

How much to tell your customer?

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A survey of three perspectives on selling strategies with incompletely specified products

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Abstract

Today's technology facilitates selling strategies that were unthinkable only a few years ago. One increasingly popular strategy uses incompletely specified products (ICSPs). The seller retains the right to specify some details of the product or service after the sale. The selling strategies' main advantages are an additional dimension for market segmentation and operational flexibility due to supply-side substitution possibilities. Since the strategy became popular with Priceline and Hotwire in the travel industry about two decades ago, it has increasingly been adopted by other industries with stochastic demand and limited capacity as well. At the same time, it is actively researched from the perspectives of strategic operations management, empirics, and revenue management.

This paper first describes the application of ICSPs in practice. Then, we introduce the different research communities that are active in this field and relate the terminology they use. The main part is an exhaustive review of the literature on selling ICSPs from the different perspectives. Here, we complement a tabular overview with an introduction into the community and a detailed description of each paper. Finally, possible directions for future research are outlined.

We see that strategic operations management has described advantages of ICSPs over other strategies in a variety of settings, but also identified countervailing effects. Today, empirical research is confined to hotels and airlines and largely disconnected from the other perspectives. Operational papers are ample, but mostly concerned with the availability of ICSPs. Research on operational (dynamic) pricing is surprisingly scarce.

Keywords: revenue management, channel-choice, supply-side substitution, probabilistic/opaque/flexible products, upgrades

1 Introduction

Today's technical progress, and especially the Internet, allows sellers to increasingly use selling strategies that were difficult to implement only a couple of years ago. In this paper, we focus on one such strategy, namely the selling of an *incompletely specified product (ICSP)* in addition to traditional, fully specified *regular products*. Only after sale does the customer learn about the exact specification of the product bought. These products are increasingly used, as the following examples show.

- The two online travel agencies Priceline (Express Deals, www.priceline.com/hotels) and Hotwire (Hot Rate, www.hotwire.com/hotels) are well-known for their discount hotel offers where brand and exact location are hidden and only revealed to the customer after purchase.
- Online retailers sell products without an exact description. For example, swimoutlet.com sells the "TYR Men's Swimsuit Grab Bag Jammer" (www.swimoutlet.com/product_p/2046.htm). Its description is straightforward: "You pick the size, we pick the print!"
- Although upgrades are widely known from the travel industry, they also occur in production. For example, CPUs for personal computers are usually offered with different base frequencies (i.e. Intel's i7-8700 operates at 3.2 GHz, the i7-8700K only differs in a frequency of 3.7 GHz). Production is often the same for several rated speeds. The final CPUs are tested and assigned a speed. If the market now requires more low speed CPUs than produced, the firm can simply print a lower speed on the product and customers will usually not notice. Only customers who try to operate their CPU at a higher speed than designated (overclocking) will notice that it can do so (see, e.g., Case (2010) for an introduction and a tutorial).

As in the examples mentioned above, ICSPs consist of a pre-specified menu of alternative *component products*, which usually are also sold as regular products. After sale, the firm assigns the customer to one component product. On the one hand, the firm adds complexity to its processes because it has to avoid overselling and guarantee that all customers can be served with the available resources. On the other hand, the inherent possibility for *supply-side substitution* has two important advantages, namely:

- Because of their inherent uncertainty, ICSP are fundamentally different to regular products. They allow the use of an entirely new dimension for *market segmentation*, namely the *strengths of customer preferences* for the component products. This enables the firm to additionally offer a cheap, inferior product to *increase its customer base* without cannibalizing too much high value demand from regular products.
- If the seller assigns the customers to component products a while after the sale, he could benefit from additional information, for example, because demand uncertainty can be lower at this later point in time. He is thus able to *improve capacity utilization*.

The component products are either vertically or horizontally differentiated. *Vertical differentiation* describes a preference relation that is shared by all customers, for example, almost everyone will prefer a business class seat instead of an economy class seat in an airplane at the same price. *Horizontal differentiation* relates to individual preferences, for example, some travelers prefer a hotel at a beach, others downtown or at an airport. The assignment of *opaque products* is decided *immediately* after sale. By contrast, the assignment of *flexible products* is *postponed* and decided at a later point in time. For both kinds of products, the flexibility can be explicit or implicit. For example, possible itineraries of air cargo are usually not disclosed to the customer (*implicit*), whereas the customer has to be informed upfront of the flexibility in the hotel and grab ag examples given above (*explicit*). *Upgrades* are probably the oldest and most widely used type of ICSPs. They can be offered with vertically differentiated component products only. The customer buys an inferior component product, but

obtains a product or service superior to what she paid for at no extra cost. Thus, it is assumed that the customer will always happily accept the upgrade and she does not need to agree regarding the upgrade possibility before the sale, which makes upgrades largely implicit. However, she may notice when she sits down in business class instead of economy. In other examples (think of the CPU described above), she may not notice at all. From a technical point of view, the upgrade can be immediate or postponed, depending on when the decision is made. Obviously, only explicit flexibility can be used for market segmentation to exploit heterogeneous customer valuations.

1.1 Focus

In this paper, we focus on quantitative research that addresses ICSPs when selling goods and services to consumers. The key issue is that the customer does not know exactly what she buys, or vice versa, the seller does not need to decide before the sale is finalized on how exactly to provide the goods or services to the customer. However, eventually he has to serve the customer. By contrast, contingent pricing (e.g. Bialogorsky and Gerstner (2004)) and callable products (Gallego et al. (2008), Li et al. (2016)) assume that sales can be ‘revoked’. This is out of this paper’s scope.

ICSPs became popular with consumers through Priceline.com, but this travel website initially offered only a proprietary pricing scheme (Name-Your-Own-Price, NYOP). This bidding scheme quickly gained a lot of attention in academia (see, e.g., Fay (2004), Hann and Terwiesch (2003), Spann et al. (2004)), but neglected the specific design of the products. However, research and practice quickly indicated that the benefits of ICSP are independent of NYOP. Thus, we restrict ourselves to work that addresses ICSP independent of the pricing scheme, and we exclude work on NYOP with regular products.

Further, the uncertainty in the agreement must relate to the product itself and not to its price (e.g. Wu et al. (2014)). Thus, all kinds of upsells (sometimes called ‘contingent upgrades’ or simply ‘upgrades’ in many companies’ marketing), where the customer is nudged to pay more to get a better product under certain conditions (e.g. Cui et al. (2017)) are out of scope. Moreover, the substitution is decided by the seller, not the customer (see Gallego and Stefanescu (2012) for a taxonomy of such products). Of course, there is also qualitative work on ICSPs. For example, a group around Nelson Granados addresses the question of *whether to conceal product information* from an Information Systems/Decision Science perspective using *qualitative reasoning and anecdotal evidence* (see Granados et al. (2006, 2007, 2010)).

1.2 ICSPs in practice

Hotel rooms and flight tickets are – due to Hotwire and Priceline – the most widely known application areas of ICSPs in practice. However, they are also used in many other industries and areas. Table 1 gives an overview of application areas we are aware of from the literature and our consulting experience. For each area, it lists the most important challenges and briefly describes the ICSPs used to tackle them. For example, in (online) retailing of fashion and apparel customers strongly differ in the amount of money they are willing to spend and some know exactly which brands and prints they want (heterogeneous customer valuations). Retailers often have to order upfront without knowing which particular item/print/color will turn out to be ‘hot’ (uncertain customer preferences). Thus, as always, capacity is limited. These challenges are addressed by grab bags. Only after having bought one, customers observe the product contained. Often, they are chosen from a set of horizontally differentiated component products (like different colors), but may also be vertically differentiated (e.g. Swatch combined watches with different retail prices in one grab bag). Customers know that they buy a grab bag (explicit flexibility) and as there is usually no pre-booking, differentiating assignment timing is difficult.

industry	area			solution approach (ICSP)			
		demand uncertainty	capacity	popular description	differentiation	flexibility	assignment time
electronics	CPU, RAM		fixed mix	upgrade	V	implicit	n.a.
media	TV/web ads		uncertain	selection, scheduling	H	explicit	pp.
(online) retailing	fashion, apparel	preferences, het. valuat.		lucky/mystery /grab bag	H, [V]	explicit	n.a.
production	ATO, MTO	het. valuat.		selection, due date quoting, scheduling	[V]	[implicit]	pp.
retailing	food		uncertain	farm basket	H	explicit	n.a.
transportation	cargo			routing flexibility	H	implicit	pp.
travel	airlines	het. valuat.		opaque prod.	H	explicit	im.
travel	airlines	level		upgrade	V	implicit	pp.
travel	car rental	het. valuat.	uncertain	mystery car	V	explicit	pp.
travel	car rental	level	uncertain	upgrade	V	implicit	pp.
travel	cruises	preferences		travel roulette	H	explicit	pp.
travel	hotel	het. valuat.		opaque prod.	H, [V]	explicit	im.
travel	hotel	level		upgrades	V	implicit	pp.
travel	package holidays	preferences		travel roulette	H	explicit	pp.

Capacity is always limited in the short run and not completely flexible in the long run. ATO: assemble-to-order, MTO: make-to-order, het. valuat.: heterogeneous customer valuations, V: vertical, H: horizontal, pp.: postponed, im.: immediate

Table 1: Overview of application areas

Please note that, although not included in the table, there is some sort of capacity limitation in all application areas. Taking a closer look, we see that upgrades are used to address a mismatch between demand and supply of vertically differentiated products, which often occurs when the overall demand level, and thus, also demand for the expensive product, varies. There is no dedicated ICSP, but customers buy a regular product and may be upgraded to a better product. Thus, upgrades are implicit and often decided as late as possible (postponed assignment). In the past, for example, they were often decided at check-in or the departure gate in an ad-hoc fashion. The mismatch occurs because capacity adjustments are not possible in the short term (car rental, dedicated business class in long-distance flights) or not possible at all (the current state-of-the-art in semiconductor manufacturing determines the mix of CPU speeds in a production batch). There are also two areas where a demand/supply mismatch is the major challenge with horizontal differentiation (advertisement and food). In advertisement, the uncertainty stems from the audience. Customers buy a certain number of ‘contacts’ and obtain additional airtime if they are not reached during the predefined breaks. Likewise, web ads may be placed on a variety of websites. Small farms cannot exactly predict the yield of fruits and vegetables and partly pass this uncertainty to the customer by selling farm baskets that contain an assortment of what is available. In these areas, flexibility is explicit. By contrast, in cargo, flexibility is usually implicit and assignment is postponed.

In some areas, there is additionally the challenge of heterogeneous customer valuations, that is, the seller aims to segment the market to apply price discrimination. In production, some customers are willing to pay a premium to obtain a good faster or need processing on an advanced production line. Although customers know about the due date (otherwise discrimination would not be possible), they usually do not exactly know which operational choices the seller has – for example, which machines can be used for production (implicit flexibility). Likewise, hotels also face heterogeneous valuations. Think of business customers who do not pay themselves and attend a conference in a certain hotel compared to leisure customers who visit a city. One way to price discriminate between these segments are opaque products that combine rooms from similar hotels. As they are

often sold through an intermediary who combines rooms from different hotels, assignment is usually immediate to simplify capacity management and allow each hotel to independently keep track of its remaining inventory. Likewise, airlines sell seats through intermediaries to exploit different customer valuations. Car rental companies combine slightly different car types themselves or through an intermediary.

Finally, when sellers want to cope with uncertain preferences, they postpone assignment until a point late in the selling horizon when most uncertainty is resolved. This is usually only possible when the seller himself creates the ICSP from his own component products (e.g. in travel roulette).

1.3 ICSPs in the literature

ICSPs are investigated in the literature by different communities, who focus on different aspects and partly use differing terms. Comparing two communities, often entirely different models are investigated.

- *Strategic Operations Management (OM)* is mostly concerned with basic aspects in stylized models, such as when and why a seller benefits from ICSPs. This is somewhat related to Economics. After all, balancing supply and demand and achieving an efficient allocation of goods is a classical theme. Economic theories on rationing, price discrimination, monopoly/oligopoly pricing and pricing under capacity restrictions come into play. This work is more theoretical than operational in nature and aims at providing fundamental insights into the mechanics at work. These insights are usually lost when operational details such as assignment timing and managing capacity over time are considered. Key aspects are an endogenous demand, often derived by assuming rational, forward-looking customers, stylized models (e.g. only two products and time periods) and neglecting operational issues like availability management.

In this community, the terms *opaque product/opaque selling* and *probabilistic product/probabilistic selling* are used interchangeably (the title of Huang and Yu (2014) is one example). Probabilistic selling emphasizes that from the customer's point of view the particular component product is assigned with exogenous or endogenous *assignment probabilities*. The customers use these probabilities to calculate their expected utility from the probabilistic product. Obviously, all these papers refer to explicit flexibility.

The component products are usually *horizontally differentiated*, for example because customers have different tastes. We explicitly mention when *vertical differentiation* (i.e. different quality) is considered.

- *Empirical papers* predominantly describe real-world ICSPs. They often focus on customer behavior and estimate demand models. Some also use their results to derive recommendations regarding tactical decisions like the price difference between regular products and ICSPs. However, they usually neglect operational issues like assignment (timing). Almost all papers use the term *opaque product*. As above, only explicit flexibility is considered and the component products are *horizontally differentiated*.
- *Revenue Management* considers *operational issues* with ICSPs which involve managing capacities throughout the selling horizon to avoid overselling. Here, the point in time at which the assignment is made is very important, because it determines whether the firm can immediately reduce capacities after a sale. This is possible for immediate assignments (*opaque products*), whereas it is not for postponed assignments (*flexible products*). The latter term is also sometimes used as an umbrella term in this research community, which usually is quite application-oriented and considers the computational tractability of the models and solution approaches developed. Product design (e.g. similarity of the component products, *explicit or implicit flexibility*) is not reflected in the models used but only indirectly captured via exogenous demand, for example, expected demand may be higher if the component products of a flexible product are more similar. For the

same reason, most models can be applied to *both horizontal and vertical differentiation*. The consideration of only vertical differentiation imposes a certain problem structure. These *upgrades* usually are implicit and a customer who bought an inferior product may obtain (and happily accept) a better one instead.

In this paper, we use the relevant terms consistently over the literature streams, which sometimes leads to a paper being described with other terms than it uses itself.

- We use *ICSP* as an umbrella term and the product consists of *component products*, which are usually also offered as *regular products*.
- An *opaque product* is *immediately assigned* to a component product after sale,
- whereas a *flexible product* is characterized by *postponed assignment*, thus potentially allowing the firm additional flexibility.
- The term *probabilistic product* is orthogonal and stresses that customers endogenously calculate the ICSP's utility using *assignment probabilities*.

this paper	strategic operations management	empirics	operations
ICSP	opaque/flexible/probabilistic product	opaque(/flexible) product	opaque/flexible product, upgrade RM with (supply-side) substitution,
selling with ICSPs	opaque selling/channel, probabilistic selling	opaque selling/booking/channel/website	RM with flexible/opaque products, RM with upgrades
selling without ICSPs	transparent selling, traditional/full information channel	transparent channel/website, full information channel/website	traditional RM
component product	component product	–	alternative, (execution) mode
regular product	regular/brand/transparent product	–	regular/specific product
opaque product	often used interchangeably	often used interchangeably	sometimes used interchangeably
flexible product			not considered
probabilistic product			
upgrade	vertically differentiated component products	–	upgrade

– : no specific common term

Table 2: Terms commonly used in the literature

Table 2 provides an overview of the most common terms used in each stream of literature. Please note that terms with only roughly the same meaning are included.

1.4 Literature selection

The literature search for publications according to the scope outlined in Section 1.1 was performed as follows: The databases Scencedirect and Scopus were queried for scientific articles with the following search terms in

title, keywords, or abstract (total hits in parentheses): probabilistic selling (18), opaque selling (26), opaque product (43), flexible product (201). As “upgrade” yielded over 40,000 hits, “upgrade AND revenue” was used (318). All papers were carefully evaluated by considering title and where promising abstract and content. The results were complemented by well-known papers from the field and those referenced in other strategic and operational OM papers. For the most prominent papers and authors, a forward search was performed, that is, the papers citing them were identified using Google Scholar and their publication records (retrieved from their websites) were evaluated, respectively. The references included in all relevant papers were considered in a backwards search. We did not explicitly search for working papers, but included those encountered with a reasonable quality. The search was last updated in August 2018. Figure 1 gives an overview of the core papers identified in the three research streams that will be discussed in detail in Sections 2-4. Please note that a small number of papers fit into more than one stream. In all streams, there is a high number of journals with only one relevant paper. Figure 2 shows the publication intensity over time.

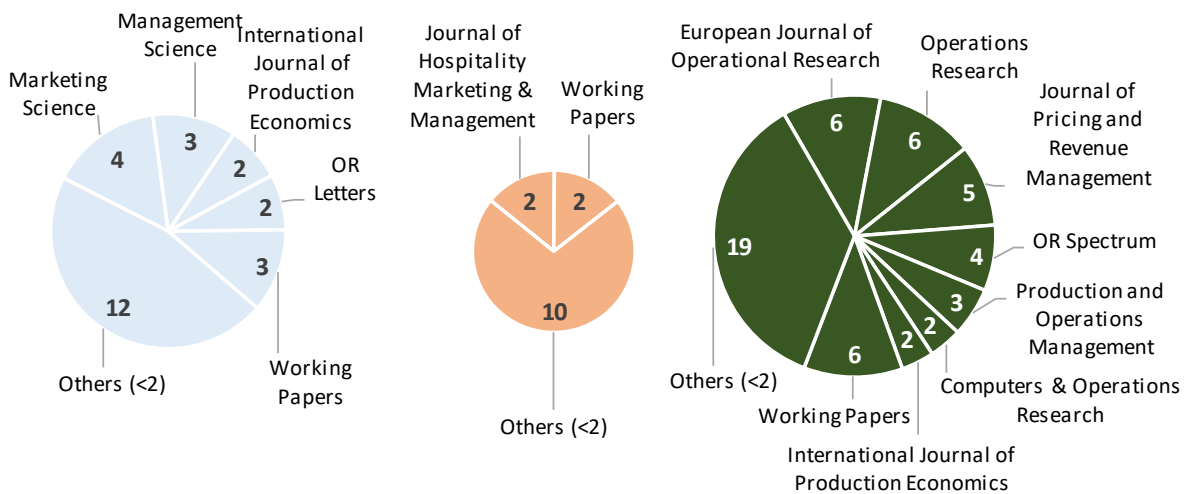


Figure 1: Literature - Strategic OM (left), Empirical (middle), and Operational (right)

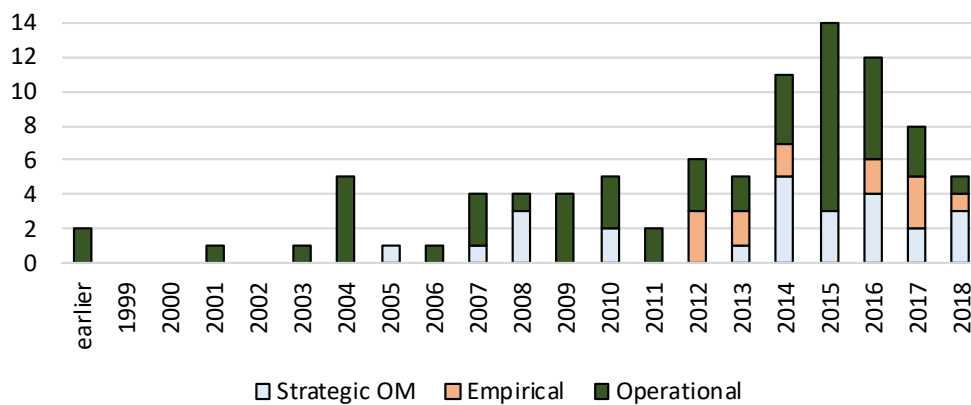


Figure 2: Publication intensity over time

1.5 Outline

Although selling with ICSPs has been intensively researched from the perspectives of strategic operations management, empirics, and revenue management during the past decade, no survey or textbook has covered the topic. To the best of our knowledge, there is only an introduction by Xie and Fay (2014, pp. 318) which contains a number of examples from practice, and nicely illustrates the mechanics of selling ICSPs using small

numerical examples. In their survey, Cleophas et al. (2017) briefly describe various areas that relate to resilient revenue management, among them one page on ICSPs.

This paper attempts to close this gap by first providing an introduction into selling with ICSPs where it carves out the perspectives of different research communities and relates the terminology used by them (Section 1). The main part in Sections 2 to 4 reviews the literature which investigates the field from the perspectives of strategic operations management, empirics, and revenue management. For each perspective, we seek to provide an exhaustive literature review. A table providing an overview is always complemented by a short introduction. In a detailed description of the existing papers we carve out common assumptions and noteworthy deviations and seek to describe their consequences for the results obtained. At the end of each section, we briefly discuss the state-of-the-art. Among others, we see that strategic operations management has described advantages of ICSPs over other strategies in a variety of settings, but also identified countervailing effects. Today, empirical research is confined to hotels and airlines and largely disconnected from the other perspectives. Operational papers are ample, but mostly concerned with the availability of ICSPs. Research on operational (dynamic) pricing is surprisingly scarce. In Section 5, we outline potential avenues for future research. The paper aims at readers with a general interest in selling with ICSPs, who may or may not have a background in strategic operations management, marketing/empirics, and revenue management; it does not presume any prior knowledge of ICSPs.

2 Strategic Operations Management: Economics of ICSPs

In this section, we review papers that investigate when and how ICSPs should be offered, and what drives the effects associated with them. This predominantly theoretical work at the interface of marketing and microeconomics aims at fundamental, industry-independent insights into the mechanics at work. Although analyzing a complete model of selling ICSPs – from product design to market conditions and the operational decisions – would be desirable, this is currently out of the technical skills of the field. Thus, stylized models that each capture selected aspects are used to analyze a limited number of variations at a time. An infinite number of customers is considered, and each customer ponders buying an infinitesimally small amount, such that total market size is usually normalized to one. Thus, although customers have stochastic individual valuations, the share of customers who buy can be directly inferred from the valuations' distributions and the model becomes deterministic (the so called *fluid approximation*). Accordingly, most models share an aggregate view without the lapse of time, because there is no new information available at “later” points in time. Even without the lapse of time, some models like Rice et al. (2014) use two periods to enable strategic customer behavior (i.e. intertemporal utility maximization, see Gönsch et al. (2013a)). Others model the lapse of time where customers' valuations only become known in the second period to model advance selling (e.g. to capture that travel plans might still be uncertain when booking a flight half a year in advance, see Section 2.2). For an individual customer, there is a big difference in expected value depending on whether she buys in the first period (with only the distribution of valuations available) or whether she buys in the second period (with valuations known). This clearly influences purchase decisions. However, on an aggregate level, the firm (and all customers) infer again from valuations' distributions in advance what is bought. Thus, postponed and immediate assignment are equivalent and most authors do not distinguish assignment timing. For example, often real-world examples for both assignment types are given in the introduction. Sometimes, the authors state that immediate assignment is used. In addition, timing is often irrelevant because of the aggregate view and ICSPs are sold only in the “last” period.

In the following, we first consider papers that analyze a monopolistic setting. Key questions investigated are the benefits of ICSPs, that is, how they allow to segment demand and the comparison to other segmentation approaches like advance selling. While most papers use horizontally differentiated component products, one

group analyzes vertical differentiation. Some authors consider isolated additional aspects, namely inventory considerations and assignment timing. Finally, a series of papers analyzes competition. Table 3 gives an overview on the research presented in this section.

	endog. variables	demand uncertainty	# periods	probab. product	limited capacity	remarks
<u>what makes ICMPs beneficial?</u>						
Jiang (2007)	price, ass.-prob.	no	1	yes	no	
Fay and Xie (2008)	price, ass.-prob.	no [pref.]	1	yes	no [yes]	
<u>comparison to other segmentation approaches</u>						
Fay and Xie (2010)	price	no	1, 2	yes	no	comparison to advance selling
Rice et al. (2014)	price, inventory	no [pref.]	2	yes	yes	comparison to markdown
Anderson and Xie (2014)	price	no	1	no	no [yes]	NYOP vs. posted price
Ogonowska and Torre (2014)	price	no	1	yes	yes, uncertain	NYOP vs. posted price
Feng et al. (2018)	price	no	1	yes	no	NYOP vs. posted price
<u>vertically differentiation</u>						
Huang and Yu (2014)	price	no	infinite	yes	no	bounded rationality
Zhang et al. (2015)	price, ass.-prob., quality	no [level]	1	yes	yes	
Ren and Huang (2017)	price, ass.-prob.	level	2	yes	yes	comp. to last minute selling
Biyalogorsky et al. (2005)	price	level	2	yes	yes	
<u>inventory issues</u>						
Fay et al. (2015)	price, product number/type	no	1	yes	no	number of products
Zhang et al. (2016)	inventory, price	preference	1	no	yes	
Zhang et al. (2018)	inventory	preference	1	no	yes	no disaggregate choice
Elmachtoub and Wei (2016)	only assignment	level, pref.	many	no	yes	also operational issues
Chen and Bell (2017)	price, booking limits	level	1	no	yes	also operational issues
<u>assignment timing</u>						
Geng (2016)	price, [ass.-prob.]	no	[1]	yes	yes	congestion/queueing
Xu et al. (2016)	price	no	[1]	yes	yes	congestion/queueing
Wu and Wu (2015)	price	level	3	no	yes	
Fay and Xie (2015)	price, inventory	preference	1	yes	yes	
<u>competition</u>						
Fay (2008)	price, inventory	no	1	yes	no [yes]	
Shapiro and Shi (2008)	price, inventory	no	1	yes	no	
Jerath et al. (2010)	price	level	2	yes	yes	comp. to last minute selling
Cai et al. (2013)	price	no	1	yes	no	asymmetric retailers
Chen et al. (2014)	price	level	2	yes	yes	NYOP vs. posted price
Chao et al. (2016)	price	no	1	yes	no	vertical differentiation
Mao et al. (2018)	price, revenue sharing	no	1	no	yes	interplay with intermediary

Table 3: Strategic operations management (OM) literature on ICSPs

2.1 What makes ICSPs beneficial?

Jiang (2007) is one of the first authors who considers selling ICSPs. His monopolist produces two different component products, which can be sold as regular products or as an ICSP. Customers are horizontally differentiated: Some customers prefer the first product, some prefer the second, according to a Hotelling type model (Hotelling (1929)), which is also used in many subsequent works. Customers who purchase ICSPs have no information on how they are assigned and assume that both component products are equally likely. A peculiarity

of this model is that if *customers' fit cost* for not receiving the ideal component product is low, all customers have the same expected willingness-to-pay for the ICSP, independent of their preferences. However, if fit cost is high, some customers who bought the ICSP and obtain the “wrong” one can decide not to use it and, thus, their expected value depends on their preferences. Jiang finds that with high fit costs (heterogeneous customers), both ICSPs and regular products are offered and all customers are served, otherwise only regular products are offered and the firm may or may not serve all customers. Social welfare can increase or decrease.

Fay and Xie (2008) introduced the term *probabilistic good* for an ICSP with known assignment probabilities. In their model, they assume rational and forward-looking customers whose expectations are confirmed in equilibrium. They emphasize that such goods enable the seller to take advantage of a special type of buyer heterogeneity, that is, *differences in the strength of buyer preferences*. The authors give the example of two different bus tours offered in a national park. Some vacationers may have a strong preference but others may have a weak preference about the tours. In the standard Hotelling model with two products at the ends of a line, this is modeled by customers that are located slightly to the left/right of the middle (weak preference for the left/right product) or near the end of the line (strong preference). They show that even if production cost is so low that a market is fully covered, the introduction of an ICSP increases profit through enhancing price discrimination. It allows the seller to raise the prices of regular products and enables the seller to separate customers with strong preferences (who buy the expensive regular products) from customers with weak preferences (who buy the cheaper ICSP). If production cost is intermediate such that there is unfilled demand without an ICSP, its introduction also leads to market expansion as the cheaper ICSP allows customers with weak preferences (and, thus, lower willingness-to-pay for the regular products) to buy. If production cost is too high, there is no advantage of selling an ICSP. A central result of this paper is that it is generally optimal to assign an equal probability to both component products (leading to all customers having the same valuation for the probabilistic product, see also the description of Rice et al. (2014) in Section 2.2) even if demand is asymmetric, because deviating would diminish the two positive effects of probabilistic selling, namely price discrimination and market expansion. In many other papers, this result justifies imposing equal probabilities. In an extension, Fay and Xie (2008) also consider demand uncertainty and capacity constraints. They find that the advantage of probabilistic selling increases, because it provides a buffer against demand uncertainty. Moreover, it can increase capacity utilization. If multiple component products represented by points on a circle are available, all ICSPs consisting of two adjacent component products, again with equal probability, should be offered. Profit increases in the number of component products as fit to customer preferences improves.

Please note that although widely used in the literature, the interpretation of a customer's location on the Hotelling line as the strength of his preference is somewhat misleading. As in the bus tour example cited above, strength in preference intuitively means that customers with high strengths strongly prefer one product, whereas those with low strengths in preferences do not care, which is usually understood as they are fine with either product. However, in the Hotelling model, customers with weak preferences are indifferent in the sense that they dislike both products. This results in having high-value customers who prefer one product and low-value ones who are more or less indifferent, which is the basis for price discrimination by ICSPs.

2.2 Comparison to other segmentation approaches

Fay and Xie (2010) compare probabilistic selling and *advance selling*. Advance selling describes a selling scheme where products are sold at a discount in a period before the later regular sales period. However, customers learn about their preferences only after the advance and before the regular sales period. Accordingly, the discount may outweigh uncertainty for some customers, while it may not for others. In their model, the seller offers two regular products and decides on the selling strategy and prices. The two component products have

equal assignment probability, as justified by Fay and Xie (2008). The authors use a proprietary preference model generalizing three common models: the Model of Common Reservation Values (Gale and Homes (1992)), the Model of Perfect Substitutes (Xie and Shugan (2001)), and the standard Hotelling Model. They show that the advance selling strategy homogenizes customers by inducing them to buy before they learn about their preferences. By contrast, the probabilistic selling strategy encourages them to reveal their preferences via self-selection. Which strategy is best depends on two types of buyer heterogeneity: The variation of customers' valuation for their preferred product, and the variation in the strength of their preferences. Neither selling strategy is advantageous unless there is sufficient variation in valuation, and a mid-range variation in strengths is necessary for probabilistic selling to be preferred.

After this initial wave of papers, publication activity in this stream somewhat dipped before it picked up momentum again about 4 years later. Rice et al. (2014) compared probabilistic selling with *markdown selling*, where the price is decreased throughout the selling horizon. The seller decides on the selling strategy, prices and the inventory to order before selling starts. The probabilistic strategy entails a probabilistic product being offered in the first of two periods, and the customer is immediately assigned one of the two component products with equal probability. They first point to a peculiarity of the standard Hotelling model for customer heterogeneity. This model often leads to equal probabilities being assigned to the two component products, and thus, all customers have the same expected utility and hence also willingness-to-pay for the probabilistic product. It is thus priced at this willingness-to-pay, customers have zero surplus, and the probabilistic product never cannibalizes a regular one. However, cannibalization is a central concern in markdown pricing because customers will become strategic, and some might delay their purchase to obtain a lower price (see Gönsch et al. (2013a), for a survey on dynamic pricing with strategic customers). The authors use a more sophisticated model that allows cannibalization, and they point out that markdown pricing exploits heterogeneity in customers' degree of patience, while probabilistic selling exploits heterogeneity in the strength of preferences. Which strategy is better, depends on which heterogeneity can be used to create a new purchase option that is attractive to low value customers, but not to high value customers. In an extension, probabilistic selling is found to cope better with demand uncertainty than markdown pricing. Although the authors' main motivation for departing from the Hotelling model is the inclusion of cannibalization, please note that it also abolishes the correlation between customer value and strength of preference discussed at the end of Section 2.1. The authors simply impose equal assignment probabilities for the component products and thus forgo the chance to discuss whether the optimality of equal probabilities might be a peculiarity of the Hotelling model.

Anderson and Xie (2014) compare selling ICSPs with *posted prices* and via *bidding* (e.g. Priceline's NYOP). Customers look to acquire travel services through either regular products or ICSPs (both posted pricing and bidding) and choose the product or sequence of products (bidding first, followed by posted prices) that will maximize their surplus. The authors do not use exogenous customer segments, and consider only one product that is valued differently by customers. Customers do not value the ICSP like a probabilistic one using the assignment expectation, instead, the hassle of buying an ICSP (at posted price or by bidding) is reflected in a lower utility gained through these products. All information is shared, with the exception of customers' individual valuations (the distribution is common knowledge) and the company's threshold price (customers assume a uniform distribution) for the bidding product. They find that firms should adopt at least two products: selling via ICSP posted prices and regular products. When opacity of ICSP bidding is significant, they should adopt it. Under conditions of decreased opacity, firms should use all three products with posted ICSP prices/auction thresholds set higher. Given capacity constraints, the authors assume that the firm does not control sales (no capacity control, see Section 4.1), customers arrive in random order and capacity is thus allocated proportional to the number of customers willing to buy. The firm still benefits from using ICSPs.

Independent of the paper described above, Ogonowska and Torre (2014) also compared these three product types, but they model demand using a proprietary model that contains two symmetric customer types each preferring one regular product. Within a type, customers only differ by a stochastic scaling factor applied to both products' gross utilities. Customers assume equal assignment probabilities. Their results are more inclined towards bidding. The products are exclusive in the sense that a customer cannot buy at a posted price after her bid was rejected. Capacity is limited, exogenous, and only its distribution is known. If buyers have full information on all buyers' valuations and are thus able to infer the threshold levels, bidding should be used, and it does not matter whether it is combined with a posted price ICSP. If buyers have incomplete information, the authors find that the combination of bidding and posted prices dominates in the most relevant cases.

Feng et al. (2018) consider this product type choice for two cooperating firms (think of one parent company). They have unlimited capacity and decide on the prices of the regular products as well as the posted price or the minimum bid for the ICSP, if applicable. The assignment probability is an exogenous parameter reflecting opacity. Different to the two aforementioned papers, customers (wrongly) assume a bid's winning probability to follow a special case of the Kumaraswamy distribution. The higher the customers' pessimism – the distribution's only parameter – the steeper is its increase for higher bids. The firms always offer an ICSP in addition to the regular products. They use posted pricing when the proportion of business customers, who have higher valuations and only buy the regular product of their preferred firm, is high and leisure customers, who choose between regular products and the ICSP, are not too pessimistic. Otherwise, bidding is preferred. This inclination towards bidding is not surprising as pessimistic customers submit higher bids.

2.3 Vertically differentiated component products

Huang and Yu (2014) investigate customers with *bounded rationality*. Their monopolist produces two *vertically differentiated products* and all customers are homogeneous. The firm can choose to sell only regular products (at the known valuations), only probabilistic products, or both. The authors' main contribution is to show that customers' bounded rationality can induce the firm to sell probabilistic products in the absence of all the motivations mentioned in the extant literature. First, their firm chooses the selling strategy and the price of the probabilistic product, if applicable. Then, an indefinite number of customer generations sequentially arrive. Each customer tries to estimate the assignment probabilities by asking previous customers about their experiences. While probabilistic selling is never preferred in such a setting with rational customers, the authors show that it is beneficial with bounded rationality, because some customers overestimate and others underestimate the probability of receiving the better component product. The overestimation allows the firm to charge a higher price for the probabilistic product. Note that the assignment probabilities are not necessarily equal (as indicated in most other papers) and that asymmetric costs are essential. In an extension, competition between two identical firms is investigated. Only one, however, can offer a probabilistic product. With rational customers, the probabilistic product is not offered and a fierce price competition evolves. With bounded rational customers, the probabilistic product is offered, which eases the price competition and creates a win-win outcome for both firms. This survey focuses on competition in Subsection 2.6.

Zhang et al. (2015) consider a firm that sells a high-quality and a low-quality product. In addition, it can sell a probabilistic product whose customer is assigned one of the component products with a preannounced probability (think of an upgrade). The seller has limited capacity and – compared to a regular sale – incurs an additional cost for each probabilistic sale. This may be an additional transaction cost for informing the customer about the component product he obtains. There are two types of customers with different valuations for the component products (similar to Rice et al. (2014)). Whereas prices for the regular products increase with probabilistic selling in horizontal markets, the authors find that prices for the high-quality product decrease for vertically-

differentiated markets. It may still be beneficial because otherwise unused capacity can be sold. In particular, the seller combines unused high-quality inventory with some low-quality products to create the probabilistic product. In doing so he determines the assignment probabilities, which are in general not equal. This still holds when the seller can choose quality or when demand is uncertain. In markets where the seller employs a strong quality differentiation, the introduction of the probabilistic product causes closer quality levels and increases customer welfare. In contrast, in markets where the seller chooses weak differentiation, the probabilistic product increases quality difference and decreases welfare.

Ren and Huang's (2017) monopolist sells high and low-quality products to two segments during the first period: high- and low-valuation customers. Customers may buy or strategically wait for the second period. After the first period, the state of first-period demand (high or low) becomes known. In the second period, leftover products are sold, either via last-minute selling or ICSPs. With two customer segments, probabilistic selling strictly dominates last-minute selling. However, it is less efficient in segmenting the customers and lowers first-period revenue. Interestingly, both the advantage and disadvantage are different from their counterparts with horizontal differentiation. This leads to opposite policy recommendations across the two settings. Under vertical differentiation, the firm may switch from probabilistic selling to last-minute selling as customers become more differentiated or the probability of the low demand realization increases. Under horizontal differentiation, the firm should always switch in the opposite direction. Competition weakens ICSPs' advantage in maintaining a high regular price. However, it introduces a new advantage that is absent with horizontal differentiation: It allows the firm to make better use of leftover low-quality products. Damaging (e.g. shorter warranty) the ICSP's components nudges customers to buy regular products, allows a price increase in the first period, and, thus, may increase profits. In line with Zhang et al. (2015), assignment probabilities are usually not equal, but the reasons for this are not discussed.

In a simpler model, Bialogorsky et al. (2005) already analyzed vertical differentiation in a multi-period setting. Besides a regular and a luxury product, customers can buy an upgradeable product, which guarantees at least the regular product and can be upgraded with a known probability to the luxury one (in case luxury demand in the second period does not materialize). They find that upgradeable products increase profits when luxury demand is relatively strong.

2.4 Inventory issues

Most papers neglect inventory considerations, probably partly because they are simply lost in the stylized models, because they may seem negligible in the often short selling horizons, or because only virtual inventory (think of booking hotel rooms or airline flights) has to be managed. However, six papers explicitly consider inventory, with three also having a strong relation to operational aspects.

Fay et al. (2015) focus on a *retailer* who has to decide on the products to offer. Inventory costs are only roughly considered by a fixed cost for each regular product offered. As an ICSP is created out of existing component products, its cost is assumed to be (or normalized to) zero. They find that probabilistic selling can encourage the retailer to offer more or fewer products, depending on demand-side and supply-side factors. When demand is asymmetric (i.e. more customers prefer the first product than the second), customers' risk aversion decreases the advantage of probabilistic selling.

Zhang et al. (2016) consider a retailer with two regular products who can offer an ICSP. Regular customers are given priority and ICSP customers obtain whatever is left. The authors focus on the capacity initially ordered and the ICSP's discount. As expected, their numerical investigations show that the ICSP can benefit the seller

with improving inventory efficiency. However, the profit advantage is higher with lower product differentiation, higher customers' price sensitivity, and higher demand uncertainty.

Zhang et al. (2018) stand out as they explicitly aim at *comparing strategic and operational OM approaches* to tackle demand uncertainty with limited capacities. In their terminology, the "Marketing and Strategy Literature" considers upfront substitution by inducing product-insensitive customers to choose the ICSP, whereas "Operations Research" resolves capacity mismatches after the selling process via inventory substitution. They use an aggregate demand model and partly depart from the fluid approximation. Demand uncertainty is not modeled via the usual high- and low-demand scenarios, but with a multivariate normal distribution. Although demand does not arrive successively, there is a basic lapse of time in the sense that the assignment decision is postponed. Regarding inventory substitution, the fluid approximation is used again and a given fraction of customers who face stock-out will accept the substitution at a given cost to the firm. As there is no uncertainty here, it remains unclear why the firm does not ask more customers to substitute. The optimal order quantity is an extension of the classical newsvendor solution and takes into account that one product may be used to meet the other's demand and vice versa. Regarding the ICSP, the authors use exogenously given demand induction and cannibalization rates. The optimal newsvendor order quantity for each product is increased by its marginal expected ICSP profit, that is, the expected profit of having one more unit of this product and dedicating it to the ICSP. If the difference between the marginal expected ICSP profits is large enough, the firm will stock more from one product and less from the other if the ICSP's price increases. If the difference is smaller, the firm increases both products' inventory. A numerical study varies substitution fraction, cannibalization, demand induction, and standard deviation as is done by some operational works (see Section 4, e.g. Gönsch and Steinhardt (2013)). The comparison of inventory substitution and ICSPs is difficult to interpret as the straightforward results seem to purely depend on the parameter values and buying decisions do not follow from a disaggregated customer choice model (like the maximum surplus rule).

Elmachtoub and Wei (2016) consider an *online retailer* who carries two component products in inventory. They explicitly discuss how customers value the opaque product and point out that risk-neutral customers without any information assume equal probabilities for the component products. This standard assumption in the strategic OM literature makes the computation of choice probabilities complex, and necessitates stylized approaches like the Hotelling model with its perfectly negative correlation of customers' valuations of the component products. Interestingly, the assumption of *risk-averse customers* who expect the less preferred product lends itself to computational tractability. The authors explicitly consider the multinomial logit model, uniform valuations, and the standard Hotelling model. While the authors position the paper in the strategic OM literature, there are also strong operational aspects which will be discussed in Section 4.1.1.

Chen and Bell (2017) consider an airline with two parallel flights A and B and three customer segments. Segment 1 only considers buying flight A, segment 2 only considers B, and the third segment considers both and an ICSP if offered. In line with literature, customers decide according to valuations and consider the ICSP as inferior. Sales quantities for deterministic demand are straightforwardly derived. Conditions for optimal booking limits and price for the ICSP are given when demand follows an arbitrary pdf. We include the paper here because of its aggregate view without a lapse of time. However, it stands out from the strategic OM literature as it does not investigate the mechanics underlying ICSPs but provides answers *to operational questions*, although the authors do not position it in the operational literature. The paper is difficult to assign to a subsection, but the discussion of the influence of the demand/capacity ratio and booking limits provide some relation to inventory.

2.5 Assignment timing

Three papers consider the timing of the assignment of the ICSP to its component products and investigate how the seller can benefit from *postponing the assignment* to the particular customers who bought an ICSP.

Geng's (2016) model is similar to Jiang's (2007), however he analyzes ICSPs without price discrimination and considers *congested systems*. The seller provides the two component products at different locations that are each modelled by an M/M/1 queue and can either sell only regular products or only an ICSP. Congestion cost due to waiting is linear in the number of customers and time, and is incurred by the firm. In the baseline model, the firm immediately assigns the component products to customers with equal probability (opaque product). In an extension, the assignment is postponed (flexible product), allowing the firm to operate a single queue and assigning products to customers directly before service provision. Even though price discrimination is not possible, ICSPs can be advantageous.

Although they do not consider assignment timing, we discuss Xu et al. (2016) here, because the paper does not fit in any subsection and is very similar to the aforementioned one. Both were developed apparently independently, but submitted and published at the same time in the same journal. Again, customers have individual tastes according to a Hotelling model for two servers, each with an M/M/1 queue. Waiting costs are incurred by the customers and customers of the probabilistic product are assigned with equal probability to one of the two queues. The authors compare three priority policies, each using its optimal price for regular and probabilistic products: first come first served, high priority for the probabilistic customers, and for the regular ones. They analytically solve the model and show that when the market size is large enough, providing the regular products is sufficient. Otherwise, both the regular and the probabilistic product should be sold. Although the optimal prices depend on the queueing priority policy, the optimal revenue does not.

Wu and Wu (2015) consider *demand postponement*, motivated by the leisure travel industry in China. In their three period model, a seller provides only one product, but at different points in time. In the advance period, customers can buy the product with guaranteed delivery in the next period, or, at a discount, they can buy an ICSP with delivery in either the next or the following (third) period. Then, the firm makes the inventory decision. In the regular period, guaranteed advance customers are served. When spot customers arrive, they are served subject to availability. Capacity remaining at the end of the regular period is used for buyers of the ICSP. Any remaining buyers of the ICSP are served in the postponement (third) period, where the firm has ample capacity. The authors show that by using postponement, the firm benefits from both stock out cost reduction and capacity waste decrease.

Fay and Xie (2015) explicitly focus on the *timing* of assignment. Their seller orders inventory upfront to offer two regular products and a probabilistic one. With immediate allocation, the allocation happens after a sale and before the seller learns which product is more popular. Thus, both component products have equal assignment probabilities. With postponed allocation, the decision is made after the sales period when the seller has learnt which product is more popular, and customers (correctly) expect to obtain the less popular one with a higher probability because more inventory from the unpopular product remains. Hence, customers associate a higher expected value with immediate allocation even though they do not care about the delay itself. In this setting, early allocation can be beneficial to the firm, even though it is associated with a higher inventory cost.

2.6 Competition

Fay (2008) is one of the earliest publications in the field and the first to consider *competition*. Two firms each offer a regular product and can sell it through a common intermediary. He points out that this setting mirrors reality, and honors Fay and Xie's (2008) finding that the component products should be similar. First, the firms

contractually agree with the intermediary on the inventory allocated to the ICSP and on transfer prices. Second, the firms choose their prices for the regular products. Third, the intermediary chooses the price of the probabilistic product. Finally, customers maximize their expected surplus and purchase, falsely assuming equal probabilities for the component products. A share of the customers is only interested in one product (loyal clients), the others consider all products (searchers) and are located on a Hotelling line. If all firms cooperate, the monopolist's profits are strictly improved by offering the probabilistic product. With competition, the probabilistic product may lead to market expansion and/or reduce price rivalry. However, if brand-loyalty is minimal, an ICSP increases the degree of price rivalry and reduces total industry profit.

Shapiro and Shi (2008) consider a more general setting with an *arbitrary number of hotels* residing on a circle and each offering a regular product. The number of hotels can be interpreted in terms of the degree of opacity of the ICSP offered by an intermediary. In addition, there are no loyal customers and each customer freely chooses what to buy. First, travelers observe their desired location in the city and their type, which is either high or low strength of buyer preference. Second, each hotel sets a price for its regular product and if offered also for its probabilistic product. The intermediary is not a player and just posts the prices without hotel identity. That is, instead of one ICSP, buyers directly buy the component products, albeit with hidden identities. Finally, travelers observe the prices and decide on their purchase. The authors concentrate on symmetric equilibria where customers know that all component products have equal probability. In the model, customers expected disutility from the probabilistic product is independent of their desired location, and increases in the number of component products. Although market size is fixed and, thus, the probabilistic product cannot expand the market as in most other studies, firms may still prefer probabilistic selling because it discriminates between high- and low-strength customers. It intensifies competition for low-strength customers, but enables the firms to charge high-strength customers higher prices.

Jerath et al. (2010) analyze probabilistic selling in a two-period model with *demand uncertainty*. Two competing firms with limited capacity are located at the ends of a Hotelling line and offer horizontally differentiated products. In the first period, the distribution of demand is known but not its realization (high or low). Both firms sell regular products in this period and sell probabilistic products in the second period if there is remaining capacity. Demand uncertainty is modeled by two possible states of the world with known probabilities: Overall demand is either low or high. Capacity is not allocated a priori. The authors find that probabilistic selling helps increase profits by inducing customers to purchase early. In *comparison to last minute regular sales* (in the second period), opaque selling is preferred when the probability of high demand is considerable, customer valuation is low, and customers have strong preferences. The book chapter by Jerath et al. (2009) explains and illustrates the developments and results of Jerath et al. (2010) in detail.

Cai et al. (2013) focus on *asymmetric equilibria*. They consider a model in which two suppliers A and B sell their products to heterogeneous customers located on a Hotelling line. A common retailer can sell both regular products and a probabilistic product. The sequence of events is as follows. First, supplier A decides on selling a probabilistic product through the retailer and selling regular products directly or through the retailer. Second, supplier B decides on whether to sell a probabilistic product and how to sell the regular ones. Of course, the probabilistic product is only created if both suppliers support it. Third, the suppliers simultaneously determine the wholesale prices (if applicable) for the regular products and the wholesale prices for the components of the probabilistic product are derived from these with a pre-specified discount. If they sell directly to customers, firms are free to choose the component wholesale price. Fourth, retail prices are set. Finally, customers decide on their purchase. Customers expect and the retailer assigns the component products with equal probability, even if component wholesale prices differ. The authors show that the presence (possibility) of a probabilistic

product may induce some suppliers to willingly give up their direct channels. This goes against the classic result that delegation reduces a supplier's profit. The authors also show that an asymmetric equilibrium may emerge in which one supplier sells directly and the other uses the retailer for the regular product. The introduction of a probabilistic product could lead to a Pareto improvement for all channel members.

Chen et al. (2014) investigate how a *retailer's decision* to use *posted pricing or NYOP for a probabilistic product* affects two competing suppliers in a two-period model. Specifically, the suppliers have limited capacity and sell their regular product via posted pricing directly to customers. There are two groups of customers, business and leisure. At the beginning of the first period, the suppliers announce their prices for the regular products. Rational, forward-looking leisure travelers decide whether to buy now or wait, taking into account their preference for the suppliers according to a Hotelling model. In the second period, business demand realizes, either at a high or low level. Business customers always buy the regular product of their preference at their willingness-to-pay. To sell excess capacity to the retailer, the suppliers each determine a wholesale price, given the realization of business demand. Then, the retailer sells excess capacity via posted pricing or NYOP and assigns as much of the cheaper product as possible. The authors find that the ability to set retail prices is critical in extracting surplus from leisure customers who wait. As long as the posted-pricing retailer has some pricing power, customers expect little benefit from waiting, and the suppliers can extract more rents during the first period. By contrast, the NYOP retailer is unable to extract surplus because he cannot credibly commit to rejecting low bids and, thus, customers are more inclined to wait. Accordingly, suppliers prefer a posted pricing retailer. When multiple undifferentiated retailers compete, posted pricing can become equivalent to NYOP. However, retailers make very little profit and prefer to differentiate. With differentiated, competing retailers the aforementioned results on the preference of posted pricing over NYOP continue to hold. In general, suppliers prefer such an environment that allows retailers some pricing power.

Chao et al. (2016) consider vertical differentiation with *consumer anticipated regret*. There are three products with given quality levels. A firm ex-ante chooses whether to sell a low-quality product, a medium-quality one, or a probabilistic one that mixes both with a chosen probability. A competitor only sells a high-quality product. Then, the firms simultaneously decide on prices and, finally, customers make their purchases. Without regret, the firm sells the probabilistic product at an ideal quality level of about half the high quality level. If this cannot be achieved via an appropriate assignment probability, only the low or medium product is sold. With regret, the probabilistic product is not simply valued at its expectation. If the lower product is assigned, customers overweigh a negative surplus (buying regret) and/or the difference between the surplus of buying the high-quality product and the surplus from the probabilistic product assigned the lower product (selection regret). Customers differ in their valuation for quality and a higher selection regret can lead to customers with a medium valuation for quality having the absolutely highest expected utility from the probabilistic product, and this utility then quickly declines as the valuation for quality increases further. When regret on buying is sufficiently large and selection regret is sufficiently small, the firm uses probabilistic selling also when it would not without regret. It continues to use it when both regrets are not too large. Profit is higher if and only if selection regret exceeds buying regret. This seems puzzling at first glance: A market with lower valuations (with regret) may lead to higher profit than a market with higher valuations (without regret). The authors track this to an involved channel which roughly goes as follows: The higher regret implies a stronger "natural" market segmentation which allows the competitor to raise his price. This again enables our firm to sell the probabilistic product at a higher price. The authors do not discuss why probabilistic customers, who know they obtain the low or medium product, anchor the regret at the high product.

Mao et al. (2018) analyze the interplay of two cooperating service providers (e.g. belonging to the same parent company) and an intermediary who can create an ICSP. In the base case, the providers jointly maximize their revenue from selling their regular products directly to customers. In addition, they can sell capacity to the intermediary who creates an ICSP. The revenue sharing between the providers and the intermediary is determined by Stackelberg bargaining. The authors find that the providers use the intermediary only if capacity is medium or high, their capacities are similar and their relative bargaining power is high.

2.7 Discussion on strategic OM research with ICSPs

Researchers have investigated various strategic aspects of ICSPs. Among others, they have shown that ICSPs mainly exploit heterogeneity in the strength of customer preferences, compared it to other segmentation approaches and addressed its benefits in the presence of horizontally/vertically differentiated component products. Comparably few authors investigated assignment timing. Similar to dynamic pricing with strategic customers, it has been shown that flexibility (i.e. postponed assignment) is not always beneficial if the firm is not able to credibly commit itself. Interestingly, almost a dozen papers showed benefits of ICSPs even without considering capacity restrictions, but we only found real-world ICSPs in application areas with limited capacity (see Table 1). All in all, the literature reviewed in this section has discovered many contributing factors with partly countervailing effects. Thus, the net effect of an ICSP and customer behavior is an empirical question.

3 Empirics: ICSPs in the real-world

Empirical research investigates existing ICSPs. Up to now, this research is restricted to the travel industry (see Table 4 for an overview) where passenger aviation (Section 3.1) and hotels (Section 3.2) are considered. An explanation might be the availability of sales and offer data there because of the longtime use of electronic sales channels and inventory systems as well as the general popularity of this industry in ICSP research. Moreover, this is the industry where most consumers experience ICSPs. Only opaque products are considered (with the exception of Mang et al. (2012)), probably because this is the most popular product type in practice. The authors usually do not mention the type of differentiation, but it is safe to assume that only horizontally differentiated component products are considered. Most papers focus on customer behavior and estimate demand models. More or less as a byproduct, the results are sometimes used to derive recommendations for predominantly tactical decisions, like the price difference between regular products and ICSPs. Some authors also try to triangulate ICSPs' profitability with short statements on their revenue share and cannibalization.

3.1 Passenger aviation

Granados et al. (2008) analyze the prices posted for regular and opaque airline tickets with a special focus on the price difference. They observe average prices of about \$100 for opaque tickets and \$160 for regular tickets, resulting in a 38% discount on opaque tickets. However, based on estimated elasticities and the estimated influence of opacity on demand, the authors suggest an optimal discount of astonishing 81%. Thus, they reason that managers should consider reducing the information difference between the products (i.e. make the opaque ones less opaque through more similar component products), or test price increases for the regular product. Of course, lowering the price for the opaque product would also increase the difference.

Mang et al. (2012) analyzed data from Freedom Air, a low-cost subsidiary of Air New Zealand. Between 2003 and 2006, coauthor David Post helped to introduce so called *variable opaque products* (flexible products in our terms). Customers were able to select their destination, length of stay, time window for travel, and when they wanted to be notified. The more opacity customers allowed, the lower the quoted price. Customers were as-

signed the most fitting underbooked flight. The authors found that a substantial number of customers were willing to book a trip which carried some level of uncertainty. Further, customers who were more flexible and were searching with high intensity (i.e. who were making more requests for price quotes) were more likely to buy tickets. Finally, a positive revenue (about 0.2% of total revenues) and profit effect was estimated. The authors underscore that allowing customers to configure their own product enables the airline to create a wide range of differentiated products, which cannot be easily matched by competitors with conventional means.

	(main) data source	unknown to customer	# observations	aim/method, remarks
passenger aviation				
Granados et al. (2008)	sales of airline tickets for 46 US city pairs 2003-2004 via online travel agencies (regular/with SSS)	opaque online travel agency, probably airline and exact departure/arrival time	2,580	estimation of industry-level demand functions (linear and Cobb-Douglas) for ICSPs
Mang et al. (2012)	query and booking data from a Australasian low cost carrier's opaque product sales website	customers self-select possible departure date ranges and assignment timing	42,264	analyze customer purchase behaviour (descriptive, binary probit), postponed assignment
Post and Spann (2012)	booking data from Lufthansa low cost subsidiary Germanwings from 2009-2010	variable opaque product: customers self-select possible destinations	not provided	description of IT, sketch of impact with descriptive statistics
Lee et al. (2012)	booking data from a European airline 08/2008 - 08/2009	see Post and Spann (2012)	not provided	estimation of multidimensional binary logit model
Granados et al. (2017)	ticket sales of a major international airline for 712 city pairs, 5 months of 2005	see Granados et al. (2008)	4,388	calibration of a market response model (proprietary)
hotels				
Lee and Jang (2013)	survey with US students	hotel brand and exact street address	346	ANOVA of fairness of regular price when opaque product offered
Courty and Liu (2013)	price and availability information crawled from Hotwire and hotels for 7 US cities	hotel brand and exact street address	4,550 opaque prices, 7,601 regular prices	analyze opaque discount using regressions
Tappata and Cossa (2014)	opaque bookings from Betterbidding.com, crawled regular rates for US hotels	hotel brand and exact street address	3,817	see Courty and Liu (2013)
Chen and Yuan (2014)	focus groups with US students	no details, opaque online travel agency	12 participants	structural coding/qualitative
Chen and Yuan (2016)	US consumer panel	hotel brand and exact street address	500	analyze structural equation model describing buying process
Chen et al. (2017)	US consumer panel	see Chen and Yuan (2016)	396	see Chen and Yuan (2016)
Huang et al. (2018)	online survey in Hong Kong	see Chen and Yuan (2016)	120 respondents	see Chen and Yuan (2016)
Xie et al. (2016)	online survey imitating online booking of US hotels	hotel brand and exact street address	5,310 from 531 respondents	estimation of multinomial logit model to compare regular, ICSPs with posted price/bidding
Xie et al. (2017)	see Xie et al. (2016), addition of a similar, second survey	see Xie et al. (2016)	plus 5,140 from 514 res.	see Xie et al. (2016)

Table 4: Empirical literature investigating ICSPs

Post and Spann (2012) mainly use descriptive statistics to report on the usage of variable opaque products at Germanwings (now Eurowings), a low-cost subsidiary of Germany's Lufthansa. The product allows customers to select travel dates and a theme like party, culture, etc. Each theme comprises several destinations, but customers can exclude a limited number of destinations by paying €5 each. Essentially, they describe how the product was integrated into the airline's IT systems, and they report on its performance. Between 2009 and 2010, the product contributed about 4% to Germanwing's profits and pushed short-term load factors up to 1.5 percentage points without cannibalizing the demand for other products. What is more, the product did not trigger competitor reactions and did not need advertising.

Lee et al. (2012) use data from an undisclosed European carrier (most probably Germanwings, given the specifics stated) offering a variably opaque product to estimate binary logit choice models. Among others, their results show that customers are more likely to exclude destinations close to their departure airport and destinations that use the same language as their departure airport. Based on their findings, they make recommendations for designing opaque products.

Granados et al. (2017) use a proprietary market response model and a dataset of economy class reservations from a major international airline to investigate demand and cannibalization effects of the ICSP. They find that the impact of the ICSP on total demand is positive in markets with high levels of competition; and the ICSP cannibalizes the online regular channel, but not the offline channel nor the full-fare segment. However, cannibalization of the offline channel moderately increases as markets become more concentrated. They further develop a methodology to assess the revenue impacts of the ICSP.

3.2 Hotels

Lee and Jang (2013) investigate customers' perceptions on the fairness of opaque hotel pricing. More precisely, a study with US students considers two identical hotels' regular products and investigates whether customers dislike a hotel that is \$1 cheaper but has offered an opaque product in the past. The reaction depends on the price. If the discount of the opaque product was 10%, 24% of customers prefer the other hotel, although it is \$1 more expensive. From a past discount of 20% on, 32% of customers prefer the hotel that did not offer opaque products. If customers who dislike the "opaque" hotel are offered a discount on its regular price, virtually all switch if the discount is comparable to the former opaque discount. However, if the discount is lower or higher (!), only two thirds switch, maybe because a too high discount is perceived as untrustworthy and unreliable.

Courty and Liu (2013) claim to be the first empirical paper on opaque selling, which is true with regard to the hoteling industry. They crawled price and availability information from Hotwire and hotel websites and analyze it in a regression with price as the dependent variable. They find that on average, opaque prices for a comparable hotel are 40% cheaper, which is surprisingly close to the 38% Granados et al. (2008) found for opaque airline tickets. Interestingly, features specific to opaque products are also investigated, namely the influence of opaque products' specific opacity. The opaque discount is 12.2% less for hotels in airport areas, as they are usually more homogeneous. Increasing the diameter of the area an opaque product's component products are located in by one mile decreases the price by 1.3% and each additional hotel covered within an opaque product's area decreases the price by 3.7%. The opaque discount is higher in markets where product differentiation is more important because more customer segments are present. However, the model also suggests that the price of regular rooms decreases by 1.2% when area size increases one mile. It is not intuitively clear why the size of the opaque area should influence the price of regular rooms. The authors reason that area size is endogenous and probably driven by density and popularity of a neighborhood. If a neighborhood is more popular, there are more hotels and, thus, more component products, which enables using a smaller opaque area. Thus, area size may be smaller in more popular areas. And, obviously, regular rooms are more expensive in more popular areas.

Tappata and Cossa (2014) conduct very similar research, albeit using another dataset. They compare booking data reported by opaque customers on Betterbidding.com with regular room rates for US and Canadian hotels crawled between October 2011 and June 2012. Surprisingly similar to prior research, they find a discount of 47% and 38% for bidding (Priceline's NYOP) and posted prices (Hotwire), respectively. They also investigate opacity. The size of the area the hotels are located in has a significant, but very small influence on discount (about half a percentage point for one standard deviation). The authors conclude that opaque booking is not

used as a last-minute resource to dispose of unsold inventory and that significant customer heterogeneity remains in the regular selling channel.

Chen and Yuan (2014) conducted two focus groups with a total of 12 US students who had booked hotel rooms, flight tickets, or rental cars by either using the bidding mechanism on Priceline or purchasing an unrevealed brand name on travel web sites such as Hotwire or Expedia. The qualitative analysis of the so-called intentional buying process showed low price, value-added deal, and fun playing with the bidding system as the main benefits. The main risks were insignificant value margin, uncertainty of product quality or performance, and, probably the most surprising item, hidden fees.

Chen and Yuan (2016) capture the intentional buying process described in Chen and Yuan (2014) in a structural equation model. The model is estimated with data from an online survey of opaque hotel booking. The results indicate that customers' perceived risks include hotel performance and website credibility; perceived risks and perceived benefits have different influences on purchase intentions; value assessment is vital for purchase intentions; and risk-propensity only influenced customers' perceived risks and benefits of booking, but past experience affected all factors except purchase intentions.

Chen et al. (2017) use an experimental design that uses both promotional and preventative messages, which are commonly used on opaque-selling websites, to manipulate information levels. Apparently building on their aforementioned papers, the authors now investigate how the levels of perceived information influence perceived risks, benefits, and value assessment. The results show that information is negatively correlated with perceived risks and positively with perceived benefits and value assessment. Perceived benefits are negatively correlated with purchase intention because customers may think it is "too good to be true".

Huang et al. (2018) conducted an online survey in Hong Kong to learn how price and star rating affect customers' expectations. As predicted, customers have lower expectations for cheaper opaque products. The difference varied between items. For a five star room, customers were more likely to compromise on room size than cleanliness. For a three star room, customers lowered their expectations most for the anticipation of guests' needs and least for amenities. Moreover, customers have higher expectations for a hotel with a higher star rating, again with differences between items. Finally, for most star ratings, a customer's expectation depends strongly on the hotel type he usually stays in.

Xie et al. (2016) use choice-based experiments to estimate a multinomial logit model and evaluate customer preferences for US hotel rooms across three product types sold online, namely regular, opaque with posted prices, and opaque with bidding. They find that loyalty programs work, lower prices increase purchase probability, with increased price sensitivity for ICSPs. Higher guest review scores increase purchase likelihood, and this impact is stronger for ICSPs. Thus, they infer that key for a successful ICSP is to have good guest reviews and low prices, especially for those with lower star ratings. A limitation is that respondents could not choose a bidding price themselves because the response option already included a price with a given winning probability. The model shows that ICSPs can improve overall revenue.

Xie et al. (2017) apparently extend their previous paper with an additional survey. In the new so-called menu-based variant, the only change is that the ICSP bidding alternative now includes a slider which allows respondents to select their bid/winning probability. The authors state that, for the most part, parameter estimates are very similar across both survey formats and that price sensitivity increases when customers can make more choices and numerous price-related parameter estimates are significant only in the menu-based variant. However, the data also shows a dramatically lower utility associated with ICSP bidding for low-star hotels. Overall, as before, price sensitivity increases with increasing product opacity. Controlling for price, lower star hotels are more attractive to customers in full information products, the opposite holds true for opaque products where

customers prefer higher star hotels. Guest reviews have a stronger impact on opaque products. Gains can be obtained in both demand and revenue by adding ICSPs with carefully selected prices (about 30% discount for opaque posted prices and 40% discount for opaque bidding).

3.3 Discussion

Compared to the two other literature streams, this one is the smallest. It is also characterized by many researchers from or inspired by the two other streams who set out to describe current industry practice and customer behavior. Nonetheless, the methods used and the research questions tackled clearly delineate this stream from the two others.

Unfortunately, the connection between this and the two other streams is still rather loose. There is no real testing of theoretical findings. Vice versa, empirical findings have yet to be plugged into strategic or operational models. One reason may be that many empirical works strongly focus on describing the status quo in a market or industry and not on providing, for example, parameters to plug into a strategic model or a demand model to use in an operational approach for one company. For example, providing a forecast for a revenue management model is quite different from empirically analyzing the air transport industry. A few papers use their results to provide guidance on tactical decision like the price difference between regular products and ICSPs.

4 Operations: Revenue management with ICSPs

In this section, we focus on the incorporation of ICSPs in operational decision-making processes and systems. These systems influence demand by controlling prices or availabilities throughout the selling horizon. The crucial issue is usually a jointly used, fixed capacity that spans the whole sales horizon. However, costs that depend on total sales (e.g. via economies of scale) have also recently been taken into consideration. The basic challenge arising from ICSPs in revenue management is to adequately manage capacity to ensure that all sales can be served with the limited capacity available. This *capacity management* is what is specific to ICSPs on an operational level. Optimization models, methods, and algorithms tackling this are what researchers focus on. Of course, data is necessary to implement them in practice, usually in the form of a demand forecast. However, this is less specific to ICSPs. At the same time, many papers use data to evaluate their approaches, but the focus of the research is clearly on optimization.

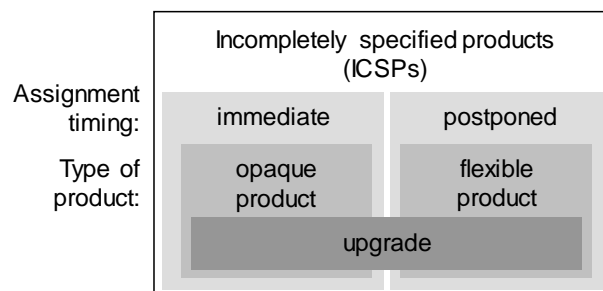


Figure 3: Product types of ICSPs considered on an operational level

Different to the strategic level discussed in Section 2, the approaches here follow classic revenue management’s transaction-oriented view, that is, customers do not update beliefs and their valuation of all products, including ICSPs, is exogenous. In any case, the assignment’s timing is important. It has severe consequences for the models used. Immediate assignment often leads to simpler models at the cost of less operational flexibility. Thus, we organize the literature according to opaque products (immediate assignment) and flexible products (postponed assignment). Moreover, we separately consider upgrades because of the popularity of the topic (see

also Figure 3). From an operations point of view, it does not matter whether the firm's flexibility is implicit or explicit, that is, whether it is obscure to the customer (as in air cargo) or she has to be informed (as in passenger aviation). On the operational level, this is exogenous. It has an impact on demand and is captured by the demand model and its parametrization. But it has no direct influence on capacity management. Although airline terminology is widely used, most models are quite general.

4.1 Capacity control

Capacity control decides on the *availability of products* offered at prescribed prices which compete for a limited, usually fixed capacity. In passenger aviation, for example, these are the different booking classes comprising an identical core service (a seat on a flight from A to B in economy class) with different additional conditions (options to change or cancel the booking, the price, etc.).

The textbook by Talluri and van Ryzin (2004, Chapters 1-3) and the detailed survey by Strauss et al. (2018), provide a good overview. These sources give the standard model formulations and, among others, explain how customer choice behavior is taken into account. The company markets a set of perishable resources with fixed capacities that become worthless at the end of the selling horizon (e.g. an airline that markets its seats during the year prior to departure). Customers arrive stochastically over time (arrival probabilities are given) and seek to buy predefined products, that is, combinations of resources at a given price. When a customer arrives, the firm has to decide on the spot whether to accept his request with the goal of maximizing expected revenue. This means that the request could be rejected in the expectation that the required capacity units can be sold later at a higher price (as part of a different product).

A Markov Decision Process (MDP) usually describes this kind of setting. The optimal expected revenue to go depends on the state of the selling process, which is captured by the remaining capacity and time, discretized into micro periods. To decide on a request at a given state, the product's price is compared to opportunity cost, that is, the difference in revenue to go from the next micro period onwards with unchanged capacity, minus revenue to go with capacity remaining after acceptance. As the number of possible capacities is exponential in the number of resources, this quickly becomes infeasible, so that several approximations have been developed (see, e.g., Talluri and van Ryzin (2004, Chapter 3)). The most important and basic one is the static, deterministic approximation known as the DLP (deterministic linear program, see, e.g., Talluri and van Ryzin (1998) for the standard formulation), that considers demand as deterministic at its expected value. To approximate a product's opportunity cost (referred to as *bid price*), the dual values associated with the resources needed to provide the product are summed up. A request is accepted if opportunity cost does not exceed revenue.

4.1.1. Opaque products

Opaque products do not need a special capacity management. As the firm decides the assignment immediately after sales, remaining capacities can be immediately reduced, the same way they are after a regular sale. Table 5 gives an overview of the literature investigating capacity control with opaque products.

Talluri (2001) investigates an airline whose customers are indifferent to the various itineraries serving the same market (routing flexibility), as long as they are similar with regard to arrival/departure times and price. The author suggests a deterministic model formulation and derives a bid-price policy.

Chen et al. (2003) investigate various approaches to determining bid prices in the context of air cargo revenue management, again with routing flexibility. Specifically, they develop adaptations of the DLP and a stochastic network model. They pay special attention to the adaptation of bid-price controls to opaque products. In addition, they mention a so-called MDP-based approach, which is never even formally stated because it is intractable.

Instead, the authors enhance the well-known certainty equivalent control (CEC) approach, which compares two DLPs' objective values (with and without acceptance) to obtain opportunity cost. More precisely, they calculate the expected revenue to go at several grid points of the state space and then fit regression splines. This allows calculating an approximation for the revenue to go at every state. If a request comes in, opportunity cost is approximated by calculating revenue to go with and without acceptance using the fitted splines. Moreover, they develop a multi-labelling routing algorithm based on a bidirectional variant of Dijkstra's algorithm, which dynamically generates routes based on the opportunity costs of the resources.

	industry/setting	choice	method
Talluri (2001)	passenger aviation with route choice	-	LP
Chen et al. (2003)	air cargo with routing flexibility	-	LP, SP
Kimms and Klein (2005)	various	-	LP
Spengler et al. (2007)	make-to-order: iron & steel	-	multidimensional knapsack
Büke et al. (2008)	passenger aviation with route choice	buy up	SP
Chen et al. (2010)	passenger aviation with two flights	-	MDP
Gönsch and Steinhardt (2013)	generic	-	MDP
Xiao and Chen (2014)	retailing, two products	-	MDP, continuous-time
Sayah and Irnich (2018)	passenger aviation with two flights	-	MDP
Sayah (2015)	passenger aviation with two flights	-	MDP
Elmachtoub and Wei (2016)	online retailing	various	MDP, infinite horizon

LP: linear programming, MDP: Markov decision process, SP: stochastic programming

Table 5: Literature on capacity control with opaque products

Kimms and Klein (2005) give an overview of linear formulations for static revenue management problems in passenger/cargo aviation, hotels, restaurants, car rental, and manufacturing. Because of their static nature, flexible and opaque products cannot be distinguished, but only for opaque products the models can be readily applied. However, the incorporation of flexible products is straightforward.

In manufacturing, there is usually a degree of flexibility regarding how and when an order is produced. Compared to other industries, product variety is larger and flexibility is so big that it is often infeasible to model each possibility as a separate component product of an ICSP. Spengler et al. (2007) consider make-to-order manufacturing. Orders are unique because of their individual, continuous capacity consumption. They extend a heuristic for the multidimensional knapsack problem to derive bid prices from the DLP formulation before the selling horizon starts. In a numerical study with data from the iron and steel industry, the approach increased the contribution margin by up to 5% compared to standard approaches like a randomized version of the DLP (RLP, Talluri and van Ryzin (1999)). Several authors considered manufacturing with postponed assignment; we discuss this work in the following subsection.

Büke et al. (2008) present three stochastic linear programming formulations for passenger aviation with routing flexibility. They also consider buy ups to more expensive products that are possible if a customer's desired product is not available.

While the aforementioned papers focus on static approximations, other papers directly analyze the basic, dynamic setting of capacity control and extend the underlying MDP. Chen et al. (2010) investigate two parallel flights, each offering several regular products at varying prices (i.e. different fare classes). Customers buying an opaque product only specify the fare class. The firm immediately assigns them to one of the two flights and they pay the corresponding (non-opaque) price. The authors state the MDP and concentrate on characterizing the structure of optimal booking policies in the form of four monotonic switching curves.

Gönsch and Steinhardt (2013) consider the standard setting of capacity control with arbitrary opaque products and adapt the generic idea of dynamic programming decomposition (see, e.g., Liu and van Ryzin (2008)). They show numerically that the approach considerably outperforms other well-known capacity control approaches adapted to the opaque setting (e.g., CEC, DLP) and give examples that illustrate how the share of opaque products, as well as the degree of opacity, demand induction, and cannibalization, influences the results.

Xiao and Chen (2014) use a continuous-time MDP to consider a retailer who stocks two similar products at the beginning of the sales period. Prices of the two regular and one opaque product are static, the retailer dynamically determines the availability of the opaque product and its assignment on the arrival of each customer. Customers have an i.i.d. willingness-to-pay for the three products, and they buy according to the max surplus rule. The authors characterize the optimal policy and show that it has a nonthreshold structure. However, if the company knew whether an arriving customer would buy down from a regular product to the cheaper opaque one if it were offered to her (which it usually does not know), the optimal policy could be easily implemented, because of its threshold structure. Given, fixed assignment probabilities – as used in the context of probabilistic products, but unknown to customers – decrease revenue.

Sayah and Irnich (2018) revisit the setting considered by Chen et al. (2010) and provide alternative proofs for the structural results obtained there. In addition, they develop a booking path approach that simplifies control in a static setting with batch arrivals, which can partially be accepted. They show that both booking paths and switching curves describe equivalent policies.

Recently, authors like Vossen and Zhang (2015) or Tong and Topaloglu (2014) have investigated reduced linear reformulations of an approximation of the MDP's linear programming formulation (approximate linear program; ALP). While the MDP grows polynomially or even exponentially with most problem parameters, they found reformulations that are compact in the sense that the reduction grows only linearly with certain problem parameters. This often enables using off-the-shelf solvers. Sayah (2015) presents a reduction for the standard setting of capacity control extended with arbitrary opaque products. He shows that the opaque products cause a gap between the ALP and the reduction, but this gap is never bigger than the upper bound of the DLP. He claims this gap is zero in settings with a particular structure, namely where all opaque products have regular component products and are priced at a discount of the cheapest component product. In any case, it seems that every problem with opaque products can be augmented by adding dummy regular products with no demand to satisfy this requirement. Unfortunately, Sayah does not mention whether this straightforward problem expansion provides an efficient way of obtaining a reduction with zero gap.

The strategic OM aspects of Elmachtoub and Wei (2016) have already been discussed in Section 2.4. The paper is also considered here as it models a lapse of time with discrete, successively arriving customers and provides guidance for operational decisions (what to do at a given inventory level). In particular, they investigate online retailing of two substitutable products that are nonperishable and incur inventory costs. In addition to the two regular products, the retailer can offer an opaque product. Customers' valuations of the opaque product are exogenous and they are assigned at the retailer's discretion. Key issues are a linear inventory holding cost and replenishment. If the inventory of either product reaches zero, the retailer re-orders without order lead time and pays a joint replenishment cost. Under symmetric demand, the retailer uses opaque product demand to myopically balance inventory levels. The cost benefit of inventory balancing can be significant, even if only a small fraction of demand is opaque. In some settings, opaque selling is more profitable than dynamic pricing.

4.1.2. Flexible products

As flexible products' assignment to a component product is postponed until sometime after the sale, the firm faces the challenge to adequately manage capacities. Essentially, there are two major ways to guarantee feasi-

bility and avoid unintentional overselling. First, in the traditional approach the firm keeps track of flexible products' sales (*commitments*), while also checking that there is a feasible assignment of commitments to component products (aka capacity) before selling a product. Second, there is also the *surrogate approach* which is intuitive for small problem settings. For example, in a problem with two resources, two regular products and one flexible product, this approach creates a third surrogate resource whose initial capacity is the sum of the two resources. Now a regular product consumes its resource and the surrogate one, while the flexible product consumes only the surrogate resource. The advantage is that the resulting surrogate problem is formally a standard capacity control problem and, hence, all existing approaches can be used. Table 6 summarizes the literature discussed in the following section.

	industry/setting	choice	method	capacity management
general contributions				
Gallego and Phillips (2004)	passenger aviation with two flights	-	2 periods, MDP	surrogate
Gallego et al (2004)	generic	- , generic	MDP, LP	commitments
Petrack et al. (2010)	generic	-	LP	immediate assign., commitments, ta., surrogate, ...
Petrack et al. (2012)	generic	-	LP	commitments, ta.
Gönsch et al. (2014)	generic	-	LP, MDP	commitments
Koch et al. (2017)	generic	generic	MDP, generic	commitments -> surrogate
Cheung and Simchi-Levi (2016)	generic	generic	LP	commitments
Vock (2015)	generic	-	LP	commitments
applications of flexible products				
Bartodziej and Derigs (2004)	air cargo	-	LP	commitments
Bartodziej et al. (2007)	air cargo	-	LP	commitments
Kimms and Müller-Bungart (2007)	TV ads	-	LP	commitments
Popescu and Crama (2016)	TV ads	-	MDP	commitments
Roels and Fridgeirdottir (2009)	web ads	-	MDP, LP	commitments
Chevalier et al. (2015)	service/production	-	MDP	commitments
Germs and van Roreest (2011)	production	-	MDP	commitments
Guhlich et al. (2015a)	MTO, single-stage	-	LP	commitments
Guhlich et al. (2015b)	ATO, multi-stage	-	LP	commitments
Gössinger and Kalkowski (2015)	MTO, single-stage	proprietary	LP	commitments
Elmachtoub and Levi (2016)	production	-	online alg.	commitments
Elmachtoub and Levi (2015)	production	-	online alg.	commitments

ATO: assemble-to-order, MTO: make-to-order, LP: linear programm, MDP: Markov decision process, ta.: temporary assignment

Table 6: Literature on capacity control with flexible products

Gallego and Phillips (2004) introduce flexible products to capacity control, although the paper lies on the interface between strategic OM (see Section 2) and operations. It utilizes a stylized model with two flights, two time-periods, two regular and one flexible product. The firm can sell the two regular products and the flexible product in the first period. In the second period, only regular products are sold. They analytically analyze the problem and derive simple algorithms for computing booking limits, as well as a corresponding dynamic programming formulation. Simulations illustrate the benefits regarding demand induction and risk-pooling.

Gallego et al. (2004) made several groundbreaking contributions. Among others, they present a generalized MDP formulation for flexible products in arbitrary resource networks, which today is standard in capacity control of flexible products. This formulation extends a traditional MDP's resource-based state space by the number of commitments. It is necessary to keep track of these commitments in order to guarantee throughout the selling horizon that the flexible products sold can be accommodated with the remaining resource capacity. The

authors also overcame the traditional assumption of independent demand by considering arbitrary customer choice behavior. They formulated the now well-known choice-based DLP (CDLP) as an approximation of the underlying MDP, which is computationally intractable in the network context. In the absence of a meaningful way to operationalize the CDLP's solution for customer demand streams, the authors only studied the corresponding primal solution.

Petrick et al. (2012) show how flexible products are integrated in existing capacity control models (e.g. DLP, RLP) and control strategies. In an appendix, they prove the consistency of the intuitive bid-price based acceptance and assignment criteria for flexible products with the DLP's optimal solution. A numerical study with artificial airline examples shows that these approaches can mitigate the negative impact of imprecise forecasts by using ICSPs and that postponement is beneficial.

In a subsequent paper, Petrick et al. (2010) focus on how mathematical models for revenue management with flexible products should be used over time within a capacity control mechanism to exploit the supply side substitution opportunities and adequately manage capacities. They propose several dynamic control mechanisms that differ regarding their complexity and the extent to which they exploit flexibility. The simplest variant is to immediately allocate flexible products (mimicking opaque products). Other variants include a surrogate approach in a restricted setting and dynamically reassigning flexible products as required. A numerical study shows the expected result: The more flexibility an approach allows, the higher is total revenue.

Whereas previous papers relied on numerical experiments to compare flexible and opaque products, Gönsch et al. (2014) use the DP formulations to analytically show that flexible products have an additional *value of flexibility*. It is not captured by DLP-based models which essentially value these products the same as opaque ones. Thus, these models steadily undervalue flexible products, resulting in lower overall revenues. The value of flexibility is quantified and the authors propose a simulation-based approach that systematically increases the value of flexible products in the DLP. The approach is successfully applied in numerical experiments.

Koch et al. (2017) present an algorithm based on Fourier-Motzkin Elimination to construct the surrogate problem for arbitrary capacity control problems with flexible products. As this enables transforming them into equivalent standard capacity control problems without flexible products, all existing approaches can be applied, while, at the same time, fully preserving the flexible product's flexibility. This does, however, run the risk that problem size can explode: With m resources, up to 2^m artificial resources could be created. However, the authors show that the number of artificial resources is much smaller for several network structures that frequently occur in practice.

Cheung and Simchi-Levi (2016) consider the DLP formulation for capacity control with customer choice, the CDLP, and they also include flexible products. They develop several approximate solution methods, among them a polynomial time algorithm with demand learning that achieves a sublinear regret for customers choosing according to a multinomial logit model with unknown parameters.

In his PhD thesis, Vock (2015) investigates how a seller can honor customers' preferences for the component products contained in a flexible product. The thesis does not build on the work endogenizing customers' choice and valuation of probabilistic products summarized in Section 2. It concentrates on including customer preferences into DLP-based models and control mechanisms.

Capacity control with flexible products has also been discussed for various *applications*. In the following, we refer to some examples. Similar to Talluri (2001) and Büke et al. (2008), Bartodziej and Derigs (2004) consider *cargo airlines* with routing flexibility, and volume as well as weight restrictions. They also consider flexible products, present linear models and develop solution algorithms based on column generation. A dozen variants

is tested in a numerical study. Compared to their previous work, Bartodziej et al. (2007) apparently has another focus regarding the presentation and the numerical study.

The literature on *media revenue management* considers flexible products to a differing extend. Depending on media type and country, advertisements are often sold through an upfront and a spot (scatter) market and scheduled dynamically depending on how popular the shows turn out to be. As a result of the process' complexity, many authors develop highly specialized models and consider the accept/reject or pricing decisions over time that are at the core of classical revenue management to a varying extend, which makes the scope here difficult to delimit. Pandey et al. (2017) provide an extensive survey. For example, Araman and Popescu (2010) focus on balancing upfront and spot market sales throughout various planning stages.

Kimms and Müller-Bungart (2007) focus the *TV broadcasting* industry's problem of selecting and scheduling advertisements to be aired. They consider the static problem with given ads to choose from and known break lengths. The authors present a linear model with five solution 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 – and test them in a computational study using Spanish TV data.

Popescu and Crama (2016) are in line with the classical capacity control setting and focus on dynamic scheduling for live broadcasting, where the time and length of breaks for ads is not known in advance. In an extension, they also consider the selection of ads to include in the scheduling process. Contrary to revenue management's standard assumption, these ad requests do not arrive successively over time, but the firm chooses from a given set of available ads.

Roels and Fridgeirsdottir (2009) maximize a web publisher's *online display advertising* revenues. The MDP captures both uncertainty in successively arriving ad requests and website traffic. It dynamically selects the ad requests to accept and the ads to show to a specific visitor. After characterizing structural properties, the authors propose a variant of the classical CEC heuristic. A numerical study shows big differences in the performance of two common heuristics and a small advantage (less than 1%) of CEC over the best.

The acceptance of orders and scheduling their dispatch has also been widely considered with regard mainly to *manufacturing*. In this context, the flexible product's component products are the points in time when the firm can produce an order. Although related to ICSPs in the sense considered here, the field is too big and special to be in our scope. In the following, we provide some examples and refer to the references therein and the survey by Slotnick (2011) for a deeper discussion of order *acceptance and scheduling*.

Chevalier et al. (2015) consider a firm that disposes of a fixed production capacity. Requests for two types of orders arrive successively over time. Urgent orders have a higher revenue, but also a shorter lead time than regular orders. The firm has to decide how many regular orders to accept and how much capacity to set aside to be able to accept urgent orders. The problem is modeled as an MDP, state reduction heuristics (aggregation) are applied and linear programming is used to solve the resulting MDP formulations in the numerical study.

Gerns and van Foreest (2011) focus on batch industries. Orders belong to product families and have family-dependent due-dates, size, and revenue. When production changes from one family to another a setup time is incurred. The acceptance/rejection and scheduling problem is modelled as an MDP and various properties based on the particular problem structure are used to reduce the state space. For example, new orders are inserted into the existing schedule, but the schedule is never rearranged. The authors use the optimal solution to benchmark various heuristics.

Guhlich et al. (2015a) consider due date quoting and scheduling in an assemble-to-order production system, and provide an extensive literature review. The availability of intermediate material as well as assembly capaci-

ty are limited. For each incoming order, the manufacturer decides whether to accept it, and if so, what due date to quote. The actual assembly dates remain subject to change until production starts. Bid prices are derived from an RLP formulation and used for order acceptance, as well as for fixing the due date. At the beginning of each planning period, a new preliminary schedule is calculated by a linear program which includes all commitments. In doing so, free capacity is valued at its bid price. Gühlich et al. (2015b) extend the approach to a multi-stage production system.

Another example from manufacturing is Gössinger and Kalkowski (2015) who consider a single-stage make-to-order system with random capacity. Flexibility arises from producing accepted orders earlier or later. A major extension to the current literature is that instead of rejecting an order, the firm can propose an alternative delivery date, which is accepted according to a simple, proprietary choice model based on a probability function. The authors put great effort in a numerical study evaluating the impact of various parameters and their interaction on profit and robustness.

Elmachtoub and Levi (2015, 2016) differ from the other papers discussed in this subsection with regard to the setting considered and the methods used. Thus, we discuss them in more detail. Instead of a fixed, jointly used capacity, Elmachtoub and Levi (2016) consider *production costs* that depend on total sales and are nondecreasing in the accepted orders. They follow a robust approach and evaluate the algorithms developed with the competitive ratio (see, e.g., Albers (2003) for its roots in the analysis of online algorithms). It is defined as the worst-case of the profit ratio (with regard to the demand stream) obtained by a so called online algorithm, in comparison to the optimal profit obtained with perfect hindsight information (offline), i.e. to have advance information on the full customer stream. The authors provide two online algorithms which are based on repeatedly solving smaller, associated problems (i.e. sub-problems) that ignore previously made decisions. The first one, Copycat, solves a sub-problem for each arriving customer, including the current and all previously observed customers (including rejected ones) and it accepts the current customer if and only if she is accepted in the sub-problem's solution. For the economic lot sizing problem, the joint replenishment problem and the facility location problem (all with constant per unit rejection cost), Copycat has a competitive ratio of $1/3$, $1/4$, and $1/4$, respectively. However, Copycat is NP-hard for the latter two problems. Thus, it is adapted to obtain a second algorithm, StablePair, which runs in polynomial time and no longer has to solve the full offline problem for every decision it takes. It accepts a customer if and only if there exists an optimal solution on a subset of the production options and a subset of all customers observed so far that includes acceptance of the current customer. The name was chosen because if a customer is accepted by StablePair, she would also be accepted if she had arrived later (which does not hold for Copycat). Obviously, all customers accepted by Copycat are also accepted by StablePair. The algorithm provides a competitive ratio of $1/3$ for all the above-mentioned problems. Both algorithms can be applied effectively to any problem in which the production cost is non-negative, non-decreasing, and submodular with respect to the set of accepted customers and arbitrary, non-negative rejection cost. These problems arise with economies of scale and have a competitive ratio of $1/2$. This is also the upper bound on the competitive ratio of any deterministic algorithm for the problem classes mentioned above.

In a follow-up paper, Elmachtoub and Levi (2015) provide a general framework to develop algorithms for this problem class. They allow arbitrary rejection costs to capture, for example, price changes over time and customer-specific prices. Then, constant competitive ratio guarantees no longer exist for the applications considered. The authors propose a FairShare algorithm that is based on a simulated cost sharing mechanism specific to the production cost function. In particular, the Moulin mechanism first collects bids from all players (customers observed so far), and – independently of the bids – assigns a cost share to each player. As long as players' cost shares exceed their bids scaled by a constant scalar, these players are iteratively removed and costs are

shared among the remaining players. FairShare accepts a customer if and only if the Moulin mechanism accepts her. This allows leveraging any existing cost sharing mechanism with largely general properties for the perfect hindsight problem with full information on demand in an algorithm for the sequential decision problem. For example, they use the cost sharing mechanism of Pál and Tardos (2003) for the facility location problem with full information (offline) to obtain an algorithm for the sequential decision problem (online). Similar problems arise, for example, in online routing (see, e.g., Larsen (2000), Thomas and White (2004) and the references they give), which has recently gained attention in the context of attended home delivery (see, e.g., Klein et al. (2017) and Yang and Strauss (2017)).

4.1.3. Upgrades

Upgrades are a well-known type of ICSPs. They usually imply that the customer receives a decidedly better product than the one initially bought and paid for – at no extra cost. Thus, it is safe to assume that customers will always happily accept an upgrade and it is not necessary to inform them beforehand. Remember that if the customer has to pay to get the better product, this is considered an upsell which is not in our scope (this also includes selling so-called conditional upgrades, see, e.g., Cui et al. (2017)). From a technical perspective, upgrades are a special case of opaque or flexible products, depending on when the upgrade decision is taken. *Full cascading* means that upgrades to any better product are possible, whereas *limited cascading* implies this is not the case, because, for example, only one-step upgrades to the next higher product are possible. Table 7 summarizes the literature discussed. We first review literature on upgrading in general, where authors often use passenger aviation as an example. By contrast, dedicated models are considered in car rental. Finally, we discuss production/retailing.

Alstrup et al. (1986) present a dynamic programming formulation for an overbooking problem with two types of resources incorporating upgrades as well as downgrades. Their aim is to optimize bookings for a flight with two compartments. Back then, the authors estimated the solution time for the dynamic program with a two-dimensional state space and a total of 110 seats at 100 hours. Thus, they applied ad-hoc simplifications like a reduction of decision variables' ranges and state aggregation with buckets of 1-5 passengers. This reduced the runtime to 5-15 seconds on an IBM 3033 computer and memory consumption to less than 1 MB, which was considered reasonable for the repeated calculations necessary in practice.

Almost twenty years later, Karaesmen and van Ryzin (2004) also incorporate overbooking but propose a two-stage model: In the first stage, optimal booking limits are determined and then used for capacity control. In the second stage, just before providing the service, the accepted customers are assigned to inventory classes to maximize net benefit. This step is performed by a transportation problem that allows for upgrades as well as downgrades.

Gallego and Stefanescu (2009) are the first to integrate upgrades into the traditional dynamic programming model for network capacity control with independent demand. The resulting MDP is computationally intractable even for a single-leg setting because different resource types still have to be considered simultaneously. Therefore, approximations are necessary and the authors focus on an extension of the DLP.

Steinhardt and Gönsch (2012) build on the MDP formulation of Gallego and Stefanescu (2009) and investigate structural properties. Most important, they show that immediate and postponed upgrading is equivalent in the classical single-leg setting where each product uses only one unit of one resource, all resources are ordered in one hierarchy, and full cascading upgrading is possible without variable costs for the resources. The optimal immediate upgrade decision is a simple and intuitive algorithm: If opportunity cost associated with the lowest-quality available resource that can be used for the request allows acceptance, the request is accepted and this resource is used. Otherwise, the request is rejected. The authors derive dynamic programming decomposition

approaches and consider the car rental industry in an extensive computational example. Note that the upgrade algorithm parallels Shumsky and Zhang (2009), who also use the lowest available capacity. If the requirements are not satisfied (for example in network revenue management, where a product might need more than one resource like a multi-day car rental), counterexamples where postponed upgrading is beneficial exist.

	industry/setting	type	method	capacity management	imm./postp. assig. equivalent
Alstrup et al. (1986)	airline, two resources, overbooking	upgrade/downgrade	MDP	commitments	no
Karaesmen and van Ryzin (2004)	generic, overbooking	upgrade	MDP	commitments	no
Gallego and Stefanescu (2009)	standard capacity control	upgrade	MDP	commitments	no
Steinhardt and Gönsch (2012)	standard capacity control	upgrade	MDP	reduction, commitments	no, [yes]
Gönsch et al. (2013b)	generic, single leg	upgrade	EMSR	immediate r.	yes
Ivanov (2015)	hotel with 3 room types	upgrade/downgrade	marginal revenue	not applicable	not applicable
McCaffrey and Walczak (2016)	single-leg, two resources	upgrade	MDP	commitments	yes
Gönsch and Steinhardt (2015)	passenger aviation	upgrade	MDP	commitments, immediate r.	yes
Geraghty and Johnson (1997)	car rental, single leg	upgrade	EMSR	immediate r.	yes
Fink and Reiners (2006)	car rental	upgrade	network flow	immediate r.	no
Oliveira et al. (2014)	car rental	upgrade/downgrade	network flow	immediate r.	no
Guerriero and Olivito (2014)	car rental	upgrade, one-step	DLP	immediate r.	no
Shumsky and Zhang (2009)	generic, one hierarchy	upgrade, one-step	MDP	immediate r.	yes
Wu et al. (2011)	retail	upgrade	MDP	immediate r.	yes
Yu et al. (2015)	retail	upgrade	MDP	immediate r.	yes

EMSR: expected marginal seat revenue, DLP: deterministic linear program, MDP: Markov decision process

Table 7: Literature on capacity control with upgrades

Gönsch et al. (2013b) build on the standard *EMSR-a heuristic* of Belobaba (1987, 1989) which is based on marginal revenue considerations and extend it to the single-leg setting with upgrades. A numerical study shows a good revenue performance which is better than dynamic programming decomposition approaches from literature or successive planning approaches widely used in practice.

Ivanov (2015) seeks to determine optimal *overbooking limits* for a single-leg setting with three resources (only one night for a hotel with three room types) and upgrades as well as downgrades. The marginal revenue analysis used is analogous to the considerations underlying EMSR, albeit an optimal solution for the special case of three types is aimed at. Unfortunately, it is impossible to understand why the number of customers who have to be denied a room does not depend on the number of total bookings. Likewise, it appears flawed that revenue is considered twice: as lost revenue in the overbooking costs and directly in the objective. No meaningful numerical example is provided.

Apparently independent from prior work on upgrades, McCaffrey and Walczak (2016) consider the simplest upgrade setting possible: the single-leg setting with two resources and independent demand. However, they extensively underline that this no restriction as the so-called fare transformation approach (Fiig et al. (2010), Walczak et al. (2010)) allows to transform problems with demand following general choice models into equivalent capacity control problems with independent demand, provided that each option considered by an individual customer uses the same resources and additional conditions hold. They work with a commitment-based MDP

and show for the first time in an upgrade setting that the value function is sub-modular and concave in the number of accepted commitments. This is equivalent to the opportunity cost of one resource being non-decreasing in the commitments accepted relating to the other resource. Moreover, opportunity cost is non-decreasing over time. These results imply certain monotonicities for the policy and are used to speed up the classical backwards induction. The core idea is to build on the optimal policy for the next time step (as opposed to only the states' values in backwards induction) and search for incremental changes. For example, in the preceding time step, a product is either offered from the same available capacity threshold onwards or the threshold is increased by one unit of capacity. This makes the two-dimensional dynamic program one-dimensional in a certain regard. A numerical study shows that the new approach is about 10x-20x faster than classical backwards induction.

Gönsch and Steinhardt (2015) consider *arbitrary airline networks* where upgrading is performed separately on each flight leg (this is the important difference to multi-day car rental, the example above). In this case, deciding immediately on upgrading and postponing the decision is equivalent even for network revenue management and equivalent MDP formulations with commitments and with just resources in the state space exist. A surrogate reformulation transforming the problem into a standard capacity control problem without upgrades is given. This is also encompassed in Koch et al. (2017) as a special case (see Section 4.1.2).

Several authors considered upgrades as a byproduct of their *car rental* models. The first paper on car rental revenue management with upgrades is by Geraghty and Johnson (1997), who describe the implementation of a reservation and fleet management system at a US company, but do not disclose specific algorithms and models. They outline an EMSR-based upgrade control for a single station, which is very similar to the one later formalized and investigated in detail by Gönsch et al. (2013b).

Full car rental models are much bigger than, for example, airlines' revenue management models because of the high number of car types combined with uncertain and migratory inventory: Rental lengths and return stations may be uncertain and frequently require costly transports of cars from one station to another. Most authors have a logistics perspective and are primarily concerned with car flows and transports necessary in large station networks. To cope with complexity, usually dedicated, deterministic network flow models are employed. In the following, we only mention authors who also consider whether or not to serve rental requests waiting for confirmation in the sense of capacity control. However, the static approaches ignore the dynamics of successively arriving requests. Oliveira et al. (2017) provide a survey of car rental fleet and revenue management. A recent publication on dynamic car rental capacity control without upgrades is Li and Pang (2017). Lazov (2017) follows a novel approach based on information theory for strategic planning.

A *static full car rental model* is investigated by Fink and Reiners (2006). In favor of tractability, their network flow model downgrades a car from the point in time it is first used for an upgrade onwards. No specifics about the solution method are given, but it is successfully tested on a problem instance with a few hundred stations, 15 car types, 18,000 cars, 20,000 requests and time-steps of 12 hours.

Oliveira et al. (2014) also use a deterministic network flow model, but allow upgrades and downgrades. The problem is solved using a relax-and-fix metaheuristic for problem instances with up to 40 stations, 5 car types, 40 cars, and 3,000 reservations. Reservations are apparently characterized by continuous start and end times.

By contrast, Guerriero and Olivito (2014) are closer to the classical revenue management perspective and consider a smaller network. They state an MDP formulation for multi-station car rental with one-step upgrading (immediate), but then concentrate on static LP formulations, which are given for single-station car rental and multi-station car rental. The authors state that only the single-station model contains starting and ending times of rentals, but the multi-station formulation seems a generalization of the other one. Whereas the abovementioned

tioned papers consider batch decisions on requests accumulated over some time, this research derives classical booking limit and bid-price policies to decide on requests immediately. As usual in revenue management, the policies are updated throughout the booking horizon. The numerical examples encompass up to 5 stations, 15 car types, and 150 cars.

The literature on *stocking under availability-based, firm-driven product substitution* is also related and often developed independently of the revenue management community. Shumsky and Zhang (2009) present a dynamic programming approach with upgrades to the next higher product (one-step upgrading). They depart from the standard capacity control setting and consider a single-leg setting with a special cost structure which implies that only one-step upgrades are profitable. In general, when all resources are ordered in one hierarchy in a single-leg setting, full cascading postponed upgrading is equivalent to immediate upgrading (see Steinhardt and Gönsch (2012) above), but this does not hold for limited cascading upgrading. However, due to the special cost structure, immediate upgrading is optimal again and the optimal solution is obvious: First, use any capacity to satisfy same-product demand, then upgrade until the capacity of the better product reaches some protection limit. The authors develop computable heuristics and use them to evaluate the impact of perfect demand information and various parameters on the value of optimal upgrading.

Apparently independent of the literature in the revenue management community, Wu et al. (2011) consider an upgrade setting that is structurally equivalent to Shumsky and Zhang (2009), but simplified. A seller has a given inventory of two quality-graded products. As usual, the problem is captured by a discrete time MDP and solved via backwards induction. Analogous to Shumsky and Zhang (2009), they find it optimal to first use low-quality products for low-quality demand and upgrade when low-quality inventory is depleted and the higher-quality inventory exceeds a certain threshold. A numerical study compares three selling policies: no upgrading, upgrading whenever possible and the optimal policy.

Yu et al. (2015) generalize Shumsky and Zhang (2009) and relax the cost structure which allows multi-step upgrading. They present an MDP formulation, characterize the structure of an optimal policy and propose a heuristic. Intuitively, again the same-quality inventory is depleted before upgrading. In addition, capacity replenishment is investigated.

4.2 (Dynamic) pricing

Dynamic pricing influences demand by *adapting prices* over time. Application areas include, for example, retailing (e.g. Zhao and Zheng (2000), Heching et al. (2002)), low cost airlines (e.g. Marcus and Anderson (2008), Malighetti et al. (2009)), hotels (e.g. Schütze (2008)), and make-to-order manufacturing (e.g. Hall et al. (2009)). Mostly, non-negotiable posted prices are used. In their textbooks Talluri and van Ryzin (2004, Chapter 5), and Philips (2005, Chapter 10) present the fundamentals of dynamic pricing in detail. Numerous review papers classify the existing publications. Bitran and Caldentey (2003) as well as Chiang et al. (2007) provide classical literature reviews on dynamic pricing in general. More recent review papers focus on current, intensively researched aspects. Gönsch et al. (2013a) provide an overview of dynamic pricing with strategic customers who anticipate that the supplier could lower the price. Den Boer (2015) summarizes the current research on dynamic pricing with learning. In this area, the firm constantly updates its demand forecast based on past sales.

The fundamental model in dynamic pricing is similar to the capacity control models in many ways. The company in question markets a given stock of inventory that is used by one or more products within a fixed sales horizon divided into micro periods. It can adjust the prices at the start of each micro period based on the current residual capacity. The probability of a sale depends on the price, and the maximization of the expected revenue

is formulated as an MDP. Research on operational pricing with ICSPs is still scarce (see Table 8 **Fehler! Verweisquelle konnte nicht gefunden werden.**).

Anderson and Xie (2012) present a sophisticated approach to pricing opaque products on Hotwire. Using data of all hotel bookings in Washington, D.C., made on Hotwire during 6 weeks, they estimate a nested logit model to capture customer choice behavior. A dynamic program then allows the characterization of the optimal pricing and inventory release policy as a function of inventory and time remaining. In particular, two dynamic programming formulations are given, one with prices fixed daily, and one with fully dynamic prices. The authors provide a complete characterization of optimal dynamic prices and a partial characterization of optimal daily fixed prices, and revenue impacts are estimated. An important limitation is that their formulation only considers selling to one opaque reseller, while it ignores other opaque and especially regular channels.

	industry/setting	choice	type	method
dynamic pricing				
Anderson and Xie (2012)	hotel	nested logit	opaque	MDP
Sierag (2017)	generic	arbitrary	flexible	MDP, heuristic
Huang et al. (2017)	generic	valuations	opaque	MDP
Ceryan et al. (2018)	retail	valuations	flexible	MDP, heuristic
static pricing				
Zouaoui and Rao (2009)	generic	logit	n.a.	analytical
Post (2010)	generic	proprietary	n.a.	heuristic
Bai et al. (2015)	generic	utility	n.a.	heuristic

MDP: Markov decision process

Table 8: Literature on pricing with ICSPs

Sierag (2017) extends parts of the classical multi-product dynamic pricing paper by Gallego and van Ryzin (1997) to flexible products. He presents a straightforward dynamic programming formulation, but focuses on a deterministic model. Analogous to the DLP in capacity control, the model is derived by substituting stochastic demand with its expectation and relaxing integrality constraints. Its solution is an upper bound on the stochastic solution. The deterministic solution is then used in two heuristics. In the make-to-stock heuristic, the firm sets the deterministic prices and stops selling a product if sales exceed the amount prescribed in the deterministic solution. In the make-to-order heuristic, the firm also uses the deterministic prices, but sells all products as long as there is sufficient capacity. Gallego and van Ryzin (1997) explain the heuristics' names using the image of a firm that produces goods before the selling horizon and produces on demand, respectively. Both heuristics are asymptotically optimal as the problem is scaled up and demand and capacity go to infinity. Among others, a numerical study shows that the heuristics' performance is as expected. Performance improves with problem size, the make-to-order heuristic is often superior as it does not suffer from capacity partitioning, and *ceteris paribus*, not offering flexible products leads to an enormous revenue loss.

Huang et al. (2017) consider two *competing sellers* each with one product at his disposal. These products can be sold directly as regular products and, via an intermediary using NYOP, as an opaque product. The paper is included here because they explicitly consider the lapse of time and the associated operational decisions at each point in time. However, they primarily target *strategic OM* questions. Among others, they show that sellers' expected profits are generally lower when they adopt the NYOP channel, and the expected profit can even be decreasing in the inventory levels, which never happens if at least one seller does not use the intermediary. Although the existence of the NYOP channel does not always benefit the sellers, in equilibrium both sellers could

adopt this channel at the same time. Areas where each type of channel structure is in equilibrium are characterized. Finally, a small experimental survey validates particular market assumptions.

Ceryan et al. (2018) belongs to the research stream on *stocking* under availability-based, firm-driven substitution discussed in Section 4.1.3 (Shumsky and Zhang (2009), Wu et al. (2011), and Yu et al. (2015)). However, whereas prices are exogenous in the aforementioned papers, Ceryan et al. (2018) consider replenishment decisions and upgrades in a multi-period setting with dynamic prices. At the beginning of each period, the firm sets prices for the two products and orders new products up to a given replenishment limit. Then demand realizes on an aggregate level as in Section 2 and, different from standard dynamic pricing, multiple customers may buy. After observing demand, the firm decides to upgrade customers and serve them with the better product. They characterize the structure of the optimal upgrade, pricing, and replenishment policies and find that firms using upgrades have a larger price differentiation between the products. By contrast, dynamic pricing without upgrades diminishes the differentiation if capacity for the inferior product is scarce. Furthermore, a heuristic is proposed and upsells are investigated.

In the following, we briefly review papers that tackle the *static pricing problem*. For example, by assuming that capacity is not scarce, looking into the future becomes obsolete and each micro period can be optimized in isolation. The approaches take for example elasticities and prices of the component products into account, and one also uses real-world data to calibrate the choice model describing customer behavior, which is the main focus of these works. Note that, especially compared to the analytical models presented above, hands-on models and heuristics are preferred to aid real-world decision making on an intuitive level. The focus seems to be adding ICSPs to an existing portfolio and the link to ICSPs is rather weak, it mostly consists of the fact that a reasonable price is between the cheapest component product's cost and a regular product's price, as this is obviously a superior option for the customer. If there is already some pricing scheme established, this price may change over time depending on a number of factors, for example because of dynamic pricing.

Zouaoui and Rao (2009) assume that an opaque product has a base cost which is less than the lowest component product's. They suggest a dynamic markup as a percentage of the difference between the lowest component product fare and the base cost. A logit model captures customer choice and an optimization model maximizes expected revenue. The authors calibrate the model with data collected across three months at TraveLOCITY.com, and test the optimized prices on an additional month's data, showing a 48% revenue increase given predicted customer choices.

Independently of the previous paper, Post (2010) presents a heuristic that maximizes incremental revenue from variable opaque products. The approach departs from the traditional forecasting of aggregated demand and instead focuses on how likely an individual customer would have been to buy the cheapest component product or the variable opaque product.

Bai et al. (2015) also consider the Germanwings example with its variable opaque products. They focus on the optimal design of the product, including price, opacity and customer selection, and then present a largely hands-on model.

4.3 Discussion on operational ICSP research

As the previous subsections have shown, research on the operational aspects of ICSPs is largely driven by revenue management and especially capacity control. In line with the traditional independent demand assumption, customer choice is often entirely neglected. If it is considered at all, it usually treats ICSPs like regular products and does not take the special nature of ICSPs into account. Instead, the focus is on managing capacity over time, that is, efficiently using available capacity and avoiding overselling. Thus, it is irrelevant whether flexibil-

ity is explicit or implicit to the customer and the focus is on “simply operating production or services profitably” as an anonymous reviewer noted. So why are ICSPs noteworthy at all? In standard revenue management, supply-side substitution is not considered. Strictly speaking, revenue management is not applicable in such settings, or tedious, costly workarounds are necessary. As we have seen, a clean integration is not straightforward.

If the flexibility is explicit, customers will prefer an opaque product (immediate assignment), which also simplifies capacity management. In some instances, an immediate assignment might also be required by the production process. For example, some intermediaries do not have their own inventory, but create an opaque product out of regular products. Thus, they have to immediately book the corresponding component product from a provider who manages capacity himself. On the other hand, only flexible products with their postponed assignment really give the firm additional operational flexibility. However, research has shown that in certain cases an immediate assignment is no worse than a postponed assignment.

On a structural level, research on opaque products focused on the integration into the capacity control models, optimal policies, and (adapted) solution methods. Research on flexible products also considered their integration into the models. While the basic integration is again straightforward, the topic is much more involved. Several possibilities for managing capacity over time have been discussed, ranging from an immediate assignment to fully retaining the flexibility, each one with its specific operational advantages and disadvantages. Moreover, some researchers always used to (equivalently) model special cases of flexible products in the standard network revenue management setting via additional resources (surrogate approach). Finally, it has been shown that this is possible for arbitrary settings with flexible products, albeit it may lead to exponentially many resources. Upgrades are formally a special case of opaque/flexible products. An important research focus has been the property that immediate and postponed assignment are often equivalent. This holds when all resources are ordered in one upgrade hierarchy and there are no upgrading restrictions (full cascading upgrading). Popular examples include a single flight and single-day car rental or hotel revenue management. The equivalence also holds when upgrades can be performed independently on each resource hierarchy. This is also called airline upgrading after the most prominent example: An economy passenger can be upgraded to business only on one leg (e.g. FRA-LON) of a connecting flight (FRA-LON-JFK), which is not possible for a two-day car rental.

Research on ICSPs in pricing in general and dynamic pricing in particular is surprisingly scarce. One reason may be that also research on multi-product dynamic pricing, which obviously is the basis, is quite scarce. The survey by Gönsch et al. (2009) only list just over a dozen papers. By contrast, capacity control is always about multiple products. In addition, Elmachtoub and Wei (2016) highlight that dynamic pricing is often demanding, both theoretically and operationally, where prices have to be adjusted over time. These adjustments may irk customers and induce them to wait strategically, which makes the models even more demanding and often lessens dynamic pricing’s benefits. Interestingly, Elmachtoub and Wei (2016) compared selling an opaque product with static prices to dynamic pricing without. Both strategies perform comparably, even though the problem of strategic waiting is neglected and they recommend opaque products as an alternative to dynamic pricing.

Compared to the strategic OM perspective, the literature is much more diverse. Especially the “simply operate production or service profitably” notion makes the field difficult to delineate. For example, successive accept/reject decisions regarding “orders” that can be flexibly scheduled during some subsequent production/service period occur in many settings.

5 Conclusion and future research

The proliferation of electronic sales processes facilitates selling ICSPs. Since their inception in the travel industry about two decades ago, ICSPs are increasingly used in practice. In parallel, they continue to be researched

from various perspectives: strategic operations management, empirics, and revenue management have all contributed to our understanding of these innovative practices. Strategic OM shows when and how ICSPs are successful, empirical papers strive to describe customer behavior, and revenue management is concerned with their operations. Despite all this work, we are convinced that there are still several interesting questions to answer.

Today, research in the three streams is largely carried out in isolation. This may lead to inconsistent assumptions. For example, strategic OM assumes given or equilibrium assignment probabilities, but on the operational level assignment is decided differently, without attention to customer preferences. Only Vock (2015) considers customer preferences in capacity control's assignment decision. Elmachtoub and Wei (2016) is probably the first paper that bridges strategic and operational models as the authors consider operational decisions in a model that largely resembles a strategic one, for example regarding customer choice. Thus, more models incorporating aspects from multiple levels would be valuable. In the following, we outline possible directions for future research. While the first subsection calls for incremental improvements in the existing research framework, the subsequent subsections aim to point out more general issues that usually all streams may contribute to.

5.1 Consideration of additional aspects

The most obvious areas requiring investigation are probably more sophisticated models in each stream of research, as work in an area usually starts with simplified, basic models that are easier to handle. For example, on the strategic level, most research assumes given assignment probabilities, risk-neutral customers, symmetric sellers and an immediate assignment of goods or services. However, research like Cai et al. (2013) on asymmetric sellers shows that deviating from these assumptions can deliver interesting results that may even contradict findings from other models. In empirical research, only airline and hotel bookings have been investigated, and only for specific markets. Covering additional industries and markets will help managers to decide on ICSPs. On the operational level, most research focuses more or less on the incorporation of ICSPs into existing capacity control models and solution approaches, of which most are ones that were developed a decade ago. However, entirely new issues might arise, as Sayah (2015) shows regarding the state-of-the-art ALP approach. Research on dynamic pricing is still scarce, but the interaction with inventory management seems promising as these areas are considered separately in most firms, or are managed via discounts.

5.2 Customer behavior in face of ICSPs

This issue relates first and foremost to the empirical research stream, which today almost entirely focusses on opaque products in the travel industry and treats them more or less like regular ones: Most questions answered also apply to regular products. For example, price elasticities and demand curves are estimated, or the influence of a hotel's star number and guest reviews is investigated. To date, only the working papers by Courty and Liu (2013) and Tappata and Cossa (2014) address the influence of opacity on prices in the market. Questions to be tackled include the following: How do customers value ICSPs? How much opacity is still attractive for them? Do they use anecdotal evidence from previous customers to form a reference? Are they risk-averse and/or loss-averse? What about trust and trustworthiness, i.e. does the firm share accurate information and the customers consider this information, because they know they can trust it – as opposed to the general paradigm of costless cheap talk? This is especially relevant given the fact that more flexibility (i.e. a postponed assignment) may not benefit the firm if it cannot credibly commit itself. While fairness perceptions are important for revenue management in general (Wirtz and Kimes (2007)), they are probably even more relevant for ICSPs. Results would help firms to design ICSPs.

In addition, these aspects should be included in operational and strategic models, as suggested by Ren and Huang (2018) in their review on bounded customer rationality. One idea would be to cover the dynamic and

repetitive nature of the selling process in a strategic model, from a methodological perspective analogous to the consideration of reference price effects in dynamic pricing (see, e.g., Kopalle et al. (1996) or Popescu and Wu (2007)). Research in this direction is still extremely scarce. On the strategic level, only Huang and Yu (2014) consider anecdotal evidence and, combining strategic and operational aspects, Elmachtoub and Wei (2016) consider risk-averse customers.

5.3 Opacity: flexibility/attractiveness trade-off

On the strategic level, Anderson and Xie (2014) and Shapiro and Shi (2008) consider briefly opacity. On an operational level, some papers showed that the flexibility due to flexible products' postponed assignment is valuable (see Section 4.1.2), but did not really quantify it as this highly depends on detailed empirical data. Obviously, the firm prefers a flexible product with lots of different component products. The less correlated demand for the component products is, the more it benefits from flexibility due to postponed assignment. However, from the customer's point of view, such a product would contain a lot of uncertainty and be very unattractive. For example, whether a flight departs at 8:00 or 9:00 am might not matter, but whether it goes to New York or San Francisco probably is a game changer.

Thus, the question how to design a flexible product arises. The answer is first and foremost application-specific, and relies on combining the empirical perspective and the operational or strategic perspective. But maybe also more general insights are possible. Of course, the basic trade-off is also valid for opaque products, albeit to a lesser extent because they offer less flexibility and segmentation is more relevant. Upgrades are usually not designed but inherent to the application and are usually assumed not to influence demand.

5.4 Risk-averse firms

Analogous to research without ICSPs, most authors narrowly restrict themselves to the consideration of expected values without exposing the variability to the reader. Even if simulations are used in capacity control, often only mean values and standard deviations of simulation runs are given. However, the standard deviation refers to the mean and its purpose is to describe the accuracy of the reported mean. It does not reflect revenue variability of a single simulation run or a single sales process in practice.

Although considering variability is clearly not completely new, we add it to our list of future research to stress its importance, and because we feel that this might disclose an additional, underexplored benefit of ICSPs, namely that they should reduce revenue fluctuations. This is a new perspective of high relevance for practice, and one that can easily be incorporated when simulations are used for evaluation (Gönsch (2017)).

The next step then is to optimize an appropriately defined target criterion (risk-averse revenue management, see, e.g., Barz and Waldmann (2007), Lim and Shanthikumar (2007), Schlosser (2016), or the survey by Gönsch (2017) and the references therein). If appropriately designed, ICSPs may have an even bigger impact in such settings on the strategic and operational level. Empirical research could investigate firms' risk-aversion. Even if firms as a whole probably should be risk-neutral, individual decision makers who are pivotal for the success of an automated pricing system may be risk-averse and need to be catered to.

5.5 Demand learning

All approaches considered on the strategic and operational level thus far assume an exogenously given information status that needs to be created with suitable forecasting instruments (see, e.g. Talluri and van Ryzin (2004, Chapter 9) for an overview) before the application of the optimization method. The methods described in this subsection abolish the strict separation of forecasting and optimization, and improve demand knowledge

by learning during the sales period, which is especially necessary in quickly changing markets or when no historical data is available for a new product.

Learning is intensively researched in dynamic pricing, as the more than 350 references in den Boer's (2015) survey show. The basic concept is to improve demand forecasts during the sales period by observing past price and sales data. If the optimal price is chosen to optimize future revenue given the current forecast, passive learning takes place. Active learning, on the other hand, additionally considers that setting a price also generates new information that improves future forecasts, as well as the value of this information for future optimization. Thus, short-term suboptimal prices, for example either extremely low or extremely high, can be set. These have been found to lead to a substantial improvement in the forecast and to a higher revenue in the long run. The field is methodologically demanding and considers various objectives.

We think that learning is especially relevant for ICSPs because these concepts are still quite new to most sellers and customers (see also Subsection 5.2 on customer behavior). Thus, there is little or no historical data on which to build forecasts. By contrast, research like that of Petrick et al. (2012) shows that ICSPs can mitigate the negative effects of imprecise forecasts. Thus, it remains to be seen whether demand learning and ICSPs are complements or substitutes.

5.6 Additional sources of variation

In line with the classical revenue management setting, where demand is the only stochastic variable, the literature on ICSPs on the strategic and operational levels focuses solely on demand uncertainty. Although demand is clearly hard to predict, all parameters – demand, capacity, and revenues – can be subject to uncertainty in practice. Environmental factors such as unexpected events, changes in the competitive landscape, or the unexpected impact of partners' flawed IT systems might influence the parameters. In aviation, capacity might change due to unexpected equipment malfunction or delays. Surprisingly, even the products' prices are uncertain in passenger aviation. Especially traditional network airlines have developed very complex fare structures, leading to a vast number of fares on the same route. However, forecasting demand for each fare category would be impossible and, even more important, most revenue management systems are still restricted to 26 booking classes (the letters of the alphabet). Thus, fares are grouped and the 'products' used in revenue management are in fact averages over several individual fares. Accordingly, their prices are uncertain as they depend on the actual mix of fares. In other industries, the net value of a sale might be uncertain because different channels charging different commissions are not distinguished, or because the cost of shipping is uncertain because it depends on the whole order as well as the customer's location.

In capacity control without ICSPs, a few authors show that the consideration of sources of variation other than demand considerably improves revenues (see also the section "beyond revenue management" in Cleophas et al. (2017) for further examples). For example, de Boer (2004) as well as Wang and Regan (2006) anticipate exogenous aircraft swaps, that is, stochastic capacity in parts of their work. However, their ultimate goal is endogenous swaps based on the development of demand. Likewise, on a strategic level, for example newsvendor variants including uncertain costs (Gurnani and Tang (1999)), yields (Yang et al. (2007)), and production (Wu et al. (2013)) have been investigated.

6 References

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