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Review

A review of marketing–operations interface models: From co-existence to coordination and collaboration

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ABSTRACT

Marketing and operations are two key functional areas that contribute to the success of a firm. By acquiring and analyzing information regarding customers and competitors, marketing can be viewed an external-focused functional area that determines "what" kind of products (or services) a company should provide through "which" channel at "what" price. By viewing this marketing plan as the "demand" from an internal customer, operations is by-and-large an internal-focused functional area that examines "how" to deliver this demand by using internal or external resources. Due to their inherent roles and responsibilities, coordination and collaborations between marketing and operations areas can be difficult in practice. As such, the conflict between marketing and operations arises when the operation's "supply" does not meet the marketing's "demand." Over the last two decades, researchers have developed different quantitative models to examine the issue of coordination/collaboration in the context of marketing operations interfaces. The intent of this paper is two-fold. We present a unified framework for classifying various marketing–operations interface models that may serve as a guide to navigate through the sea of research articles in this important area. Also, by examining some missing gaps, we discuss some topics for potential future research.

Contents

1. Introduction: a historical perspective

Due to their inherent roles and responsibilities, conflicts between marketing and operations are commonly observed in practice. On one hand, marketing is an external-focused function area with a responsibility to monitor market condition (consumer trend, competition) and develop a marketing plan to increase

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market share or revenue. Usually, the marketing plan specifies "what" kind of products (or service) to offer at "which" location (or channel) at "what" price. For a given marketing plan, operations is an internal-focused functional area with a duty to develop an operational plan that specifies "how" to utilize internal and/or external resources to deliver the marketing plan in an effective manner.

Marketing and operations can co-exist in harmony within a firm when the market condition is stable (same product, same market, same price, same competition, etc.). However, when facing fierce global competition, firms need to develop and launch new products and services quickly. The marketing group can use various marketing mechanisms (promotion and pricing) to set (or change) customer expectations quickly, but the operations group may find it challenging to meet these expectations because its production plans (i.e., Where to produce? In-house or outsource? What to produce? How much to produce?) cannot be changed quickly due to its inherent process. To compete successful in a dynamic market, each firm needs to manage the conflict between marketing and operations. This underlying conflict motivated Shapiro (1977) to question the co-existence of marketing and operations.

Clearly, both marketing and operations need to co-exist so that a firm can do the right thing (by the marketing group) and do the thing right (by the operations group). One would expect the co-existence would generate research interests in examining ways to improve the coordination between the marketing and operations functional areas. However, not much marketing–operations interface models have been developed until the late 80s for two plausible reasons:

(1) *No external pull*. Up till the early 80s, most firms were operating according to functional areas, each of which focused on its own performance measures. As the "over the wall" approach was a common practice, there was no pressing need for researchers to develop ways to improve marketing and operations coordination.
(2) *No internal push*. Researchers were focusing on area-specific research in the early 80s. For example, marketing research was focusing on how pricing (or promotion) affects brand choice (or sales) (e.g., Guadagni and Little, 1983), and operations research was focusing on manufacturing issues such as total quality management, flexible manufacturing systems, and just-in-time production systems (Garvin, 1988; Karmarkar, 1989, 1993).

Despite the use of various marketing instruments (promotional pricing, special financing) and various manufacturing strategies (flexible manufacturing systems, just-in-time systems, total quality management), the market share of many US manufacturers continued to fall. The decline of sales in the manufacturing sectors in the 80s motivated practitioners and researchers to identify the underlying causes and develop effective competitive strategies in the late 80s.

In the mid 80s, Porter (1985) articulated that, in addition to cost, differentiation via "value creation" is a competitive strategy to increase demand as well as customer's willingness to pay. Besides quality, various researchers argued that value can be created through different means: (a) reduce response time through "time based competition" (Blackburn, 1990; Stalk, 1988); (b) reduce product development cycle time and development costs (Clark and Fujimoto, 1991); (c) align external demand and internal capability using the "house of quality" (Hauser and Clausing, 1988); and (d) implement a competitive strategy by using the "balanced scorecard" (Kaplan and Norton, 1992). These innovative ideas have motivated firms to develop different strategies to differentiate their products and services. Table 1 highlights the role of marketing and operations as well as different measures of differentiation. To improve these performance measures of differentiation, marketing–operations interfaces are critical for a firm to compete successfully.

Table 1
Value creation through marketing and operations.

Marketing	Operations	Differentiation measures
Establish customer expectation	Create customer perception	Core values: product, service, price, quality, delivery, functionality, etc.
Focus on value creation	Focus on value delivery	Additional values: product/service variety, response time associated with after sales services such as returns, repairs, technical support, socially/environmentally responsible, etc.
Use marketing instruments to generate customer demand	Use operations mechanisms to meet customer demand	Customer service level.

Without a well defined marketing plan to establish the right expectation for the right customers, a well executive operations plan is insufficient (Hill, 1985). For example, even with operations excellence at Disney and WalMart, Disney Hong Kong failed to market its American-derived theme park to the Chinese due to mismatched expectations about the shows and food services in Hong Kong. Also, WalMart found it difficult to market its American-derived product assortments without accounting for the diverse taste of Chinese consumers in different regions (Farhoomand and Wang, 2008; Lau and Yim, 2007). Without coordinating with the operations area, an excellent marketing plan for offering products and services that meet customer needs can result in disappointment. For example, Boeing promised to develop its new 787 Dreamliner aircraft that creates excellent value. However, without coordinating its marketing plan with its supply chain operations, Boeing is facing major delays (Tang and Zimmerman, 2009). Ultimately, marketing and operations co-ordination is essential for a firm to establish and deliver customer expectations. By analyzing a stylized model, Hess and Lucas (2004) showed that a firm can improve its profit by allocating its resources between marketing research for new product and production planning.

Since the late 80s, various researchers explored different forms of marketing–operations interfaces ranging from strategic level (e.g., new product/process development) to operational level (e.g., joint demand and supply management). Eliashberg and Steinberg (1987) presented one of the first marketing–operations interface models that examined the coordination of pricing and production decisions between a manufacturing and a retailer over a selling season.[1] They considered a continuous time dynamic control model in which the retailer faces a deterministic and non-stationary demand that is price-dependent over the selling season. Specifically, they assumed that the retailer and the manufacturer act "sequentially" as follows. First, given the customer demand function, the retailer determines her optimal retail price and order quantity over time. Then the manufacturer determines the production plan over time by treating the retailer's order as his own demand over time. They characterized

[1] For earlier models that examine various aspects of joint pricing and production planning model, the reader is referred to Eliashberg and Steinberg (1987) and (1993) for details.

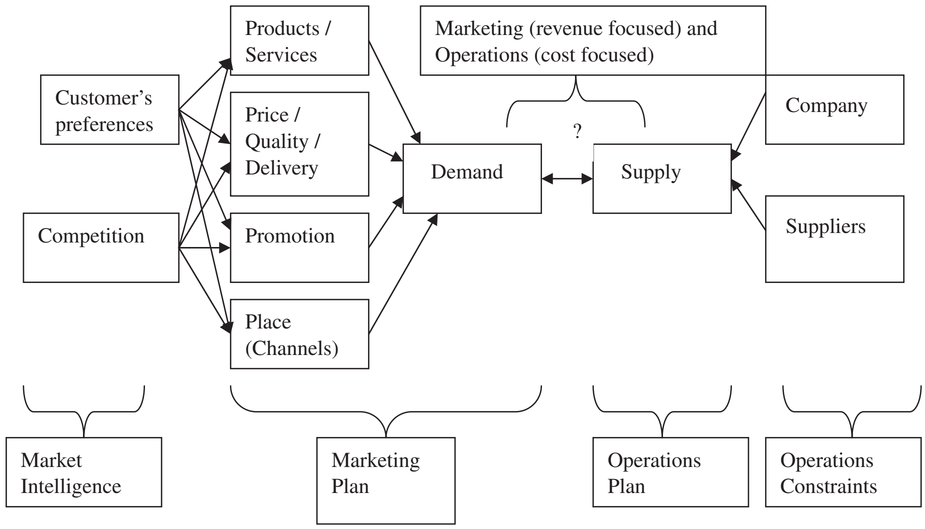

Fig. 1. Traditional marketing/operations interface.

the retailer's optimal pricing and ordering policy and the manufacturer's optimal production plan.

Early conceptual work in the marketing–operations interface research area includes Hausman and Montgomery (1993) and Karmarkar (1996). The former article used empirical data to establish the linkages between marketing priorities (price, quality, features, product variety, etc.) and manufacturing priorities (cost, quality, flexibility, innovation, etc.), while the latter article discussed different areas of coordination between marketing and operations (e.g., joint pricing and production decisions). Since 2000, there were three different special issues focusing on marketing/operations interfaces (Malhotra and Sharma, 2002; Ho and Tang, 2004, 2009).

Because our focus is on quantitative marketing–operations interface models, we shall briefly review four empirical articles that provide empirical evidence about the benefits of coordinating marketing and operations. First, based on the survey response provided by 390 executives, Hausman et al. (2002) presented a path model for assessing the benefits of marketing–operations interface. Their statistical analysis indicated support for two important hypotheses: (1) marketing–operations interfaces can improve a firm's competitive position; and (2) marketing–operations interfaces can improve a firm's profit. Second, Hausman and Montgomery (1997) conducted conjoint analysis of customer preferences based on survey data collected from a high technology company, and showed how these customer preferences can be used to shape manufacturing priorities. Third, Sawhney and Piper (2002) conducted a survey of 180 printed circuit board manufacturing companies to examine the benefit of marketing–operations interfaces. By measuring the quality of marketing–operations interfaces within a firm according to the extent communication and coordination are carried out between marketing and manufacturing and by measuring customer value creation according to defect rate, production cost, and late deliveries, they found statistical support for the hypothesis that tighter marketing–operations interfaces can enable a firm to reduce defects, cost, and late deliveries. Fourth, Kulp et al. (2004) use path analysis to examine the impact of various marketing–operations interfaces (information sharing and collaboration between manufacturers and retailers) on the manufacturer profit margins. By analyzing the survey data, they showed that collaborative planning such as vendor management inventory (VMI) can have positive impact on the manufacturer's profit margins.

2. Marketing operations interfaces: a framework

In general, marketing is an external-focused functional area that focuses on 2Cs (customers and competition) and 4Ps (product, place, price and promotion), and leaves the remaining C (company's capability) to an internal-functional area (i.e., the operations group). To a certain extent, this division of labor is practical especially because the operations group is responsible to utilize internal/external resources to meet the demand imposed by the marketing group in an effective and efficient manner. This also explains why most companies are organized in this manner. Fig. 1 depicts a traditional planning process between marketing and operations so that each area focuses on its own performance measure.

Observe from Fig. 1 that the marketing group utilizes market information (customer's needs and preferences, competitors' current and future plans) to make certain marketing decisions and generate certain demand forecasts for different products (and services) offered in different channels at different prices for different quality levels (or delivery commitments). Because marketing does not have direct control of cost, the objective (or performance measure) for the marketing area is either market share or sales. Given these demand forecasts, the operations group needs to utilize the company (and other external suppliers' capabilities) to meet these demand forecasts at the most cost-efficient manner. As marketing is focusing on revenue (or demand) generation and as operations is focusing cost (or waste) reduction, each functional area can make its own decisions in a disjoint manner. Although this "decoupling" mechanism enables marketing and operations to focus on their own activities, it can result in suboptimal plans.[2] In addition, the decoupling mechanism can lead to major conflicts when the marketing decisions need to be adjusted frequently according to market dynamics and when the operations decisions cannot be adjusted dynamically (due to its inherent process) (e.g., Piercy, 2007).

Recognizing the pitfalls of this decoupled decision making mechanism, many firms now employ various planning mechan-

[2] Kiley (2002) argued that firms can double their profits if they can develop and execute a well coordinated marketing and operations plan. However, coordinating marketing and operations do not always yield higher profits. For instance, when dealing with price and quality competition in a duopolistic environment, Balasubramanian and Bhardwaj (2004) and Xiao et al. (2009) showed that a firm can be better off with decentralized planning.

isms such as "house of quality" for new product development, "balanced scorecard" for developing strategic implementation plan, "cross-functional teams" for developing coordinating plans. In general, a *coordinated* plan is usually developed through an iterative negotiation process among different functional groups, each of which has its own performance measures. It is natural to expect that many firms now encourage marketing and operations groups to exchange information and consult each other when developing a coordinated plan. In general, a well coordinated marketing and operations plan would reduce the conflicts between marketing and operations. Fisher and Raman (1996) presented a model for coordinating the responsive supply operations and the dynamic market demand. Their model has been shown to be effective in making supply meet demand at Obermeyer (Fisher and Raman, 1996).

To anticipate and respond to market dynamics better, a firm may need to go beyond coordination by having the marketing and operations groups to jointly develop a *collaborative* plan. As articulated in Donohue (2005), a joint performance measure between marketing and operations is needed to develop a collaborative plan. For example, Sogomonian and Tang (1993) presented a model for examining the benefit of integrating promotion and production plan. To capture the promotional effect on demand found in the marketing literature (Guadagni and Little, 1983), they assumed that the demand in each period is a decreasing function of the time elapsed since the last promotion. By solving a deterministic dynamic program, they showed that a firm can increase his profit significantly by integrating its promotion and production plan in a collaborative manner. Essentially, to facilitate the collaboration between marketing and operations, one needs to change the planning process from the one depicted in Fig. 1 to the one depicted in Fig. 2.

By encouraging marketing and operations groups to develop a joint marketing and operations plan, it is natural for the operations group to learn of the market dynamics and for the marketing group to learn of its supply chain capability in a proactive manner. By imposing a joint performance measure such as the firm's profit, the marketing group would set the "right" customer expectations and promise the "right" values to be created. At the same time, it would allow the operations group to meet the customer expectations and deliver the values as promised. Ultimately, by having both groups to develop a joint marketing and operations plan, the company should focus on maximizing its profit subject to meeting customer expectations and delivering the promised values.

Although one may argue that a company can perform even better if the marketing and operations groups are merged into one so that they are completely integrated. Although this makes sense in theory, it may not be *t* practical because of different roles and responsibilities of these two groups. In addition, complete integration of these groups would create cultural and personality conflicts due to different backgrounds, experiences, expertise, personality, and cultures (Crittenden et al., 1993; Piercy, 2007). This may explain why few companies merge the marketing and operations into a single entity.

By using the joint marketing and operations planning process as depicted in Fig. 2, we can classify different marketing/operations interface models according to different combinations. For example, some models deal with the interactions between customer selection and the company internal capability, other models may examine the interactions between promotion and the company internal capability, and some models may investigate the interactions among product selection, competition, and the company internal capability. The remainder of this paper is organized as follows. In the next section, we review briefly about some common demand models and some common measures for supply capabilities. In Section 4, we provide a review of quantitative marketing–operations interface models that focus on different combinations of marketing and operations factors. Table 2 provides an overview of each subsection in Section 4 that deals with a specific combination of marketing and operations factors as depicted in Fig. 2. We present some recent operations management models that incorporate certain strategic consumer behavior in Section 5. In Section 6, we end this paper with a discussion of future research. Due to many different combinations and due to numerous marketing–operations interface models developed since the early 90s, this review is not meant to be exhaustive. As such, we apologize for any omission that is due to our negligence.

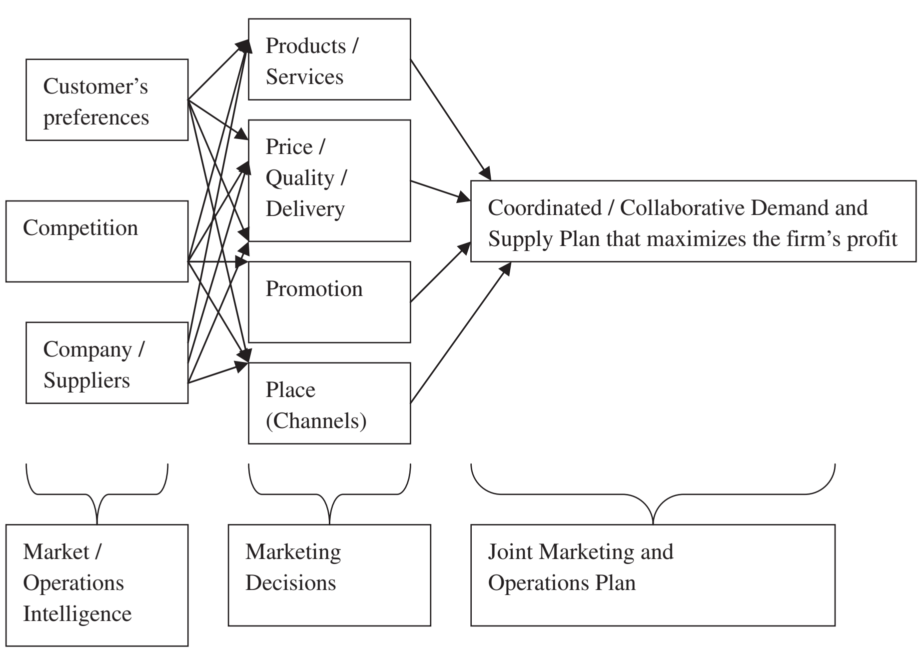

Fig. 2. Coordinated and collaborative marketing and operations planning process.

Table 2
Marketing and operations factors examined in Section 4.

Section	Marketing issue(s)	Operations issue(s)
4.1	Customer portfolios	Production quantity
4.2	Customers, competition	Capacity, waiting time in systems
4.3	New product development	Quality, product rollovers
4.4	Product assortments, pricing, competition	Production capacity, process flexibility, shelf-space capacity
4.5	Pricing, competition	Production planning
4.6	Pricing, competition, channel coordination	Production planning

3. Demand and supply issues

Before we review different marketing–operations interface models, let us first describe some basic factors that affect customer demand and a firm's supply capability.

3.1. Basic customer demand models

As articulated in Lilien et al. (1992), consumer tends to go through 5 steps in the purchase cycle: (1) need arousal through internal stimuli (normal drives) and/or external drive (advertisement); (2) information search to identify a potential set of brands or products that satisfies the identified need; (3) product evaluation through determination of the utilities associated with different product attributes (price, quality, functionality, rebates, returns policy, brand reputation, etc.); (4) purchase decision that is based on the comparison of the utilities of different products; and (5) post-purchase feelings (e.g., satisfaction) that may trigger post-sales activities (product returns, technical support services). From a firm's perspective, most quantitative models tend to focus on examining the factors that affect consumer purchasing decision. For the sake of simplicity, let us consider a situation in which there are 2 competing products offered by the same firm (or by 2 competing firms). For any given selling price p_j for product j, $j=1, 2$, there are four basic consumer choice models for determining the demand function for each product. These four basic demand models are: (1) exogenous demand models; (2) constant-utility attraction models; (3) constant-utility location choice models; and (4) random-utility multinomial logit models. (The reader is referred to Kok et al. (2008) for a discussion about the strengths and weaknesses of each of these demand models discussed in this section.)

Exogenous demand models: For any given price p_j, the aggregate demand for product j satisfies:

$$D_j = a_j - b_j p_j + \delta_j (p_j - p_k), \quad \text{for } j = 1, 2, \ k \neq j, \tag{1}$$

where a_j represents the base demand for product j, b_j represents the sensitivity of the demand to the regular retail price, and δ_j represents the relative sensitivity about the price difference between products j and k. It is plausible that the parameter values of a_j, b_j, and δ_j depend on the product attributes of products j and k. Raju et al. (1995) provided justifications of the exogenous demand model and employed this exogenous demand model to determine the conditions under which a retailer should launch its own store brand to compete with a national brand. Kok et al. (2008) described a generalized version of the exogenous demand model.

Constant-utility attraction models: Each consumer i derives utility U_{ij} from purchasing product j, where U_{ij} is a deterministic function that depends on various marketing and operations factors such as product attributes (functionality, price, quality) and service attributes (convenience, delivery). In the constant-utility attraction models that are based on Luce's axioms, the probability that consumer i purchases product j is equal to

$$P_{ij} = \frac{U_{ij}}{U_{ij} + U_{ik}}. \tag{2}$$

By noting that the market share of product j, $P_j = \Sigma_i P_{ij}$, one can determine the demand function for each product (Lilien et al., 1992).

Constant-utility location choice models: The multiple attributes of each product is represented by a vector x_j and each consumer i has her own ideal vector y_i.[3] In this case, the utility that consumer i can obtain from purchasing product j is given as:

$$U_{ij} = R - p_j - g(y_i, x_j) \quad \text{for} \quad j = 1, 2, \text{ and for all } i, \tag{3}$$

where R represents the basic reward for acquiring the product, p_j is the retail price of product j and $g(.,.)$ is the "distance" function that penalizes the degree of misfit (when a product is far away from the customer's ideal location). In this model, consumer i will purchase product j instead of k when $U_{ij} > U_{ik}$. Consider the following situation. Both products have a single attribute: products j and k are located at x_j and x_k with $x_k > x_j$, respectively. The ideal point of each consumer y_i is uniformly distributed over [a, b], and the distance function is given as $g(y, x) = (y - x)^2$. Then, for any consumer i with an ideal point y, consumer i will purchase product j if $U_{ij} > U_{ik}$. In this case, we can apply (3) to show that a consumer i with an ideal point y will purchase product j if $y < (p_k - p_j)/2(x_k - x_j) + x_j + x_k/2)$. Because y is uniformly distributed over [a, b], one can compute the market share and the demand function for each product.

Random-utility multinomial logit models. Unlike previous three types of models, the random-utility multinomial logit model is based on the assumption that the utility for each consumer i to purchase product j is random that satisfies:

$$U_{ij} = u_{ij} + \varepsilon_j, \quad \text{for} \quad j = 1, 2, \text{ and for all } i, \tag{4}$$

where u_{ij} is the deterministic component of the utility and ε_j is a random variable.[4] By considering the case when ε_j is a double exponential random variable with, the probability that consumer i will purchase product j is equal to $\text{Prob}\{U_{ij} > U_{ik}\}$, where $Pr\{U_{ij} > U_{ik}\} = e^{u_{ij}}/e^{u_{ij}} + e^{u_{ik}}$. Based on this choice probability, one can determine the demand function of each product. The reader is referred to Anderson et al. (1992) for a proof of the generalized version of the above purchase probability that includes the option of not purchasing any product. Instead of a definitive purchasing decision imposed by the rational choice model, the choice probability in the multinomial logit model enables researchers to use historical purchasing behavior of each consumer to estimate the value of the parameters associated with the utility function and to estimate the demand for each product (Guadagni and Little, 1983; Anderson et al., 1992). More recently, Chong et al. (2001) extended the model developed by Guadagni and Little (1983) to capture the similarities and differences among products within a brand and across different brands in a product

[3] These models are based on a deterministic utility function examined by Hotelling (1929). The reader is referred to Lancaster (1990) for an extensive review of location choice models.

[4] A consumer is *rational* if he chooses the product with the highest expected utility; i.e., choose product j over product k if and only if $E(U_{ij}) > E(U_{ik}) \geq 0$. In additional to rational choice model, Su (2009) introduced the notion of consumer inertia that captures the "strategic" *purchasing behavior*. Specifically, a consumer is inertial if she makes a purchase if $U > U' + \tau$, where U is the utility associated with the product, U' is the expected utility from "waiting" (the value of future purchase opportunities), and $\tau \geq 0$ is a threshold. We shall discuss the issue of strategic purchasing behavior in the context of marketing–operations interfaces in Section 5.

category. By using panel data collected from 5 supermarkets, they showed how a category manager can use their model to reconfigure a brand in order to achieve a higher brand share.

3.2. Basic company supply models

For any given demand function of each product, it is the responsibility of the operations group to utilize internal and external resources to develop a plan to meet the product/service delivery schedule. In the operations literature, basic factors that affect a firm's supply capability are: (1) capacity; (2) product/process flexibility; and (3) production planning.

Capacity: In most models, a firm's capacity is assumed to be a known constant (at least in the short term). However, the firm can expand its capacity as the demand increases over time. The reader is referred to Luss (1982) for a comprehensive review of capacity expansion models. In addition, a firm may be able to acquire additional capacity using new technology that is more cost efficient (Gaimon, 1988). In some cases, a firm's capacity is actually uncertain especially when the processing time (or the customer arrival time) is uncertain that is commonly observed in the service industry, or when the process yield is uncertain that is inherent to the production process in the wafer fabrication industry. In general, the queueing model is a common way to model uncertain processing time (and/or customer arrival time). See Yano and Lee (1995) for a comprehensive review about product planning with yield uncertainty.

Flexibility: When producing multiple products or serving multiple classes of customers, the effective capacity of a process depends on the flexibility of the process. A completely flexible process (such as flexible manufacturing system) or a flexible product (designed or produced using the postponement concept) would enable a firm to change its production from one product to another without incurring significant setup time (or setup cost). The reader is referred to Buzacott and Yao (1986) and van Hoek (2001) for comprehensive reviews about models that examine the notion of flexible manufacturing and the concept of postponement, respectively. However, when the product or the process is not completely flexible, one needs to incorporate the setup time in the model that can certainly affect the firm's production capacity.

Production planning: Given the production capacity, the actual physical output for meeting customer demand depends heavily on the production plan (how much to produce?) and the production schedule (which product to produce?). Depending on various cost factors (operating cost, inventory cost, understocking cost), a firm may decide to smooth its production by producing the same amount in each period and by using the excessive inventory produced during the low demand period to meet the production shortfall during the high demand period. The reader is referred to Mula et al. (2006) for a comprehensive review of models for production planning under uncertainty. Also, depending on the switchover cost or time, a firm may decide to produce a batch of one product before switching over to produce a different product (Graves, 1981).

4. Marketing–operations interface models

In this section, we review different marketing–operations interface models that are based on the following combination of different factors. The first two subsections examine models that are customer-centric. Recognizing the demand function affects the operating cost, we present some existing models in which the marketing group can "shape" the demand function by choosing the "right" customer portfolio so as to maximize a firm's profit in Section 4.1. Then in Section 4.2, we examine models arising from situations in which firms guarantee certain customer service level so as to compete for market share.

Besides competing on customer service level, many firms extend their product lines by offering different products to satisfy the needs of different market segments or simply to satisfy customer's variety seeking behavior. As such, competing firms are under tremendous pressure to develop, produce and sell new products quickly. In Section 4.3, we review models that deal with the issue of new product development and new product sales channels. Then we describe different models that examine the costs (operations costs) and the benefits (market share) of product extensions in Section 4.4. Finally, we examine the issue of joint product pricing and production planning in Section 4.5.

4.1. Customer portfolio selection models

Consider a manufacturer who produces and sells a single product at unit price p in a single market over a single selling season. The probability distribution of the product demand D is known, say, D is normally distributed with mean μ and standard deviation σ. The unit product cost is c, the salvage value for each unit of unsold item at the end of the season is s, and the backorder cost for each unit of unmet demand is b. In the traditional newsvendor problem, the manufacturer needs to decide on the capacity Q that maximizes his expected profit. Specifically, the optimal newsvendor production capacity Q^* satisfies:

$$Q^* = \arg\max\{pE(D) - cQ - sE([Q-D]^+) - bE([D-Q]^+) : Q > 0\},$$

where Q^* satisfies the well-known fractile solution. Also, it has been shown that the newsvendor's optimal expected profit is decreasing in the demand uncertainty, say, the standard deviation σ. The reader is referred to Khouja (1999) for an extensive review of various extensions of the newsvendor problem developed between 1988 and 1998. When the demand D is price dependent, say, μ is a linear decreasing function of p, Petruzzi and Dada (1999) determined the joint optimal retail price p^* and optimal capacity Q^*.

Single Level Supply Chains. In the operations research literature, the probability distribution of the product demand D is usually assumed to be given exogenously (by the marketing department). However, in the context of marketing–operations interfaces, the probability distribution of the product demand D may not be fixed especially when the marketing department can choose which customer (or market) to serve. For instance, in the industrial (B2B) market, the newsvendor can "shape" the probability distribution of demand D by selecting a certain set of customers (i.e., customer portfolio) to serve. By selecting a set of markets to serve carefully, the firm may be able to reduce the variance of the resulting product demand and improve the firm's optimal expected profit. This basic intuition has motivated researchers to develop several customer (or market) selection models that can be described as follows.

First, Taaffe et al. (2008) examined the case in which the newsvendor has n potential markets. The demand D_i in market i is normally distributed with mean μ_i and standard deviation σ_i, and the unit retail price in market i is p_i. The market selection decision can be captured by a binary decision variable y_i that equals 1 is market i is chosen and equals 0, otherwise. For any given y_i and given production capacity Q, the total product demand $D = \sum_i y_i D_i$ and the newsvendor's expected profit can be expressed as a function of the capacity Q and the market selection variable y_i, where,

$$\prod(Q, y_1, y_2, \ldots, y_n) = E(\sum_i p_i y_i D_i) - cQ - sE([Q-D]^+) - bE([D-Q]^+).$$

By exploring the underlying mathematical structure of the expected profit function given in the above equation, Taaffe et al. (2008) developed an efficient solution method for determining the optimal market selection y_i^* and optimal capacity Q^*.

Second, as discussed in Section 3.2., there are many situations in which the capacity is uncertain due to random yield or quality issues. When the capacity Q is normally distributed with a known mean and standard deviation, Carr and Lovejoy (2000) developed a solution method for determining the optimal market selection y_i^* that maximizes the newsvendor's expected profit function $E_Q(\prod(Q, y_1, y_2, \ldots, y_n))$, where $\Pi(Q, y_1, y_2, \ldots, y_n)$ is given above. In addition, they extended their analysis to the case when the set of potential markets is partially known.

Two-Level Supply Chains: Kalkanci and Whang (2009) extended the single period model developed by Taaffe et al. (2008) to the case of multiple periods in the following manner. They considered a two-level supply chain that is comprised of a manufacturer and n retailers. The demand D_{it} faced by retailer i in period t follows the first-order auto-regressive AR(1) process so that $D_{it}=\mu_i+\rho_i D_{i,t-1}+\varepsilon_{i,t}$ for $i=1,\ldots, n$, where $\varepsilon_{i,t}$ is normally distributed with mean 0 and standard deviation σ_i. As each retailer i uses the information regarding its demand D_{it} to determine its optimal order quantity $X_{i,t}$, $X_{i,t}$ is a function of the realized demand up to period $t-1$. In this case, it is well known that the "bullwhip" effect will occur; i.e., $\mathrm{Var}(X_{i,t}) > \mathrm{Var}(D_{it})$. The reader is referred to Lee et al. (1997) for details. By noting that the manufacturer will treat the retailer's order $X_{i,t}$ as the "demand" generated from retailer i, Kalkanci and Whang (2009) discussed how the manufacturer should select an efficient set of retailers in each period t that maximizes his expected profit over time. Specifically, let $y_{i,t}=1$ if retailer i is chosen in period t, and $y_{i,t}=0$, otherwise. For any given y_{it} and given manufacturer's capacity Q_t, the total product demand $X_t=\sum_i y_{it} X_{it}$ and the newsvendor's total expected profit can be expressed as a function of the capacity Q_t and the market selection variable y_{it}, where:

$$\sum_t \prod(Q_t, y_{1t}, y_{2t}, \ldots, y_{nt}) = \sum_t \left\{ E_X(\sum_i p_i y_{it} X_{it}) - cQ_t - sE_X([Q_t - X_t]^+) - bE_X([X_t - Q_t]^+) \right\}$$

They determined the manufacturer's optimal customer portfolio selection y_{it}^* and capacity Q_t^*.

In addition to the above models, there are situations in which the manufacturer can "shape" the demand by accepting/declining customer orders over time. In this setting, Donohue (1994) presented a queueing model that would enable the manufacturer to reduce the congestion in the plant by having the marketing to accept customer orders only with certain operating characteristics measured in terms of the mean and the variance of the service time. In the same vein, Hall et al. (2009) considered a situation in which the manufacturer serves two types of customers: regular customers at a fixed pre-negotiated price, and "walk-in" customers with price dependent arrival rate. They developed a queueing model to examine different pricing and admission policies for the walk-in customers. They showed a constant pricing scheme and a simple admission policy (accept a walk-in customer when there are less than n customers in the system) is close to optimal.

4.2. Guaranteed customer service models

In the context of time-based competition, many service providers offer guaranteed service to their customers as a way to compete for market share (Blackburn, 1990). For example, Lucky supermarkets in California launched the "3 is a crowd" marketing campaign in the early 90s: Lucky guarantees a new checkout counter will be opened if there are more than 3 customers waiting in its checkout lines. Also, in the event when Lucky failed to deliver this promise, it will offer \$1 compensation to each customer who waits in that line. Also, Denny's, Black Angus Restaurants, and Domino's Pizza guarantee their meals will be served (or delivered) within a specific time, and offer free meals if they failed to deliver their guaranteed services. This form of marketing campaign would certainly increase market share, but it is unclear if the service providers can keep their promises. Unless the firm incorporates the changes in customer demand when deciding on its service capacity, customer disappointment is likely to occur. For instance, Lucky cancelled its "3 is a crowd" campaign quietly after failing to deliver its promise. We now review some marketing–operations interface models that deal with guaranteed customer services.

Customer Response: The first model is motivated by Lucky's "3 is a crowd" campaign under which the number of "active" servers depends on the number of customers present in the system (So and Tang, 1996). Consider a service facility that has N parallel service counters, each of which has a service rate μ. Also, there are N servers who can provide back-end services when not operating a service counter. Each counter has its own waiting line and customers can switch from one line to another at any point in time. The marketing department is planning to launch the "K is a crowd" campaign, where K is a decision variable. For any given K, the customer arrival rate $\lambda(K)$ is decreasing in K; i.e., more customers will arrive if the firm guarantees a more efficient service. In this case, the firm failed to deliver its promise when the number of customers in the system exceeds NK. By considering the case when customer arrivals follow a Poisson process and when the service time is exponentially distributed, So and Tang (1996) determined $p_x(K)$; i.e., the steady state probability of having x number of customers in the system under the "K is a crowd" policy. Hence, the probability that the firm failed to keep its promise is equal to $\sum_{x>NK} p_x(K)$. By imposing a customer service level constraint $\Sigma_{x>NK} p_x(K) \le \alpha$, So and Tang (1996) evaluated the interactions between the marketing campaign based on K and the customer service level α.

In the second model, So and Song (1998) considered the case in which the marketing department launches a campaign that guarantees the service time is less than t by charging each customer p. For any given p and t, the customer arrival rate $\lambda(p, t)$ is decreasing in p and t; i.e., more customers will arrive if the firm offers a lower price or guarantees a more efficient service. The service rate is given as μ. By modeling the system as an $M/M/1$ queue (i.e., Poisson arrivals, Exponential service time, and single server), the probability distribution of the actual delivery time T in steady state satisfies: $\mathrm{Prob}\{T \le t\}=1-\exp\{-(\mu-\lambda(p,t))t\}$ (Kleinrock, 1975). By solving the following non-linear mathematical program, one can determine the optimal price p, optimal guaranteed delivery time t, and the optimal capacity μ that maximizes the firm's net profit subject to a customer service level constraint:

$$MAX_{p,\mu,t}\{(p-c)\lambda(p,t)-c\mu\}, \quad \text{subject to } \mathrm{Prob}\{T \le t\} \ge \alpha.$$

By considering the case when the customer arrival rate follows the log-linear (Cobb–Douglas) demand function so that $\lambda(p, t)=\lambda p^{-a} t^{-b}$, So and Song (1998) characterized the optimal decisions.

Service competition: We now describe some models that examined the issue of guaranteed customer delivery time under competition. First, So (2000) presented a model that deal with N competing service providers who compete in terms of price and guaranteed delivery time. In his model, the total customer demand rate λ is assumed to be a known constant. For any given price p_j and guaranteed delivery time t_j offered by firm j, the utility function for each customer i derived from firm j is a deterministic (Cobb–Douglas) function $U_{ij}=L_j p_j^{-a} t_j^{-b}$. By using the constant-utility attraction model given in (2) as described in Section 3.1, So (2000) determined P_j, the market share of each firm j. By modeling each firm operates according to an $M/M/1$ and by considering each firm is interested in maximizing his own profit subject to a customer service level constraint, he characterized the best response and presented an iterative procedure to determine a Nash equilibrium.

By using a similar setup as presented in So (2000), Ho and Zheng (2004) considered a situation in which two competing service providers compete in terms of guaranteed delivery time t and customer service level α, where α=Prob{$T \le t$}. In their model, the retail price is fixed (market price), but each firm j selects his guaranteed delivery time t_j. (Notice that the service quality α_j is a function of t_j.) In their model, it is assumed that the utility function for each customer i obtained from firm j is random that satisfies: $U_{ij}=u_{ij}+\varepsilon_j=\beta_0-\beta_t t_j+\beta_\alpha \alpha_j+\varepsilon_j$, where ε_j is a double exponential random variable. By applying the random-utility multinomial logit model as described in Section 3.1, the market share for firm j satisfies: $P_j = e^{u_{ij}}/e^{u_{ij}}+e^{u_{ik}}$. By modeling each firm operates according to an $M/M/1$ with a known constant customer arrival rate λ and by considering each firm is interested in maximizing his own market share, they proved the existence of a Nash equilibrium. In addition, they showed that this game is analogous to a Prisoner's Dilemma in a duopolistic competition so that both service providers would end-up in a lose–lose situation in equilibrium.

All of the above models assume that customer's utility function is based on the steady state performance of the service providers. Li and Lee (1994) considered a different duopolistic model in which the retail prices and service rates of firm j and firm k are given as p_j, μ_j and p_k, μ_k, respectively. Customers arrive according to a Poisson process with rate λ. Upon arrival, it is assumed that each arriving customer has information about the actual number of customers waiting at firm j and firm k. By using this information, the expected waiting time is denoted by $E(T_j)$, and the expected utility associated with firm j for consumer i is given as $U_{ij}=u_{ij}-\beta p_j-\gamma E(T_j)$, where β, γ are parameters. By assuming that each customer i is rational in the sense that she will join firm j if $U_{ij}>U_{ik}$ (Section 3.1), one can determine the market share of each firm $\lambda_j(p_j, p_k)$. By considering each firm is interested in selecting an optimal price that maximizes his own revenue, Li and Lee (1994) characterized the optimal price p_j^*, where $p_j^* = \text{argmax}\{p_j\lambda_j(p_j,p_k) : p_j>0\}$. They show that the firm with a higher service rate always enjoys a price premium by charging a higher price. In the same vein, Lederer and Li (1997) considered a more general problem by considering multiple classes of customers with general service time that is class-specific. The reader is referred to Upansani and Uzsoy (2008) for a comprehensive review of models that focused on delivery time competition.

4.3. *New product development and sales channel models*

To compete in a dynamic marketplace, shortening the new product development cycle time can be a competitive weapon (Clark and Fujimoto, 1991). To obtain market growth, many firms introduce many new products frequently. The reader is referred to Krishnan and Ulrich (2001) for an excellent review about research work that focused on the product development planning process within a firm that ranges from product concept development, product design, to project management. As more new products become available, many old products could become obsolete, and hence, they should be phased out. Consequently, we have witnessed shorter product life cycles in many industries such as personal computers, cellular phones, electronics, various types of toys, etc. Therefore, when managing new product development, a firm needs to examine the following strategic issues: (1) When should the firm launch its new product? (2) In view of the old product and market dynamics, what is the target performance of the new product? (3) How should the firm manage the process for introducing the new product and eliminating the old product? (4) How should the firm decide on the pricing mechanism for the old product (before and after the introduction of the new product) and for the new product (before and after the elimination of the old product)? (5) Should the firm sell its products through multiple channels or an exclusive channel. We now review models that deal with some of these strategic issues.

New product development: Cohen et al. (1996) presented a new product development model in which a firm has an old product with a given quality level Q_0 that competes with a competitive product offered by a competitor that has a quality level Q_c. The firm would like to launch a new product with quality Q_1 at time t, where $0<t\le T$. The planning process is divided into two phases: product development and marketing. The quality of the new product $Q_1(T_D, T_P)$ and the new product development cost $C(T_D, T_P)$ depend on two decision variables that captures the time (or effort) associated with two product development stages: (1) the time to design the new product T_D; and (2) the time for prototyping and testing T_P. As the new product is launched at time (T_D+T_P), the product development phase occurs over [0, (T_D+T_P)], and the marketing phase occurs over [(T_D+T_P), T]. In their model, it is assumed that the old product is eliminated at the instant when the new product is launched at time (T_D+T_P).

By treating the quality as the utility associated with each product, they used the attraction model as described in Section 3.1 to determine the market share for the old product before time (T_D+T_P) and the market share for the new product after time (T_D+T_P). By assuming that the competitor is passive, that the profit margins of the old and the new products are r_0 and r_1, respectively, and that the total market size M is a constant, they formulated the following optimization problem:

$$\max_{T_D,T_P} M\left\{ r_0\frac{Q_0}{Q_0+Q_c}(T_D+T_P)+r_1\frac{Q_1}{Q_1+Q_c}(T-(T_D+T_P))\right\}-C(T_D,T_P)$$

$$s.t.\quad 0<T_D, 0<T_P, \text{ and } T_D+T_P\le T.$$

In their model, the tradeoff between the quality and the product development time is capture by the fact that $Q_1(T_D, T_P)$ is an increasing function of T_D and T_P. Also, the above program captures the tradeoff between the profit associated with the old and the profit associated of the new product. Cohen et al. (1996) solved the above program and determined the optimal time to launch the new product. As a follow on study, Cohen et al. (2000) developed a model to show that it is suboptimal for a firm to impose a target for each of the common product development metrics including time-to-market (T_D+T_P), product performance Q_1, and product development cost $C(T_D, T_P)$. The models developed by Cohen et al. (1996, 2000) were based on the assumption that the competitor is passive. Motivated by the competitive dynamics of two motion picture studios, Krider and Weinberg (1998) presented a competitive game model that is intended to examine the timing for each firm to introduce its movie in equilibrium. By using the attraction model to characterize the demand function of each movie over time, they determined the conditions under which one firm would "avoid the competition" by delaying its movie opening in equilibrium.

Product rollovers: When managing the product rollover process (i.e., the process of introducing the new product and eliminating the old product), there are two basic strategies: (a) solo-product roll—eliminate the old product at the instant when the new product is launched so that there is a single product in the market; and (b) dual-product roll—sell both old and new products simultaneously during the "introduction phase" of the new product and then eliminate the old product later. In most new product development models, it is commonly assumed that the firm adopts the solo-product roll (e.g., Cohen et al., 1996). However, as articulated in Billington et al. (1998), many firms encountered various challenges when implementing the solo-product roll strategies due to various risk factors including technology risks (the new product may not performed as expected) and market risks (the market may not respond to the new product as expected). However, there are other risk factors associated with the dual-product roll strategy including product cannibalization (the old produce cannibalize the sales of the new product) and additional cost of managing two products in the channel.

Lim and Tang (2006) developed a model for determining the time at which the new product is introduced (T_n) as well as the time at which the old product is eliminated (T_o) over a planning horizon [0, T]. In their model, the solo-product roll strategy is captured by the case when $T_{n=}T_o$, and the dual-product roll strategy is capture by the case when $T_n < T_o$. Under the solo-product roll strategy, they assumed that the old product demand over the time window [0, $T_o(=T_n)$] is linearly decreasing in the selling price p_o, and that the new product demand over [$T_n(=T_o)$, T] is linearly decreasing in the selling price p_n. However, under the dual-product roll strategy, there is a time window [T_n, T_o] within which both products are available in the market. They used the exogenous demand model as described in Section 3.1 to model the demand of the old and the new product over this time window. By formulating each strategy as an optimization problem, they determined the optimal timing for introducing new products and for phasing out old products. Also, they determined the conditions under which a dual-product roll is preferred over a single-product roll.

Sales channels: To capture customers in different market segments, many firms sell their products through multiple channels involving in-store, mail-order, and online channels. In many instances, the online channel is an attractive option for manufacturers and retailers to market and sell their products due to its easy access and low entry cost. Selling through multiple channels can certain increase revenue, but it can increase cost as well.[5] When a firm sells its products through their traditional (brick-and-mortar) channels and other online channels (self-owned or other online retailers), the firm needs to make pricing and ordering/stocking decision for each channel. Recent empirical studies suggest that firms usually sell their products at a lower price through their online channels (Brynjolfsson and Smith, 2000 and Tang and Xing, 2001). However, there are occasions in which the online selling price is the same (Huang and Swaminathan, 2009) or slightly higher than the traditional channel (Cattani et al., 2006).

Cattani et al. (2006) examined a situation in which a manufacturer with a traditional channel partner (e.g., traditional retailer) launches its own sales channel (e.g., specialty store or online store) to compete with the traditional channel partner. The product is identical across channels, but customers expend different effort to purchase in each channel. For any given retail price offered by each channel, they determined the demand function in each channel by assuming that customers buy through the channel with a higher net utility (net of the channel's price and effort). Using this demand function, they presented a Stackelberg game in which the manufacturer acts as the leader who sets the wholesale price (and his own retail price for his own sales channel) and the traditional retailer acts as the follower who sets her own retail price. They analyzed the manufacturer's and the retailer's profits based on three different pricing strategies: (1) the manufacturer offers the same wholesale price as before (i.e., before he launches his own channel); (2) the manufacturer offers a wholesale price that would induce the retailer to set the same retail price as before (i.e., before the manufacturer launches his own channel); and (3) the manufacturer sets the wholesale price and the retail price that maximize his profit generated from the traditional retailer and from the sales of his own channel. In the case where the manufacturer is committed to match the price set by the traditional retailer, they showed that both the manufacturer and the retailer would prefer pricing strategy (3). They show numerically that the manufacturer's loss from committing to match prices is slight as long as the customer's average effort in the direct channel is significantly greater than the effort in the traditional channel. In contrast, if the effort in the two channels is relatively comparable, then as he sets prices in the direct channel, the manufacturer has a great incentive to undercut prices in the traditional channel.

Motivated by different pricing strategies between the traditional channel and the online channel, Huang and Swaminathan (2009) developed a deterministic model to compare different pricing strategies for the case when a firm sells its products through two channels. These strategies include: (1) Independent pricing—each channel selects its own selling price that maximizes its own channel profit; (2) Coordinated pricing—both channels charge the same price that maximizes the firm's profit; and (3) Collaborative pricing—each channel selects its own selling price that maximizes the firm's profit. By using the exogenous demand model as described in Section 3.1 to specify the demand function in each channel, they determined the optimal profit under each pricing strategy. Clearly, the collaborative pricing strategy dominates other pricing strategies; however, under certain conditions, they showed that the optimal profit derived from the coordinated pricing strategy is close to the optimal profit obtained from the collaborative pricing strategy.

Traditionally speaking, manufacturers usually sell their products though multiple competing channels under non-exclusive arrangements. However, there is a recent trend that certain new products are sold through exclusive channels. For example, Apple launched its iPhone via an exclusive partnership with AT&T in the United States. This new trend has motivated Andritsos and Tang (2009) to develop two separate models to determine the manufacturer's optimal profit under the non-exclusive and the exclusive arrangements, respectively. Each model is based on a Stackelberg game in which the manufacturer acts as the leader by setting the wholesale price and the retailers act as the followers by choosing the retail prices. For any given retail price under each arrangement, they used the exogenous demand model as described in Section 3.1 to specify the demand function for each channel. By using this demand function, they solved the Stackelberg game by determining the optimal wholesale price and optimal retail price in equilibrium under the non-exclusive and the exclusive arrangement. In addition, they identified conditions under which the manufacturer should sell its new products through an exclusive channel.

4.4. Product assortment models

Over the last two decades, many companies have extended their product lines to compete for market share. As articulated in Kahn (1995), consumers derive additional utility from broader product lines that better satisfy their needs and/or their variety

[5] Alptekinoglu and Tang (2005) developed a model to analyze the impact of the number of channels on the distribution cost in a two-stage multi-channel distribution system.

seeking behavior. By taking this additional utility into consideration, Chong et al. (2001) presented a multinomial logit model to estimate the demand for the ice cream category and found that firms with broader product lines tend to have higher market share. This result is consistent with earlier empirical studies conducted by Kekre and Srinivasan (1990) and Bayus and Putsis (1999). Besides higher market share, brands with broader product lines can charge a higher selling price. The reader is referred to Ho and Tang (1998) and Ramdas (2003) for details. Despite the effort in extending product lines, many firms failed to improve their profits mainly because they did not account for various hidden costs (additional production and administrative costs) when planning their line extensions (Quelch and Kenny, 1994). To incorporate the issue of production capacity, production technology and product assorting and pricing issues, Yano and Dobson (1998) provided a review of deterministic product assortment problems that can be formulated as integer programming problems.

As companies extend their product lines, researchers developed models to examine the following questions: (1) What are the benefits and costs associated with product line extension? (2) Is the benefit derived from higher demand or higher selling price? (3) How should a firm determine its product assortment under competition? (4) What is the impact of a firm's production capacity on its product assortment decisions? We now review some models that examine these questions. In a recent study that examines a situation in which 2 firms compete on the product-line length, Draganska and Jain (2005) presented a multinomial logit model and characterize the product-line length in equilibrium. They tested their model by using the actual sales data for the yogurt category, and found that a broader product line has a positive effect on market share, but this effect diminishes as the line length increases.[6] They suggested that line length and selling price are complements: if a firm wishes to increase its price (market share) in a competitive environment, then the firm can keep its market share (price) constant by increasing its line length. More recently, Cachon et al. (2005) studied a product assortment model in which a consumer may not purchase a product at a store even though the utility is positive. This is because this consumer is uncertain about the products available elsewhere; hence, there is a probability that she can get a higher utility by searching for better products available elsewhere. By considering the case when a consumer is willing to search for a better product with higher utility at other stores by incurring a search cost, they showed that it is beneficial for a store to carry even non-popular products as a mechanism to deter consumers to search elsewhere. Ultimately, their results support the notion of broader product lines.

We now review certain product assortment models that explicitly incorporate certain marketing and operational issues such as product substitution, competition, production capacity, and shelf-space. Because the focus of these models is on the optimal product assortment, we do not address the issue of production planning in this section. We shall discuss the interaction between pricing and production planning in the next section.

Product assortment: Consider a firm who produces and sells different horizontally differentiated products within a single category.[7] Gaur and Honhon (2006) studied a product assortment problem that is based on the choice location model discussed in Section 3.1. For a given product assortment, it is assumed that the salient feature of each product j can be characterized according to a location x_j over [0, 1]. By considering the case that y_i, the ideal location of each customer i, is distributed over [0, 1] according to a continuous (and unimodal) distribution, it is easy to utilize the distance function $g(x_j, y_i)$ and the utility function U_{ij} given in (3) as discussed in Section 3.1 to show that there exists an interval $[a_j, b_j]$ for each product j that contains the ideal locations of all consumers whose utility for purchasing product j is non-negative; i.e., $U_{ij} \geq 0$ for all i in $[a_j, b_j]$. For any given product assortment, it is possible that these intervals may overlap each other. In the event when the ideal location of a consumer is located within an overlapped interval, this consumer will select the product with the highest utility among the set of available products. By consider the case when customers arrive according to a Poisson process, Gaur and Honhon (2006) characterized the optimal assortment under static substitution and dynamic substitution.

Product substitution: Instead of using the location choice model, Smith and Agrawal (2000) developed a product assortment planning model based on the exogenous demand model that can be described as follows. The demand of each product j is based on three streams of demand: (1) demand generated from customers who desired for product j; (2) demand generated from customers who desired for product k, but product k is not in the assortment; and (3) demand generated from customers who desired for product k that is in the assortment, but product k is out of stock. Smith and Agrawal (2000) formulated the problem as a non-linear integer programming problem and developed an approach to determine an optimal assortment. Agrawal and Smith (2003) extended their earlier work to deal with the issue of product assortment planning with multiple categories. In a duopolistic environment, Cachon and Kok (2007) examined a 2-product category model in which some consumers would like to buy products from both categories. By using the multinomial logit model, they determined the store choice probability for each consumer and the product choice probability of each consumer who shops at a particular store. They examined whether a store should carry only one or both product categories. The reader is referred to Kok et al. (2008) for a comprehensive review of other product assortment models that deal with product substitution in a static and dynamic fashion.

Competition: By considering the case when the cost of producing each product is concave in its quantity, De Groote (1994) examined a product assortment problem arising from a firm who produces and sells horizontally differentiated products. He showed that, in a monopolistic setting, it is optimal for a firm to have a N-product assortment so that each product j will yield an interval $[a_j, b_j]$ for $j=1, \ldots, N$. Also, he showed that these intervals will collectively cover the entire interval of the ideal locations of all consumers; i.e., the interval of [0, 1]. Moreover, for any given N, he showed that the ideal location for each product i satisfies $x_j^* = 1/N$; i.e., the ideal product locations are equally spaced. Alptekinoglu and Corbett (2008) extended deGroote's model to incorporate competition. In their model, there are two competing manufacturers who need to decide on market entry, product assortment, and pricing decisions. One firm (mass customizer) has complete flexibility to offer infinite product variety over [0, 1] through mass customization, while the other firm (mass producer) has limited variety under mass production. By considering the upfront investment and the unit product cost

[6] As the increase in market share is decreasing in the line length, it is common for a firm to use the "lame duck" strategy to eliminate products that perform poorly in terms of their contribution to the market share of the brand. By using the attraction model as described in Section 3.1 and by considering the dependency among the products within a product line, Chong et al. (2004) showed that the lame duck strategy is not optimal when the market share of the brand is a non-separable function of the product portfolio.

[7] Horizontally differentiated products are products with features such as color or flavor that cannot be ordered.

that depends on the product assortment, they determined the optimal product assortment for both firms in equilibrium. They showed that the mass producer should offer fewer products in order to reduce the price pressure in equilibrium. Along the same vein, Mendelson and Parlakturk (2008) examined a similar problem as described in Alptekinoglu and Corbett (2008) in a different setting. Specifically, they incorporated the stochastic customer arrival process and the stochastic processing time associated with the make-to-order process adopted by the mass customizer. They determined the optimal product assortment and the optimal price for both firms in equilibrium. More recently, Xia and Rajagopalan (2009) considered an additional element that involves store choice and obtained similar results. The reader is referred to Parlakturk (2009b) for a comprehensive review on the issue of competition through customization.

Production cost and capacity: There are various models that deal with vertically differentiated products that can be ordered according to their objective "quality" so that a higher quality product is more desirable than a lower quality product. The reader is referred to Lancaster (1990) for a comprehensive review of marketing models that deal with vertically differentiated products. Moorthy (1984) examined the product assortment problem for a monopolistic manufacturer produces and sells vertically differentiated products. As a way to incorporate the production cost in a multi-product production environment, Netessine and Taylor (2007) studied the product assortment problem by using the economic order quantity (EOQ) model to capture the tradeoff between the fixed setup cost and batch size. By assuming that the inventory holding cost is proportional to the unit production cost and by considering the case when there are only 2 market segments, they presented the conditions under which the firm should serve only the high-quality segment by selling only the high quality product. More recently, Tang and Yin (2010) examined a product assortment model for vertically differentiated products. To model the fact that all consumers prefer products with higher quality, they assumed that all consumers derive utility U_{i1} from product 1 (with the lowest quality) is uniformly distributed over [0,1]. Also, all consumers derived U_{ij} for product j satisfies $U_{ij}=\beta_j\, U_{i1}$, where $\beta_{j+1}>\beta_j>1$, for j=2, 3, …, N. Then they used the rational choice model to determine the market share of each product j. By incorporating the fact that higher quality products are more costly to produce, they determined the optimal product assortment and the optimal price of each product in a monopolistic environment. Also, they extended their model to incorporate two additional issues: production capacity and price competition. More recently, Chayet et al. (2009) considered a more general product assortment model that incorporates stochastic customer arrivals and competition. Aydin and Ryan (2000) studied a product assortment problem that deals with products that cannot be differentiated horizontally or vertically. By using the multinomial logit model to capture the demand function, they characterized the optimal assortment and the optimal pricing of each product in the assortment.

Shelf space constraint: Kok and Fisher (2007) developed a product assortment model that addresses the issue of limited shelf space in a store that has no backroom so that the maximum inventory of each product depends on f_j —a decision variable that specifies the number of facings allocated to project j. In addition, by considering the physical width of product j, w_j, the number of facings f_j is subject to a "knapsack" constraint:

$$\sum_j w_j f_j \leq \text{Shelf Space}.$$

By considering the case when the demand function of each product j depends on the number of facings f_j, the original demand for product j, d_j, and the demand derived from product k when product k is not available, Kok and Fisher (2007) formulated the product assortment problem as a nonlinear integer programming problem with a non-separable profit function. Due to the complexity of this problem, they developed an iterative heuristic approach for determining near-optimal product assortment and near-optimal number of facings for each product in the portfolio. Their model has been implemented at Albert Heijn, BV, a leading supermarket chain in the Netherlands.

Dynamic product assortment: Due to long manufacturing lead time, most manufacturers usually decided on the product assortment for a single selling season only once so that the product assortment remains the same throughout the selling season. However, as companies develop new design and manufacturing processes to reduce product development cycle time and manufacturing lead time, companies such as Zara (Spain) and World Co. (Japan) are now able to reduce its design-to-shelf lead time from 6 months to 4 weeks. The shortened lead time would enable companies such as Zara to adjust its product assortments dynamically over time within a selling season. By assuming that the assortment is limited to K products at any point in time, Caro and Gallien (2007) formulated the dynamic assortment problem as a Bayesian dynamic programming problem. By imposing various simplifying assumptions, they proposed one heuristic that is based on Lagrangian relaxation and decomposition to determine near-optimal dynamic assortment. This heuristic is based on an index policy that balances immediate revenues (exploitation) and future gains from learning (exploration). Later on, they extended this heuristic to incorporate other operational issues including production lead time, switching costs, and product substitution.

More recently, Caro and Martinez-de-Albeniz (2009a, 2009b) examined a dynamic assortment problem by considering a situation in which each customer utility depends on her purchase history. Specifically, they applied the discounted utility model developed by Baucells and Sarin (2007) in which a customer will obtain a higher utility by purchasing products that are substantially new or different from the products she purchased in the past. By incorporating this new element in the utility function, they presented a model that deals with dynamic product assortment and pricing decisions over time under competition. They showed that a firm can obtain a competitive advantage by having the capability to introduce new products more frequently.

4.5. Production and pricing models

The issue of joint production and pricing decision has been examined since late 1950s, probably because it is a natural extension to incorporate the pricing decision when dealing with production planning. In the traditional operations management literature, most joint production and pricing models focused on the mathematical analysis for determining the optimal pricing and production (or replenishment) planning decisions for a single product over a single period. The reader is referred to Petruzzi and Dada (1999) for a comprehensive review and an innovative approach for solving this class of problems. To determine the optimal pricing and production decisions for a single product over multiple time periods, the analysis becomes highly complex and only structural results are available (Chan et al., 2004; Yano and Gilbert, 2004). Recently, Zhu and Thonemann (2009) extended previous work to the two-product case in which the product demand of each product is based on a deterministic and a stochastic component: (a) the deterministic component is based on the exogenous demand model as described in Section 3.1; (b) the stochastic component is a random variable with a product-specific distribution. They showed that the retailer can improve his profit significantly by considering both products jointly when planning its ordering decisions. Dong et al. (2009) studied a multi-product case in which the product demand is based on the multinomial logit model as described in Section 3.1. In their model, the retailer can only order once at the beginning of the selling season, but he can adjust his selling price dynamically throughout a selling season. By analyzing a stochastic dynamic program, they derived the optimal dynamic pricing of each product in each period. They showed that a retailer can increase his expected profit by using dynamic pricing especially when inventory is scarce. Essentially, Zhu and Thonemann (2009) and Dong et al. (2009) illustrated the importance of the linkage between pricing, replenishment planning, and product assortment. In view of two extensive reviews presented by Chan et al. (2004) and Yano and Gilbert (2004), we shall highlight some recent development in this area as a supplement.[8] Specifically, we shall discuss joint pricing and production planning models that incorporate the following operations strategies: (a) accurate response; (b) advance booking discounts; and (c) responsive pricing and responsive production.

Accurate Response: Due to long replenishment lead time, most retailers can only place a single order prior to the start of a selling season. Due to this restriction, there is a challenge for the retailer to make supply meet uncertain demand especially when the order quantity is based on the initial demand forecast. As a way to reduce the negative impact of this restriction, Fisher and Raman (1996) considered a situation in which the manufacturer is able to shorten his lead time so that the retailer can place an order prior to the start of the selling season and another order during the selling season. By allowing the retailer to place the second order in a later period, the retailer can plan the second order by using a more accurate demand forecast generated from the market signals observed during the time between the first order and the second order. Fisher and Raman referred the second order as an "accurate response" for managing uncertain demand. By analyzing a two-period model with demand updating, they showed that accurate response can yield significant benefit for the retailer. By extending the model to multiple products, they implemented their model successfully at Obermeyer (Fisher and Raman, 1996).

Advance booking discounts: Tang et al. (2004) considered a situation in which a retailer offers each customer two options to purchase the product. Specifically, each arriving customer can either pre-commit an order at a reduced price before the selling season, or buy the product at the regular price during the selling season. Clearly, the reduced price serves as an incentive for the customers to pre-commit their orders before the selling season. By using the exogenous demand choice model, they determine the pre-commit order quantity associated with different discount level. By analyzing a two-period model with demand updating, Tang et al. (2004) showed how the retailer can use these pre-committed orders to generate more accurate demand forecasts, which would enable the retailer to place more cost effective orders and manage uncertain demand more efficiently. They determined the optimal advance booking discount price and the optimal order for the retailer and they showed the benefit of advance booking discounts can be substantial.

Responsive pricing and responsive production: While accurate response and advance booking discount can certainly improve supply chain performance, these two ideas can be difficult to implement. To implement the accurate response concept, the manufacturer needs to have sufficient capacity to handle the second order on short notice. Also, to implement the early commitment program, the retailer needs to show its customers a sample of the seasonal products before the selling season, which could make the retailer or the manufacturer vulnerable to copycats. In the event these two ideas are not practical, van Mieghem and Dada (1999) considered a situation in which the retailer can place exactly one order and select only one retail price at the beginning of the selling season. They referred this concept as "responsive pricing," and they presented a two-stage stochastic model in which the retailer places an order in the first period. Then the retailer would determine the retail price after the demand uncertainty is resolved at the end of the first period but before the selling season that starts at the beginning of the second period. They showed the benefits of delaying the pricing decision until the demand uncertainty is resolved. While Van Mieghem and Dada (1999) focused on the issue of demand uncertainty, Tang and Yin (2008) examined the benefits of responsive pricing under supply uncertainty. By analyzing a two-stage stochastic model, they showed that the retailer can use responsive pricing as an effective mechanism for managing uncertain supply.

Motivated by the product postponement concept examined in Lee and Tang (1997), Chod and Rudi (2005) extended the work of Van Mieghem and Dada to the two-product case. Specifically, they considered the case in which the retailer places an order of a "generic" product in the first period. Then, after the demand uncertainty is resolved, the retailer can implement a "responsive production" strategy by having the manufacturer to customize this order of generic product into two individual products first, and then implement a "responsive pricing" strategy by determining the retail price for each of these two products. With the additional flexibility gained from delaying the product identity and delaying the pricing decision until demand uncertainty is resolved, Chod and Rudi (2005) illustrated the benefit of product postponement under responsive pricing. More recently, Anupindi and Jiang (2008) generalized the model presented in Chod and Rudi by considering duopoly models where firms needs to decide on the postponement capability (or flexibility) in addition to the decisions about capacity, production quantity, and price under demand uncertainty. By examining price dependent demand curves (additive and multiplicative), they showed that each firm's flexibility strategy in equilibrium depends on the upfront cost associated with the postponement capability. Moreover, they showed a firm that opts for the postponement capability tends to possess more production capacity and earn a higher profit. Ultimately, their analysis suggested that the postponement capability plays an important role in mitigating the negative effect of competition when demand curve is additive but not multiplicative. Therefore, it is crucial for a firm to gain a better understanding about the underlying demand curve before investing in the postponement capability.

All previous models are based on a key assumption that the pricing decision can be made after demand (or supply) is realized. To examine the benefit of responsive pricing and responsive production strategies further, Chan et al. (2006) relaxed this key assumption by analyzing a multi-period model for a single product. Under the responsive production strategy, the pricing decision is made a priori but the production decision is made at the beginning of each time period by using the updated demand forecast. Under the responsive pricing strategy, the production plan is made a priori but the pricing decision is made at the beginning of each time period. In addition to responsive production and responsive pricing strategies, they examined an additional strategy that is called "discretionary sales." Under this strategy, the retailer has the option to set aside some inventory in one period and use this inventory to satisfy demand in future

[8] For an in-depth treatment of dynamic pricing models with a given supply (i.e., revenue management), the reader is referred to a comprehensive review provided by Bitran and Caldentey (2003).

periods. By analyzing a finite horizon Markov decision problem, they developed heuristics based on deterministic approximations and analyzed their performances associated with different strategies numerically.

4.6. Channel coordination models

So far, we have reviewed models that deal with the coordination of marketing and operations within a firm. We now present some marketing–operations interface models arising from the case when a manufacturer sells its products through a retailer (independent from the manufacturer). Specifically, the manufacturer focuses on the production planning decision and the retailer focuses on the marketing decisions (sales efforts, retail price, etc.). Because the manufacturer and the retailer belong to different firms, the manufacturer needs to develop various incentive mechanisms to entice the retailer to coordinate with the manufacturer so as to achieve channel coordination so that both firms will act as a centralized organization.[9] We now review three types of marketing–operations interface models arising from a decentralized channel that is comprised of a manufacturer and a retailer.

Incentives in make-to-order environment: Consider the case when the manufacturer produces make-to-order units that are sold through a retailer. The product demand D depends on the retail price p quoted by the retailer and the leadtime L quoted by the manufacturer. Specifically, Pekgun et al. (2008) considered a deterministic demand $D(p, L)$ function

$$D(p,L) = a - bp - cL.$$

By assuming that the system behaves according to an $M/M/1$ queue in which customers arrive according to a Poisson process with rate λ and the manufacturer's processing time is exponentially distributed with rate μ, they analyzed the optimal quoted retail price and the optimal quoted leadtime for both centralized and decentralized systems. Relative to the centralized system, Pekgun et al. (2008) showed that, the total demand generated is larger, leadtimes are longer, quoted retail prices are lower, and the total profit of both firms are lower in the decentralized system. However, if the retailer pays a transfer price to the manufacturer for each unit produced and if both firms share a bonus payment as the fraction of the total revenue generated, then channel coordination can be achieved with a win–win outcome.

Sales-force incentivesand inventory management: Consider the case when the retailer does not own any inventory so that she focuses mainly on her selling effort (e.g., making sales calls and visiting customer sites). This situation occurs when the retailer/distributor acts as a sales agent who takes the order from the customers and sends the order to the manufacturer. Once the order is received, the manufacturer ships the order to the customers directly.[10] Chen (2000, 2005) considered a demand model under which the demand (or sales quantity) in period t would depend on the retailer's sales effort a_t, market condition θ, and random noise ε_t so that

$$D_t = a_t + \theta + \varepsilon_t.$$

For any sales efforts $a_1, a_2, \ldots, a_K$ the retailer makes over a finite horizon (K months), she generates a total demand of $(\sum_t D_t)$. If the manufacturer rewards the retailer $r(\sum_t D_t)$, then the retailer's net profit is equal to $N = r(\sum_t D_t) - c(\sum_t a_t)$, where $c(\cdot)$ is the "cost" associated with the sales effort. Because the retailer will select her optimal sales efforts that maximize her expected profit $E(N)$, her optimal sales efforts depend on the reward structure $r(\cdot)$. Also, given any reward structure $r(\cdot)$ and the corresponding optimal sales efforts $a_1, a_2, \ldots, a_K$, the manufacturer needs to solve a finite horizon production planning problem so as to determine his production plan over K periods.

When the market condition θ is common knowledge, Chen (2000) considered two different reward structures specified by the manufacturer. The first reward structure is based on a standard sales quota reward system where the retailer earns $r(\sum_t D_t) = \alpha + \beta\,[\sum_t D_t - q]^+$ at the end of period K so that the retailer earns β per unit if the total demand exceeds the quota q. The second reward structure is based on a moving time-window sales quota reward system that can be described as follows. At the end of each period t, the firm determines the total demand in the past $L+1$ periods w_t, where $w_t = D_t + D_{t-1} + \cdots + D_{t-L}$ and L is the replenishment lead time. The retailer earns a reward at the end of period t that can be defined as $r_t(w_t) = \alpha + \gamma\, I\{w_t > m\}$, where $I\{\cdot\}$ is the indictor function and m represents a pre-specified quota.

By noting that the first reward structure is based on the total demand over K periods, Chen (2000) showed that it is optimal for the retailer to postpone her sales effort until period K. Because of this behavior, there is a demand surge in period K, which would cause the production and inventory cost to increase. On the contrary, as the second reward structure is based on the moving time-window demand over $L+1$ periods and the reward is determined in each period, it generates an incentive for the retailer to exert sales effort in each period. As such, the second reward structure induces the retailer to smooth the demand process, which would reduce the production and inventory costs. By considering various numerical examples, Chen (2000) showed that the second reward structure is more efficient. When the market condition θ is only known to the retailer, Chen (2005) examined different reward structures that are intended to entice the retailer to reveal the market information truthfully.

Channel rebates and inventory management: Consider the case when the manufacturer focuses on his production planning decisions and sell his product through a retailer who makes her marketing decisions (sales efforts or selling price). While the retailer orders from the manufacturer, the retailer owns her inventory. To encourage the retailer exerts her sales efforts, it is common for the manufacturer to offer different channel rebate programs. Popular forms of channel rebate programs that are *sales*-based include: (1) linear rebates—a fixed rebate value for each unit sold; (2) target sales rebates—a fixed rebate value for each unit sold beyond a pre-specified target level (e.g., Taylor, 2002); and (3) progressive rebates—the rebate value for each unit sold is progressive according to different tiers. Notice that the progressive rebates program is a general form of the target sales rebates program, which is also a general form of the linear rebates program.

Taylor (2002) examined a situation in which the retail price p is fixed and the demand $D = aX$, where a is the sales effort selected by the retailer and X is a random variable. He showed that channel coordination cannot be achieved by using linear or target sale rebates. However, a properly designed target rebate and returns contract achieve channel coordination and a win–win

[9] In the supply chain management literature, many researchers have examined different incentive mechanisms to coordinate the manufacturer's and the retailer's decisions. For example, Cachon (2003), Lariviere (1998) and Tang (2006) offered different reviews of supply chain contracts (wholesale price contracts, buyback contracts, revenue sharing contracts, etc.) for achieving channel coordination so that each supply chain partner's objective is aligned with the supply chain's objective. We omit the details here.

[10] This situation can also occur when the retailer's inventory is managed and owned by the manufacturer under the VMI (vendor managed inventory) agreement.

outcome.[11] Instead of dealing with sales effort, Chiu et al. (2009) examined the case in which the demand depends on the retail price p selected by the retailer. They showed that the manufacturer can use a contract that combines the use of wholesale price, target sales rebate, and returns to coordinate a channel for linear and multiplicative price-dependent stochastic demands.

5. The implications of strategic customers

In the previous sections, the demand functions are based on the models described in Section 3.1. Essentially, these demand functions are based on the assumption that the selling price is static so each customer will commit to purchase a product or that the customer is "myopic" in the sense that each customer will neglect the utility associated with the option of purchasing the product later at a possibly lower retail price. However, due to uncertain demand and due to product obsolescence, companies often adjust their selling prices over time. When customers anticipate potential price drops in the future, they may postpone their purchasing decisions until the selling price drops below a certain threshold. During the current economic crisis, most customers are becoming more "strategic" in the sense that they are more willing to wait for price drops (McWilliams, 2004; O'Donnell, 2006). More formally, a customer is strategic if she purchases the product at the current selling price only if her current utility is greater than her "expected" future utility associated with the option of postponing the purchasing decision. As customers become more strategic, companies such as Best Buy, Ann Taylor, and Gap are losing their profit margins. Hence, it is commonly believed that this kind of strategic purchasing behavior hurts retailers' profits. For instance, through extensive numerical experiments, Aviv and Pazgal (2008) reported that a retailer can suffer a 30% reduction in revenue if he ignores the customer's strategic waiting behavior. We now review different models that examine the implications of strategic waiting behavior and ways to mitigate the negative impact of strategic purchasing behavior.[12]

Customer valuation and patience: Su (2007) is the first to develop a dynamic pricing model that incorporates strategic waiting behavior. In his model, a monopolistic firm has Q units to sell and the firm has to decide on the selling price over time. Customers arrive according to a deterministic and constant rate, and the customer population can be divided according to their valuation (high or low) and their patience level (impatient or patient). Each impatient customer has a higher cost to wait for future price drops so that she is more willing to buy the product at a higher selling price. By formulating this problem as a continuous time model, Su (2007) determined the optimal dynamic pricing policy that maximizes the retailer's expected revenue over time. He showed that there are situations in which strategic waiting can benefit the retailer because, due to the limited product availability, those low-value and patient customers who wait may force those high-value and impatient customer to purchase earlier at a higher selling price. More recently, Cho et al. (2009) considered a dynamic pricing model in which the strategic customer arrival follows a price-sensitive Poisson process with rate that depends on the price at time t. They determined the customer's optimal purchasing policy and showed that there are instances in which dynamic pricing can benefit the firm and the customers.

Opaque selling: As a way to reduce the negative impact associated with the strategic waiting behavior, Jerath et al. (2009) considered a duopolistic two-period model in which two retailers sell limited inventories over two periods. In the first period, each retailer j sells the product directly to the customers by charging p_{j1}. In the based model, both retailers will sell the remaining inventories themselves in the second period by charging p_{j2}. In the model that deals with "opaque selling", both retailers sell the remaining inventories in the second period through an intermediary as follows. By charging a selling price p_I, the intermediary will disguise the identity of the retailer. For example, several airlines (Delta, Northwest, and United Airline) sell their tickets directly, but they do sell their tickets through an intermediary Hotwire as these tickets are close to their expiration dates. Hotwire provides customers about the origin and destination of each ticket, but it does not reveal the identity of the airline and the exact itinerary. By considering the case when all customers have identical valuation and the number of customers is deterministic, Jerath et al. (2009) showed that both retailers can obtain a higher profit by selling the leftover inventory through an intermediary in an opaque manner. However, when the number of customers is stochastic, they show that opaque selling in the second period dominates when the customer valuation is below a certain threshold. For other research avenues associated with opaque selling, the reader is referred to Jerath et al. (2009) for more details.

Limited inventories: As articulated by Su (2007), the risk of not being able to obtain the product would entice some customers to purchase earlier at a higher price. This observation has motivated Liu and van Ryzin (2008) presented a monopolistic 2-period model in which the firm announces the total number of units Q available at the beginning of the first period and the selling price of its product in both periods so that $p_1 > p_2$. By assuming that all N customers are present at the beginning of period 1, that customer valuation V has a known probability distribution, and that all customers are risk-averse with identical utility functions $U(\cdot)$, they showed that each customer with valuation v will purchase the product in period 1 if and only if $U(v-p_1) > qU(v-p_2)$, where q is the firm's fill rate in period 2 (in equilibrium). By using this purchasing rule and by assuming a constant unit cost, they determined the optimal stocking level Q^* that maximizes the firm's total profit over both periods. They showed that, when customers are risk averse, it is optimal for the firm to reduce its stocking level so that its fill rate $q < 1$ (i.e., rationing). When $q < 1$, the firm can use insufficient supply to induce fear of not getting the product. By doing so, the firm can earn a higher profit because more customers with high valuation will purchase the product in period 1 at a higher price. Therefore, when customers are strategic, a firm can use rationing as a mechanism to counteract the strategic waiting behavior. Liu and van Ryzin (2008) extended their model to determine the joint optimal pricing and stocking level. More recently, Liu and van Ryzin (2009) examined the case when customers will use the realized fill rates in the past to estimate the future fill rate when making their purchasing decisions.

When the customer valuation deteriorating over time in the form of $V\ e^{-\alpha t}$, where V has a known distribution, and when customers arrive at the retailer according to a Poisson process, Aviv and Pazgal (2008) presented a model in which the customers

[11] A returns contract allows the retailer returns unsold items to the manufacturer and receives partial credits.

[12] Besides customer's strategic waiting behavior, there is evidence in which customers exhibit "herding" behavior. As articulated in Becker (1991) and Bikhchandani et al. (1993), customer valuation of a product or service can be influenced by the behavior of other customers. For example, Debo and Veeraghavan (2009) examined a queueing model in which each customer would first use the observed queue length to infer the quality of a service and then decide whether to join the queue or not. By analyzing the model with one queue and two queues, they developed insights regarding how buffer size, service rates, customer's waiting costs affect customer's herding behavior. The reader is referred to Debo and Veeraghavan (2009) for details.

know the regular selling price over the selling season p_1 and customers will form their beliefs about the post-season selling price p_2. By assuming that customer's utility function is risk-neutral, they showed that each arriving customer will purchase the product immediately at the regular price p_1 if the surplus $V e^{-\alpha t} - p_1 > 0$ and $V e^{-\alpha t} - p_1$ is larger than the expected surplus associated with the customer's belief about the post-season price and the likelihood that a unit will be available at the end of the season. By using the strategic customer's purchasing behavior, Aviv and Pazgal (2008) determined the optimal stocking level Q^* and the post-season pricing policy p_2 that is contingent on the number of remaining units to be sold at the end of the season. The reader is referred to Aviv et al. (2009a) for details.

Reservation and contingent pricing: Recognizing the fact that customers do anticipate price drops over time, some companies such as Filene's Basement in Boston and TKTS discount ticket booths for Broadway shows in New York and London pre-announce the future prices of their products. As companies pre-announce their future prices, strategic waiting behavior will become more prevalent. As a way to mitigate the negative effect associated with strategic waiting behavior, Elmagrabhy et al. (2009) developed a model to examine whether the retailer should allow customers to reserve their units during the season that are non-cancellable in the sense that each customer is committed to purchase the reserved product at the post-season clearance price if the product is available at the end of the selling season.[13] In their model, each arriving customer has 3 options: buy the product at a higher price, reserve the product at the post-season clearance price, or join a lottery for winning the product at the post-season clearance price at the end of the season. By considering a situation in which customers with either high or low valuation arriving at the retailer according to a Poisson process, they examined the customer's purchasing behavior in equilibrium. By anticipating the customer's purchasing behavior in equilibrium, they showed that the retailer can obtain a higher expected profit by allowing customers to reserve the product.

Partial information: All previous models assumed that each customer can observe the actual inventory level upon arrival. While some retailers such as Expedia.com and Benetton offer perfect information about the inventory level, many online retailers only provide information to each arriving customer about the availability but not the actual inventory level (i.e., partial information). Effectively, perfect inventory information can be conveyed when the retailer displays all available units (Display All) and the product availability status can be conveyed by displaying only one unit (Display One). In the absence of actual inventory information, strategic customers will form their own beliefs about the inventory level in order to determine whether to purchase the product immediately at a higher price or postpone their purchasing decisions until the end of the selling season in the hope of getting the product at the post-season clearance price. Yin et al. (2009) examined the implications of these two inventory display formats (Display All and Display One) in the presence of strategic customers. By considering the case in which the retailer pre-announces the regular selling price p_1 during the season and the post-season clearance price p_2, where $p_2 < p_1$ and by considering the case when customers arrive at the retailer according to a Poisson process, they determined the customer's optimal strategic purchasing policy in equilibrium under each inventory display format. By anticipating the customer's purchasing policy in equilibrium, they showed that the firm can obtain a higher expected profit under the Display One format. This result is based on the intuition that the Display One format could potentially create an increased perception of scarcity among customers, which would entice high-value customers to purchase the product immediately at a higher price p_1 upon arrival. Therefore, a retailer can mitigate the negative effect of strategic waiting behavior by providing partial information about the actual inventory level to the customers. The reader is referred to Aviv et al. (2009b) for more details.

Product variety: Parlakturk (2009a) presented a model to explore the interaction between product variety and dynamic pricing in the presence of strategic customers. He examined a situation in which a firm sells two vertically differentiated products (j and k) over two time periods. In his main model, the firm announces the selling price of each product at the beginning of each period. In addition, he considered the market is comprised of different types of customers, and he assumed that the firm knows the distribution of the customer type but not the type of each customer. To capture the notion of deteriorating quality over time, each customer who belongs to type i can obtain a utility U_{ijt} from product j, where U_{ijt} is decreasing in the selling price and the time of purchase. For any given price path of each product over both time periods, he examined the case when each customer is rational in the following sense: (1) even though the actual selling price of the product in period 2 is not known to the consumers in period 1, each customer can form the correct rational expectation about the selling price in period 2; and (2) each customer i will purchase product j in period 1 if (a) $U_{ij1} \geq U_{ik1} > 0$; and (2) $U_{ij1} \geq \max\{E(U_{ij2}),\ E(U_{ik2})\} > 0$, where $E(\cdot)$ denotes the expected utility associated with the rational expectation of the selling price in period 2. By anticipating each customer's purchasing decision, Parlakturk (2009a) determined the firm's optimal price path for each product and the firm's optimal profit. His analysis generated the following insights: (1) strategic customer purchasing behavior can hurt the profitability of a firm; and (2) a firm can use product variety to entice some customers to purchase the product earlier so as to mitigate the negative effect associated with strategic purchasing behavior. Hence, when dealing with strategic customers in a heterogeneous market, a firm can yield a higher profit by offering products that are unprofitable in a homogeneous market with non-strategic customers.

Quick response: Due to long replenish lead time, it is commonly assumed that the retailer is unable to replenish his inventory during the selling season. Cachon and Swinney (2009a) presented a two-period model in which a retailer sells its product at p_1 and p_2 ($p_2 < p_1$) to an uncertain number of customers with identical valuation $v_1 > p_1$. For any number of customers who arrives at the beginning of the first period, a certain proportion of them is myopic who will purchase the product at price p_1 immediately. However, the remaining customers are strategic whose valuation in the second period v_2 is random and it may drop below p_1. Therefore, some of these strategic customers may postpone their purchasing decision until the second period. However, a large number of bargain hunters with valuation $v_b < c$ may arrive at the beginning of the second period, where c is the unit cost. When replenishment in the second period is not allowed, Cachon and Swinney (2009a) showed that the strategic waiting behavior would reduce the retailer's optimal expected profit in equilibrium. However, when replenishment in the second period is allowed under the quick response initiative, they showed that the retailer

[13] This form of non-cancellable reservations is akin to the callable product examined by Gallego et al. (2008). The notion of non-cancellable reservation can also be viewed as a form of contingent pricing in which the actual selling price depends on the realization of a certain event (Biyalogorsky and Gerstner, 2004). Specifically, Biyalogorsky (2009) presented a model that illustrates how contingent pricing can generate an incentive for more customers to arrive earlier at the retailer. Because the competition among these customers intensifies as more customers appear earlier in the selling season, these customers would become more willing to purchase the product at a higher price upon arrival.

can order less in the first period (because the retailer has the "option" to replenish his inventory at the beginning of the second period). By ordering less in the first period and by having the option to replenish the inventory later, the retailer can create a sense of scarcity in the first period, which can entice the strategic customers to purchase the product at a higher price p_1 in the first period. Based on a numerical analysis, they showed that quick response can enable a retailer to obtain a higher profit when dealing with strategic customers. The reader is referred to Cachon and Swinney (2009b) for more details.

6. Discussions and future research

Over the last 20 years, we have observed significant advances in the research area of marketing/operations interfaces. Specifically, we have gained a much deeper understanding in the area of product assortment planning models as described in Section 4.4 and the area of production and pricing models as presented in Section 4.5. In view of the vast literature in these two areas, it appears the development in these two areas is getting saturated. Besides the need to test some of theoretical results empirically, we believe there are many remaining research areas that deserve attention.

First, as observed from Section 4.1, the issue of customer portfolio selection in the context of marketing–operations interfaces is not well understood. Specifically, to align a firm's marketing plan and operations plan so as to improve the firm's profitability, it is important for a firm to integrate its decision on the target customer segment (customer acquisition plan) so that the firm can satisfy its target customers. There is an opportunity to develop models to examine the tradeoffs among customer acquisition plans, marketing plans and operations plans.

Second, as customers have easy access to different retail channels, a firm needs to coordinate its channel strategies with its marketing and operations plan. For example, as retailers are launching private labels to compete with national brands, should a national brand develop additional brands that are sold at lower prices to compete with the retailers? If yes, what are the implications of these additional brands on the market share of the existing national brands? Also, how would these additional brands impact the firm's existing manufacturing operations? How should these additional brands be promoted? In view of the models presented in Section 4.3, there are opportunities to develop new models to examine these issues.

Third, due to recent concerns about environmental friendly, sustainability, pending regulations, there is an increasing trend for firms to develop mechanisms to reduce waste. Specifically, many firms now manage closed-loop supply chains that deal with the "forward" flow of materials from suppliers to end customers and the "reverse" flow of used products from end customers to the manufacturer for disposal or remanufacturing. The reader is referred to Guide and Van Wassenhove (2009) and Ferguson and Souza (2010) for a comprehensive review of various quantitative models that examine different operational aspects of closed-loop supply chains.

As more manufacturers such as Kodak, Pitney Bowes, Xerox, are committed to recycle their products, many firms remain skeptical about the viability of remanufacturing as a business. Clearly, a manufacturer can develop mechanisms to reduce the cost associated with various aspects of remanufacturing including (a) leasing instead of selling a product to improve returns rate (Agrawal and Toktay, 2010); (b) design for remanufacturing using new process technology or new product designs (Debo et al., 2005; Subramanian et al., 2009); and (c) outsource the remanufacturing process to a third party (Ferguson, 2010). However, besides the concern about the fact that remanufactured products (with lower selling prices) may cannibalize the sales of new products (with higher selling price), many firms have legitimate concerns regarding the sales of remanufactured products affect their brand image and product liabilities. We think this dilemma presents a research opportunity in the area of marketing/operations interfaces. We highlight two potential research topics for future research. The reader is referred to Agrawal and Toktay (2010) and Ferguson (2010) for other strategic issues arising from closed-loop supply chains.

Take back: Suppose a manufacturer decides to "take back" its products by offering certain "residual" value of the products upon end-of-use. Then by viewing this "take back" process as an "option" for customers to redeem the residual value, customers are likely to recognize the imputed option value and the manufacturer can charge a higher selling price (Anderson et al., 2008). By using this option value to specify the demand function, it is of interest to develop a model to examine the impact of the "take back" offer on the firm's profit.

Sales channels: Clearly, if the manufacturer sells both new and remanufactured products through the same channel in the same geographical region, then the remanufactured products may cannibalize the sales of the new products. However, in many instances, the cannibalization effort can be reduced significantly if these two products are sold in different channels in different geographical regions targeting different market segments. For example, in some developing countries, it is not uncommon for a firm to sell its new cell phones in major cities and refurbished cell phones in rural areas. It is of interest to develop a model that examines the impact of sales channels for new and remanufactured products on the profit.

In conclusion, the research area of marketing–operations interfaces has certainly flourished over the last 20 years, but there are some new areas that deserve attention in the near future.

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