Chapter 13
Risk Models for Supply Chain Management

Abstract This chapter reviews quantitative models that deal with supply chain risks. While this review is not exhaustive, it provides indicative research literature and quantitative models proposed by supply-chain management researchers. Because most quantitative models in the literature are designed primarily for managing high-frequency-low-impact *operational* risks, we present potential research ideas for managing low-frequency-high-impact *disruption* risks.

13.1 Introduction

After discussing strategic and tactical approaches for managing supply chain risks and actual case studies in Part II, we now turn to reviewing the existing academic research literature that pertains to supply-chain risk management in Part III. Even though the literature reviewed in Chapters 13–15 in this part deals primarily with ways to mitigate "normal" supply chain risks rather than the "abnormal" risks (i.e., disruptions), this review is useful for providing a good starting point for two reasons: (1) this literature can be extended for disruptions, and (2) unlike the general risk management literature that motivated most of Part I of this book, the chapters in this part are firmly rooted in the supply chain literature and practice.

In this chapter, we review primarily quantitative models that deal with supply chain risks. For general approaches to risk management, we refer the reader to the review by Chapman et al. (2002). This chapter (Chapter 13) is not an exhaustive review; rather, it provides indicative research literature and quantitative models proposed by supply-chain management researchers. Chapter 14 deals with modeling of various types of supply-chain flexibility. The final Chapter 15 in this part reviews the use of stochastic programming in the literature to plan for demand uncertainty. Also, we relate various supply chain risk management strategies examined in the literature with actual practices.

In general, we can categorize *supply chain management* efforts and the corresponding risk mitigation models in the literature as follows: (1) supply manage-

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ment, (2) demand management, (3) product management, and (4) information management. For each of these categories, we have supply-chain topics for which we provide indicative literature. Table 13.1 lists the four aforementioned categories and the topics within each along with the corresponding section and subsection numbers in this chapter.

Table 13.1 Topics in the supply chain management literature for managing risks

13.2. Supply Management	**13.3. Demand Management**	**13.4. Product Management**	**13.5. Information Management**
13.2.1 Supply network design 13.2.2 Supplier relationships 13.2.3 Supplier selection 13.2.4 Supplier order allocation 13.2.5 Supply contracts 13.2.6 Robust strategies for supply management	Product rollovers and pricing to: 13.3.1 Shift demand across time 13.3.2 Shift demand across markets 13.3.3 Shift demand across products 13.3.4 Robust strategies for demand management	13.4.1 Postponement 13.4.2 Process sequencing 13.4.2 Robust strategies for product management	Supply chain visibility; information sharing; vendor-managed inventory, and collaborative planning, forecasting and replenishment for 13.5.1 Managing "fashion" products and 13.5.2 Managing "functional" products 13.5.3 Robust strategies for information management

Although we focus our review on "robust strategies", most quantitative models presented in this chapter are designed for managing operational risks (i.e., normal risks) rather than disruptive ones. (This is not surprising as these models are for *supply chain management* in general rather than for *supply chain risk management*—see Chapter 16 on researchers' perspectives in this regard.) So, although these quantitative models often provide cost-effective solutions for managing operational risks, they do not address the issue of disruption risks in an explicit manner.

While having robust supply chains is desirable, firms will be more willing to implement "robust" supply chain strategies for mitigating disruption risks if these strategies possess two specific properties: (1) efficiency—the firm could manage operational risks (normal risks) efficiently regardless of the occurrence of major disruptions and (2) resiliency—the firm can sustain its operation during a major disruption and recover quickly afterwards. Christopher (2004), Chopra and Sodhi (2004), and Lee (2004) offer different approaches for establishing resilient supply chains.

Both efficiency and resilience are critical for firms to ensure profitability and business continuity, the latter having elements of supply chain risk management as defined in Section 13.1. Also, when a robust strategy is efficient, most firms can perform cost/benefit analysis or return on investment to justify strategies for improving efficiency under operational risks. As such, the management is more willing to implement a strategy that would enhance the efficiency and resiliency. The notion of efficiency and resiliency is akin to the S.M.A.R.T. supply chain management approach developed by De Waart (2006) for quick and effective response to risk events to ensure cost effectiveness and speedy recovery.

The organization of this chapter is as follows. In Sections 13.2 to 13.5, we review some of the research literature with topics as shown in Table 13.1. In Section 13.6, we discuss managerial attitudes toward risk as these are pertinent to supply chain risk. Section 13.7 concludes this chapter with some suggestions for future research in supply chain risk management.

13.2 Supply Management

To gain cost advantage, many firms outsourced certain non-core functions so as to maintain a focus on their core competence (c.f., Porter, 1985). Since the 1980s, we witnessed a sea change in which firms outsourced their supply chain operations including design, production, logistics, information services, etc. Essentially, supply management deal with six inter-related issues:

1. Supply network design
2. Supplier relationships
3. Supplier selection process (criteria and supplier selection)
4. Supplier order allocation
5. Supply contract
6. Robust strategies for supply management.

13.2.1 Supply Network Design

When designing a global supply chain network, we need to address the following issues:

1. Network configuration: Which available suppliers, manufacturing facilities, distribution centers, and warehouses should be selected?
2. Product assignment: Which facilities (suppliers, manufacturing facilities, distribution centers, etc.) should be responsible for processing which subassemblies, semi-finished products, or finished products?
3. Customer assignment: Which facility at an upstream stage should be responsible for handling the "demand" generated from downstream stages?
4. Production planning: When and how much should each facility produce?

5. Transportation planning: When and which mode of transportation should be used?

Most of the published work in the area of supply network design is based on different deterministic models. For example, by considering the fixed and variable processing cost at each facility, Arntzen et al. (1995) implemented a mixed integer programming model at Digital Equipment Corporation that serves as a planning system for determining optimal decisions related to issues 1, 2, 4, and 5 above. In addition, Camm et al. (1997) develop an integer programming model for Procter and Gamble (P&G) to deal with issues 1 and 3. However, these papers do not deal with risk in any explicit manner.

Some researchers have investigated supply chain network design by capturing certain risk related issues arising from global manufacturing. For instance, Levy (1995) presents a simulation model to examine the impact of demand uncertainty and supplier reliability on the performance of different supply chain network designs (issues 1 and 5). This simulation model has helped a personal computer manufacturer to evaluate the costs and lead times associated with two sourcing alternatives between Singapore and California.

Likewise, Lee and Tang (1998b) develop a stochastic inventory model to examine the tradeoff between the "consignment" and "turnkey" arrangements under demand uncertainty. Their analysis has helped Hewlett Packard (HP) to determine specific arrangements with different contract manufacturers in Singapore and Malaysia. Consignment and turnkey are two common approaches for the contract manufacturers to obtain the requisite parts from various suppliers in outsourced manufacturing. Under consignment, the original equipment manufacturer (e.g., HP) purchases the requisite parts from different suppliers (to enjoy the volume discount), sorts the parts to create kits, and then ships the kits to the corresponding contract manufacturers. However, this arrangement has drawbacks in terms of long lead time and high shipping and handling costs. Turnkey is an alternative arrangement under which the contract manufacturers order the parts directly from suppliers designated by the OEM and then charge the OEM accordingly.

There are also some papers that use stochastic programming to extend supply chain network design under different types of uncertainties pertaining to five issues listed at the beginning of this section. For instance, Huchzermeier and Cohen (1996) develop a modeling framework to show how one can exploit currency exchange rates by shifting production within a global supply chain network. By incorporating network design issues 1, 3, 4 and 5, they formulate the problem as a multi-period stochastic programming problem that aims to maximize the discounted after-tax profit. They also show how flexible global supply chain can provide real options to hedge against exchange rate fluctuations. Likewise, Kouvelis and Rosenblatt (2002) develop a two-stage global supply chain network model that addresses all five issues listed above. More importantly, they consider the case in which government subsidies and tax incentives are present in certain countries for certain products or operations. Their mixed integer programming model provides insights on the effects of financing, taxation, regional trading zones and local content rules on the design of a global supply chain.

13.2.2 Supplier Relationships

As more manufacturers recognized the strategic value of suppliers in the late 1980s, supplier relationships changed from adversarial to cooperative in the U.S. (Helper, 1991). Many firms realized that suppliers could enable a firm to focus on core competence and to reduce cost and product development cycle time at the same time. In addition, various e-markets and information technologies enabled companies to foster different types of relationships with the suppliers, ranging from one-time purchase to virtual integration via information sharing.

Dyer and Ouchi (1993) and Dyer (1996) studied various Japanese and U.S. firms and support the idea of having long-term supplier relationship with fewer strategic suppliers. Tang (1999) has identified four types of supplier relationships: (1) vendor, (2) preferred supplier, (3) exclusive supplier and (4) partner. These four types differ from each other in terms of types of contracts, length of contracts, type of information exchange, pricing scheme, and delivery schedule. By considering the market condition that is measured in terms of the strategic importance level of the part to the buyer and the buyer's bargaining power, Tang recommends different supplier relationship for different market conditions.

Much of the literature reviewed by Tang (1999) focuses on qualitative analysis or strategic analysis rather than operational or short-term opportunities. Closing this gap, Cohen and Agrawal (1999) present an analytical model for evaluating the tradeoff between the flexibility offered by short-term contracts and the improvement opportunities and price certainty associated with long-term contracts. They show analytically that long-term contracts may not always be optimal and provide conditions under which short-term contracts are actually more effective. As firms expand their business globally, their supply chains involve more global partners. For some regional markets, a firm may source locally so as to reduce transportation cost, replenishment lead times and inventory; there may also be tax benefits and low local labor costs. Consequently, firms may source from multiple suppliers. Firms may source from multiple suppliers also to reduce the impact of various operational and disruption risks. Indeed, according to an empirical study conducted by Shin et al. (2000), dual or multiple sourcing is a common business practice.

13.2.3 Supplier Selection Process

Boer et al. (2001) provide a comprehensive review of different methods for selecting suppliers. They divide the supplier selection process into developing of selection criteria, and approving and selecting suppliers. We discuss these in detail below.

Developing supplier selection criteria. Boer et al. (2001) report two decision methods—interpretive structural modeling and expert systems—for forming selection criteria. The interpretive structural modeling technique proposed by Mandal and Deshmukh (1996) that separates dependent criteria from independent criteria:

the independent criteria are important for screening acceptable suppliers while the dependent criteria are critical for final supplier selection. The expert system developed by Vokurka et al. (1996) captures the previous supplier selection process in a knowledge base, which can be used to suggest selection criteria for future supplier selection process. Choi and Hartley (1996) investigate 26 supplier selection criteria used by different partners (automotive assemblers, first-tier suppliers, second-tier suppliers) across the supply chain in their empirical study of the auto industry. These criteria include cost reduction capability, quality improvement capability, and the ability to change production volumes rapidly. By using various multivariate statistical techniques (factor analysis, clustering analysis, multivariate analysis of variance) to analyze the supplier selection criteria reported in 156 surveys, they make the following conclusions:

- The supplier selection criteria are reasonably consistent across the supply chain in the automotive industry. At all levels, commitment to establish cooperative/long-term relationship is an important selection criterion.
- Price is one of the least important criteria, while quality and delivery are important criteria.
- Supplier's technological capability and financial stability are more important criteria for the auto assemblers.

Note that *volume flexibility*, i.e., the ability to change production volumes rapidly, is not considered to be as important as other criteria such as *quality* and *long-term relationship*. Moreover, with disruptions by way of terrorist attacks, hurricanes, earthquakes, and SARS that have occurred since the study by Choi and Hartley (1996), one may also speculate that *business continuity* would become an important supplier selection criterion.

Approving and selecting suppliers. At this stage of the process, the goal is to reduce the set of all potential suppliers to a smaller set of approved suppliers. To do so, the decision maker has to classify all suppliers into approved or disapproved categories. Based on the supplier's performance on the selection criteria, Boer et al. (2001) report the use of the following methods for supplier approval: clustering analysis, data envelopment analysis, and an Artificial Intelligence approach called case-based-reasoning method.

For the final supplier selection out of the approved suppliers list, Boer et al. (2001) report the use of the following decision methods in different settings:

- **Linear weighting models.** By assigning different weights to different criteria, one can compute the overall rating of a supplier by considering the weighted sum of different criteria. In this case, the supplier with the highest rating will be selected.
- **Total cost of ownership.** This method is developed by Ellram (1990) to include all quantifiable costs incurred throughout the life cycle of the item purchased from a supplier. The supplier with the lowest total cost of ownership will be selected.

- **Mathematical programming models.** Most of the methods reported in Boer et al. (2001) are based on various deterministic models including: linear programming, goal programming, data envelopment analysis, etc. The idea is to select supplier(s) with minimum cost.
- **Simulation models.** This method enables the decision maker to capture some of the uncertainties (yield loss, stochastic lead times, etc.) related to supplier selection. By simulating the performance of different suppliers for different criteria under different scenarios, the method can help a decision maker to select a supplier under uncertainty.

There are other quantitative models for supplier selection. For example, Weber and Current (1993) present a mixed integer programming formulation that is intended to capture multiple supplier selection criteria. Current and Weber (1994) formulate the supplier selection problem as a variant of facility location problem. Weber et al. (2000) present an approach for evaluating the number of suppliers to employ by using multi-objective programming and data envelopment analysis. Dahel (2003) extends the model presented in Weber et al. (2000) by incorporating the order quantity decision for each supplier.

While most supplier selection models are deterministic in nature, a few articles specifically address operational risks tied to supplier selection. Tang (1988) presents a supplier selection model that captures the interaction of the supplier's quality and the buyer's quality control (inspection policy). Tagaras and Lee (1996) develop a different supplier selection model that captures different degrees of imperfections in the buyer's manufacturing processes by considering the interaction between the supplier's quality and the buyer's internal manufacturing process. Specifically, they consider that there are two states of the buyer's process: normal or abnormal. When the buyer's process is in the normal state, the output of the process is perfect if the supplier's input is. However, when the buyer's process is in the abnormal state, the output of the process is defective regardless of the supplier's input is or is not. By considering different costs that depend on the output quality, they develop the optimal supplier selection criterion that minimizes the buyer's expected total cost (ordering cost and cost of quality). Kouvelis (1998) presents a supplier selection model that captures the stochastic nature of exchange rate. In his model, the buyer needs to decide the suppliers to be selected and the quantity to be ordered from each of those selected suppliers. As a way to respond to fluctuating exchange rates, the model captures the flexibility for the buyer to shift the order quantity among suppliers dynamically at the expense of switchover costs. When the switchover cost is significantly high, he shows that the buyer may continue to source from suppliers that are more expensive so as to avoid switchover costs.

13.2.4 Supplier Order Allocation

After a set of suppliers is chosen, the buyer needs to determine ways to allocate the order quantity among these selected suppliers. We classify the literature in this area according to different types of operational risks:

1. Uncertain demand
2. Uncertain supply yields
3. Uncertain supply lead times
4. Uncertain supply capacity, and
5. Uncertain supply costs.

Uncertain demand. There is voluminous amount of published works that focus on analytical models for determining optimal order quantity for a *single* supplier under demand uncertainty. For a review of analytical models that deal with a single supplier, the reader is referred to the books by Porteus (2002) and by Zipkin (2000). For models that deal with *multiple* suppliers, Minner (2003) provides a more comprehensive review. When the supply lead times are deterministic, all models assume that the supplier with a shorter lead time charges a lower cost per unit. Due to the complexity of the analysis, most discrete-time models are restricted to two suppliers with lead times that differ by one period. By contrast, Zhang (1996) deals with *three* suppliers with lead times that differ by one and two periods respectively and characterize the optimal ordering policy for each supplier.

To make the analysis of multiple-supplier inventory models more tractable, some researchers consider two supply modes: regular and emergency. The regular supply model is based on a regular supply lead time with finite lead time, while the emergency supply is available instantly. Fukuda (1964) shows that the optimal ordering policy takes on the form of "two order-up-to levels", x and y, where $x < y$. Specifically, the optimal ordering policy can be described as follows: If the inventory at the beginning of a time period z is less than x, then order $(x-z)$ units by using the emergency mode and order $(y-x)$ units by using the regular mode; if $x < z < y$, then order $(y-z)$ units according to the regular mode; otherwise, order nothing. Vlachos and Tagaras (2001) extend Fukuda's model to the case in which the emergency model is capacitated. Scheller-Wolf and Tayur (1999) consider a Markovian periodic review inventory model and show that the optimal ordering policy for the buyer is a modified state-dependent base-stock policy. Specifically, they show that there exists a state-dependent optimal inventory level (target) in each period. In each period, the buyer should first order an amount from the regular supplier so that the inventory position after ordering is as close as possible to the target. The buyer can place an emergency order to fill the gap between the target and the inventory position after ordering from the regular supplier.

Due to the complex analysis of the optimal ordering policies for the multi-supplier case, various researchers restrict their analysis to certain classes of ordering policies. For example, Moinzadeh and Nahmias (1988) analyze an (s_1, s_2, Q_1, Q_2) ordering policy for a continuous time model with regular and emergency supply. Specifically, when the inventory reaches s_1, a regular order of size Q_1 is placed. If the inventory reaches s_2 within the lead time of the regular order, an emergency order Q_2 is placed. Janssens and de Kok (1999) analyze an ordering policy in which the buyer will always order Q units from one supplier in each period, and will order $[S-Q]+$ units from the second supplier so as to bring the inventory position to S. The reader is referred to Minner (2003) for more details.

Instead of focusing on optimal ordering policies, Nagurney et al. (2005) develop a model for analyzing the equilibrium behavior of a three-level supply chain comprising manufacturers, distributors and retailers. By considering uncertain demands at the retailer level, they formulate the problem at each level as a non-linear programming problem. For the retailers, the goal is to determine the optimal order quantity for each retailer based on the wholesale price set by the distributors. However, for the distributors, the goal is to determine the optimal wholesale price based on the manufacturers' price. The manufacturers set their prices to maximize profit adjusted by risk. By considering the first-order conditions of these three inter-related problems, they show how to recast the first order conditions as a set of variational inequalities. Bazaraa et al. (1993) provide details about the relationship between variational inequalities and Nash equilibrium. By exploiting the structure of these variational inequalities, they establish the existence of a unique equilibrium and provide certain characteristics of the equilibrium.

Uncertain supply yields. Consider some single-stage-multiple-period models first. Gerchak, Vickson and Parlar (1988) analyze a finite horizon problem with stationary demand distribution and show that order-up-to policies are not optimal when a buyer receives a random fraction of the order quantity from the supplier. Henig and Gerchak (1990) further show that there exists a critical point for each period such that an order should be placed only when the on-hand inventory at the beginning of the period is below the corresponding critical point. However, the exact order quantity is a complicated function of the system parameters. Agrawal and Nahmias (1998) present a model for evaluating the tradeoff between the fixed costs associated with each selected supplier and the costs associated with yield loss. They show how to determine the optimal number of suppliers with different yields when the demand is known. To limit our focus to supply chain management, we shall highlight some of the models that deal with multiple stages/products. Yano and Lee (1993) provide a thorough review of single stage/period models that deal with lot-sizing models with random yields.

As regards multiple-stage-multiple-period models, Bassok and Akella (1991) consider a two-stage-multiple-period model in which one stage corresponds to raw material ordering and the second stage corresponds to actual production, where yield uncertainty occurs only at the material ordering stage. They show that the existence of two critical points, one for the raw material ordering stage and one for the production stage, and the optimal ordering quantity and the optimal production quantity depends on whether the sum of (on-hand) finished goods and raw materials is larger or smaller than these two critical points, respectively. Because exact analysis of multiple-stage-multiple period models is intractable, Tang (1990) restricts his analysis of a linear control rule for a multi-stage serial production line with uncertain yields at each stage and uncertain demand. This linear control rule intends to "restore" the buffer stock at each stage to its target value in expectation. Hence, this control rule minimizes the expected deviation of the buffer stock levels from their targets. Denardo and Lee (1996) generalize Tang's model by incorporating rework and unreliable machines.

Although, multi-product, multi-stage, and multi-period models are intractable and not much work has been done with such models, there are some exceptions. Akella, Rajagopalan and Singh (1992) study a multi-stage facility with rework that produces multiple parts. Their analysis aims to determine an optimal production rule at each stage that minimizes the total inventory and backorder cost. They assume that the cost function is quadratic, which leads to optimal linear decision rules. Linear decision rules have been analyzed by Gong and Matsuo (1997) as well. Specifically, Gong and Matsuo consider a more general multi-stage facility with re-entrant routings. They formulate a control problem with the objective to minimizing the weighted variance of work-in-process inventory while ensuring that production capacity constraints are satisfied with a pre-specified probability. Their numerical experiments suggest that the linear decision rules perform well when compared with the optimal production policy.

Uncertain lead times. When replenishment lead times are stochastic, most researchers restrict their analyses of multiple supplier models to the case of deterministic demand. When both suppliers have identical lead time distributions (uniform or exponential), Ramasesh et al. (1991) consider an (s,Q) ordering policy where the order quantity Q is split evenly between two suppliers. Due to the complexity of the analysis, the optimal values for the reorder point s and the order quantity Q are determined numerically. By restricting the attention to the (s,Q) ordering policy, Sedarage et al. (1999) extends the model of Ramasesh et al. (1991) by considering more than two suppliers and a non-identical split among these suppliers. Based on the numerical analysis presented in Sedarage et al. (1999), they show that it might be beneficial to order from some suppliers with poor lead time performance in terms of the mean and standard deviation of the lead time. In general, although the exact analysis of multiple suppliers with stochastic lead times is intractable, exact analysis can be obtained for some special cases. For example, Anupindi and Akella (1993) consider a two-supplier model with random demand in which the replenishment lead time of supplier j is equal to one period with probability p_j and two periods with probability $(1-p_j)$, where $j=1,2$. They derive the optimal ordering policy that minimizes the total ordering, holding and backordering costs over a finite horizon. They show that the optimal ordering policy in each period n depends on two critical points x_n and y_n, where $x_n < y_n$, and the on-hand inventory at the beginning period n, z_n. Specifically, order nothing if $z_n \geq y_n$; order from one supplier if $x_n \leq z_n < y_n$; and order from both suppliers if $z_n < x_n$.

Uncertain supply capacity. Most models assume that the supply capacity is unlimited or known. However, unexpected machine breakdowns could affect the supply capacity. Relative little amount of work has been done in the area of uncertain supply capacity. Parlar and Perry (1996) present a continuous time model in which the availability of each of the n suppliers is uncertain because of disruptions like equipment breakdowns, labor strikes, etc. By considering the case that each supplier is either "on" or "off," there are 2^n possible number of states for the whole system. For each of these 2^n states, they analyze a state-specific (s,Q) ordering policy so that the buyer would order Q units when the on-hand inventory reaches s. Ciarallo et al. (1994) develop a discrete time model in which the supply capacity is random with known probability distribution. By considering the total (undiscounted) expected costs (ordering, inventory holding and backordering costs), they show that the objective function is quasi-convex, which implies that an order-up-to policy is optimal. Wang and Gerchak (1996) examine a periodic review model with uncertain supply capacity, uncertain yields and uncertain demand. The objective is to minimize the total discounted expected costs over a finite horizon. They show that the optimal policy possesses the same structure as the optimal policy obtained by Henig and Gerchak (1990) for the case in which only random yield is considered and that the order-up-to policy is optimal.

Uncertain supply cost. While most work focus on demand uncertainty, not much work has been done in the area of uncertain supply cost. For models that examine the issue of uncertain supply cost imposed by an upstream supply chain partner, Gurnani and Tang (1999) analyze a situation in which a retailer has two instants to order a seasonal product from a wholesaler prior to the beginning of a single selling season. They consider the case in which the wholesale price at the second instant and the demand are uncertain; however, the retailer can improve the demand forecast by using market signals observed between the first and second instants. In order to determine the profit-maximizing ordering policy, the retailer needs to evaluate the trade-off between the benefit of having a more accurate forecast and a potentially higher wholesale price at the second instant. By formulating the problem as a 2-period dynamic programming program, they develop an optimal way to allocate the optimal order quantity to be placed at the first and second instants and they provide the conditions under which the retailer should delay his ordering decision until the second instant.

Some researchers develop models for exploiting uncertain currency exchange rates in a global supply chain. Kogut (1985) develops a framework to argue that the benefit of a global supply chain lies in the operational flexibility, which permits a firm to exploit uncertain exchange rates. To examine this issue in a quantitative manner, Kogut and Kulatilaka (1994) develop a stochastic model to examine the value of the flexibility to shift production between two plants located in two different countries. By formulating the problem as a T-period dynamic programming problem and by modeling the exchange rate process as a discrete-time mean reverting stochastic process, they determine the option value of maintaining two manufacturing locations with excess capacity instead of having a single manufacturing location. However, they assume that the capacity of each plant is unlimited so that exactly one plant will be used to produce the required quantity to meet the total demand in each period.

Dasu and Li (1997) generalize Kogut and Kulatilaka's (1994) model by considering the case in which both plants have limited capacity so that both plants will be used to meet the demand in each period. They formulate the problem as an infinite horizon dynamic program with discounting. When the production cost is concave and when the cost of production shifting is linear, they show that the optimal production shifting policy is a two-barrier policy if the exchange rate process satisfies certain conditions. Specifically, under the two-barrier policy, there exists two critical points a and b so that it is optimal to shift the production between two manufacturing locations when the exchange rate is below a or above b. If the exchange rate is between a and b, then it is optimal to keep the same production quantity at each location without any shifting so as to reduce any unnecessary switch-over cost.

However, the models by Kogut and Kulatilaka (1994) and by Dasu and Li (1997) become intractable for more than two countries. For supply chain networks across three or more countries, Huchzermeier and Cohen (1996) present a stochastic dynamic programming problem for evaluating different global manufacturing strategy options. For any given exchange rate in each period, they solve a mixed integer program to determine the optimal production and distribution plan for the entire supply chain network that maximizes the global, after-tax profit. They construct various numerical examples by considering 16 different supply chain network designs, each of which specifies the location of the supplier(s), production plant(s), and market(s). Through these numerical examples, they illustrate the value of a global supply chain network that enables firms to shift its production and distribution plan swiftly as the exchange rates fluctuate.

13.2.5 Supply Contracts

When the partners across a supply chain belong to different firms or divisions, they tend to focus on their own objectives and make their decisions independently. Consequently, locally optimal decisions can cause operational inefficiency and globally suboptimal decision for the entire supply chain. There are two studies highlighting the pitfalls of an *un-integrated* (or decentralized) supply chain. First, when each supply chain partner places their order independently for the case in which the customer demand follows an AR(1) process, Lee et al. (1997c) show this locally optimal ordering decisions will create the "bullwhip" effect that causes operational inefficiency. Second, when each supply chain partner makes their ordering decision by maximizing their own profit for the case and when the customer demand is a deterministic and decreasing function of retail price, Bresnahan and Reiss (1985) show that these locally optimal decisions would result in lower total profit for the entire supply chain.

To improve operational efficiency and/or supply chain coordination, there has been a growing research interest in supply chain contract analysis. Most supply contract models usually deal with a supply chain that consists of one manufacturer (supplier) and one retailer (buyer) who faces customer demand. Even though the economics literature in the area of supply contracts is voluminous, economics researchers usually assume that that the customer demand is either deterministic or stochastic in the sense that demand uncertainty is resolved before the buyer places his order. Tirole (1988) provides a comprehensive review of supply contracts literature in economics.

There are three excellent reviews of supply chain contract analysis by Cachon (2003), by Lariviere (1998), and by Tsay et al. (1998), respectively. These reviews offer different perspectives: Tsay et al. (1998) provide a qualitative overview of various types of contracts when the demand is deterministic and random; Lariviere (1998) shows quantitative analyses of different types of contracts when the demand is uncertain; and Cachon (2003) examines how supply contracts can be used to achieve channel coordination in the sense that each supply chain partner's objective becomes aligned with the supply chain's objective. Since our focus is on supply-chain *risk* management, we focus on a limited set of supply chain contract literature that deals with various types of uncertainties. For this reason, we shall classify the supply chain contract literature according to different risk elements and contract types. Specifically, we shall review different types of supply contracts that can be characterized according to the financial flow and material flow as depicted in Fig. 13.1.

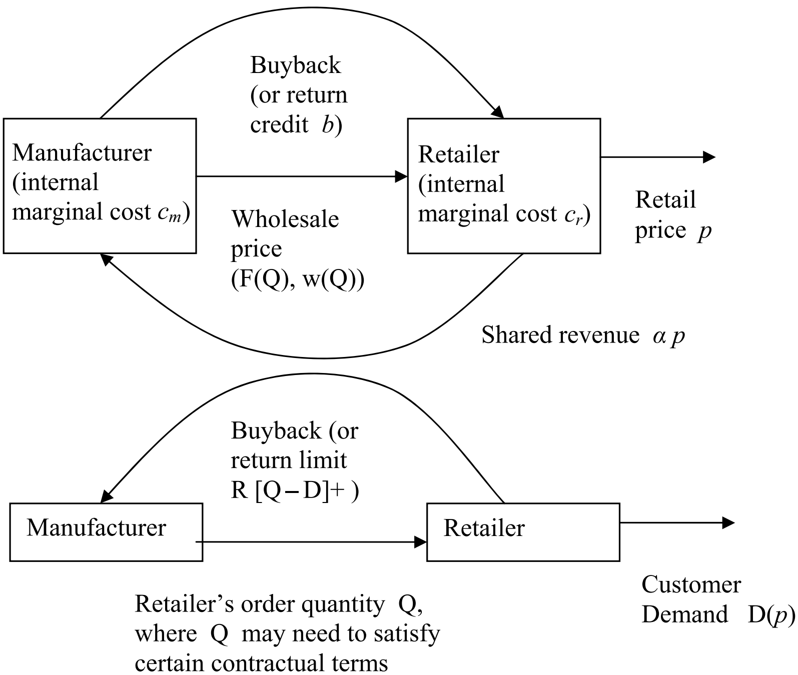

Fig. 13.1 Financial flow and material flow under different supply chain contracts

Wholesale price contracts. Consider the following scenario: the retail price p is fixed, the retailer retains the revenue p and retains the possession of any excess stock that can be salvaged at a price s. Suppose that the manufacturer offers a per unit wholesale price w so that the fixed cost $F(Q) = 0$, and the variable wholesale price $w(Q) = w$. In a single period setting, it is optimal for the retailer to order according to the newsvendor solution based on the corresponding cost structure. Given the retailer's order quantity, the manufacturer needs to determine the optimal w that maximizes his net profit. Lariviere and Porteus (2001) show that the manufacturer's profit function is unimodal when the customer demand distribution $F(x)$ with density function $f(x)$ has an *increasing generalized failure rate* (IGFR); i.e., when $xf(x)/(1-F(x))$ is increasing in x. Many distributions such as normal, exponential, truncated Normal, Gamma, and Weibull are IGFR. Hence, when the demand distribution is IGFR, one can determine the optimal wholesale price by considering the first order condition. However, Lariviere and Porteus show that a simple price contract w will not achieve channel coordination. Anupindi and Bassok (1999) extend Lariviere and Porteus' single period model to the case in which the retailer faces an infinite succession of identical selling seasons so that it is optimal for the retailer to order up to the newsvendor solution at the beginning of each season. Cachon (2004) generalizes Lariviere and Porteus' single period model to a two-period model with inventory holding and demand updating. Specifically, in Cachon's model, the retailer can place two separate orders at two separate instants before the selling season starts; however, the wholesale price at the second instant is known to be higher. Notice that Cachon's model reduces to Lariviere and Porteus' model when the second order is not allowed. By having the flexibility to place two separate orders, Cachon develops conditions under which channel coordination is achieved.

Next, there are many situations in which a supply chain partner would keep his information private. Corbett and de Groote (2000) consider a situation in which the manufacturer does not know the retailer's holding cost in a deterministic EOQ-type environment. By imposing a prior distribution on the retailer's holding cost, Corbett and de Groote compare various channel coordination schemes in which $F(Q)$ and $w(Q)$ take on different functional forms.

When the demand is deterministic and decreasing linearly in the retail price, Corbett and Tang (1998) examine the case in which the manufacturer does not know the retailer's internal marginal cost c_r study the optimal behavior of each party under different scenarios. By imposing a prior distribution $F(x)$ on the retailer's internal marginal cost c_r and by assuming that the prior distribution $F(x)$ has increasing failure rate; i.e., $f(x)/(1-F(x))$ is increasing in x, they compare the retailer's and the manufacturer's profits under different scenarios: one-part linear contracts $(F(Q) = 0, w(Q) = w)$, two-part linear contracts $(F(Q) = F \neq 0,\ w(Q) = w)$, and two-part nonlinear contracts $(F(Q) \neq 0,\ w(Q) \neq 0)$.

Ha (2001) generalizes Corbett and Tang's (1998) model by analyzing two-part non-linear wholesale price contracts for the case when the demand is stochastic and price-sensitive. Ha shows that channel coordination is not achievable under asymmetric information. When the manufacturer does not know the retailer's fixed ordering cost or the backorder penalty cost, Corbett (2001) examines the benefit of having the manufacturer to own the retailer's inventory (i.e., consignment stock). He shows that consigning stock may not always help the manufacturer.

Babich et al. (2004) analyze supply contracts with supplier default risk. They consider a single product model in which competing risky suppliers compete for business with a retailer. In their model, the suppliers are leaders in a Stackelberg game so that the suppliers would first establish the unit wholesale prices. Then the retailer would determine the order quantity for each supplier by taking demand uncertainty and supplier default uncertainty into consideration. By considering the retailer's discounted expected profit, they show that it is optimal for the competing suppliers to increase their wholesale prices at the equilibrium when the supplier default correlations are low and it is optimal for the retailer to order from suppliers with highly correlated default rates.

Buy-back contracts. In a single-period setting, it is optimal for the retailer to order according to the newsvendor solution. To induce the retailer to order more, it is quite common for the manufacturer to offer a return policy (also known as buy back contracts) so that the manufacturer would "buy back" up to $R\%$ of the retailer's excess inventory $[Q-D]+$ units at a unit rate of b, where $R \leq 100\%$ and $b \leq w$. Therefore, a return policy can be specified by two parameters (R,b). Pasternack (1985) is the first to show that a policy that allows for unlimited returns at partial credit; i.e., $R = 100\%$ and $b < w$, would achieve channel coordination. Moreover, Lariviere (1998) analyze the properties of the manufacturer's and retailer's profits for a class of return policies that coordinate the channel.

Emmons and Gilbert (1998) extend Pasternack's model to the case in which the retailer determines the order quantity Q as well as the retail price p. By considering a specific demand distribution of $D(p)$, they show that return policies or buy back contracts cannot coordinate the channel. However, there exists certain buy back contracts under which both the manufacturer and retailer can obtain higher profits.

Padmanabhan and Png (1997) consider the case in which two competing retailers facing a linear demand curve with an uncertain intercept. Under a full returns policy (i.e., $b = w$), they show that these retailers would increase their order quantities in a competitive environment.

Brown, Chou and Tang (2005) examine a multi-product returns policy in which the retailer can return up to a percentage of the total order quantities; i.e., the allowable return limits are pooled. By comparing the pooled returns policy with the non-pooled returns policy (i.e., the allowable return limits are product-specific), they provide conditions under which the retailer would actually order less under the pooled returns policy.

Revenue-sharing contracts. In retailing, stocking out a product could have a larger impact on the manufacturer's profit because the customer would usually buy a similar product from the retailer. This motivates manufacturer to provide incentive for the retailer to stock more. Clearly, a buy back contract (or a return policy) can serve this purpose; however, the buy-back contract may not be practical in certain situations. For example, in the video rental industry, it is not practical for the video rental stores to return excess inventory of old DVDs to the manufacturer (distributor). This may have triggered the idea for the manufacturer to develop a risk sharing scheme in the form of a revenue sharing contract. The revenue sharing contract can be characterized by the wholesale price w and the portion of the revenue to be shared α. As depicted in Fig. 13.1, the retailer would get a lower wholesale price $w$upfront but the retailer is required to remit αp for each rental unit to the manufacturer. For instance, as suggested by Mortimer (2004), Blockbuster shared 30–45% of their rental revenue in exchange for a reduced wholesale price of around \$8 instead of \$65 for each DVD. Tang and Deo (2005) determine the conditions for w and α under which the retailer will obtain a higher profit under the revenue sharing scheme.

In the economics literature, Dana and Spier (2001) show that revenue sharing contracts can be used to coordinate the supply chain, and would induce the retailers to reduce their rental prices under competition. Mortimer (2004) conducted statistical analysis based on the panel data collected at 6,137 video rental stores in the U.S. between 1998 and 2000. She shows that revenue-sharing contracts can enable a retailer to earn more for popular titles or new releases. Pasternack (2002) investigated the effect of a revenue sharing on the optimal order quantity in a newsvendor environment and shows analytically that a revenue-sharing contract can be used to achieve channel coordination. Cachon and Lariviere (2005) show analytically that the revenue sharing contracts are equivalent to buy-back contracts.

Quantity-Based contracts: Quality flexibility and minimum order. To achieve operational efficiency under demand uncertainty, a manufacturer would prefer contracts that would entice retailers to commit their orders in advance while a retailer would prefer contracts that would allow them to adjust their orders when necessary. As a compromise, some manufacturers offer Quantity Flexibility (QF) contracts to their retailers. A QF contract is specified by three parameters: a wholesale price w, an upward adjustment parameter u, where $0 \leq u \leq 1$, and a downward adjustment parameter d, where $0 \leq d \leq 1$. Consider the case in which a retailer placed an order x sometime earlier. Suppose the retailer updates his demand forecast and would like to revise this particular order. Under the QF contract, the retailer can adjust his order to Q by paying w per unit as long as $(1-d)x \leq Q \leq (1+u)x$. Notice that the QF contract can be recast as a buy back contract under which the retailer had to buy $(1+u)x$ units up front but could return or cancel his commitment down to $(1-d)x$ for a full refund of the wholesale price w. Lariviere (1998) analyzes a QF contract with parameters w, d, and u that coordinates the channel in a single-period setting. Tsay and Lovejoy (1999) provide a detailed analysis of QF contract in a multi-period setting.

When it is costly for a manufacturer to obtain more production capacity, a manufacturer may develop a supply contract to entice each retailer to commit to a minimum quantity in advance. Anupindi and Akella (1997) consider the case in which the retailer is committed to a fixed quantity in each period. In return, the manufacturer offers a discount based on the level of this fixed commitment. They prove that a modified order-up-to policy is an optimal policy for the retailer. Anupindi (1993) examines the case in which the order quantity that a retailer can place in each period is bounded pre-specified lower and upper limits. Bassok and Anupindi (1997) consider the case in which the retailer is committed to order at least $K \cdot N$ units in total over N periods. When demand is independent and identically distributed, they prove that the retailer's optimal order policy in each period is a modified order-up-to policy. As a variation, instead of focusing on the minimum total commitment for each product, Anupindi and Bassok (1998) analyze a multi-product supply contract under which the retailer is committed to a minimum total monetary (i.e., "dollar") value of the products to be purchased over N periods.

For selling seasonal goods, Fisher (1997) and Fisher and Raman (1996) confirm that the early sales data has informational value in the sense that this data can help the retailer to obtain more accurate forecast about the total sales for the whole season. Fisher and Raman show that it is advantageous for the retailer to place a second order after observing the first few weeks of sales data. To ensure that the second order will be replenished within the selling season, the manufacturer needs to impose certain restrictions on the second order quantity. Eppen and Iyer (1997) analyze a "backup agreement" that has been used in the fashion apparel industry. The backup agreement can be characterized by three parameters β, w, k). Prior to the selling season, the retailer commits to Q units for the entire selling season and confirms the first order $(1-\beta)Q$ at wholesale price w. The retailer can place a second order up to the remaining βQ units (i.e., the backup units) at wholesale price w and receive quick delivery. There is a penalty cost of k for any of the backup units not purchased. Brown and Lee (1997) consider a variant of the backup agreement arising from the semiconductor manufacturing industry.

Uncertain price. While most work focus on demand uncertainty, not much work has been done in the area of uncertain wholesale price. Li and Kouvelis (1999) consider a case in which the wholesale price is a geometric Brownian motion with drift. Facing with uncertain wholesale price, the retailer is required to procure exactly D units by time T, where D is the ultimate demand at time T. Also, an inventory holding cost $h(T-t)$ will be incurred for each unit purchased at time t, where $0 < t < T$. Li and Kouvelis evaluate the cost associated with three different supply contracts. First, in a "time-inflexible contract," the retailer must state up front about the purchase time. In a "time-flexible contract," the retailer may observe price movements and decide dynamically when to buy. They extend their model to the case in which they can procure the item from two manufacturers.

13.2.6 Robust Supply Management Strategies

The multi-supplier strategy is the most common approach for reducing supply chain risks. For example, both Sheffi (2001) and Kleindorfer and Saad (2005) recommend the use of multiple suppliers as a way to manage supply chain operational and disruption risks. For example, as articulated in Huchzermeier and Cohen (1996) and others, using multiple suppliers in multiple countries can enable a firm to manage operation risks such as normal exchange rate fluctuations efficiently. Moreover, doing so can make a supply chain more resilient during a major disruption. For example, as we mentioned in an earlier chapter, when the Indonesia Rupiah devalued by more than 50% in 1997, many Indonesian suppliers were unable to pay for the imported components or materials, and, hence, were unable to produce the finished items for their U.S. customers. However, with a network of 4,000 suppliers throughout Asia, Li and Fung (www.lifung.com), the largest trading company in Hong Kong for consumer-durable goods such as textiles and toys, shifted some production from Indonesia to suppliers in other Asian countries.

In many instances, the buyer does not have the luxury to shift production among different suppliers because of the very limited number of suppliers available in the market. To cultivate additional suppliers, certain supply contracts described in Section 13.2.5 could serve as robust strategies that would make a supply chain more efficient and resilient. For instance, revenue (or risk) sharing contracts are known to be efficient because their use can coordinate the channel partners in the face of uncertain demand (c.f., Pasternack, 2002). In addition, revenue sharing contracts could make a supply chain more resilient. For example, due to uncertain specification of the flu vaccine in any given year, the uncertain market demand, and the price pressure from the U.S. government, there are only two remaining vaccine makers for the U.S. market. This created a shortage of 48 million flu shots in 2004 when Chiron's Liverpool plant was suspended due to bacteria contamination (c.f., Brown, 2004). To make the flu vaccine supply chain more resilient, the U.S. government could consider offering certain risk-sharing contracts to entice more suppliers to enter the flu vaccine market. For instance, the government could share some financial risks with the suppliers by committing to a certain quantity of flu vaccine in advance at a certain price and to buy back the unsold stocks at the end of the flu season at a lower price. With more potential suppliers, the U.S. government would have the flexibility to change their orders from different suppliers quickly when facing major disruptions.

Table 13.2 lists references to the articles mentioned in Section 13.2.

13.3 Demand Management

In this section we focus on articles that emphasize on the use of demand management strategies to "shape" uncertain demand so that a firm can use an inflexible supply to meet the modified demand. In the previous section, we described how manufacturers can use different supply management strategies to mitigate various supply chain operational risks. However, these supply management strategies are ineffective when supply is inflexible. For instance, in the service industry or in the fashion goods manufacturing industry, the is usually fixed. When the supply capacity is fixed, many firms attempt to use different demand management strategies so that they can manipulate demands dynamically to match demand with the fixed

Table 13.2 Summary of supply management articles

Supply Management Aspect	Type of risk	References (in the order of appearance in the subsection)
Supply network design	General	Porter (1985), Arntzen et al. (1995), Camm et al. (1997), Levy (1995), Lee and Tang (1998), Huchzermeier and Cochen (1996), Kouvelis and Rosenblatt (2002),
Supplier relationship	General	Helper (1991), Dyer and Ouchi (1993), Dyer (1996), Shin et al. (2000), Tang (1999), Cohen and Agrawal (1999).
Supplier selection Supplier selection criteria	General	Boer et al. (2001), Mandal and Deshmukh (1996), Vokurka (1996), Choi and Hartley (1996), Ellram (1994)
Supplier approval/selection	General	Boer et al. (2001), Ellram (1994), Weber and Current (1993), Weber (2000), Dahel (2003), Tang (1988), Tagaras and Lee (1996), Kouvelis (1998)
Supply order allocation	Uncertain Demand	Porteus (2002), Zipkin (2000), Minner (2003), Zhang (1996), Fukuda (1964), Vlachos and Tagaras (2001), Scheller-Wolf and Tayur (1999), Moinzadeh and Nahmias (1988), Janssens and de Kok (1999), Nagurney (2005), Bazaraa et al. (1993),
	Uncertain Supply Yields	Gerchak, Vickson, and Parlar (1988), Gerchak (1990), Agrawal and Nahmias (1998), Yano and Lee (1995), Bassok and Akella (1991), Tang (1990), Denardo and Lee (1996), Rajagopalan and Singh (1992), Gong and Matsuo (1997)
	Uncertain Supply Lead Times	Ramasesh et al. (1991), Sedarage et al. (1999), Akella et al. (1993)
	Uncertain Supply Capacity	Parlar and Perry (1996), Ciarallo (1994), Wang and Gerchak (1996), Henig and Gerchak (1990)
	Uncertain Supply Cost	Gurnani and Tang (1999), Kogut (1985), Kogut and Kulatilaka (1994), Li (1997), Kogut and Kulatilaka (1994), Dasu and Li (1997), Huchzermeier and Cohen (1996)
Supply contracts	General	Lee et al. (1997), Bresnahan and Reiss (1985), Cachon (2003), Lariviere (1998), Tsay (1998)
Wholesale price contracts	Uncertain Demand	Lariviere and Porteus (2001), Anupindi and Bassok (1999), Cachon (2002), Corbett and de Groote (2000), Corbett and Tang (1998), Ha (2001), Corbett (2001), Babich et al. (2004)
Buy-back contracts	Uncertain Demand	Lariviere (1998), Emmons and Gilbert (1998), Padmanabhan and Png (1997), Brown, Chou, and Tang (2005),
Revenue sharing contracts	Uncertain Demand	Dana and Spier (2001), Mortimer (2004), Pasternack (2002), Cachon and Lariviere (2005),
Quantity-based contracts	Uncertain Demand	Lariviere (1998), Tsay and Lovejoy (1999), Anupindi and Akella (1997), Anupindi (1993), Bassok and Anupindi (1997), Fisher (1997), Fisher and Raman (1996), Eppen and Iyer (1997), Brown and Lee (1997)
Time-based contracts	Uncertain Price	Li and Kouvelis (1999)
Robust supply management	General	Sheffi (2001), Kleindorfer and Saad (2005), Huchzermeier and Cohen (1996)

supply. We refer the reader to Elmaghraby and Keskinocak (2003), who provide an extensive review of dynamic pricing models and clearance pricing models for selling a fixed number of units over a finite horizon. For literature that deals with coordination of pricing and ordering decisions, we refer the reader to comprehensive reviews by Yano and Gilbert (2004), by Petruzzi and Dada (1999), and by Eliashberg and Steinberg (1993).

Carr and Lovejoy (2000) develop a single-period model for a firm to handle multiple customers with random demand distributions when a firm's supply capacity is fixed. For each customer, they consider the case in which the firm can choose to accept only a fraction of the customer's demand distribution. The objective is to choose different fractions of customer demand distributions so that the firm's expected profit is maximized for a given supply capacity. By analyzing the mean and variance of the total demand generated from different fractions of customer demand distributions, Carr and Lovejoy determine the optimal portfolio of demand distributions.

Van Mieghem and Dada (1999) consider a single product firm that faces a linear demand curve with uncertain intercept and has to decide on its production quantity and price. They consider different strategies including the *price postponement* strategy. Under price postponement, the firm needs to decide on the order quantity in the first period and then determine the price in the second period after observing updated information about the demand. Essentially, the supply is fixed after the first period. Hence, the price postponement strategy enables a firm to use price as a response mechanism to change demand so that the modified demand is better matched with the fixed supply. By formulating the problem as a two-period stochastic dynamic programming problem, Van Mieghem and Dada show that the price postponement is more effective than other strategies being considered.

Besides the demand management strategy examined by Carr and Lovejoy (2000) and Van Mieghem and Dada (1999), it appears that the remaining demand management strategies are designed to generate one or more of the following effects:

1. Shifting demand across time;
2. Shifting demand across markets; and
3. Shifting demand across products.

In the context of supply chain *risk* management, there are also

4. Robust strategies for demand management.

We now review the relevant literature in each of these four categories.

13.3.1 Shifting Demand Across Time

In the service industries such as utilities, airlines and hotels, firms usually set higher prices during peak seasons in order to shift demand to off-peak seasons and to profit from price-inflexible demand during the peak season. This type of pricing mechanism is also known as revenue management or yield management. Offering different prices at different times, it would enable the firm to increase the profit generated from a fixed supply capacity by capturing customers in different segments who are willing to pay different prices for the service offered in different times. For revenue management literature that deals with hotel bookings, we refer the reader to Bitran and Gilbert (1996), to Badinelli (2000), and to the references therein. In most cases, due to uncertain customer arrivals and uncertain cancellations, these models are usually formulated as dynamic programming problems. For revenue management literature that deals with airline reservations, the reader is referred to Dana (1999) and a comprehensive survey provided by Weatherford and Bodily (1992). For revenue management literature that deal with peak-load pricing for managing public utilities, the reader may refer to Crew and Kleindorfer (1986) for a review of economics literature that deals with peak load pricing with uncertain demand. Essentially, many economists have developed various models using different types of demand curves and different types of demand uncertainties to determine the peak-load pricing so that the service provider with fixed capacity can obtain a higher profit. Besides the work by Dana (1999), most economists assumed that the firm knows the time at which peak demand occurs. The reader is referred to a review of revenue management by Talluri and Van Ryzin (2005).

In the context of service marketing, many service firms offer price discount to entice customers to commit their purchase in advance. In many instances, advance-purchase discount can be easily implemented due to new technologies such as smart cards, online payments, electronic money, etc. As articulated in Xie and Shugan (2001), advance-purchase discount can be a win-win strategy for the service provider and their customers. First, advance-purchase discount enables a firm to use this discriminatory pricing mechanism to increase sales by serving different market segments. For example, by considering two-market segments with different reservation values of the service, Dana (1998) shows analytically that it is rational for customers with relatively more certain demands (planned trips) and customers with relatively lower reservation value (leisure travelers) to commit their purchases in advance. This result also implies that customers with less certain demands (unplanned trips) and customers with relative higher reservation value (business travelers) would expect to pay a potentially higher price in the spot market.

Advance-purchase discount enables customers to receive a discount over the spot price or to reserve capacity that may not be available during the spot period. Xie and Shugan (2001) present a two-period model in which the advance-purchase price is announced in the first period but not for the second period; however, the probability distribution of the price for the second period is known to all customers. Since the price in the second period is unknown to the customers and since the reservation price is uncertain for each customer, they would make their purchase in the first period if the surplus obtained from purchasing in advance is higher than the expected surplus obtained from purchasing later. By using backward induction, Xie and Shugan develop the conditions under which the firm should offer advance-purchase discount. By considering an extension in which the prices in both periods are pre-announced, they determine the conditions under which the firm should offer advance-purchase discount.

In the context of supply chain management, we need to address the production planning and inventory control issues that are not addressed in the economics or marketing literature. In most cases in the literature, retailers pre-announce the prices for both periods to their customers. Weng and Parlar (1999) are the first to analyze the benefit of advance-commitment discount. They consider the case in which a retailer offers price discount to entice customers to pre-commit their orders prior to the beginning of the selling season. The advance-commitment discount program can be a win-win solution. First, the customers can enjoy a lower price by pre-committing their orders early. Second, the retailer can benefit from the reduction in demand uncertainty because the advance-commitment discount enable the retailer to convert some uncertain customer demands to pre-committed orders that are known in advance. By considering the demand uncertainty reduction generated by the advance-commitment discount, Weng and Parlar determine the optimal order quantity and the optimal discount rate for the retailer.

Tang et al. (2004) extend Weng and Parlar's (1999) model by considering a more general situation: First, they consider a situation in which the market consists of two customer segments with different purchasing behaviors toward advance-commitment discount. They show how advance-commitment discount would enable the retailer to increase the total expected sales. Second, they consider the case in which the retailer can use the pre-committed orders obtained prior to the beginning of the selling season to improve the accuracy of the forecast of the demand that would occur during the selling season. They show how this improved forecast would enable the retailer to reduce the total expected over-stocking and under-stocking costs. Moreover, they examine various benefits associated with advance-commitment discount programs.

McCardle et al. (2004) extend the Tang et al. (2004) model to the case in which two competing retailers need to decide whether to launch the advance-commitment discount program or not. They show that both retailers would offer the advance-commitment discount program at the equilibrium. However, when there is a fixed cost for implementing this discount program, they develop conditions under which exactly one retailer would offer the discount program at the equilibrium.

The advance-commitment discount program is applicable to non-seasonal products as well. By studying the supply chain operations associated with steel processing, Gilbert and Ballou (1999) present a continuous time model in which the steel distributor offers price discount to customers who pre-commit their orders in advance. By knowing these pre-committed orders earlier, they show that the standard deviation of the demand over the replenishment lead time periods is reduced. By using a traditional approximate cost model for lost sales, they show how advance-commitment discount programs would enable a steel distributor to increase his expected profit and to improve customer service level at the same time. By examining the profits before and after the launch of the advance-commitment discount program, Gilbert and Ballou present an approach for determining the optimal discount price.

These advance-commitment discount models are based on the single product case. In a subsequent paper, Weng and Parlar (2005) examine a situation when a manufacturer produces two products, a standardized product and a make-to-order customized product. The manufacturer offers advance-commitment discount to customers who pre-commit their orders for the standardized product. By considering the case in which the market consists of two segments with different purchasing behaviors toward advance-commitment discount, Weng and Parlar formulate the manufacturer's problem as a stochastic dynamic programming problem. They show that the advance-commitment discount program would enable the manufacturer to increase the total expected demand and to reduce demand uncertainty. When the standardized product is cheaper to produce, they develop conditions under which the manufacturer should offer the advance-commitment discount program.

While the advance-commitment discount program designed to enable a firm to shift customer demand to an earlier period, there is another strategy that would entice customers to shift their demands to a later time. This strategy is called *demand postponement* and is intended to entice some customers to accept shipments at a later time. Iyer et al. (2003) is the first to examine the benefits of the demand postponement strategy. To manage uncertain demand with a fixed supply capacity, they consider the case in which a firm would offer price discount to customers willing to accept late shipments. Essentially, this strategy is akin to the overbooking situation in which an airline may offer incentive to entice some customers to take a later flight. Iyer et al present a two-period model and determine the optimal fraction of customer demands to postpone. In addition, they characterize conditions under which a firm should adopt the demand postponement.

13.3.2 Shifting Demand Across Markets

When selling products with short life cycles in different markets, firms need to manage product rollovers (the process of phasing out old products and introducing new products). As articulated by Billington et al. (1998), different firms have implemented various rollover strategies with different degrees of success. One of the key challenges for managing product rollovers successfully is uncertain demands in different markets. To mitigate the demand risks in different markets, Billington et al. present a "solo-rollover by market" strategy that calls for selling the new product in different markets with non-overlapping selling seasons. The solo-rollover by market strategy is more suitable for situations when there is a natural time delay of the selling season in two different markets. For example, the selling season of ski wear in North America ends in May whereas the selling season in South America begins in June.

Suppose a firm adopts the solo-rollover-by-market strategy. Then the firm has to decide how much to stock for the first market during in first period; how much of the unsold inventory from the first market to transship to the second market at the end of the first period; and how much to stock for the second market at the beginning of the second period. Kouvelis and Gutierrez (1997) examine this stocking and transshipment decisions for two markets with non-overlapping selling seasons. They consider a firm that sells seasonal goods in a primary market in the first period and in the secondary market during the second period. By capturing the possibility of shipping some of the leftover inventory from the primary market to the secondary market at the end of the selling season of the primary market, they present a two-period stochastic dynamic program to determine the optimal production quantity for the corresponding market in each period and the optimal amount of leftover inventory to be shipped from the primary market to the secondary market. Due to the possibility of selling the leftover from the primary market at the second market, they show that the optimal production quantity for the primary market is higher than the case when the secondary market does not exist.

Petruzzi and Dada (2001) extend Kouvelis and Gutierrez's (1997) model to the case in which the firm can use a pricing mechanism to shift some of the demand from the primary market to the secondary market. Specifically, Petruzzi and Dada consider the case that the firm can use information to make better pricing and ordering decisions as follows: First, the firm can choose the selling price as well as the stocking level for the primary market during the first season. Second, the firm can use the actual sales observed in the primary market to improve the accuracy of the forecast of the demand for the secondary market in the second season. Third, given the updated forecast, the firm can determine the transshipment quantity to be shipped from the primary market to the secondary market, the stocking level and the selling price of the product for the secondary market in the second selling season. By formulating the two-period problem as a stochastic programming problem with recourse, Petruzzi and Dada establish the characteristics of the optimal pricing and ordering decisions for both markets.

13.3.3 Shifting Demand Across Products

When selling multiple products in a single market, many marketing researchers have examined various pricing and promotion strategies to entice customers to switch brands or products. The ultimate goal of various marketing strategies is to help a firm to increase market share, sales, or revenue. For example, Raju et al. (1995) present a model to capture the brand switching behavior when a store introduces a store brand to compete with the existing national brands. They show how to determine the optimal retail prices for the national brands and the new store brand so as to maximize the store's revenue. Chong et al. (2001) show how a retailer can obtain higher revenue by adjusting its product assortments and pricing so that the store can offer its customers the right products at the right price. Lilien et al. (1992) provide an extensive review of marketing models that deal with pricing and promotion strategies.

However, in general, these marketing models do not deal with the operational issues arising from supply chain management. In the context of supply chain management, some researchers have developed models by considering the possibility of shifting the supply/demand from one product to another. It seems there are two basic mechanisms that would enable to firm to shift the supply/demand from one product to another. These two mechanisms are

1. *Product substitution*, and
2. *Product bundling*,

as discussed below.

Product substitution. Product substitution can occur in different settings: (1) selling products with similar features, (2) selling products when one dominates another in quality or performance, and (3) using pricing to entice customers to shift demand from one product to another. Let us consider the three in turn.

First, by selling products with similar features, a firm can increase the product substitutability. Chong et al. (2004) show how a firm can increase product substitutability by selecting a specific combination of products with similar attributes/features. Moreover, they show how product substitutability can reduce the variance of the aggregate demand. Rajaram and Tang (2001) present a single-period stochastic model of a firm that sells two substitutable products. Specifically, they consider a situation in which a product with surplus inventory can be used as a substitute for out of stock products. Hence, the demand of one product can be satisfied by the supply for another product. They develop conditions under which product substitutability would enable a firm to reduce the variability of the effective demand for each product. Moreover, they show that the optimal order quantity of each product and the retailer's expected profit increase as product substitutability increases.

Second, consider the case when one product dominates another in terms of quality or performance. For example, in integrated circuit (IC) manufacturing, the output of each production run consists of a random number of chips with different grades measured according to the processing speed. When higher grade chips can be used as substitutes for the lower grade chips, Bitran and Dasu (1992) and Hsu and Bassok (1999) present different models for determining the optimal production quantity at a wafer fabrication facility with random yields.

Third, consider the case when the firm can use pricing to entice customers to shift their demand from one product to another. Parlar and Goyal (1984) consider a case in which the retailer would offer price discount for the old product, say, one-day old doughnut. Clearly, the new and old products are substitutable and the retailer can change the level of product substitution by varying the discount factor. By formulating the problem as a Markov Decision Process and by considering the demands for the old and new products, they determine the optimal order quantity for the new product in each period. Chod and Rudi (2005) examine another situation in which a firm can use differential pricing to entice customers to shift the demand for one product to another. They consider the case in which the firm needs to decide on the production quantity of two similar products in the first period; however, the firm can postpone the pricing decision of the each product until the second period. By extending the model developed by Van Mieghem and Dada (2001), Chod and

Rudi show a firm can obtain a higher profit by delaying the pricing decision until the second period.

Product bundling. In addition to product substitution, a firm can change the demand of the products by developing bundles. There is an increasing number of retail products being bundled together and sold. Examples can be found across a range of products including food (cans of chicken broth), apparel (under garments), cosmetics (shampoo and conditioner), and electronics (computers and printers). When products are sold in bundles, they force the customers to buy all products as a bundle, which will affect the effective demand of the products. Ernst and Kouvelis (1999) examine how product bundles affect the inventory ordering decisions of a firm. Specifically, they consider the case in which the products are sold as a bundle and as individual products. Based on their analysis of a two-product model, they establish the necessary and sufficient conditions for the optimal ordering quantities. They provide insights into the degree of sub-optimality of profits when inventory decisions are made without explicit consideration of demand substitution between the bundles and the individual products. McCardle et al. (2005) present a model for determining optimal bundle prices, order quantities, and profits. By capturing the customer's valuation of individual products, they generate the demand distribution of the product bundle. In addition, they determine how product demand, costs and the relationship of demand between products affect optimal bundle prices and profits. Moreover, they present conditions under which a firm should bundle their products. See Stremersch and Tellis (2002) for a comprehensive review on product bundling literature.

13.3.4 Robust Demand Management Strategies

There are at least two robust demand management strategies already reviewed in this section. First, as described in the previous Section 13.3.3, there are many demand management strategies that would enable a supply chain to shift demand across products. By having the capability to shift demand across products, these strategies can make a supply chain more efficient and resilient. For example, when facing uncertain demand, Chod and Rudi (2005) present a responsive pricing strategy that would enable a firm to increase profit by shifting demand across products. Hence, a responsive pricing strategy would improve supply chain efficiency. In addition, a responsive pricing strategy could improve supply chain resiliency as well. For example, when facing a supply disruption of computer parts from Taiwan after an earthquake, Dell immediately offered special price incentives to entice their online customers to buy computers that utilized components from other countries. The capability to shift customer choice swiftly enabled Dell to improve its earnings in 1999 by 41% even during a supply crunch (c.f., Veverka (1999)).

Second, the demand postponement strategy described in Section 13.3.1 can be a robust demand management strategy that would enhance supply chain efficiency and resiliency (cf. Iyer et al., 2003). Under the demand postponement strategy, a manufacturer may offer price discounts to some retailers to accept late shipments. Essentially, this strategy is akin to the overbooking situation in which an airline may offer incentive to entice a fraction of customers who are willing to take a later flight. By having the capability to shift some of the demands to a later period, it would certain help a firm to manage both operational risks and disruption risks.

Table 13.3 lists references to the articles mentioned in this section.

Table 13.3 Summary of demand management articles

Demand Management Issue	**Risk Issues**	**References (in the order of appearance)**
Demand Management	General	Elmaghraby and Keskinocak (2003), Yano and Gilbert (2004), Petruzzi and Dada (1999), Eliashberg and Steinberg (1993), Carr and Lovejoy (2000), Van Mieghem and Dada (1999)
Shifting demand across time	Uncertain demand	Gilbert (1996), Badinelli (2000), Dana (1999), Weatherford and Bodily (1992), Crew and Kleindorfer (1986), Talluri and Van Ryzin (2005), Dana (1998), Xie and Shugan (2001), Weng and Parlar (1999), Tang et al. (2004), McCardle et al. (2004), Weng and Parlar (2005), Iyer et al. (2003),
Shifting demand across markets	Uncertain demand	Billington et al. (1998), Kouvelis and Gutierrez (1997), Petruzzi and Dada (2001),
Shifting demand across products	Uncertain demand	Raju et al. (1995), Chong et al. (2001), Lilien et al. (1992),
Product substitution	Uncertain demand	Chong et al. (2004), Rajaram and Tang (2001), Bitran and Dasu (1992), Hsu and Bassok (1999), Parlar and Goyal (1985), Chod and Rudi (2005), Van Mieghem and Dada (1999)
Product bundling	Uncertain demand	Ernst and Kouvelis (1999), McCardle et al. (2005), Stremersch and Tellis (2002)
Robust demand management strategies	Uncertain supply	Chod and Rudi (2005); Iyer et al. (2003)

13.4 Product Management

To compete for market share, many manufacturers expand their product lines. As reported in Quelch and Kenny (1994), the number of stock keeping units (SKUs) in consumer packaged goods has been increasing at a rate of 16% every year. Marketing research shows that product variety is an effective strategy to increase increasing market share because it enables a firm to serve heterogeneous market segments and to satisfy consumer's variety seeking behavior. However, while product variety may help a firm to increase market share and revenue, product variety can increase manufacturing cost due to increased manufacturing complexity. Moreover, product variety can increase inventory cost due to an increase in demand uncertainty for each product. These two concerns have been illustrated in an empirical study conducted by MacDuffie et al. (1996). They show that the production and inventory costs tend to increase as product variety increases. Therefore, it is critical for a firm to determine an optimal product portfolio that maximizes the firm's profit. The reader is referred to Ramdas (2003) for a comprehensive review of literature in the area of product variety.

To reduce the design and manufacturing costs associated with product variety, firms can increase product variety by developing different variants based on a common platform. For example, in the personal computer industry, different computer models are based on a common platform. Hence, the products would share some common attributes, which make these products mutually substitutable to a certain extent. As discussed in the previous Section 13.3.3, product substitution and product bundling would enable a firm to shift demands across products so that the firm can satisfy more customers without incurring the risk of over-stocking.

However, product substitutability is a key challenge for researchers to develop analytical models to evaluate market share, revenue, and manufacturing cost associated with different product portfolio. As articulated in Ulrich et al. (1998), there is no explicit analytical model for determining an optimal product portfolio with substitutable products.

Still, various researchers have examined product variety issues using different approaches; Ho and Tang (1998) review of articles in the area of marketing, operations management and economics that deal with product variety. For example, Ulrich et al. (1998) study the mountain bikes industry and suggest that firms need to take their internal capabilities such as process technology, distribution channels, product architecture, supply chain network, etc., into consideration when making product variety decision. Krishnan and Kekre (1998) develop a regression model to examine the impact of functional features on software development cost. Martin et al. (1998) present a method for examining the impact of product variety on replenishment lead time. Moreover, by considering the attribute levels of different products associated with a product portfolio, Chong et al. (2004) develop a logit model for determining the mean and variance of the sales associated with different compositions of a product portfolio. Caro and Gallien (2005) present a multi-armed bandit model for selecting an optimal product portfolio of fashion items that maximizes the expected profit over a finite horizon.

In the context of supply chain risk management, the key concern is to determine ways to reduce inventory cost associated with a given portfolio of products. Based on the classical inventory theory (c.f., Porteus, 2002 and Zipkin, 2000), it is well known that the average inventory level associated with the order-up-to policy depends on mean and the standard deviation of the demand over the replenishment lead time. Therefore, to develop cost-effective product variety strategies, researchers have developed different approaches for reducing the standard deviation of the demand over the replenishment lead time. For instance, as explained in Section 13.3.1, we can reduce the demand uncertainty over the replenishment lead time periods by using pricing mechanisms such as advance-commitment discount, peak load pricing, etc. In this section, we shall review articles based on three specific product management strategies: postponement, process sequencing, and product substitution as well as robust strategies. We have already discussed product substitution in Section 13.3.3 so we shall limit our discussion in this section to

1. Postponement,
2. Process sequencing, and
3. Robust strategies for product management.

13.4.1 Postponement

Consider a manufacturing system that produces two end-products. The system has N processing stages, where stage 0 is a "dummy" stage. As depicted in the Fig. 13.2, the first k stages are common to both end-products and after this stage the products are differentiated in the sense that they may require different operations or different components. We call stage k as the "point of differentiation." Lee and Tang (1997) describe how delayed product differentiation can be achieved via standardization of components and subassemblies, modular design, postponement of operations, and re-sequencing of operations. Recall that stage 0 is a dummy stage; hence, there is no postponement if $k = 0$. Let T be the total lead time of the entire manufacturing process, and $L(k)$ be the lead time from stage 0 to stage k.

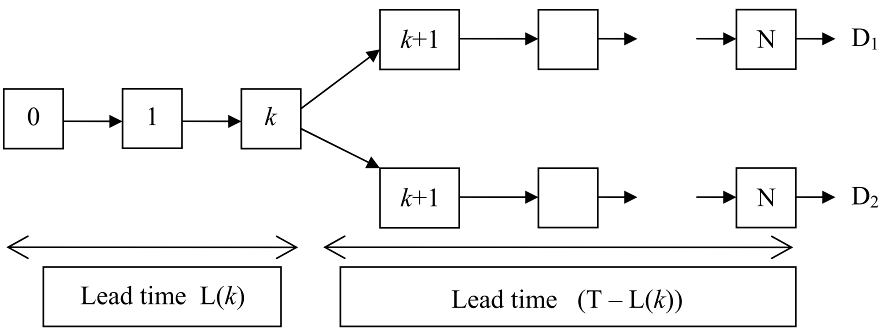

Fig. 13.2 A system with point of differentiation at stage k

The postponement models can be classified according to (a) operating modes (make-to-stock and make-to-order) and (b) demand forecasts (no forecast updating and with forecast updating). Although this two-by-two classification suggests four categories, we are not aware of models that deal with make-to-order systems with forecast updating. The remaining three are discussed at length below:

Make-To-Order systems without forecast updating. Lee (1996) develops a theoretical analysis of the postponement strategy. When there is no demand forecast updating, he examines the benefits of postponement in a make-to-order (MTO) system and a make-to-stock (MTS) system. In the MTO system, work-in-process inventory is held only at stage k and each end product is customized on demand. Depending on the availability of the inventory at stage k and the processing capacity at stages $(k+1)$ through (N), the time it takes to respond to a customer is uncertain. In an MTO system, it is common to measure the system performance according to the mean response time and the probability of the response time being less than a target response time. Using these two performance measures, Lee shows that the optimal order up level S is decreasing in k. Hence, one can reduce the inventory level by delaying the point of differentiation. While the base stock level S is decreasing in k, the inventory holding cost rate is likely to be increasing in stage k; i.e., it is more costly to hold inventory at a later stage. By considering the tradeoff between lower inventory level and higher inventory holding rate, Lee provides conditions under which postponement is beneficial.

In Lee's (1996) model, the end products are differentiated according to a single feature. As such, all end products can be customized from a single point of differentiation. However, when the end products are differentiated according to multiple features, there could be multiple points of differentiation. This observation motivates Swaminathan and Tayur (1998a) and (1998b) to define the semi-finished products held at different points of differentiation as "vanilla boxes." Essentially, the firm will stock these vanilla boxes and then customize different types of vanilla boxes into different end products on demand. By considering the capacity for the customization process and different demand scenarios, Swaminathan and Tayur formulate the problem as a stochastic programming problem with recourse. By examining the structure of the stochastic programming, they develop a solution methodology for determining the optimal configuration of vanilla boxes that minimizes the expected stock-out cost and the inventory holding cost of vanilla boxes.

Make-To-Stock Systems without forecast updating. For a make-to-stock system, Lee (1996) consider the case in which only finished product inventory is held; i.e., inventory is held after stage N. Conceptually speaking, this system is akin to the single-depot, multi-warehouse distribution system examined by Eppen and Schrage (1981). By assuming that the demand distributions for the end-products are independently normal across time but may be correlated within a time period, Lee applies the approximate analysis developed by Eppen and Schrage to determine the base-stock level and the average inventory level for each end-product. Moreover, Lee shows that the finished product inventory level for each end-product is decreasing in the point of differentiation k.

As articulated by Lee (1996), the postponement strategy can be implemented in a MTO or a MTS system. This observation motivates Su et al. (2005) to develop a model to compare the total supply chain costs associated with postponement in a

MTO and a MTS system. Their analysis shows that the MTO system is more cost effective when the number of end products exceeds a certain threshold level.

When the end products are differentiated according to different features, the corresponding manufacturing process can have multiple points of differentiation. Garg and Tang (1997) extend the model presented by Lee (1996) by considering a system with multiple points of differentiation. Since system with multiple points of differentiation is akin to a multi-echelon distribution system, Garg and Tang (1997) first extend Eppen and Schrage's (1981) two-echelon model to a three-echelon model. Then they show that postponement at each of the differentiation points would result in inventory savings. Instead of relying on the approximate analysis developed by Eppen and Schrage to evaluate different postponement strategies, Aviv and Federgruen (1998b) show how one can develop an exact analysis of the model presented in Garg and Tang (1997).

Lee and Tang (1997) examine a system that can keep work-in-process inventory at every single stage. They develop a stochastic inventory model by capturing the investment cost per period for redesigning the products and/or processes, the unit processing cost, and the inventory holding cost at each stage. Their analysis is based on a decomposition scheme in which the manufacturing process is decomposed into N independent stages, each of which will follow an order-up-to level policy. The decomposition scheme enables them to approximate the system-wide cost function associated with the point of differentiation k. By examining the underlying property of this explicit cost function, they develop conditions under which no postponement is optimal; i.e., the optimal point of differentiation is stage 0. Also, they discuss the conditions under which postponement is beneficial.

In the postponement literature, most researchers assume that the production capacity is unlimited. To examine how production capacity can affect the value of postponement, Gupta and Benjaafar (2004) develop a queuing model for examining the benefits of postponement in a MTO and a MTS system with limited production capacity. When the production capacity for stages 1 through k (point of differentiation) is limited, Aviv and Federgruen (2001a) present a multi-product inventory model for the case when the product demand is random and periodical. They show that the underlying inventory model can be formulated as a Markov Decision Process, and that delayed product differentiation is always beneficial even when the system has limited capacity.

Make-To-Stock Systems with forecast updating. In the postponement literature, most researchers assume that the product demands in each period are random, but they are independent across time and their distributions are known. As a result of these assumptions, the benefit of postponement is derived from "risk pooling" in the sense that all stages before the point of differentiation (stage k) would plan according to the "aggregate demand" instead of individual product demand. Besides risk pooling, postponement enables a firm to delay the product differentiation so that the production quantity decision for the final products can be made in a later period of time. When the timing of this decision is delayed, the firm can use the actual demands observed in earlier period to obtain more accurate forecasts of future demands. To explore further about the benefit of postponement with forecast updating, Whang and Lee (1998) extend the make-to-stock model presented in Lee (1996) by considering the case in which the demand $D_i(t)$ of end-product i in period t possesses the following form:

$$D_i(t) = \mu_i + \sum_{j=1}^{t} \varepsilon_{ij} \quad \text{where } i = 1,2,\dots,n,\ t = 1,2,\dots,T,\ \text{and } \varepsilon_{ij} \approx N(a_{ij}, \sigma_{ij}^2)$$

Whang and Lee assume that the parameters a_{ij} and σ_{ij} are known for the normally distributed error term. This demand distribution is a form of random walk that enables one to capture a series of random shocks (economic trends, random noises, etc.). As time goes on, the decision maker can use the shocks observed in earlier periods (i.e., some of the ε_{ij}'s are now known) to develop a more accurate forecast of $D_i(t)$. By incorporating the capability to obtain more accurate demand forecast as time goes on, Whang and Lee show that one can obtain substantial reduction in the end-product inventory by using more accurate forecasts. In addition, they show analytically that significant inventory savings can occur even when the point of differentiation k occurs in the early stage.

Aviv and Federgruen (2001b) consider a more general demand distribution in which the parameters of the demand are unknown. In their model, they consider the case in which the decision maker would update the demand forecast in a Bayesian manner. They show analytically that the standard deviation of the total demand over the lead time periods decreases over time. Furthermore, they show that this standard deviation decreases with the point of differentiation k. This implies that it is more beneficial to update the demand forecast when postponement occurs in a later stage. The reader is referred to Garg and Lee (1998), Aviv and Federgruen (1998b), and Yang et al. (2004) for comprehensive reviews of the research literature that examines different postponement-related issues.

13.4.2 Process Sequencing

As noted in Section 13.4.1, postponement is an effective way to reduce variability in a supply chain. Lee and Tang (1998a) suggest that variability can also be reduced by reversing the sequence of manufacturing processes in a supply chain. Their suggestion is motivated by the re-engineering effort at Benetton. In the woolen garment industry, virtually all manufacturers will use the dye-first-knit-later sequence; i.e., dye the yarns into different colors first and then knit the colored yarns into different finished products. However, as a way to reduce inventory, Benetton pioneered the knit-first-dye-later process by reversing the “dyeing” and “knitting” stages (c.f., Dapiran, 1992). Intuitively speaking, the knit-first-dye-later strategy would be beneficial when there is only one style of woolen sweaters with multiple colors. This is because it would result in delaying product differentiation after the “knitting” stage. However, when there are multiple styles and multiple colors, it is not clear which strategy is better. To determine the conditions under which a particular process sequence is better, Lee and Tang (1998a) develop a model of a production system that produces products with 2 features (A and B), each of which has 2 choices (1 and 2). As depicted in Fig. 13.3, the product demands (X_{11}, X_{12}, X_{21}, X_{22}) are assumed to be multinomially distributed with parameters (N; θ_{11}, θ_{12}, θ_{21}, θ_{22}), where the total demand N is normally distributed with mean μ and standard deviation σ, and θ_{ij} corresponds to the probability that the customer will choose choice i of feature A and choice $j$of feature B. By considering p as the probability that a customer will purchase a product with choice 1 of feature A and by examining the conditional probabilities: $\text{Prob}(\text{B1} \mid \text{A1}) = f(p)$ and $\text{Prob}(\text{B1} \mid \text{A2}) = g(p)$, one can express θ_{ij} in terms of p, $f(p)$ and $g(p)$.

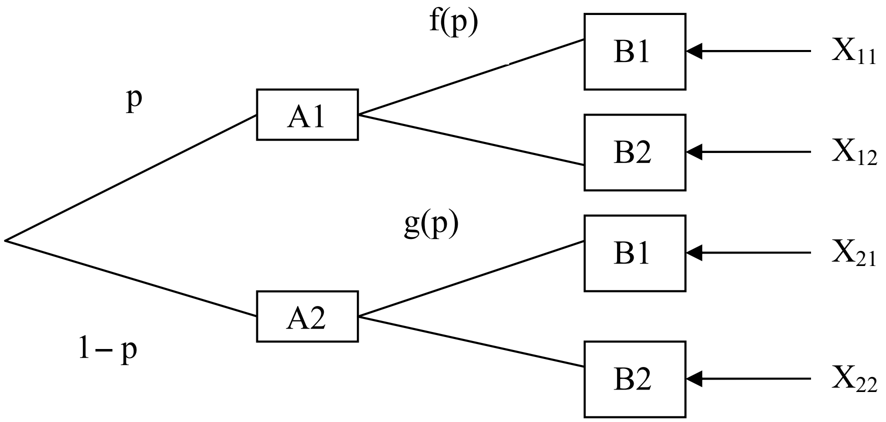

Fig. 13.3 A two-stage system with 2 features and 2 choices

Lee and Tang argue that the total expected cost associated with the intermediate products is proportional to the sum of the variances of demands in a period. As such, they show that the process sequence A-B has a smaller variance than the process sequence B–A if

$$(\mu - \sigma^2)\{p(1-p) - [pf(p) + (1-p)g(p)]\{1 - [pf(p) + (1-p)g(p)]\}\} < 0$$

This result has the following implications. Consider the special case in which $f(p) = g(p) = q$, where q is independent of p. If the product demand is stable (i.e., when $\mu > \sigma^2$), then the process sequence A–B has a lower variance when feature (attribute) A is less variable than attribute B (i.e., when $|0.5 - p| > |0.5 - q|$). However, the reverse is true when $\mu < \sigma^2$.

By considering the sum of the standard deviations as an alternative measure, Kapuscinski and Tayur (1999) conduct their analysis associated with the special case. They show that it is optimal to process the attribute with less variability first, regardless of the values of μ and σ^2.

Other researchers have generalized Lee and Tang's (1998) model in other ways. Federgruen (1998) develops a general definition of when attribute A is more variable than attribute B in terms of θ_{ij}. He shows a more general conditions under which the process sequence A–B has a smaller variance than the process sequence B–A. Jain and Paul (2001) generalize Lee and Tang's model by incorporating two important characteristics of fashion goods markets, namely, heterogeneity among customers and unpredictability of customer preferences. Yeh and Yang (2003) develop a simulation model by incorporating additional factors such as lead times, ordering policies, and inventory holding cost. By using the data obtained from a garment manufacturer, they show how their simulation model can be used to select a process sequence that minimizes the total expected cost.

13.4.3 Robust Product Management Strategies

Among the product management strategies reviewed in this section, the postponement strategy described in Section 13.4.1 is a robust strategy for enhancing the efficiency and the resiliency of a supply chain. As reported in Lee (1996), postponement is an effective strategy for improving supply chain efficiency when facing uncertain demands for different products. In addition, the postponement strategy can increase supply chain resiliency. For example, as discussed in an earlier chapter, after Philip's semiconductor plant was damaged in a fire in 2000, Nokia was facing a serious supply disruption of radio frequency chips. Since Nokia's cell phones were based on the modular design concept, Nokia was able to postpone the insertion of these radio frequency chips until the end of the assembly process. Due to this postponement strategy, Nokia was able to reconfigure the design of their basic phones so that the modified phones could accept slightly different chips from other suppliers. Consequently, Nokia satisfied customer demand smoothly and obtained a stronger market position. The reader is referred to Hopkins (2005) for details.

Table 13.4 lists the references in this section.

13.5 Information Management

Fisher (1997) classifies most consumer products as fashion products or functional products. Basically, fashion products usually have shorter life cycles and higher levels of demand uncertainties than the functional products. Therefore, different information management strategies would be needed to manage for different types of products especially in the presence of supply chain risks. For this reason, we classify the work in this section according to the product types: (1) fashion products and (2) functional products. In addition, we consider (3) robust strategies for information management.

Table 13.4 Summary of product management articles

Product Management Issue	Risk Issue	References (in the order of appearance)
Product Management	General	Quelch and Kenny (1994), MacDuffie et al. (1996), Ramdas (2003), Ulrich et al. (1998), Krishnan and Kekre (1998), Martin et al. (1998), Chong et al. (2004), Ho and Tang (1998), Caro and Gallien (2005), Porteus (2002), Zipkin (2000)
Postponement	General	Lee and Tang (1997),
Make to order systems without forecast updating	Uncertain demand	Gunasekaran and Ngai (2005), Lee (1996), Tayur et al (1998a), Tayur et al. (1998b)
Make to stock systems without forecast updating	Uncertain demand	Lee (1996), Eppen and Schrage (1981), Su et al. (2005), Garg and Tang (1997), Aviv and Federgruen (1998b), Lee and Tang (1997), Gupta and Benjaafar (2004), Aviv and Federgruen (2001a)
Make to stock systems with forecast updating	Uncertain demand	Whang and Lee (1998), Lee (1996), Aviv and Federgruen (2001b), Garg and Lee (1998), Aviv and Federgruen (1998b), Yang et al. (2004)
Process Sequencing	Uncertain demand	Lee and Tang (1998), Kapuscinski and Tayur (1999), Federgruen (1998), Jain and Paul (2001), Tayur (1999), Yeh and Yang (2003)
Robust strategies	Uncertain supply	

13.5.1 Information Management Strategies for Managing Fashion Products

As articulated in Section 13.4, reducing the standard deviation of the demand over the replenishment lead time would result in inventory reduction for the entire supply chain. When managing products with short life cycles, short replenishment lead times could enable a retailer to place more than one order over the selling season. For example, various researchers have considered the situation in which a retailer can place two orders over the selling season. Specifically, the retailer can place one order prior to the beginning of the selling season and another order during the selling season. In the fashion goods industry, this type of replenishment system is called the "quick response" system. Clearly, the second order provides a great opportunity for the retailer to obtain more accurate demand forecast by using the actual sales data. As mentioned before, Fisher and Raman (1996) develop a two-period stochastic dynamic programming model with demand forecast updating to analyze the quick response system. By implementing their model at a skiwear company called Obermeyer, they illustrate how the quick response system would enable Obermeyer to achieve a higher customer service level with a lower level of inventory. The reader is referred to Raman (1998) for a review of quantitative models of quick response systems.

Gurnani and Tang (1999) analyze a similar quick response system except that the unit cost for the second order is uncertain. By formulating the problem as a two-period dynamic programming problem, they show that an order-up-to level policy is optimal. Instead of focusing on the retailer's perspective, Iyer and Bergen (1997) and Iyer (1998) analyze the impact of a quick-response system on both retailers' and manufacturers' inventories. They show that, when the customer service level is at least 0.5, the quick-response system is not Pareto in the sense that the retailer would obtain a higher expected profit and the manufacturer would achieve a lower expected profit. They develop conditions under which a quick-response system is beneficial to both the retailers and manufacturers. Donohue (2000) considers a variant of the quick-response system in which the retailer can place their orders in two modes: low cost with long lead time and high cost with short lead time. By formulating the problem as a two-period dynamic programming problem, she derives an optimal ordering policy and an optimal contract that coordinates the supply chain.

All quick response models assume that the manufacturer can always fill the second orders placed by the retailers. However, as articulated in the Benetton case prepared by Signorelli and Heskett (1984), manufacturers may not be able to guarantee complete fulfillment of the second order. Smith et al. (2002) investigate the retailer's optimal order quantities, the retailer's profit, and the manufacturer's profit for the case when the manufacturer can only fulfill the second order partially. By considering a stylized model, they show that the manufacturer should provide either complete fulfillment or no fulfillment of the second orders when the underlying demand distribution is either uniform or exponential. Specifically, they show analytically that partial fulfillment of the second orders is never optimal for the manufacturer.

13.5.2 Information Management Strategies for Managing Functional Products

When managing products with long life cycles, market information is critical for generating accurate demand forecasts. However, since wholesalers, distributors, manufacturers, and suppliers are farther remove from the consumer market, they usually do not have first-hand market information such as point of sales data, customers' preferences, and customer response to various pricing and promotion strategies. Instead, upstream supply chain partners usually generate their demand forecasts based on the orders placed by their downstream partners. Planning according to the orders placed by the downstream partners would create a phenomenon termed the "bullwhip effect" as coined by Procter and Gamble. Essentially, the bullwhip effect depicts the phenomenon in which the orders exhibit an increase in variability up the supply chain, even when the actual customer demands were fairly stable over time (c.f., Sterman, 1989). The increase in variability of the orders up the supply chain can cause many problems for the upstream partners including higher inventory, lower customer service level, inefficient use of production and transportation capacities, etc. In order to mitigate the bullwhip effect, one needs to identify the root causes.

Lee et al. (1997b) is the first to show that the bullwhip effect can occur even when every supply chain partners operate optimally and rationally. The bullwhip effect has also been shown independently by Bagahana and Cohen (1998). To establish the existence of the bullwhip effect, Lee et al. develop a 2-level supply chain that consists of a retailer and a manufacturer. They assume that the retailer "knows" that the underlying demand process follows an auto-regressive process AR(1) so that the demand in period t, denoted by D_t, is equal to:

$$D_t = d + \rho D_{t-1} + \varepsilon_t.$$

Notice that d represents the base demand level, ρ represents the correlation of demands in successive periods, where $|\rho| < 1$, and ε_t represents the error term that is normally distributed with mean 0 and standard deviation σ. Lee et al. (1997b) consider the case in which the retailer would act rationally by following an order-up-to level policy and by placing an order Q_t in period t. To show that the bullwhip effect occurs, they prove that $\mathrm{Var}(Q_t) \geq \mathrm{Var}(D_t)$.

Gilbert (2005) generalizes Lee et al. model by considering a more general demand process than the AR(1) process that is known as the Autoregressive Integrated Moving Average (ARIMA) time-series. When the underlying demand process is an ARIMA process, Gilbert shows that the order quantity Q_t associated with the order-up-to level policy is also an ARIMA process. Li et al. (2005) develop a simulation model for the case when the demand process is an ARIMA process. By varying the values of the parameters associated with the ARIMA process, they show that the bullwhip effect does not always occur. More importantly, they discover an "anti-bullwhip effect" that would occur for certain values of the parameters by showing that $\mathrm{Var}(Q_t) \leq \mathrm{Var}(D_t)$; i.e., the variance of the order quantity is lower than the variance of the demand.

While Lee et al. (1997b) show that the bullwhip effect will occur when the retailer has knowledge about the demand distribution, Chen et al. (1998), (2000a) and (2000b) investigate the occurrence of the bullwhip effect for the case when the retailer does not know the underlying demand process follows an AR(1) process; however, the retailer would use a moving average or an exponential smoothing method to forecast future demands. They show that the bullwhip effect will occur and that the bullwhip effect will be larger when the retailer uses an exponential smoothing forecast instead of a moving average forecast. Zhang (2004) extends the work of Chen et al. by examining the impact of different forecasting methods on the bullwhip effect. Sodhi and Tang (2011) show the bullwhip effect, at its core, is due to demand characteristics and leadtime, with information distortion by way of batch size etc. contributing to an incremental effect, which they quantify for an arborescent supply chain.

To mitigate the bullwhip effect, Lee et al. (1997c) identify four root causes of the bullwhip effect: demand forecasting, batch ordering, supply shortage, and price variations. In addition, they propose strategies for mitigating the bullwhip effect including:

1. Information sharing,
2. Vendor managed inventory, and
3. Collaborative forecasting and replenishment planning.

Below we review articles that examine these three strategies.

Information sharing. Lee et al. (2000) study the benefits of information sharing in a two-level supply chain. They consider the case in which the retailer has the information about the underlying demand distribution (i.e., an AR(1) process) and the retailer would order according to an order-up-to policy in each period.

When there is no information sharing, the manufacturer has the information about the underlying demand distribution and the retailer's ordering policy; however, the manufacturer does not have the information about the actual demand realized in period t (i.e., the manufacturer does not know the realization of the error term ε_t in period t).

When there is information sharing, the retailer would share the information about the actual demand realized in period t as well. By assuming that there exists a reliable exogenous source of inventory, information sharing has no impact on the retailer because the retailer's orders are always received in full. By examining the inventory level and the relevant costs incurred by the retailer and the manufacturer, Lee et al. show analytically that information sharing is beneficial to the manufacturer, not the retailer. Moreover, information sharing is most beneficial to the manufacturer especially when the correlation coefficient ρ is high. Also, in order to entice retailer to share demand information with the manufacturer, Lee et al. suggest various mechanisms including price discount and replenishment lead time reduction.

Cheng and Wu (2005) extend Lee et al.'s model to the multi-retailer case and they conclude that information sharing would enable the manufacturer to reduce both the inventory level and the total expected cost. Lee et al. commented that information sharing would be less valuable to the manufacturer if it uses the historical stream of orders from the retailer to forecast demand. Raghunathan (2001) confirms this analytically for the case when the underlying demand is an AR(1) process. Gaur et al. (2005) extend Raghunathan's model to the case in which the demand process is a more general process than the AR(1) process, namely, the AR(p) process for $p \geq 1$ and the autoregressive moving-average process ARMA process.

By assuming that the underlying demand is independent and identically distributed, Gavirneni et al. (1999) develop a model to examine the benefits of information sharing for the case in which the manufacturer has limited production capacity. In their model, the retailer has the information about the underlying demand distribution and the retailer would order according to an (s,S) policy. Under the (s,S) policy, the retailer would place an order in a period only when the inventory level drops below s. When there is no information sharing, the manufacturer has the information about the underlying demand distribution and the retailer's ordering policy; however, the manufacturer does not have the information about the retailer's inventory level. When there is information sharing, the retailer would share the information about the actual inventory level with the manufacturer in each period. They show that information sharing is beneficial to the manufacturer especially when the manufacturer's production capacity is higher or when the demand uncertainty level is moderate. Cachon and Fisher (1997) and (2000) analyze the benefits of information sharing for the N-retailer case in which the manufacturer has limited production capacity. By assuming that each retailer implements a (R, nQ) policy, they show analytically that information sharing is beneficial to the retailer and the manufacturer. In addition, Cachon and Fisher (2000) show numerically that lead time reduction will be more beneficial than information sharing.

Zhao et al. (2002) develop a simulation model to examine the impact of forecasting methods such as moving average, exponential smoothing, and Winters' method, etc., on the value of information sharing in a supply chain that has 1 manufacturer and N retailers. They show that the cost savings for the entire supply chain are more substantial when the retailers share information about future orders with the manufacturer than the case in which the retailers share information about the customer demand.

While many companies reported that sharing information (such as customer demand, inventory level, or demand forecast) among supply chain partners is beneficial, there are several obstacles for supply chain partners to share private information. For instance, retailers are reluctant to share information with the manufacturer because of fear (lower bargaining power, information leakage, etc.). Besides fear, there are other problems associated with forecast sharing in practice. Terwiesch et al. (2005) articulate that when a retailer revises his forecasts (or soft orders) frequently before placing a firm order, the manufacturer may ignore the revisions. Also, when a manufacturer is unable to fulfill the firm order in one period, the retailer may inflate his soft orders in future periods to ensure sufficient supply. As such, this could lead to a "lose-lose" situation. By using the data collected from a semiconductor company, Terwiesch et al. (2005) show empirically that the manufacturer would penalize the retailer for unreliable forecasts by delaying the fulfillment of forecasted orders. Also, they show that the retailer would inflate their orders resulting in excessive order cancellations. Therefore, both manufacturer and retailer would lose when sharing forecast information.

Vendor Managed Inventory. As articulated in Lee et al. (2000), information sharing is beneficial to the manufacturer, not to the retailer. As such, many manufacturers develop various initiatives to entice the retailer to share demand information with the manufacturer. Besides offering price discount, various manufacturers launched an initiative called Vendor Managed Inventory (VMI). Under the VMI initiative, the retailers delegate the ordering and replenishment planning decisions to the manufacturer. In return, the manufacturer gains direct information access regarding customer demand and retailers' inventory positions. To ensure the retailer achieves higher customer service levels with lower inventory costs, the manufacturer either owns the inventory at the retailer's warehouse subject to a minimum inventory level or issues some form of promises that the inventory at the retailer's warehouse will stay within certain pre-specified limits.

Under the VMI initiative, the retailer can reduce the overhead and operating costs associated with replenishment planning, while enjoying certain guaranteed service levels. Even though the manufacturer takes on the burden to manage the retailer's inventory under the VMI initiative, the manufacturer can derive the following benefits: (1) reduced bullwhip effect due to direct information access regarding customer demands and (2) reduced production/logistics/transportation cost due to coordinated production/replenishment plans for all retailers. Disney and Towill (2003) develop a simulation model to analyze the bullwhip effect under the VMI initiative. Their simulation results confirm that VMI can reduce the bullwhip effect by 50 percent. Clearly, reducing the bullwhip effect and coordinated planning would enable the manufacturer to reduce inventory. Johnson et al. (1999) examine the performance of VMI in different settings: (a) the manufacturer has limited capacity and (b) some retailers adopt the VMI scheme while the remainders adopt the information sharing scheme. By considering the case that VMI would enable the manufacturer to coordinate the replenishment plan by consolidating the customer demands (instead of orders placed by the retailers), they show that VMI would reduce inventories for the manufacturer and the retailer.

Aviv and Federgruen (1998a) develop an analytical model to evaluate the retailer's and the manufacturer's operating cost under an information-sharing scheme and an VMI initiative. Under both systems, the manufacturer has information about customer demand. However, the replenishment plans are determined by the retailers under the information sharing scheme, while the manufacturer decides on the timing and magnitude of the replenishment shipments to the retailers. Therefore, under the information sharing scheme, the effective demand process faced by the manufacturer is essentially the superposition of orders placed by the retailers in an uncoordinated manner. By considering that the underlying demand distribution is normal and by using the fact that the manufacturer has the authority to coordinate the customer demands under the VMI initiative, Aviv and Federgruen show that the manufacturer can reduce the production and inventory costs under both systems. To examine further about the benefit of the VMI initiative under which the manufacturer has the authority to determine the delivery schedule and quantity for each retailer, Cetinkaya and Lee (2000) presents an analytical model for determining an optimal coordinated replenishment and delivery plan for different retailers located in a given geographical region. By assuming that the demands at the retailers are independent Poisson processes, they compute an optimal replenishment quantity and delivery schedule that minimizes the total production, transportation and inventory carrying costs while meeting certain customer service levels.

Besides the analytical models that examine the benefits of the VMI initiative, there are other studies using simulation models. The reader is referred to Sahin and Robinson (2005) and the references therein. Several retailers and manufacturers reported successful implementations of VMI. For example, Clark and Hammond (1997) show that the VMI initiated by Campbell Soup provided a win-win situation for Campbell Soup and the retailers. For additional examples of successful implementations of VMI, please see Aviv and Federgruen (1998a), Cetinkaya and Lee (2000), and the references therein.

Collaborative forecasting. Under the information sharing scheme or the VMI initiative, not much collaborative effort is needed. To induce collaboration between the retailers and the manufacturers, Voluntary Inter-industry Commerce Standards (VICS) association developed an initiative called Collaborative Planning, Forecasting and Replenishment (CPFR). Under this initiative, both parties would develop mutually agreeable demand forecasts jointly. To develop mutually agreeable demand forecasts, the manufacturer would generate an initial demand forecast based on his market intelligence on products, and the retailer would create her own initial demand forecast based on customer's response to pricing and promotion decisions. Both parties would share their initial demand forecasts and would reconcile the differences in their forecast to obtain a common forecast. Once both parties agree on the common demand forecasts, the retailer would develop a replenishment plan and the manufacturer would develop a production plan independently. See www.cpfr.org for details.

The crux of CFPR is collaborative forecasting. Aviv (2010c) is the first to develop a framework for modeling the collaborative forecasting process between a retailer and a manufacturer. To specify the demand process when there is no collaborative forecast, he specifies the demand process based on an individual party p's perspective, where $p = r, m$, where r denotes the retailer and m denotes the manufacturer. Specifically, when there is no collaborative effort, the underlying demand process D_t from party p's perspective is given by:

$$D_t = d + \psi_t^p + \varepsilon_t^p, \quad \text{for } p = r, m,$$

where d represents the base demand level, ψ_t^p represents the cumulative forecast adjustment made by party p in past periods up to the beginning of period t, and ε_t^p represents the residual forecast error of party p's forecasting method.

By considering the correlation between ψ_t^m and ψ_t^r, one can capture the correlation between the forecast adjustments made by the retailer and the manufacturer. Under the collaborative forecasting initiative, Aviv assumes that the retailer and the manufacturer would select the best forecast adjustment ψ_t so that the forecast error is minimized. Based on this specific construct, he computes the optimal collaborative forecast adjustment in each period. For the retailer, he computes the variance of the total demand over the replenishment lead time with no collaborative forecasting and that with collaborative forecasting. For the manufacturer who needs to satisfy the order placed by the retailer, he computes the mean and the variance of the total aggregate order quantity to be placed by the retailer under no collaborative forecast and under collaborative forecast. Even when these quantities can be expressed in closed form expressions, it is intractable to evaluate the benefit of collaborative forecast analytically. As a surrogate, Aviv develops an aggregate supply chain performance measure that is based on the variance of the whole system: the sum of the variance of the total demand over the retailer's replenishment lead time and the variance of the total order quantity over the manufacturer's replenishment lead time. He shows analytically that collaborative forecast would reduce the system-wide variance. In a subsequent paper, Aviv (2002) extends this analysis to auto-correlated demand. Specifically, he considers the case in which the demand process possesses the following form:

$$D_t = d + \rho D_{t-1} + \psi_t^p + \varepsilon_t^p, \quad \text{for } p = r, m.$$

Aviv (2005) further extends the analysis to the case in which the manufacturer operates in an environment that calls for production smoothing.

As articulated by Aviv (2001), it is very difficult to evaluate the benefit of CPFR analytically even for a two-level supply chain. Therefore, many of the comparisons are conducted numerically. While these numerical examples provide some insights, there is no guarantee that this insight is applicable to a realistic supply chain. This observation has motivated Boone et al. (2002) to develop a simulation model to compare the performance of the CPFR initiative with the performance of a traditional replenishment policy based on a reorder point. By using the data collected from a Fortune-500 company and by using a simple process to generate demand forecast, their simulation model suggests that CPFR would increase customer service level and reduce inventories for both the manufacturer and the retailer. Aviv (2004) provides a comprehensive review of CPFR literature.

13.5.3 Robust Information Management Strategies

As reported in this section thus far, strategies based on information sharing, vendor managed inventory, or collaborative forecasting and replenishment planning would increase "supply chain visibility" in the sense that the upstream partners have access to information regarding the demand and inventory position at downstream stages. As supply chain visibility improves, each supply chain partner can generate more accurate forecast of future demands and better coordination. We have cited various articles that show how these strategies would enable a supply chain to become more responsive to customer demand with less inventory and lower cost. Hence, the information management strategies reported in this section would increase supply chain efficiency.

However, there are few articles on how these information management strategies would increase supply chain resiliency. Still, we have reasons to believe that the CPFR strategy can enable a supply chain to develop a production planning system that would improve resiliency. While Aviv (2005) discuss the mechanism for supply chain partners to generate a common demand forecast in a collaborative manner, we are not aware of specific models in the literature that deal with the collaborative replenishment planning. We envision a more complete CPFR system may improve supply chain resiliency. For example, consider a CPFR system in which all supply chain partners generate a common demand forecast, share inventory information, and adopt a common ordering rule that is based on the “proportional restoration rule” developed by Denardo and Tang (1992). Specifically, under the proportional restoration rule, the retailer would order Q_t^r and the manufacturer would order Q_t^m in period t, where:

$$Q_t^r = d + (T^r - I_t^r)\alpha^r \quad \text{and} \quad Q_t^m = d + [(T^m - I_t^m) + (T^r - I_t^r)]\alpha^m.$$

Notice that d represents the common demand forecast, T^p represents the “target” inventory position for party p, I_t^p represents the inventory held at party p at the beginning of period t, and $0 < \alpha^p \leq 1$ represents party p’s restoration factor, where $p = r, m$ (i.e., retailer and manufacturer, respectively). Denardo and Tang (1992) use numerical examples to show that this ordering rule is efficient. In addition, in a later paper, Denardo and Tang (1996) show analytically that this ordering rule would “restore” the inventory level at each stage to its target even when the demand forecast $d$is inaccurate. Thus, one can conclude that such a CPFR system would improve supply chain efficiency and resiliency.

Table 13.5 lists references in this section.

13.6 Managerial Attitudes

Given the prominence of supply-chain risk in the business press, it is worthwhile asking what role managers play in tolerating or even engendering supply-chain risk. Consider managerial attitudes towards risk in general and towards initiatives for managing supply-chain disruptions in particular.

Managers’ attitude towards risks. Sharpira (1986) and March and Sharpira (1987) study managers’ attitude towards risks and conclude that:

- Managers are insensitive to estimates of the probabilities of possible outcomes.
- Managers tend to focus on critical performance targets, which affect the way they manage risk.
- Managers make a sharp distinction between taking risks and gambling.

The first conclusion can be explained by the fact that managers do not trust, do not understand, or simply do not much use precise probability estimates. This is consistent with the observations reported in De Waart (2006) and the results obtained by other researchers (c.f., Kunreuther, 1976 and Fischoff et al., 1981). Since managers are insensitive to probability estimates, March and Sharpira (1986) noted that managers are more likely to define risk in terms of the magnitude of loss such as “maximum exposure” or “worst case” instead of expected loss. The second conclusion is based on the observation that most managers are measured by a set of performance targets. March and Sharpira (1986) argue that these performance targets would cause the managers to become more risk averse (or risk prone) when their performance is above (or below) certain target. Finally, the third conclusion

Table 13.5 Information management references

Information Management Aspect	Risk Issue	References (in the order of appearance)
Information Management	General	Fisher (1997)
Managing Products with *Short* Life Cycles	General	Fisher and Raman (1996), Gurnani and Tang (1999), Iyer and Bergen (1997), Iyer (1998), Donohue (2000), Signorelli and Heskett (1984), Smith (2002)
Managing Products with *Long* Life Cycles	General	Sterman (1989), Lee et al. (1997b), Bagahana and Cohen (1998), Gilbert (2005), Li et al. (2005), Chen (1998), (2000a) (2000b), Zhang (2004), Sodhi and Tang (2011), Lee (1997c)
Information sharing	Uncertain demand	Lee et al. (2000), Cheng and Wu (2005), Raghunathan (2001), Gaur et al. (2005), Gavirneni et al. (1999), Cachon and Fisher (1997), Cachon and Fisher (2000), Zhao et al. (2002), Terwiesch et al. (2005)
Vendor managed inventory	Uncertain demand	Lee et al. (2000), Disney and Towill (2003), Johnson et al. (1999), Aviv and Federgruen (1998a), Cetinkaya and Lee (2000), Sahin and Robinson (2005), Clark and Hammond (1997)
Collaborative forecasting	Uncertain demand	Aviv (2001), Aviv (2002), Boone et al (2002), Aviv (2004)
Robust Information Management Strategies	Uncertain demand	Denardo and Tang (1992; 1996)

is driven by the fact that companies tend to reward managers for obtaining "good outcomes" but not necessarily for making "good decisions."

Managers' attitude towards initiatives for managing supply chain disruption risks. According to various major case studies conducted by Closs and McGarrell (2004), Rice and Caniato (2003) and Zsidisin et al. (2001) and (2004b):

- Most companies recognize the importance of risk assessment programs and use different methods, ranging from formal quantitative models to informal qualitative plans, to assess supply chain risks. However, most companies invested little time or resources for mitigating supply chain risks.
- Due to few data points, good estimates of the probability of the occurrence of any particular disruption and accurate measure of potential impact of each disaster are difficult to obtain. This makes it difficult for firms to perform cost/benefit analysis or return on investment analysis to justify certain risk reduction programs or contingency plans.

- Firms tend to underestimate disruption risk in the absence of accurate supply chain risk assessment. As reported in Kunreuther (1976), many managers tend to ignore possible events that are unlikely. This may explain why few firms take commensurable actions to mitigate supply chain disruption risks in a proactive manner. As articulated in Repenning and Sterman (2001), firms rarely invest in improvement programs in a proactive manner because "nobody gets credit for fixing problems that never happened."

13.7 Conclusions

In this chapter we have reviewed various quantitative models for managing supply chain risks. We found that these quantitative models are designed primarily for managing operational risks, not disruption risks. However, some of these strategies have been adopted by practitioners for managing risk because these strategies are robust: they can make a supply chain become not only more efficient in terms of handling operational risks but also more resilient in terms of managing disruption risks.

As there are not many models for managing disruption risks, we present six potential ideas for future research:

1. **Demand and supply stochastic processes.** Virtually all models reviewed in this paper are based on the assumption that the demand or the supply process is stationary. To model various types of disruptions mathematically, one may need to extend the analysis to deal with non-stationary demand or supply process. For instance, one may consider modeling the demand or the supply process as a "jump" process to capture the characteristics of major disruptions.
2. **Objective function.** The performance measures of the models reviewed in this paper are primarily based on the expected cost or profit. The expected cost or profit is an appropriate measure for evaluating different strategies for managing operational risks. When dealing with disruption risks that rarely happen, one may need to consider alternative objectives besides the expected cost / profit. For instance, Sharpira (1986) and March and Sharpira (1987) articulated that managers tend to focus on performance targets. Hence, when developing strategies for managing supply chain disruption risks, one may consider using certain performance targets such as recovery time after a disruption. The reader is referred to Brown and Tang (2005) and the references therein regarding various alternative performance targets in the context of single-period inventory models.
3. **Supply management strategies.** When developing supply management strategies for managing disruption risks, both academics and practitioners suggest the idea of "back-up" suppliers. To capture the dynamics of shifting the orders to these back-up suppliers when a major disruption occurs, one need to develop a model for analyzing dynamic supply configurations of suppliers including contract manufacturers, transportation providers, and distribution channels.
4. **Demand management strategies.** Among the demand management strategies presented in Section 13.3, it appears that dynamic pricing / revenue manage-

ment has great potential for managing disruption risks because a firm can deploy this strategy quickly after a disruption occurs. In addition, revenue management looks promising especially after successful implementations of different revenue management systems in the airline industry for managing operational risks.

5. **Product management strategies.** When selling products on line, e-tailers can change their product assortments dynamically according to the supply and demand of different products. This idea can be extended to brick and mortar retailers for managing disruption risks. Chong et al. (2001) show that store manager can manipulate customer's product choice and customer's demand by reconfiguring the set of products on display, the location of each product and the number of facings of each product. They suggest that one can utilize dynamic assortment planning to entice customers to purchase certain products that are widely available (when other products are in short supply).
6. **Information management strategies.** Among the information management strategies described in Section 13.5, we think the Collaborative Planning, Forecasting and Replenishment (CPFR) strategy is promising because it fosters a tighter coordination and stronger collaboration among supply chain partners. While Aviv (2005) develops a mechanism for generating collaborative forecasts, there is no model that captures the collaborating replenishing planning. It is conceivable that the value of a more complete CPFR system is much higher than a system that is solely based on collaborative forecasting.