 shows the publications focusing on other industries. In Table 3, we group non-traditional industries into hospitality organizations, transportation-related industries, and other miscellaneous industries.
Table 4 provides examples of revenue management application in different industries. We are not going to discuss the application of revenue management in every industry. In the following section, we provide a brief overview and examples of revenue management research in three non-traditional industries.

2.1 Cargo and freight

The cargo industry focuses on providing a seamless door-to-door delivery service for parcels of all shapes and sizes. Most of current revenue management research in this area is on air cargo. The air cargo industry shares many common characteristics with airlines. However, unlike the wide application of revenue management in airlines, the revenue management concept in air cargo industry has not well-developed until recently.

<table>
<thead>
<tr>
<th>Industry</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airlines</td>
<td>Chatwin (1998), Cooper and Menich (1998), Coughlan (1999), Barlow (2000a),</td>
</tr>
<tr>
<td></td>
<td>Ingold and Huyton (2000), Johns (2000), Lehrer (2000), Kuyumcu and Garcia-Diaz</td>
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<td></td>
<td>de Boer et al. (2002), Gosavi et al. (2002), Pak and Piersma (2002), Skugge</td>
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<td></td>
<td>Boyd and Bilegan (2003), Brumelle and Walczak (2003), Cote et al. (2003),</td>
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<td></td>
<td>Elliott (2003), Farley (2003), Hassan (2003), Lancaster (2003), Lieberman</td>
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<td></td>
<td>(2003), Oliveira (2003), Parker (2003), Toh and Raven (2003), Trivizas (2003),</td>
</tr>
<tr>
<td></td>
<td>Yuen (2003), Barlow (2004a), Boyd and Kallesen (2004), Chandler et al. (2004),</td>
</tr>
<tr>
<td></td>
<td>(2004), Eguchi and Belobaba (2004), Gorin and Belobaba (2004), Hassan (2004),</td>
</tr>
<tr>
<td></td>
<td>Neuling et al. (2004), Zeni and Lawrence (2004), Burger and Fuchs (2005),</td>
</tr>
<tr>
<td></td>
<td>Bertsimas and de Boer (2005a), Dunleavy and Westermann (2005), Zhang and</td>
</tr>
<tr>
<td></td>
<td>Copper (2005), Harris (2006).</td>
</tr>
<tr>
<td></td>
<td>Kimes and McGuire (2001), Kimes and Wagner (2001), Baker et al. (2002),</td>
</tr>
<tr>
<td></td>
<td>(2003), Weatherford and Kimes (2003), Anjos et al. (2004), Chen and Freimeter</td>
</tr>
<tr>
<td></td>
<td>and Cohen (2004), Vinod (2004), Choi and Mattila (2005), Jain and Bowman (2005),</td>
</tr>
<tr>
<td></td>
<td>Lai and Ng (2005), Koide and Ishii (2005), Choi and Mattila (2006).</td>
</tr>
</tbody>
</table>
Table 3  Revenue management research in non-traditional industries

<table>
<thead>
<tr>
<th>Hospitality organisations</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital and health care</td>
<td>Lieberman (2004)</td>
<td></td>
</tr>
<tr>
<td>Cruise lines and ferry lines</td>
<td>Hoseason (2000), Lieberman and Tamara (2002)</td>
<td></td>
</tr>
<tr>
<td>Saunas</td>
<td>Yeoman et al. (2004)</td>
<td></td>
</tr>
<tr>
<td>Entertainment events</td>
<td>Volpano (2003)</td>
<td></td>
</tr>
<tr>
<td>Golf</td>
<td>Kimes (2000a), Kimes and Wirtz (2003c)</td>
<td></td>
</tr>
<tr>
<td>Sports events</td>
<td>Barlow (2000b), Barlow (2004b)</td>
<td></td>
</tr>
<tr>
<td>Conference</td>
<td>Hartley and Rand (2000)</td>
<td></td>
</tr>
<tr>
<td>Transportation-related industries</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Boat</td>
<td>Bermudez et al. (2004)</td>
<td></td>
</tr>
</tbody>
</table>

| Subscription services     | |
| IT Services and Internet Services | Nair and Bapna (2001), Wynter et al. (2004), Dube et al. (2005) |
| Cellular network services | Lindemann et al. (2004) |
| TV services               | Rautio et al. (2006) |

| Miscellaneous             | |
| Natural gas, petroleum storage and transmission | Valkov and Secomandi (2000), Harvey et al. (2004) |
| Project management        | Pinder (2005) |
| Apartment renting         | Druckman (2003) |
| Sales management          | Siguaw et al. (2003) |
| Inclusive holiday industry | Laws (2000) |
| Nonprofit sector          | Metters and Vargas (1999) |
Table 4  Revenue management practices in different industries

<table>
<thead>
<tr>
<th>Industries</th>
<th>Example of practices</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Hospitality organisations</strong></td>
<td></td>
</tr>
<tr>
<td>Hotels</td>
<td>Provide special rate packages for periods of low occupancy; use overbooking policy to compensate for cancellation, no-shows.</td>
</tr>
<tr>
<td>Restaurants</td>
<td>Move customers to off-peak periods by offering discount coupons, or charging reservation fees and higher meal prices on Friday and Saturday nights.</td>
</tr>
<tr>
<td>Attractions</td>
<td>Set different admission charge levels, provide joint-entry tickets, group discounts, coupons, membership rates.</td>
</tr>
<tr>
<td>Cruise lines and ferry lines</td>
<td>Provide luxury class, economy class; change prices frequently according to demand; sell more tickets than seats to avoid cancellation and no show.</td>
</tr>
<tr>
<td>Casinos</td>
<td>Customize offers such as complimentary room, tickets, gifts, discounts, etc., based on customers’ profitability.</td>
</tr>
<tr>
<td>Saunas</td>
<td>Determine price based upon factors such as room type, duration, and service type.</td>
</tr>
<tr>
<td>Resort</td>
<td>Provide different resort packages to attract different customers.</td>
</tr>
<tr>
<td>Golf</td>
<td>Use different prices to reflect the value of different times of the golf course.</td>
</tr>
<tr>
<td>Sports events and entertainment events</td>
<td>Determine ticket price for an event based on customer tastes and area of seating; determine the price of season tickets; determine the number of tickets sold for each seat segment.</td>
</tr>
<tr>
<td>Conference</td>
<td>Provide different packages and rates to satisfy different customers’ requirements.</td>
</tr>
<tr>
<td><strong>Transportation-related industries</strong></td>
<td></td>
</tr>
<tr>
<td>Airlines</td>
<td>Provide business class, economy class; adjust prices frequently according to demand; provide more tickets than seats to avoid cancellation and no-show.</td>
</tr>
<tr>
<td>Rental cars</td>
<td>Adjust prices frequently according to demand; serve high-valued fleet utilisation with priority; accept or reject booking requests based on length-of-rent controls.</td>
</tr>
<tr>
<td>Boat</td>
<td>Provide discount to stimulate demand.</td>
</tr>
<tr>
<td>Railways</td>
<td>Divide customers into standard class and first class; provide different prices based on the day of travel and the time of the day.</td>
</tr>
<tr>
<td>Cargo and Freight</td>
<td>Determine price based on cabin space, location and comfort; determine the optimal ship size and capacity for each class.</td>
</tr>
<tr>
<td><strong>Subscription services</strong></td>
<td></td>
</tr>
<tr>
<td>IT Services and Internet Services</td>
<td>Allocate resources such as human resource, computing capacity, storage and network capacity among segments of customers and determine appropriate price for each segment, high class customers will be served with priority.</td>
</tr>
<tr>
<td>Cellular network services</td>
<td>Control call admission based on customer priority, higher class customers will be served with priority.</td>
</tr>
</tbody>
</table>
Table 4  Revenue management practices in different industries (continued)

<table>
<thead>
<tr>
<th>Industries</th>
<th>Example of practices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Miscellaneous</td>
<td></td>
</tr>
<tr>
<td>Retailing</td>
<td>Use early discount pricing to maximise the revenue from sales of a ‘seasonal’ product.</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>Determine the right price for every product to every customer segment through every channel in response to changing market conditions.</td>
</tr>
<tr>
<td>Natural gas, petroleum storage and transmission</td>
<td>Make the right price for the transportation services so that the pipelines stay full.</td>
</tr>
<tr>
<td>Project management</td>
<td>Use capacity planning and scheduling to reserve specific capacity for customers willing to pay higher prices to have critical activities.</td>
</tr>
<tr>
<td>Apartment renting</td>
<td>Establish optimal rates for individual units, adjust prices based on competitor’s price, supply and demand, optimal renew price adjustment.</td>
</tr>
<tr>
<td>Inclusive holiday industry</td>
<td>Provide early booking discount, child discounts, late sales reductions to stimulate demand.</td>
</tr>
</tbody>
</table>

Cargo revenue management has been discussed and compared with passenger revenue management by Kasilingam (1997a), Kasilingam (1997b), Billings et al. (2003), and Slager and Kapteijns (2004). Billings et al. (2003) identify the unique characteristics of cargo revenue management as multi-dimensional and variable capacity, irregular and multi-dimensional service-level-bound demand, and pre-determined mid-term commitment. Slager and Kapteijns (2004) present that cargo transportation has several differences from passenger transportation. Cargo capacity is measured in weight and volume and is dependent on the number of passengers, the amount of baggage, and the amount of fuel on the plane; cargo has different routing and booking behavior; and cargo is a business-to-business market.

Kasilingam (1997b) presents a cost model to optimize overbooking level for air cargo with variable capacity. Slager and Kapteijns (2004) provide a practical case of implementing revenue management in KLM, an organization in cargo industry, and present insights and critical success factors during implementation.

2.2  IT service and internet service

Revenue management also has application opportunities in subscription services, such as on-demand information technology service and Internet service. Internet service is, in fact, a special case of on-demand information technology service.

Nair and Bapna (2001) find that Internet Service Providers (ISP) have perishable capacity for users to log on, a fixed number of units, and the possibility of segmenting price-sensitive customers. These three characteristics are common with industries where revenue management is traditionally applied. They also identify that revenue management in Internet service is different than traditional applications. The Internet service is continuous in state and time, the request and the service happen simultaneously, and overbooking is impossible for ISP. Furthermore, they formulate the revenue management problem for ISP as a continuous time Markov Decision Process to maximize the discounted value while improving service levels for higher class customers.
An overview of research on revenue management

Wynter et al. (2004) introduce a revenue management model for a specific information technology service – on-demand computing service. Dube et al. (2005) make a further analysis on the model of Wynter et al. (2004) both analytically and numerically, and conclude that the application of revenue management can significantly increase revenue of on-demand computing service providers.

2.3 Retailing

Revenue management principles can be applied to certain retailing industries such as ‘seasonal’ retailers and groceries.

Coulter (2001) suggests that revenue management is appropriate in ‘seasonal’ retailing industry in which capacity (inventory) is not necessarily ‘perishable’ but the value of the capacity may decline significantly after the selling season. He investigates how to use discount pricing to maximize the revenue gained from selling a ‘seasonal’ product. Aviv and Pazgal (2005) perform a quantitative analysis on how to apply dynamic pricing to sell fashion-like goods for ‘seasonal’ retailer.

Hatwin (2003) and Lippman (2003) focus on issues such as pricing strategy, market share preservation, and customer loyalty when applying revenue management techniques on grocery retail outlets.

3 Major revenue management problems

Revenue management problems can be categorized into several different, but related, areas: pricing, auctions, capacity control (or inventory control), overbooking, and forecasting. In the following subsections, we will review each of these areas, but before we start, there are two points that need to be mentioned. First, although we categorize revenue management into several areas, this does not mean that these areas are completely isolated. In fact, these areas are highly correlated and need to be considered jointly when solving practical problems and some researchers are indeed trying to solve these problems jointly. For instance, Feng and Xiao (2006) present a comprehensive model to integrate pricing and capacity allocation. Second, auction is a specific type of pricing strategy. Here we separate auctions from pricing, because we want to emphasise the importance of auctions in the future application of revenue management.

In addition, in this section, we also discuss other related issues regarding revenue management, including economic theory, the impact of competition and consolidation, customer perception and behaviour, the development and implementation of revenue management, performance evaluation of revenue management and techniques used for solving revenue management problems.

3.1 Pricing

The objective of pricing is to answer the question of how to determine the price for various customer groups and how to vary prices over time to maximize revenues or profits. The first question is whether it is possible for a company to use pricing strategies to maximise revenues. Desiraju and Shugan (1999) make an investigation into pricing strategies to find under what conditions revenue management can gain a good performance; their research suggests that revenue management is far more profitable
when there are different market segments of customers that will arrive at different times to purchase a service. Burger and Fuchs (2005) argue that the application of a dynamic pricing strategy has a neutral or a positive effect on revenues, and it can lead to a decrease in process complexity and transaction cost.


Baker and Collier (1999) use simulation to compare the performance of two pricing methods: pricing setting method (PSM) and bid price method (BPM). Based on statistically significant tests, they conclude that the PSM outperforms the BMP in 27 out of the 32 cases. In addition, the PSM produces an average 34% increase of revenue.

Curry (2001) presents a market-level pricing model to answer the question of whether an airline should or should not match the new fare of a competitor. Weatherford (2001) presents an approach to optimize the price for three types of problems:

1. up to $n$ price classes, distinct asset control mechanism and no diversion
2. up to three price classes, nested asset control mechanism and no diversion
3. up to three price classes, nested asset control mechanism, and diversion. Anjos et al. (2004) present a methodology to find the optimal price structure for a flight under one-way pricing; their methodology has been implemented in a major British airline.

Frank (2003) discusses the application of Six Sigma process to pricing management. Approaches to find the optimal or approximate optimal solution for pricing problems have been proposed by Feng and Xiao (2000), Feng and Gallego (2000), Cote et al. (2003), Maglaras and Constantinou (2005), and Aviv and Pazgal (2005). Feng and Xiao (2000) propose an intensity control model to address a continuous-time pricing problem in which reversible price changes are acceptable. Feng and Gallego (2000) use a general Poisson process with Markovian, time dependent, predictable intensities to represent the stochastic demand of perishable assets and propose an efficient algorithm to compute the optimal value functions and the optimal pricing policy. Cote et al. (2003) present an approach based on the bilevel programming paradigm, which is a special case of hierarchical mathematical optimization, to find the joint solution for pricing and capacity control problem. Their approach takes into account customer segmentation, customer behaviour, and the interactions induced by overlapping routes. Maglaras and Constantinou (2005) first obtain a ‘fluid-optimal’ solution for a deterministic relaxation of the pricing problem, and then use diffusion limits to refine the results and get approximate solutions for the stochastic problem. Aviv and Pazgal (2005) develop a stylised partially observed Markov decision process to study a dynamic pricing problem and propose an active-learning heuristic pricing policy for retailers of fashion-like goods.
3.2 Auctions

Auctions provide another way to dynamically adjust prices. In recent years, with the prevalence of the Internet, online auctions have acquired great popularity in selling perishable excess inventory, and researchers have begun to incorporate auctions in revenue management in different industries.

There are only a few publications that discuss how to apply auctions in revenue management. Cooper and Menich (1998) propose a Vickrey-Clarke-Groves mechanism to auction airline tickets on a network of flights. Valkov and Secomandi (2000) focus on using capacity auctions to allocate pipeline capacity in the natural gas transmission industry. Eso and Watson (2001) present an iterative sealed-bid auction to trade excess seat capacity for an airline. The iterative mechanism gives bidders the opportunity to get instant feedback, including minimum bid suggestion for declined bids. Furthermore, they present an integer-programming model to solve the problem.

Vulcano et al. (2002) focus on a specific dynamic auction model for revenue management. In such an auction, a seller with $C$ units to sell faces a sequence of buyers in $T$ time periods. They prove that dynamic variants of the first-price and second-price auction mechanisms can maximize the expected revenue and provide a model to compute and implement these optimal auctions. van Ryzin and Vulcano (2002) also explore the optimal auction and replenishment policy for dynamic infinite-horizon auction problem.

Baker and Murthy (2002) propose a stochastic model to explore the potential benefits of incorporating single sealed-bid Vickery auctions into revenue management. They evaluate the revenue performance of using the fixed price, the pure auction and the hybrid auction under a variety of conditions and find that the hybrid approach is robust and outperform the other two. Furthermore, Baker and Murthy (2005) examine auctions in revenue management in the presence of forecast errors associated with key parameters for an environment where two market segments book in sequence and auctions are considered in neither, one, or both segments.

3.3 Capacity control (inventory control)

The objective of capacity control is to determine how to allocate capacity of a resource or a bundle of different resources to different classes of demand so that the expected revenue or profit is maximised. In the airline industry, capacity control is often referred to as seat inventory control. Capacity control has made significant progress from relatively simple single-resource capacity control to more complicated network capacity control.

3.3.1 Single-resource capacity control

Single-resource capacity control is referred to as single-leg seat inventory control in the airline industry. It tries to allocate capacity of a resource to different classes of customers. Since Kenneth Littlewood proposed his famous Littlewood’s rule for two fare classes in Littlewood (1972), researchers have proposed many solutions for different single-resource capacity control problems. A review of this research is provided by McGill and van Ryzin (1999).

Gosavi et al. (2002) state that a realistic model for single-resource capacity control should consider multiple classes, overbooking, concurrent demand arrivals of customers from different classes, and class-dependent random cancellations. In order to consider all
of these factors, they describe the single-leg problem as a continuous-time Semi-Markov Decision Process (SMDP) with random demand arrivals and cancellations over an infinite time horizon, and solve it using a stochastic optimisation technique called Reinforcement Learning.

Bertsimas and Shioda (2003) present two classes of optimisation models for restaurants. For restaurants that don’t accept reservations, they use integer programming, stochastic integer programming, and Approximate Dynamic Programming (ADP). For restaurants with reservations, they use a stochastic gradient approach to solve the static reservation-booking model and an ADP approach to solve the dynamic seat allocation model with reservations. By comparing the results of these models with those of nesting models and a bid-price model, they discover that the ADP model has the best performance of all and increasing the sophistication of the models can improve revenue without sacrificing waiting time.

Koide and Ishii (2005) consider the hotel room allocation policies with early discount, cancellations, and overbooking, but without no-shows. The presented model can provide the optimal solution under certain conditions. They also derive an optimal allocation for a simplified problem, which considers early discount but ignores cancellations and overbooking. Savin et al. (2005) consider the allocation of capacity for rental businesses with two classes of customers. Their research suggests that the capacity reductions enabled by allocation schemes can help to lift profit margins significantly.

Zhang and Cooper (2005) address the simultaneous seat inventory control of a set of parallel flights between a common origin and destination with dynamic customer choice among the flights. They solve this stochastic optimization problem through simulation-based techniques.

Most of the current capacity control practices are based on forecasting. However, forecasting is difficult, costly and the results are sometimes unsatisfactory. Therefore, researchers are trying to find alternative approaches. van Ryzin and McGill (2000) present a simple adaptive approach to optimize seat protection levels in airline revenue management. Instead of using the traditional method that combines a censored forecasting method with a seat allocation heuristic (EMSR-b), this approach uses historical observations of the relative frequencies of certain seat-filling events to guide direct adjustments of the seat protection levels. Their preliminary numerical studies suggest that this method can be used to augment traditional forecasting and optimisation approaches.

### 3.3.2 Network capacity control

Network capacity control addresses the capacity allocation problem when customers require a bundle of different resources. For example, a customer may require a sequence of nights at a hotel, or require two or more connecting flights. In the airline industry, this problem is also known as origin-destination control. In the hotel and rental car industry, network capacity control is used to represent the problem of multi-night stays or multi-day rentals, respectively. With the prevalence of airline’s hub-and-spoke networks since the 1980s, how to account for network effects in revenue management becomes increasingly important; however, this problem can not easily be solved by using single-resource capacity control. Researchers and practitioners have developed a number of methods to address this specific revenue management problem; among them, virtual nesting and bid price methods are the two most widely used methods. De Boer et al.
An overview of research on revenue management

(2002) make a comparison on different mathematical programming models for airline seat inventory control by using a stochastic programming model, which includes a deterministic model as a special case.

Feng and Xiao (2001) focus on a specific airline inventory control problem, which has multiple origins, one hub and one destination. They propose a stochastic control mathematical model to allocate seats among competing origin-destination routes and present optimal control rules. Then they use a numerical example to prove that their proposed optimal seat control method is simple and efficient for this specific problem. Talluri (2001) presents a model named the Route-Set model to incorporate passenger routing with seat inventory control. In addition to control low fare sales on high demand flights, this model can exploit the presence of low demand alternative routes and increase revenue significantly for large airlines with multiple hubs and alternative routes without reducing their service level.

Bertsimas and Popescu (2003) propose an algorithm based on approximate dynamic programming to solve the stochastic and dynamic network revenue management problem and report that their algorithm leads to higher revenues and more robust performance than the bid price method. Their algorithm uses adaptive, nonadditive bid prices from a linear programming relaxation and incorporates oversales decisions in the underlying linear programming formulation to handle cancellations and no-shows.

Möller et al. (2004) present another stochastic programming approach. They use scenario trees to approximate the stochastic demand process. Their approach does not require any assumptions on the underlying demand distributions or on the correlations of the booking process. The revenue management problem is modeled by a multistage stochastic program and solved by standard linear programming software.

El-Haber and El-Taha (2004) formulate a discrete time, finite horizon Markov decision process to solve the two-leg airline seat inventory control problem with multiple fare classes, cancellations, no-shows and overbooking. Furthermore, they generalize a formulation for the multi-leg airline seat inventory control problem. They conclude that their model provides solutions that are within a few percentage points of the optimal solution.

Pölt (2004) realizes that double counting exists when calculating a high aggregation level of Origin and Destination (O&D) availability data and presents two different linear programming models to avoid and factor out this double counting problem.

Revenue management of hotels has some differences from revenue management of airlines. One of the differences is that hotels face the network structure of length of stay: the arrival demands for multi-night stays and the lengths of stay are random. This randomness in demand is addressed by Lai and Ng (2005). They present a stochastic programming model to formulate the problem and apply robust optimisation approaches to find the solution.

3.4 Overbooking control

Overbooking is concerned with increasing the total volume of sales by selling reservations above capacity to compensate for cancellations and no-shows. This policy can increase capacity utilization when the cancellations of orders are significant. The usual objective of overbooking control is to find an optimal overbooking level to maximise the expected revenue and to minimise the potential risk of denied service. Of all major revenue management problems, overbooking has the longest history and most
successful practices. A number of overbooking models have been proposed and a number of mathematical models have been formulated by researchers to solve different kinds of overbooking problems in airline and hotel industries.

Since McGill and van Ryzin (1999) had already presented a list of publications in overbooking, we will only discuss the new publications. Hadjinicola and Panayi (1997) focus on the overbooking problem for hotels with multiple tour-operators and conclude that an overbooking policy that treats the capacity of the hotel as a whole gives better cost savings than an overbooking policy that allocates the capacity to each tour-operator separately. Chatwin (1998) proposes two models (stationary-fares model and nonstationary-fares model) to deal with a multi-period airline-overbooking problem for a single-leg flight with a single service class and use the model to calculate the optimal booking limits. Coughlan (1999) presents an airline revenue maximisation-overbooking model at a fare class level for one service compartment-cabin where class level demand is used to determine the number of bookings for each class. He concludes that this model shows significant improvement over previous methods by testing the model with data of Ireland’s national airline, Aer Lingus. Biyalogorsky et al. (1999) propose that a strategy using overbooking with opportunistic cancellations can increase expected profits and improve allocation efficiency, then derive a rule of how to allocate capacity to consumers optimally. Under their strategy, the seller can oversell capacity when high-paying consumers show up, even if capacity has already been fully booked, then the seller will cancel the sale to some low-paying customers while providing them with appropriate compensation. Toh and Dekay (2002) create an overbooking model for hotels to find the optimal level of overbooking considering customer service level, unexpected stayovers, and cost of walking displaced guest.

Ringbom and Shy (2002) focus on determining the optimal number of business- and economy-class bookings when ‘adjustable-curtain’ strategy is applied before boarding. ‘Adjustable-curtain’ strategy means that the airline can adjust the size of the business-class section of the aircraft shortly before boarding takes place and therefore allows overbooking for business-class passengers. Karaesmen and van Ryzin (2004) propose a stochastic gradient algorithm to find the joint optimal overbooking levels for the overbooking problem with multiple reservation and inventory classes. In this paper, the multiple inventory classes may be used as substitutes to satisfy the demand of a given reservation class. Bertsimas and de Boer (2005) combine a stochastic gradient algorithm and approximate dynamic programming to improve the quality of overbooking limits.

### 3.5 Forecasting

Forecasting is a critical part of revenue management. The quality of revenue management decisions, such as pricing, capacity control, or overbooking, depends on an accurate forecast. Pölt (1998) estimates that a 20% reduction of forecast error can translate into a 1% incremental increase in revenue generated from the revenue management system. Revenue management forecasting includes demand forecasting, capacity forecasting, and price forecasting, each of which has its specific requirements. All forecasting tasks need to address issues such as what to forecast, the type of forecasting method, the aggregation level, the data to use and the accuracy of forecast. Forecasting can have different aggregation levels, from full aggregated forecasting to semi-aggregated forecasting and to fully disaggregated forecasting. The data used in forecasting can be based on historical arrivals or bookings. In addition, forecasting must be adjusted according to special
events, for example, holidays. Zaki (2000) gives a summary of forecasting for airline revenue management.

Weatherland et al. (2001) discuss different ways to forecast demand for hotel revenue management systems and assess the effectiveness of aggregated approach and desegregated forecast. Furthermore, Weatherford and Kimes (2003) use data from Choice Hotels and Marriott Hotels to conduct a comparative test on a variety of forecasting methods for hotel revenue management systems to find the most accurate method. Their research suggests that exponential smoothing, pickup method and moving average models provide the most robust forecasts.

Weatherford and Pölt (2002) use methods of unconstraining bookings to demand to improve forecasting accuracy for airlines. Neuling et al. (2004) present the opportunities of using passenger name records (PNR) as a data source to improve forecasting accuracy and use a machine learning algorithm as the prediction model to address PNR-based no-show forecasting.

Despite the mounting forecasting methods, human judgment is still indispensable in forecasting demand. Schwartz and Cohen (2004) make a study on 57 experienced revenue managers to evaluate the bias of this kind of subjective judgment. They find that the nature of the user interface can influence the way the revenue managers adjust the computers’ forecasts, although the managers are given the same predictions. The managers with a deliberate computer and no chart made the smallest volume of adjustments to the computer’s forecast, while the managers with a slow computer and an interactive chart made the highest volume of adjustments.

### 3.6 Other issues about revenue management

#### 3.6.1 Economics

To better apply revenue management in the industry, practitioners must have a thorough understanding of underlying economic theory, such as supply and demand, opportunity cost, competition, consolidation, etc. Dana (1999) presents how revenue management techniques, such as price dispersion, can shift demand even when the peak time is unknown. Edgar (2000) focuses on the economic theory underlining the concept of revenue management within the context of the hospitality and tourism industry. van Ryzin (2005) suggests that a model of demand is in the heart of revenue management and that demand models based on customer behaviour will overcome the limitations of current product-level models. Ziya et al. (2004) discuss the relationships with three revenue management assumptions: decreasing marginal revenue with respect to demand, decreasing marginal revenue with respect to price, and increasing price elasticity of demand. They discover that none of these three assumptions can be claimed to be more restrictive than any other, but they can be ordered from the strongest to the weakest when restricted to certain regions. Economic implications can be drawn from their research. For example, over the region where demand is inelastic, decreasing marginal revenue with respect to demand means increasing price elasticity and decreasing marginal revenue with respect to price.

Firms must compete with each other to get customers, so revenue management decisions of one firm unavoidably affect the demand for other firms in the same industry. In addition, airlines, hotels, and other industries have formed alliances to cooperate with
each other to maximise their revenue. These issues have been discussed in several publications. Curry (2001) presents a market-level pricing model to take into account competitors’ actions inherent in the pricing decision. Netessine and Shunsky (2005) use pure-strategy Nash equilibrium to examine the seat inventory control problem under horizontal competition and vertical competition for airlines. Friesz et al. (2005) use Cournot-Nash dynamic game theory to describe pricing for service providers who are involved in oligopolistic competition. They build a differential variational inequity formulation of a dynamic non-zero sum evolutionary game and use a fixed-point algorithm to solve the formulation. Dai et al. (2005) focus on the pricing strategies of multiple firms providing the same service in competition for a common pool of customers; they derive the existence and conditions of Nash equilibrium and calculate the explicit Nash equilibrium point. Vinod (2005a) presents the key challenges of alliance in revenue management decisions and the key steps that need to be taken to maximise revenues across an alliance network. Harris (2006) presents a case of how Piedmont Airlines implemented revenue management increased the service quality to its higherr-yield loyal business customers and deterred the large scale entry of its competitors in the Southeast region.

3.6.2 Development and implementation of revenue management

How to develop and implement revenue management systems is another key issue. Kimes (1999) and Kimes et al. (1999) present a 5-step approach for implementing restaurant revenue management and provide insights from the implementation. Secomandi et al. (2002) present a case of how PROS Revenue Management Inc. worked with three non-airline companies to determine the applicability of revenue management, and to design, develop, and implement Revenue Management systems. Skugge (2002) discusses issues that need to be considered when implementing a revenue management system. He presents risks associated with development and implementation and ways to reduce these risks, and then proposes a two-step process to maximise the likelihood of a successful project completed on time and within budget. Okumus’s (2004) research reveals the complexity and difficulty of developing and implementing a centralised revenue management project. He argues that this is because revenue management implementation is often viewed as a tactical activity, but this is not correct. He suggests that researchers and practitioners should view the implementation from the perspectives of strategic management, and they should change management fields.

Revenue managers play a crucial role in implementing revenue management. Skugge (2004) finds that one of the reasons why some companies enjoy much greater success with revenue management is they have more effective revenue managers and suggests several methods to improve revenue management education and training programs. Zeni (2003) presents a study performed at US Airways to measure the value of revenue managers’ contributions to a revenue management system and concludes that analysts can add up to 3 percent in incremental revenue. Parker (2003) presents that airlines need to establish and provide support for a ‘community of practice’, which is a group of revenue management related people who interact on an ongoing basis. This group takes responsibilities of establishing protocols and standard procedures with respect to revenue management.

The implementation of revenue management requires management to make a series of business decisions. Yeoman and Ingold (2000) discuss the decision-making processes
using examples from airlines and hotels. All business decisions have risks, as do revenue management decisions. Therefore, every company must evaluate the potential risks of revenue management. Lancaster (2003) focuses on the risk incurred in the revenue management policies and analyses how risk management measurements and methods can be applied to the revenue management practices.

In addition, companies want to make sure that their investment on revenue management can achieve the expected return. Delain and O’Meara (2004) illustrate how a company can build a business case to estimate the incremental revenues and costs associated with developing or enhancing a revenue management programme.

### 3.6.3 Customer behaviour and perception

Customer behaviour has a direct influence on the performance of revenue management. Talluri and van Ryzin (2004b) focus on the impact of customer choice behaviour, such as buy-up and buy-down, on revenue management. Revenue management practices may induce customer conflicts and detriment companies’ long-term success. Wirtz et al. (2003) address such conflicts and present different marketing and organisational strategies to resolve these conflicts. Anderson and Wilson (2003) find that when customers are using an informed and strategic approach to purchasing, using standard yield management approaches to pricing can result in significantly reduced revenues.

Another concern about revenue management is that customers may perceive revenue management practices, such as overbooking or demand-based pricing, as unfair, or even illegal. Kimes and Wirtz (2003a) make a study on the perceived fairness of five demand-based pricing methods for restaurants. They suggest that demand-based pricing in the form of coupon, time-of-day pricing, and lunch/dinner pricing are perceived as fair, weekday/weekend pricing is perceived as neutral to slightly unfair, and table location pricing is perceived as somewhat unfair with potential negative consumer reactions. Kimes and Wirtz (2003c) also make a study on the perceived fairness of six revenue management practices in the golf industry. McMahon-Beattie et al. (2004) provide a case study on the impact of variable pricing on buyer-seller relationship. Choi and Mattila (2005) conduct a scenario-based survey to study how much and what type of information hotels should provide customers to enhance their perception of fairness. Choi and Mattila (2006) make a comparison of customer’s fairness perceptions of pricing practices between the US and Korea.

The legal issue of revenue management is the major topic of Boella (1997) and Huyton et al. (1997). In addition, Boella and Hely (2004) present five case studies regarding the major legal issues with the application of revenue management in the hospitality and tourism industries.

### 3.6.4 Performance evaluation

A revenue management practice means that a firm needs to make a wide variety of business decisions, and it is necessary to measure the performance of these decisions to evaluate their effectiveness. Performance evaluation can be accomplished through different methods. Practitioners can compare the difference between treatment and control groups in a randomized experiment. They can compare the pre- and post-revenue management performance under comparable conditions, they can find a percentage of the
theoretical maximum that can be achieved, and they can use simulations to compare the pre- and post-revenue management policy.

Researchers and practitioners have also developed a variety of more sophisticated methods to perform quantitative measurement. For example, Passenger Origin-Destination Simulator (PODS) is a simulator developed and applied by airlines to examine the impact of revenue management methods. Weatherford (2002) and Weatherford (2004) illustrate using simulations to analyze the impact of more realistic fare value assumptions on the performance of a seat allocation optimisation model EMSR and different heuristic decision rules such as Leto Bid Price and Dispersed Fare Rule (DFR). Rannou and Melli (2003) propose a method for measuring the impact of revenue management in hotels in Western Europe. Oliveira (2003) presents a computer simulation to investigate the consequences of revenue management by airlines on the Brazilian Rio de Janeiro – Sao Paulo route. Eguchi and Belobaba (2004) demonstrate using a modified-PODS to investigate the impact of revenue management on Japan’s domestic airline market. Anderson and Blair (2004) present a phased approach called Performance Monitor to measure the impact of revenue management via a dissection of the lost revenue opportunities of historic decisions. Their approach was designed and implemented at Dollar Thrifty Automotive Group. Lieberman and Raskin (2005) propose a method named Comparable Challenges to provide a quantitative measure of how well revenue management decisions perform. They believe that their method has widespread applicability and, more importantly, provides insights on specific actions to take to improve the performance of revenue management decision-making. Jain and Bowman (2005) propose a method to measure the benefits of length-of-stay control for the hotel industry. They conclude that their method can provide accurate and objective results because it has removed the influence of external trends, seasonal effects, and internal changes. Their method can also be used to evaluate the benefits of other revenue management strategies such as overbooking and rate controls.

3.6.5 Techniques for solving revenue management problems

Researchers have developed a variety of approaches to solving different revenue management problems. Raeside and Windle (2000) give an introduction of quantitative techniques used in revenue management. Pak and Piersma (2002) present an overview of operations research techniques used in solving airline revenue management problems.

From Section 3.1 to 3.5, we have already reviewed some techniques for solving specific revenue management problems. We will present a brief summary of these techniques used in solving revenue management problems, including forecasting, pricing, capacity control, and overbooking.

Lee (1990) divides revenue management forecasting methods into three types: historical booking models, advanced booking models and combined models. Exponential smoothing methods, moving average methods, linear regression and ARIMA time series methods are historical booking models; they use historical data to derive forecasts. Advanced booking models use the existing booking data to forecast the demand. Advanced booking models include classical pickup, advanced pickup, the synthetic booking curve model, and a time series of advanced booking models. Combined forecasting models include weighted average of historical and advanced booking forecasts, regression methods, and full information model.
The deterministic solution of the pricing problem can be obtained by using standard optimisation techniques, nonlinear programs, or greedy algorithms. The stochastic solution of pricing problem can be acquired by using the action-space-reduction approach, Markov decision processes, and the Hamilton-Jacobi-Bellman (HJB) equation (Bitran and Caldentey, 2003).

Single-resource capacity control problems were first solved by Littlewood’s rule (Littlewood, 1972). From that time on, the decision tree approach, expected marginal seat revenue (EMSR) heuristics (EMSR-a, EMSR-b, and modified EMSP heuristics), bid pricing method, adaptive methods (van Ryzin and McGill, 2000) and Markov decision processes (Gosavi et al., 2002) have been proposed as solution techniques.

Virtual nesting booking control, network bid pricing method, and dynamic virtual nesting have been proposed to model the network capacity control problems. These problems have been solved by linear-programming approaches, approximate dynamic programming (Bertsimas and Popescu, 2003), scenario tree approaches (Möller et al., 2004), and Markov decision processes (Gosavi et al., 2002).

The continuous time approach (Kosten, 1960), the dynamic programming approach (Bertsimas and de Boer, 2005), and the stochastic gradient algorithm (Ringbom and Shy, 2002), Karaesmen and van Ryzin (2004), Bertsimas and de Boer (2005) have been proposed to solve the overbooking problem.

Table 5 illustrates a list of these approaches and related research in recent years.

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<td>Linear programming</td>
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<td>Integer programming</td>
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<td>Markov model</td>
<td>Bertsimas and Popescu (2003), Bertsimas and Shioda (2003), Brumelle and Walczak (2003), El-Haber and El-Taha (2004), Bertsimas and de Boer (2005a), Savin et al. (2005)</td>
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<td>Dynamic programming</td>
<td>Kraft et al. (2000)</td>
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<td>Bid-price methods</td>
<td>Karaesmen and van Ryzin (2004), Bertsimas and de Boer (2005a)</td>
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<td>Stochastic gradient algorithm</td>
<td>Lai and Ng (2005)</td>
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<td>Stochastic programming</td>
<td>Oliveira (2003), Anjos et al. (2004), Kimes and Thompson (2004), Zhang and Cooper (2005), Bertsimas and de Boer (2005a)</td>
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<td>Simulation</td>
<td>Kuyumcu and Garcia-Diaz (2000)</td>
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<td>Polyhedral graph theory approach</td>
<td>Gosavi et al. (2002)</td>
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<td>Reinforcement learning</td>
<td>van Ryzin and McGill (2000)</td>
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<td>Adaptive algorithm</td>
<td>Neuling et al. (2004)</td>
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<td>Machine learning algorithm</td>
<td>Cote et al. (2003)</td>
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<td>Hierarchical mathematical optimisation</td>
<td>Friesz et al. (2005)</td>
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<td>Fixed point algorithm</td>
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<td>Continuous time approach</td>
<td>Koide and Ishii (2005), Lai and Ng (2005)</td>
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4 Issues for future research

Revenue management research has made great achievement in different industries. This presents a great opportunity for further research. Several researchers have tried to explore the future of revenue management. Trivizas (2003) analyses the trends related to the practice of pricing and revenue management for airlines and other hospitality companies. Shoemaker (2003) explores the future of pricing strategy and customer loyalty. Lieberman (2004a) and Cary (2004) discuss the future opportunities of revenue management as technology develops and the business environment evolves. Boyd (2004) presents the challenges of the dramatic changes in distribution on pricing and revenue management models.

We identify several directions for future research.

4.1 Application in non-traditional industries

The traditional application of revenue management is primarily in the airline, hotel and rental car industries. These industries have the following characteristics: perishable inventory, relatively fixed capacity, predictable demand and relatively high fixed costs. Researchers have discovered that the application of revenue management in other industries is promising. Most service industries, even manufacturing, share some common characteristics with traditional revenue management applications. Therefore, it is possible for them to improve their revenues and profit from an appropriate application of revenue management.

But so far the research on these non-traditional industries is still in the beginning stage. Just as the Tables 2 and 3 demonstrate, most of the current research still focuses on traditional areas. To apply revenue management in non-traditional industries effectively, the assumptions under the traditional revenue management approach must be relaxed. However, the relaxed problem cannot be solved easily and optimally. In addition, the benefits of applying revenue management in the non-traditional industries are not as significant as applying it in the traditional industries.

The advancement of technology presents great opportunities for researchers and practitioners to overcome the difficulties of applying revenue management in non-traditional industries. We believe that revenue management will be applied more and more widely in the future. Among these non-traditional industries, hospitality, transportation, and subscription services deserve to be addressed, because they share most characteristics with the traditional industries.

4.2 Integration of revenue management with new technologies

Since the 1990s, Internet and e-commerce began to play a more and more important role in revenue management, and this trend will continue in the foreseeable future. In the internet era, customers can compare prices among competitors much easier, while service providers can get detailed information about customer behavior much quicker. Choi and Kimes (2002) and Marmorstein et al. (2003) discuss the opportunities and challenges of revenue management in the internet era. Boyd and Bilegan (2003) present an e-commerce model of dynamic, automated sales enabled by central reservation and revenue management systems. How to integrate e-commerce and revenue management presents both a great opportunity and a challenge to academicians and practitioners. Toh and
An overview of research on revenue management

Raven (2003) propose to use Integrated Internet Marketing (IIM) concept to achieve revenue management goals. They undertook web-based experiments and observed advantages of using IIM in this area. Their work represents a beginning of a new research area. Many problems need to be solved. For example, mathematical models of how to apply IIM in revenue management have not yet been developed. Auctions, especially online auctions, have proven to be a feasible and effective alternative to traditional pricing policies. Researchers need to conduct further research to answer questions such as how to integrate auctions into a company’s pricing policy and under what kind of situations auctions are effective to maximise revenues.

4.3 Impact of competition and alliance

Most research treats revenue management in an independent environment without considering the impact of competition and collaboration. However, in today’s world, no company can operate under such a completely independent environment; all companies must compete and collaborate with other companies. In fact, partnership in an alliance has become a fundamental requirement for an airline to survive in the industry and to capture market share. This gives rise to new questions that need to be addressed. For example, any company needs to know how to adjust revenue management decisions according to competitors’ actions. Members of an alliance need to know how to synchronize revenue management decisions effectively across the alliance network and how to share revenues with alliance equitably. However, only a few publications so far have focused on the impact of competition and collaboration on revenue management decisions such as pricing, capacity control and overbooking and the impact has yet to be fully understood.

4.4 Forecasting

The accuracy of forecasting has a direct impact on the performance of revenue management. Researchers have developed a number of different models to improve the performance of forecasts. In addition, with the wide application of Management Information Systems, companies have accumulated an enormous amount of data. The computing power of computers has increased exponentially during the earlier decades, which enables researchers to make considerably more complicated calculations. Equipped with these data, new models and technologies, practitioners are able to make more accurate forecasts than ever before. However, as Zaki (2000) notices, there are also many challenges that exist for practitioners to achieve a higher level of forecasting accuracy: the dynamic nature of revenue management, the unpredictable change of schedules, the size of the problem, the limitations of reservation systems, etc. In addition, as new business models keep on emerging, the old forecasting methods that worked well before may not work well in the future. Facing these challenges, researchers need to continue to develop new and better forecasting methods.

5 Conclusions

Over the last 30 years, revenue management has been an active field of research. Researchers and practitioners have made enormous studies on different areas of revenue
management: on the economic implications of revenue management; on specific problems such as pricing, capacity control, overbooking and forecasting; on how to implement revenue management in different industries and on how to evaluate the impact of revenue management. Despite its growing body of literature, the research of revenue management is far from over with new types of problems emerging. How to apply revenue management in non-traditional industries other than airlines, hotels, and rental cars; how to use new methodologies such as auctions, e-commerce and internet marketing to improve the performance of revenue management; how to make revenue management decisions more effectively under a competitive and collaborative environment and how to make forecasts more accurately are just several of the questions that need to be answered.

References


An overview of research on revenue management


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