

Supply Chain Performance – The Impact of Interactions between Flexibility Enablers and Uncertainty

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between Flexibility Enablers and Uncertainty

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UNIVERSITÉ DE NEUCHÂTEL
FACULTÉ DES SCIENCES ÉCONOMIQUES

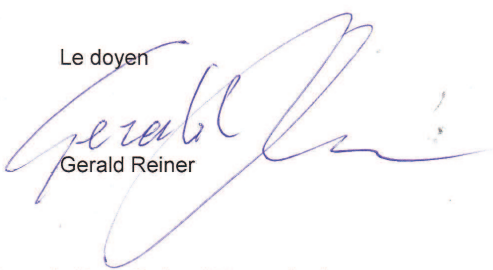
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Le doyen


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Summary

This doctoral dissertation in the field of Supply Chain Management focuses on the dynamic interactions between uncertainty, flexibility, and performance in the supply chain. In particular, it provides evidence that the improvements related to uncertainty reduction practices are modulated by the flexibility enablers engaged by the companies involved in the supply network. Consequently, it highlights the need for system-wide evaluation that captures the dynamics of the specific operational characteristics of a network. Further, this dissertation explores the issue of the interaction between uncertainty and flexibility in model-based supply chain evaluation. The results denote that neglecting these relationships might lead to mistaken estimation of the supply chain performance.

The impact of both uncertainty and flexibility on supply chain variability leads to multiple dynamic interactions, which creates complex problems at the time of assessing the impact of supply chain improvements on the performance of the system. Indeed, if general supply chain behavior has been identified, the impact of the interactions between specific operational settings on the system dynamics remains largely unknown. In particular, serious gaps remain in the understanding of the dependencies between flexibility enablers. This understanding is important because of its direct implications on the dynamic of the system. Interactions between flexibility enablers are assumed to influence the general ability of the system to demonstrate flexibility and therefore directly affect the behavior of the system. This knowledge is therefore required in order to better understand the mechanisms underlying supply chain performance, and then to enable model to capture better the dynamics of the systems.

The core of this dissertation is constituted by three articles that can be read separately. All of these studies are related to the interaction between uncertainty and flexibility with regard to supply chain performance; however, the detailed research questions considered in each study are distinct.

- The first study investigates the interaction between forecasting and flexibility enablers with regard to managing demand. It is assumed that superior knowledge

regarding demand influences the production process as well and, consequently, the flexibility enablers' effect on company performance. This analysis evidences that the impact of forecasting on performance is due to the mediating effect of flexibility enablers. In particular, it shows that the relationship between forecasting and customer satisfaction is mainly due to process flow management, while the relationship with cost efficiency is mainly due to layout. Therefore, this study not only provided evidence of the existing relationships between forecasting and performance, but it provided as well some insights on the causality of this relationship. In particular, the study showed that the availability of additional information helps the actors involved in a specific process to make prompt decisions and align different units that manage each separate part of the production process. The performance improvements (i.e., increased cost efficiency as well as effectiveness) related to improved forecasting can then be magnified by process or layout modifications.

- The second study examines the real-life situation of a supply chain where the flexibility of the production facility is directly influenced by the level of uncertainty in demand. In this setting, better demand information (i.e., uncertainty reduction) allows for wiser decision making regarding capacity adjustments and reduces the trade-off between volume flexibility and production efficiency. The simulation results shows that, for the specific settings of the study, the benefits from the uncertainty reduction provided by advance demand information are strongly influenced by the production and inventory management constraints engaged in the supply network. In particular, the value of advance demand information is magnified by the realistic situation where uncertainty reduction enables the manufacturer to improve the alignment of its production capacity with the forthcoming demand. Also, the value of the advance demand information is dependent on the policy regulating the interaction between the distribution center and the manufacturer. These interactions combine to determine the ability of the supply chain to satisfy demand in an effective and efficient manner and are therefore of critical importance to support decision making.
- The third study considers the implications of integrating the non-constant variability of the demand variance with periodic reviews of up-to-level inventory policy. Such variability is traditionally observed in seasonal demand patterns where the demand variance is generally correlated to the average demand. This research work demonstrates the potential trade-off existing between safety stock accuracy and safety stock variability in inventory control with seasonal demand. Specifically, it highlights how the improvement achieved in adapting the safety stock to the fluctuation of the variability of the perceived uncertainty (i.e., the non-constant vari-

ability of the forecast error) is balanced by the resulting increase in replenishment order variability. Further, this study demonstrates that this dynamic dependency can only be captured if the relationship between the capacitated production system and the inventory system is explicitly modeled (i.e., the lead time is endogenous).

In general, the above-mentioned contributions highlight the need for a better understanding of the relationships between uncertainty, flexibility, and performance at the supply chain level, integrating in the performance measurement both efficiency and effectiveness. Further, it provides evidence that valuable estimation of performance based on supply chain modeling requires integrating the detailed interaction existing between the specific operational characteristics of the network under study. From a managerial point of view, these findings stressed the danger inherent to decision making supported by over-simplified supply chain models and propose, through an example, a methodology to tackle this issue.

Keywords: Supply chain dynamics, Flexibility, Forecasting, Simulation.

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Chapter 1

Introduction

1.1 Problem statement

Supply chain management is no longer in its infancy, and the benefits related to managing the supply network as a whole rather than as a group of autonomous companies have been discussed extensively in the literature. In particular, the positive influence of supply chain management practices on the dynamics of the system have been highlighted, putting forward the opportunity for better end-customer service at lower cost Lee et al. (1997). First, improving transparency with end-customer demand was seen to reduce uncertainty in supply chains. Consequently, the upstream amplification of demand variability that is often observed in supply network (the bullwhip effect) can be better controlled. Second, evidence has shown that centralized decision making confers the chain with opportunities to reduce the strategic misalignment of partners' capabilities. Companies' practices and interaction policies require the company to be well coordinated in order to achieve supply chain objectives effectively and efficiently. Above all, the level of flexibility should be specifically aligned to the uncertainty of both the demand and the supply processes. Without the ability to answer to uncertainty, the resulting unreliability of the system leads to more variability in supply chain flows. As observed by Hopp et al. (2001), increased variability in processes always damages the performance of the systems.

The impact of both uncertainty and flexibility on supply chain variability leads to multiple dynamic interactions, which creates complex problems at the time of assessing the impact of supply chain improvements on the performance of the system. If the potential advantages of supply chain practices such as information sharing or decision synchronization are well described, quantifying their related benefits in advance remains an open challenge. Specifically, a supply chain where each entity manages its production and inventory independently from the situation of its up- or downstream partners stays

widely represented. Decision making is then decentralized, and the interactions between partners become more complex and yield more uncertainty in the system. Furthermore, the dynamic of the system is also triggered by the capabilities of each member of the supply network. These specific capabilities determinate the ability of the company to cope with uncertainty and then determine the way variability propagates in the system. Consequently, supply chain evaluation goes beyond the general knowledge that is brought by supply chain dynamics and performance analysis is required to be product- and company-specific in order to provide valuable results (Reiner and Trcka, 2004).

The latter is highly relevant in the context of model-based supply chain evaluation. Indeed, meaningful insights concerning the performance of a specific supply chain, i.e. a given set of operational characteristics, can only be obtained from models that are close enough to the reality of this network. In other words, all the relevant dynamic dependencies that influence the behavior of that particular system should be modeled. Of particular concern is the question of the interaction between the inventory and production systems. This interaction should generally be explicitly modeled in order to enable the lead time characteristics to be dependent on the workload of the production process, and then on the customer orders pattern. The assumption of independent lead time rarely holds in reality (Benjaafar et al., 2005). This relationship is however not straightforward. As explained by the queuing theory, the throughput time of a production process is influenced by its average process time, its average level of utilization, and the variability of both the production time and of the arrival of the production orders. Therefore, understanding the interaction between the order pattern and lead time extends to the dynamic of the uncertainty and the flexibility of the system. A particular topic of interest is that of the mechanisms underlying supply chain flexibility, particularly the interactions between the distinct components of flexibility, such as for instance the ability to increase capacity or to modify scheduled deliveries. Flexibility is generated by flexibility enablers: practices and policies that are applied by companies that contribute to the ability to respond to uncertainty. As highlighted by Kumar et al. (2008), serious gaps remain in the understanding of the dependencies between flexibility enablers, and this understanding is important because of its direct implications on the dynamic of the system. Interactions between flexibility enablers are assumed to influence the general ability of the system to demonstrate flexibility and therefore directly affect the behavior of the system.

From a managerial perspective, this issue is highly relevant as it might provide valuable insight on unachieved benefits related to process improvements. Failing in understanding the interactions between uncertainty, flexibility and performance, or neglecting these interaction at the time of evaluating a scenario might lead to erroneous decisions that could threaten supply chain performance. Developing further the comprehension

of supply chain dynamics and cascading this knowledge in modeling to provide accurate evaluation tool is without doubt a key to strengthen decision making in supply chain.

1.2 Research objective

The overall objective of the thesis is to extend the understanding of the dynamic relationships between uncertainty, flexibility, and performance in supply chain. Literature has been devoted to the problem of supply and demand management in uncertain contexts and flexibility was identified as a key success factor in responding to this uncertainty (Ho et al., 2005). However, little consideration has been given to the mechanisms underlying supply chain flexibility, specifically to the interactions between the distinct practices enabling flexibility. This knowledge is nevertheless necessary in order to first extend the understanding of supply chain dynamics, and then to enable supply chain modeling to better capture the behaviors of real-life systems. Therefore, the focus of this dissertation will be on investigating the issue of the interactions between flexibility enablers and their relationships to uncertainty and performance, in the sense of both efficiency (total cost) and effectiveness (customer satisfaction).

Building knowledge on these interactions is needed to allow modeled supply chain behaviors to get closer from reality and to provide better support to evaluation. A key dimension of this work is that it aims not only to extend the understanding in supply chain dynamics, but also to integrate that knowledge in models to look at the resulting impact on evaluation outcomes. To achieve this goal, this work, first, aims to extend theory on the interactions between uncertainty and flexibility with regards to performance. And second, it aspires to take advantage of this knowledge to build improved supply chain models and test for the benefits of these additional interactions. Figure 1.1 illustrates this hierarchy in the distinct parts of this work.

In particular, this dissertation, first, aims to identify the potential interactions between flexibility enablers. Uncertainty reduction practices (e.g. better forecasting) and volume flexibility enablers are generally apprehended as complementary yet separate management levers to deal with uncertainty. Analysis of their potential interrelation is assumed to allow for better insight on how these elements develop into better performances. It is assumed that uncertainty reduction regarding forthcoming demands allow the processes to perform better. Furthermore, the identification of causal relationships between flexibility enablers and performance will strengthen the understanding of supply chain dynamics. In particular, the focus is on examining the relationships between forecasting, other flexibility enablers, and performance in terms of effectiveness and efficiency.

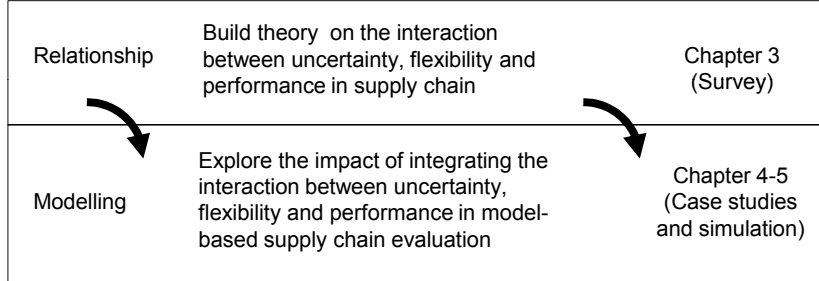


Figure 1.1: Organization of the research studies. The first study aims to develop knowledge on supply chain dynamics that is to be used to strengthen the models build in the second and third studies

Second, this dissertation explores the potential influence of the interaction between uncertainty and flexibility on model-based supply chain performance evaluation outcomes. Flexibility and uncertainty are two cornerstones of supply chain dynamics; neglecting their interrelationships could lead to misleading performance evaluations. Building on empirical information from real-life situations, this work aims to examine the consequences of the interaction between flexibility and uncertainty on the model-based performance evaluation for specific supply chain improvement. These analyzes seek to contribute to the challenge of quantifying the benefits of improvement for specific supply chain environments. In addition, it aims to highlight the pitfalls that are related to supply chain management relying on over-simplified models as support for decision making.

Finally, an important motivation in this research work is to link the (new) theory to the practice by enabling the knowledge on supply chain dynamics to serve and challenge on-going practices from the industry.

1.3 Thesis Outline

Chapter 2 introduces the main concepts that are involved in this research and reviews the literature related to the problem stated above. The primary focus is on the issue of uncertainty in supply chain and its influence on variability. Then, this chapter expands on supply chain flexibility and collaboration. Finally, model-based supply chain performance evaluation will be addressed.

Chapters 3 through 5 present three research studies in the form of articles that can be read separately. All of these studies are related to the interaction between uncertainty

and flexibility with regard to supply chain performance, however, the detailed question considered in each study is distinct. Chapter 3 investigates the nature of these relationships (between uncertainty, flexibility, and supply chain performance), while Chapters 4 and 5 examine the implications of these interactions for model-based supply chain performance evaluation.

In particular, Chapter 3 explores the interaction between forecasting and flexibility enablers with regard to managing demand. It is assumed that superior knowledge regarding demand influences the production process as well and, consequently, the flexibility enablers' effect on company performance. The underlying objective is to examine the mediation effect of forecasting based on structural equation modeling methodology through flexibility enablers on company performance. The performance is measured based on customer satisfaction and cost efficiency in order to capture both the effectiveness and the efficiency of the systems.

Chapter 4 examines the real-life situation of a supply chain where the flexibility of the production facility is directly influenced by the degree of uncertainty in demand. In this setting, better demand information allows for wiser decision making regarding capacity adjustments and reduces the trade-off between volume flexibility and production efficiency. The objective of this chapter is to assess, based on quantitative empirical models, the impact of the relationship between uncertainty and volume flexibility on the value of information sharing that is organized in the form of advance demand information.

Chapter 5 considers the implications of integrating the non-constant variability of the demand variance with periodic reviews of up-to-level inventory policy. Such variability is traditionally observed in seasonal demand patterns where the demand variance is generally correlated to the average demand. In other words, based on quantitative empirical models, this chapter assesses the impact of improving the accuracy of the estimations that are related to demanding uncertainty used in safety stock evaluation. Intuitively, superior information will lead to greater variability. Therefore, a trade-off might exist between safety stock accuracy and variability. This potential relationship is directly related to the variability of the order pattern and to the overall dynamic of the system.

Finally, Chapter 6 summarizes the insights of the previous chapters and discusses some managerial implications and opportunities for further research.

Chapter 2

Theoretical background

2.1 Supply chain management

One of the most relevant evolutions of modern business management is that companies compete as networks of partners, rather than as single autonomous companies. Traditionally composed of suppliers, manufacturers, wholesalers, and customers, these partners form a network of relationships that is known as a “supply chain.” Closely related to supply chains is the concept of “supply chain management” which emerged from the natural intuition that adequate management of supply chain products, information, and funds will improve supply chain competitiveness and profitability (Chopra and Meindl, 2001). Christopher (1998) defined supply chain management as:

“the management of upstream and downstream relationships with suppliers and customers to deliver superior customer value at less cost to the supply chain as a whole.” (Christopher, 1998)

The foundation of supply chain management is underscored in this definition in that supply chain management focuses on the optimization of system-wide performance, not the narrow interests of single partners. There is a significant amount of evidence in the literature that networks’ bottom-line performance can be improved by counterintuitive decisions at the echelon level. For instance, Billington et al. (2004) detailed how Hewlett-Packard Company saved \$80 million in desk printer supply costs by switching transoceanic freight lanes from air to sea. To avoid expensive air shipment charges without affecting its customer service level, Hewlett-Packard had to resize upward inventory at the distribution centers, which was against the trend of inventory reduction generally found in manufacturing companies. Also, Ferdows et al. (2004) showed how the supply chain from ZARA, one of the leading European fashion retailers based in Spain, benefited from partnerships with local suppliers despite higher production costs. The flexibility resulting from their streamlined supply chain enabled them to quickly adapt to changing

fashion trends and to significantly reduce end-products obsolescence costs. The benefits of this strategy largely outweighed the investment in underutilized and expensive related to local suppliers. In both of these examples, one of the partners had to support higher costs – either from larger inventory or from expensive production capacity – in order to increase the overall performance of the system.

Despite the supply chain management’s goal being straightforward, decision making in order to design, plan, and operate a supply chain in an efficient manner remains challenging. One main concern is that centralized decision settings in a supply chain, such as the ones presented in the above examples, are not always present in supply networks. Indeed, often, supply chains are composed of a network of companies with equal rights and power (Reiner, 2005). If allocation policies, such as revenue-sharing contracts, are valuable enough to strengthen the incentive of centralized decisions, these are difficult to achieve in practice. Therefore, traditional supply chains in which each echelon manages its production and its inventory without considering the situation at its up- or downstream supply chain partners remain widely represented (Holweg et al., 2005). The individualistic decisions made by companies in a decentralized network are often suboptimal for the system as a whole and lead to complex relationships. Consequently, a relevant issue in supply chain management is the complicated dynamics of the network. The interactions among partners and their related consequences imply complex cause-and-effect mechanisms with potential counterintuitive outcomes. Meadows (1982) highlighted that well-intentioned efforts to answer a problem are often delayed, blurred, or canceled by unforeseen reactions of partners or by system constraints. The reason for that is that it is hardly possible in a dynamic system to act without inducing side effects, as everything is interrelated. Therefore, the complexity of the system behavior is not directly related to the complexity of the system components themselves, but rather to the interactions between those components (Sterman, 2000). A famous example of such a dynamic phenomenon in a supply chain is the artificial demand variance amplification propagating upstream the chain. This observable behavior known today as the “bullwhip effect” was first discussed by Forrester (1958) in his seminal work on industrial dynamics. In this work, the author pointed out how the interactions between the rational replenishment policies of consecutive supply partners lead to undesirable comportment of the supply chain, including a characteristic augmentation in the demand variance. This effect is clearly counterintuitive because, as highlighted by Baganha and Cohen (1998), the inventory management policies are likely to increase demand variability when the main role of inventories is to absorb demand variability. This observation can easily be reproduced through simple business games, such as the famous “Beer Game” (Sterman, 1989). Since this first finding, numerous examples of dynamic relationships have been

identified in supply chains, involving both supply and demand processes (see Sterman, 2000, for a comprehensive discussion on supply chain dynamics).

The dynamic complexity of supply chains inflicts on companies problematical uncertainty regarding the outcomes of their own actions and the reactions of their partners. Uncertainty constitutes a real issue in managing and controlling networked processes (Davis, 1993). Therefore, it is of primary interest to identify and understand supply chain uncertainty in order to support supply chain performance.

Currently, most supply chains are facing more competition due to global competitors, accelerating technological change, and increasing customer requirements. Offering a wide variety of customized products with low prices and short delivery times is becoming increasingly more important in various industries (Stevenson and Spring, 2007). Consequently, supply chain network complexity and dynamics have become more challenging due to factors, such as the outsourcing of various aspects of production, multiple production sites, or global distribution. At the same time, uncertainty in the system is increasing, supported by the fact that uncertainties may appear virtually anywhere along the chain, from downstream unpredictable demand change to upstream unplanned modification in the quantity or timing of raw material supply (Lee and Billington, 1995). Van der Vorst and Beulens (2002) defined supply chain uncertainty as:

“decision making situations in the supply chain in which the decision maker does not know definitely what to decide as he is indistinct about the objectives; lacks information about (or understanding of) the supply chain or its environment; lacks information processing capacities; is unable to accurately predict the impact of possible control actions on supply chain behavior; or, lacks effective control actions (non-controllability).”
(Van der Vorst and Beulens, 2002)

It is clear from this definition that supply chain uncertainty is induced by a lack of truthful and detailed information that is generally related to forthcoming events. The causes limiting the availability of accurate information constitute sources of uncertainty. Davis (1993) classified the sources of supply chain uncertainty into three categories: supply uncertainty, manufacturing uncertainty, and demand uncertainty. Supply uncertainty is generated by the unreliability of suppliers' performance due to inaccurate or delayed deliveries. Manufacturing uncertainty results for instance from unpredictable breakdowns in the production process. Finally, demand uncertainty comes from inaccurate forecasts. A key issue related to supply chain uncertainty is the randomness associated with processes variability. In the absence of randomness, the problems related to material and product supply would easily be eliminated. In such situation, the behavior of demand, production, and distribution would be completely fixed and, therefore, exactly predictable

(Sabri and Beamon, 2000). In such a setting, the most challenging and important issues in supply chain management would be solved because uncertainty would no longer exist. Unfortunately, unpredictable variability is inherent in complex systems and supply chain management stays in front of open challenges (Davis, 1993).

2.2 Variability in supply chain

Random or unpredictable variability produces uncertainty in supply chains. However, due to dynamic effects, uncertainty is likely to induce variability as well. A relevant example of this phenomenon is the aforementioned bullwhip effect. This dynamics issue (i.e., the variance amplification of order quantities observed in supply chains) is primarily generated by rational inventory replenishment rules used by supply chain partners to protect themselves against demand uncertainty (Lee et al., 1997). Rational actions against demand uncertainty at one stage of the supply chain induces greater variability upstream the chain. Based on empirical data, Dejonckheere et al. (2003) showed that the coefficient of variation of production orders are typically 4 to 20 times greater than the coefficient of variation of the sales in a classical two-stage retail chain. For the sake of completeness, it should be added that next to rational inventory decisions, Lee et al. (1997) identified four additional major causes for the bullwhip effect: non-zero lead time, order batching, price fluctuations, and rationing and shortage gaming. It is clear from this example that the dynamics of variability, regardless of whether it is predictable or not, is a significant issue in complex supply networks. Consequently, this issue should be appreciated in order to be adequately managed.

Hopp et al. (2001) defined variability as:

“the quality of the non-uniformity of a class of entities.” (Hopp et al., 2001)

In this definition, Hopp et al. (2001) clearly referred to variability as the manner in which a set of data is spread out across the range of its possible values. Therefore, the notion of variability is closely related to the concepts of probability and random variable in the sense that the exact results of events are generally beyond full controllability (Hopp et al., 2001). Due to the probabilistic nature of variability, classic measures from statistics are traditionally used to quantify it. The variance or its square root (i.e., the standard deviation) is commonly utilized to assess the absolute variability of a class of entities. Further, a relative measure called the “coefficient of variation” is also widely used to measure variability. The coefficient of variation is obtained by dividing the standard deviation of a variable by its mean (Hopp et al., 2001). It is worth noting that, despite being a relative measure, the coefficient of variation is context-specific. For instance, in

the context of process time variability, a coefficient variation of 0.75 is considered to be low (Hopp et al., 2001), whereas, in the context of demand variability, a coefficient of 0.5 is considered to be high (Selcuk et al., 2006).

Quantifying and monitoring process variability is highly relevant from a management perspective, given that it is well known that increasing process variability always damages process performance (Hopp et al., 2001). For example, Lee and Wolfe (2003) showed mathematically how increasing replenishment lead time variability had a greater impact on inventory performance than increasing the lead time mean itself. Beyond this illustration, it can be generalized that variability negatively affects the system along three elementary dimensions: inventory, capacity, and time (Hopp et al., 2001). To respond to inherent variability, a system has no other option than to buffer it through a combination of these leverages, with the obvious consequence of decreased system efficiency. This direct relationship to performance explains the tremendous efforts made in order to reduce process variability. Practices, such as total quality management programs or manufacturing control systems, are relevant examples of the achievements of these efforts. However, it is important to keep in mind that variability can never be completely eliminated from complex systems; therefore, buffers can never be totally removed. The way of organizing buffers is a strategy question that depends on the variability as well as the system constraints.

To further develop this discussion, the nature of variability is noteworthy. In this context, Klassen and Menor (2007) proposed a topology of system variability characterizing “forms” and “sources” of variability. On the one hand, the authors distinguished between internal and external sources of variability. Internal variability is generated at the process level, whereas external variability is related to the network level (i.e., induced by interactions between supply chain partners). On the other hand, the topology described by Klassen and Menor (2007) differentiates between random and predictable variability. Although random variability is generated by events occurring accidentally, predictable variability is generated from at least partially controllable actions, which are potentially predictable. Table 2.1 presents this topology and proposes practical examples for each type of variability.

First, this classification is useful to discuss the impact of variability between supply chain partners (i.e., the interaction between external and internal variability for a given echelon). This interaction constitutes a cornerstone in understanding the impact of variability on performance at the network level. Second, the distinction between random and predictable variability helps to establish the link between variability and uncertainty.

2.2.1 Variability interactions in supply chain processes

In order to control the dynamic impact of variability in a supply chain, the propagation of the variability between partners must be worked out. Gribble (2001) observed that within the complexity of the supply chain, small perturbations can result in large changes in the behavior of the system. That is, one should figure out how, for a given stage of the supply chain, the variability issued from external processes merges with internal variability and influences performance.

Toward this purpose, the contribution from queuing theory is meaningful. By studying the behavior of entities that are standing in line while waiting to be processed, queuing theory allows researchers to mathematically analyze the impact of both the variability of the incoming entities (i.e., external variability) and the variability of the process itself (i.e., internal variability) on selected performance measures. A basic queuing system is traditionally composed of an arrival process, a service process, and a queue. The service process can be a manufacturing activity, such as a production or an assembly process (Hopp et al., 2001). Despite its simplicity, this basic structure helps to understand the basic principles of real-life manufacturing or service activities. This relevance is further ensured through the parametrization of the basic structure. For instance, the arrival of entities can consist in individual entities or in batches. Also, the process activity can rely on a single server or a group of parallel servers. A complete overview on queuing systems can be found in Kleinrock and Gail (1976). To illustrate the complex influence of variability on system performance, a relevant insight of queuing theory is the mathematical description of the impact of variability on process throughput time. Considering a process achieved by a single machine with finite capacity, it is intuitive that, in the case of excessive workload, congestion periods can occur. These congestion events influence the

Table 2.1: Typology of the sources and forms of system variability. Source Klassen and Menor (2007)

Source	Form	
	Random	Predictable
Internal (i. e., process)	Quality defects Equipment breakdown Worker absenteeism	Preventive maintenance Set-up time Product mix (i. e., number of SKUs)
External (i. e., supply chain)	Arrival of individual customer Transit time for local delivery Quality of incoming supply	Daily or seasonal cycle of demand Technical support Supplier quality (learning curve)

waiting time of entities that are pending processing and, consequently, the throughput time. In such a setting, the average throughput time, T , can be expressed as the sum of the average process time, P , and the average waiting time, W , which results from the congestion issues. Formally, the throughput time can then be written as:

$$T = P + W, \quad (2.1)$$

In queuing theory, if the average process time is seen as independent from the variability of the system, the same is not true for the waiting time. It is intuitive that the average inter-arrival time of orders as well as its variability affects the workload pattern and, consequently, the behavior of the queue (i.e., the waiting time). Similarly, the mean and the variability of the process time also impact the waiting time by influencing the congestion. At that point, it is already clear that both the external variability (i.e., the variability of the system input) and the internal variability (i.e., the variability of the process) influence the waiting time. However, one more factor is needed in queuing theory to model the waiting time: the average utilization of the process. A lowly utilized process is less likely to face congestion issues than a heavily loaded one. Based on queuing theory, the waiting time can be expressed as:

$$W = P \cdot \frac{C_i + C_e}{2} \cdot \frac{U}{1 - U}, \quad (2.2)$$

where C_i and C_e , respectively, are the squared coefficients of variation of the process time (internal variability) and the inter-arrival time of orders (external variability). U is the average utilization assessed as the percentage of occupied time from the total available time. Figure 2.1 shows a numerical example highlighting the impact of variability on the throughput time. As expected, the strength of the impact depends on the utilization of the process. Further, a non-linear relationship exists between throughput time and utilization. This non-linear pattern is generated from the fact that congestion events have stronger and longer-lasting effects in a highly utilized system. This statement is modeled in Equation 2.2 by the so-called “magnifying effect of utilization” written as $U/(1 - U)$ (Suri, 1998).

In the context of capacitated make-to-order supply chains, the relationship described above is of interest because it strongly impacts the dynamics of lead time (i.e., the time that elapses between the shipment of an order and the reception of the ordered items). The situation of a manufacturer’s aiming to fulfill its customer orders based on a make-to-order strategy and relying on a single capacitated machine is, from a mathematical point of view, a queuing system that is identical to the one described above. The resulting lead time can, therefore, be accurately described based on Equations 2.1 and 2.2. Empirical evidence of this relationship between the distribution of the workload and the lead time is

provided in the literature (Pahl et al., 2007). In addition, Benjaafar et al. (2005) observed that it was generally unrealistic to decouple the production systems and inventory systems (i.e., to treat the products and the order flows as independent). He argued that it makes sense when inventory and production are separated by significant inventory buffers. Also, it should be considered when the inventory and production systems belong to distinct organizations and the production one guarantees a fixed delivery date. Finally, it may be reasonable when post-manufacturing delivery activities, such as transportation, are significantly longer than the production time itself. However, Benjaafar et al. (2005) insisted that, in most supply chains, these assumptions rarely hold. Consequently, supply chain partners can be directly influenced by congestion and delays that are happening at one of the echelons of the chain.

This interaction between incoming order variability and lead time is relevant to working out the dynamics of variability in the supply chain as it converts downstream variability (demand variability) into upstream variability (supply variability). In this context, the notion of a feedback loop used in system dynamics is important. According to Sterman (2000), all of the dynamics are generated from the sum of only two types of feedback loops: self-reinforcing and self-correcting loops. In self-reinforcing loops, initial modifications lead to further changes. In self-correcting loops, initial modifications lead to reactions that balance the initial change. Therefore, in order to further analyze the dynamics of variability, the reactions to an increased lead time should be analyzed. In terms of replenishment, larger lead times lead to forecast demand for longer periods. This question is discussed with greater detail in the next section (see Section 2.2.2); however, it can already be anticipated that the longer the forecast horizon, the more uncertainty in the predictions. As a result, the order variability increases as explained along with the bullwhip effect. This behavior closes a self-reinforcing loop that is initiated by the congestion issue. As summarized by Boute (2007), when supply lead times are generated

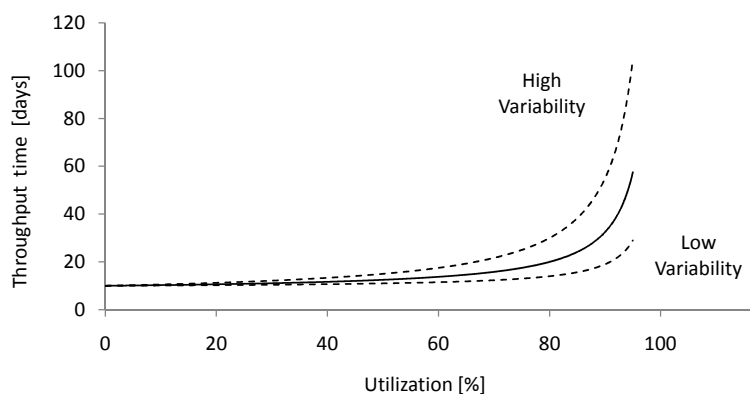


Figure 2.1: Impact on variability on lead time. Source: Suri (1998)

by a finite-capacity production system, the variability in demand has a direct impact on the variability of the lead times because demand variability determines the arrival pattern of production orders and the backlog. In addition, large orders require longer production times and, consequently, replenishment time. This causes a longer lead time, which induces a larger order size. This observation is schematized in Figure 2.2. For the sake of completeness, it has to be mentioned that demand is likely to influence the behavior presented in Figure 2.2. The increase in lead time mean and variability leads to lower customer satisfaction which negatively impact the demand level. Consequently, the increase in lead time in supply chain is likely to be balanced by a reduction in demand.

It is obvious that the instability that is initiated by self-reinforcing loops is unwanted in supply networks. Variability must be controlled and, to this purpose, buffers based on time, capacity, or inventory are of interest. Nevertheless, before further discussing the benefits of such buffers, the role of uncertainty in the supply chain should be developed.

2.2.2 Variability and uncertainty

Uncertainty in the supply chain is closely related to the nature of variability, as uncertainty is issued from the part of variability perceived as random by the decision maker (Van der Vorst and Beulens, 2002). As presented by Klassen and Menor (2007), there are two forms of variability: random and predictable variability (see Table 2.1). If both forms negatively affect the performance, the predictable variability offers a chance for forecasts and, consequently, uncertainty reduction. Therefore, the impact of uncertainty and variability can in some settings be decoupled based on more accurate forecasts, which provides an opportunity to respond to variability in a wiser manner. This phenomenon

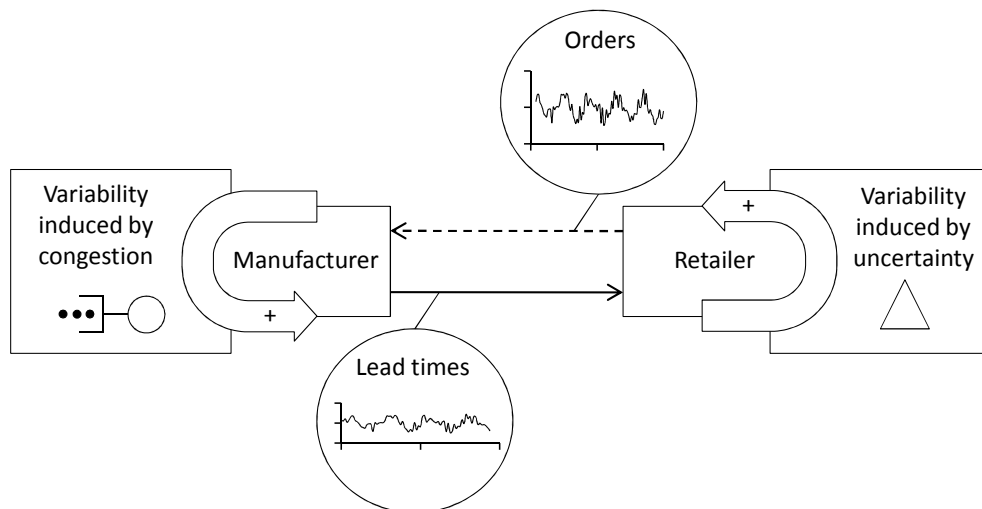


Figure 2.2: Dynamic feedback loop in two-stage make-to-order supply chain

can be well illustrated through demand forecasting and inventory management because, in this context, customer service level is dependent on the forecast error, especially its standard deviation, rather than the variability of the demand itself (Silver et al., 1998).

In classical inventory control policies, customer service level is ensured through safety stocks, which are maintained to cover unexpected variations in customer demand (Silver et al., 1998). With no distinction with regard to the underlying type of control systems, traditional inventory policies are all concerned with the same two challenges at the time of deciding upon replenishment order quantities. First, the quantity needed to cover the demand during the next replenishment has to be estimated. Second, the quantity needed to hedge the error of the first estimation must be evaluated. Once these two steps are completed, the remaining part of the order size decision process is no more than additions and subtractions. To illustrate this statement, the following describes the policy underlying a classical periodic-review inventory control based on order-up-to-level system. First, the order-up-to point, S , is defined as:

$$S = D_{R+L} + z\sigma_{R+L}, \quad (2.3)$$

where D_{R+L} is the forecast (or expected) demand over a review period, R , plus a replenishment lead time, L . In addition, σ_{R+L} is the standard deviation of errors of forecasts over a review period plus a replenishment lead time, and z is a safety factor selected to ensure a given service level (Silver et al., 1998). In Equation 2.3, the first term of the sum refers to the first general challenge of inventory management (i.e., defining the demand during lead time), whereas the second term refers to the second challenge (i.e., defining the safety quantity). Both of these quantities require complex analyzes in order to predict the expected demand average as well as its variability. In addition, the problem quickly becomes complex, as the mean and the variability of the lead time also require integration. In this context, Hadley and Whitin (1963) proposed one of the first contributions to compute the mean and the standard deviation of the demand during lead time based on both probabilistic demand and probabilistic lead time. The technical details of the determination of these quantities are not further discussed here, although a complete overview of inventory policies with probabilistic demand and lead time can be found in Silver et al. (1998). Moreover, selected extensions of these basic procedures are detailed in the next chapters (see Chapters 4 and 5). The implications of the lead time mean on the order quantities is consistent with the implications discussed in the previous section. If the lead time increases, so does the order quantity. Also, lead time increase has a direct impact on performance, as it is clear from Equation 2.3 that increasing the lead time leads to more safety stock and lower efficiency in inventory. Further, as mentioned above, the remainder of the computation of the order quantity, Q , is nothing more than

arithmetic operations, such as:

$$Q = S + B - I_h + I_p, \quad (2.4)$$

where B is the order backlog, I_h is the on-hand inventory, and I_p is the inventory on-order (i.e., pending receipt (Silver et al., 1998)). Without uncertainty, supply chain interaction would be substantially eased, as illustrated above, as coping with uncertainty constitutes the key issue in inventory management. Therefore, reducing uncertainty is highly desirable in the supply chain.

The benefits of reducing uncertainty have long been acknowledged in demand management. In addition, it is common knowledge that the ability to predict forthcoming demand with as little error as possible is important to ensuring competitive inventory control. Consequently, demand forecasting has been studied extensively. For instance, (Mentzer and Moon, 2005) identified 70 demand forecasting procedures based on time series techniques alone. To evaluate forecasting processes, researchers traditionally consider accuracy to be the relevant performance measure (Chase, 1999). Indicators for accuracy are generally directly issued from the statistical analysis of the forecast error, such as for instance the MAPE (mean absolute percent error) or the MSE (mean squared error). As a result, it can be viewed as a measure of the uncertainty remaining in a variable process.

As seen in the illustration of the inventory policy, the difference between variability and uncertainty is crucial, given that, for a given variability, the resulting performance of the system is influenced. Results of research show that when forecast accuracy increases (i.e., uncertainty decreases), performance consequently improves, this being true regarding both the mean and the variability of the forecast error (both being directly related to the order quantity, as discussed above). For instance, inventory levels and related costs can be reduced. Further, manufacturing systems can be better managed because equipment utilization improves and companies can effectively plan actions to undertake in advance. Moreover, delivery performance improves because when forecast accuracy is higher, it is more probable that products are available when the customer orders them (Enns, 2002; Fisher and Raman, 1996; Kalchschmidt et al., 2003; Ritzman and King, 1993; Vollmann et al., 1992). In contrast, forecast inaccuracy creates major rescheduling and cost difficulties for manufacturing (Ebert and Lee, 1995). Also, it can impact logistic performance, such as delivery timeliness and quality (Kalchschmidt and Zotteri, 2007).

To support performance, it is the role of supply chain management to carefully understand process variability and uncertainty in order to accurately respond to it. It is well known that processes that deal best with uncertainty are most likely to produce

bottom-line performance (Mason-Jones and Towill, 1998). Supply chain processes must then be prepared to deal with variable and only partially predictable flows.

2.3 Supply chain flexibility

There is a consensus that flexibility is the answer to uncertainty (Ho et al., 2005). Upton (1994) defined flexibility as:

“the ability to change or react with little penalty in time, cost, or performance,” (Upton, 1994)

and it is then no surprise that flexibility represents an appealing solution to uncertainty. Indeed, the opportunity of responding to uncertainty without serious impact on performance is of interest. This last statement is consistent with the findings of Stevenson and Spring (2007), who observed that many companies that were used to focusing on low cost standardized production to win orders had to become more flexible in order to compete in a new volatile market.

The interest in flexibility first started at the process level, and manufacturing flexibility received a large amount of attention (Kara and Kayis, 2004; Koste and Malhotra, 1999; Vokurka and O’Leary-Kelly, 1999). At this level, four elements are generally considered (Slack, 1987):

1. *Volume flexibility* refers to the ability to change the system’s aggregated output.
2. *Mix flexibility* is the ability to alter the product mix within the existing product range that the system delivers.
3. *Delivery flexibility* is the ability to alter agreed-upon delivery agreements, such as shortening lead times or even changing the products’ destination. If there are in-sequence delivery arrangements, such as those in the automotive component industry, delivery flexibility also includes the ability to make changes to the agreed-upon delivery sequence.
4. *New product flexibility* describes the ability to introduce new products or changes to existing products.

Boyer and Leong (1996) argued that the combination of these elements constituted an important part of companies’ manufacturing strategy. Empirical evidence has shown that manufacturing flexibility can appropriately solve problems that result from uncertainty and environmental dynamics (Swamidass and Newell, 1987). However, based on a supply chain perspective, the focus on internal (i.e. manufacturing) flexibility might reveal

inefficiencies (Tachizawa and Thomsen, 2007). The elements of manufacturing flexibility do not reflect the perspectives offered by supply chain management. Consequently, there were incentives to look beyond the company borders and extend this approach to the network level (see Krajewski et al., 2005; Slack, 2005). In this context, Stevenson and Spring (2007) provided an important contribution by offering a definition for supply chain flexibility through five elements:

1. *Robust network flexibility* is the range of events with which the existing supply chain structure is able to cope.
2. *Re-configuration flexibility* is the ease with which the supply chain can be reconfigured (adaptability). The need to reconfigure is largely determined by the range of the existing structure.
3. *Active flexibility* is the ability to act as a chain either as a response to or in anticipation of changes or events (i.e., a reactive or proactive capability).
4. *Dormant (or potential) flexibility* refers to the notion that the flexibility of the supply chain is partially a contingent resource (i.e., it does not have to be a demonstrable capability).
5. *Network alignment* refers to the notion that entities are focused on aligning their capabilities in order to meet the objectives of the supply chain and compete as a chain (i.e., internal goals are subordinated to those of the supply chain).

These elements deviate from the classical definition of manufacturing flexibility. Through this set of elements, Stevenson and Spring (2007) highlighted the potential benefits from the collaborative aspects on supply chain flexibility. If evidence of the positive impact of flexibility on performance has been provided at the supply-chain level (e.g., Das, 2001; Hallgren and Olhager, 2009; Jack and Raturi, 2002; Suarez et al., 1996), a unanimous framework on how to quantify supply chain flexibility is still missing. In addition, important knowledge regarding flexibility mechanisms and their relationship with network performance is still unknown. Barriers to that lack of knowledge include the complex multidimensional nature of supply chain flexibility and the numerous difficulties that arise when attempting to encapsulate flexibility as a whole into a single construct (Kalchschmidt et al., 2009). One method of resolving this issue is to focus on the practices and policies applied by a company that contribute to flexibility, rather than seeking to quantify flexibility.

Factors that generate flexibility are described in the literature under several names, such as flexibility enablers (e.g., More and Subash Babu, 2008), internal determinants (e.g., Reichhart and Holweg, 2007), and sources (e.g., Tachizawa and Thomsen, 2007).

For instance, lead time reduction, based on practices such as setup time reduction, promotes flexibility, as it is known to increase the capacity to cope with uncertainty in demand (Reiner and Trcka, 2004). An extensive list of supply chain flexibility enablers can be found in More and Subash Babu (2008). Flexibility enablers constitute the internal flexibility of the system, which can be used to support the system's ability to achieve external flexibility with its environment (Upton, 1994). This distinction between internal and external flexibility separates the capabilities of operations resources from the market requirements; therefore, they are considered to be dual influences that need to be reconciled via operations strategy (Slack and Lewis, 2002). Consequently, it can be summarized that some approaches or practices that are applied enable flexibility to fulfill changes in customer requirements and ensure customer satisfaction.

This way of considering flexibility is attractive, as it allows researchers to analyze the ability of each echelon to generate flexibility (i.e., by studying the flexibility of enablers). This is particularly relevant because collaborative supply chain management in many supply chains is combined with decentralized planning. Further, it primarily focuses on logistics networks of independent companies based on partnership-oriented business relations with equal rights and power (Reiner, 2005). Consequently, supply chain flexibility is dependent upon the flexibility of each stage of the supply chain. In addition, the role of supply chain management is to organize these capabilities in order to achieve sustainable higher performance. It is worth mentioning that both the effectiveness (i.e., customer satisfaction) and the efficiency (i.e., total cost) should be considered during the performance evaluation performance (Jammerneegg and Reiner, 2007).

2.4 Collaboration in supply chain

The rise of supply chain management reinforces the incentive for developing collaboration (i.e., organizing interactions) between suppliers, manufacturers, logistic service providers, distributors, and customers in order to increase performance. Close relationships between network partners are believed to represent the key to success in the near future (Sahay, 2003). For instance, Lee (2002) argued that collaboration has a positive impact on the bullwhip effect, inventory costs, and supply chain flexibility. Exploring the collaboration concept further, Simatupang and Sridharan (2004) identified three core dimensions in supply chain collaboration, which they labeled as “information sharing,” “decision synchronization,” and, “incentive alignment.” Information sharing is related to the capacity to access and disseminate information to and from supply chain partners. This information can be actual orders, order commitments, forecasts, inventory status, production capacity, or any relevant information that supports the planning and the con-

trol of supply chain processes. Decision synchronization represents the ability to manage the system as a whole at different levels and time horizons to achieve common goals. This process includes the strategic alignment of capabilities and the synchronization of relevant activities. Finally, incentive alignment refers to the extent to which partners share costs, risks, and benefits to enable the network to operate in a sustainable (or improved) manner. These dimensions can be seen as collaborative levers to achieve higher performance (better efficiency and effectiveness). Interestingly, Lee (2000) presented similar dimensions in discussing the related concept of supply chain integration. In this context, he highlighted the importance of “information integration,” “coordination and resource sharing,” and “organizational relationship linkage.”

In the context of the interaction between uncertainty and supply chain flexibility, the focus is on the two first dimensions of collaboration: information sharing and decision synchronization. Information sharing is believed to directly influence the level of uncertainty in the network, whereas decision synchronization is assumed to support the ability of the partners to efficiently behave as a chain, improving the supply chain flexibility. The third dimension, incentive alignment, is clearly necessary to make sure that the network members are willing to act as a chain and to support the supply chain management initiative in a sustainable manner. As discussed above, networks are often made of independent companies (Reiner, 2005); therefore, it is realistic to consider that some partners might decide not to be part of system-wide management approaches. This fact highlights another issue in supply chain management that is not discussed in this work. In addition, partners are assumed to behave in order to support the performance of the network as a whole. It is believed that commitment can be generated by contract design (see Özer, 2006) or by evidence of potential benefits (see Section 2.5).

2.4.1 Information sharing

Information sharing can include end-customer demand, sales forecasts, order status, inventory levels, capacity availability, lead times, and quality (Stevenson and Spring, 2007). However, from these distinct types of data, the main focus is generally on demand information. According to (Holweg et al., 2005), “creating a transparent, visible demand pattern that paces the entire supply chain” is the primary objective of collaboration in the supply chain. The fact is that non-transparent demand is closely related to uncertainty, as forecasting is made more difficult. Therefore, artificial demand amplification is likely to occur. As a direct consequence, significant efforts have been made to flush demand information upstream in the chain in a timely manner, generally based on IT technology solutions, such as electronic data interchange systems or Internet technologies. These solutions facilitate the sharing of real-time information in the supply chain and allow

the organization to be more effectively coordinated at the network level (Stevenson and Spring, 2007). In particular, demand information exchange in the form of actual orders, order commitments, and forecasts have been shown to reduce the need for inventory, increase service level, and improve production efficiency (Huang et al., 2003).

Further, even though demand information generally constitutes the core of information-sharing strategies, additional types of information, such as inventory levels and capacity availability, should not be neglected. For instance, Federgruen and Zipkin (1986) showed that optimal order decisions could not be reached in a periodic replenishment system without information on available production capacity at the supplier level. Also, information about capacity and inventory levels are required for collaborative practices, such as “vendor-managed inventor” and “collaborative forecasting planning and replenishment.” Evidence of the value of capacity or inventory levels information has been highlighted in the literature (e.g., Huang et al., 2003).

However, despite the fact that it is theoretically well understood, the actual impact of collaboration and information sharing in practice is not clear (Holweg et al., 2005). As observed by Lapide (2001), the manner in which demand information contributes to improving production and inventory performance still partially remains to be worked out. From this point of view, the situation of information sharing is similar to that of forecasting discussed above (see Section 2.2.2) in the sense that necessary knowledge is still missing to fully understand their value. A potential reason for this situation is that the impact on uncertainty affects the supply chain dynamics, making more complex the relationship between information and performance. This complexity is believed to play a crucial role in explaining the lack of understanding of the value of information sharing and physical flow coordination observed by Sahin and Robinson (2002). Next, despite critical information is not all in supply chain collaboration. As stated above, a further key element in supply chain performance is to align strategic capabilities and to synchronize relevant activities.

2.4.2 Decision synchronization

It is clear that the core of supply chain management is support of networked processes to better achieve common goals. However, it is important to note that the objectives may differ, given that targeted competitive advantages may be different. Indeed, some supply chains are competing for service when others do on costs. Mason-Jones et al. (2000) referred to this decisive competitive factor as the “market winner.” Further, the authors argued that the market winner was closely related to the strategy of the supply chain, mentioning that the market winners for agile and lean supply chains are, for instance, service level and costs, respectively. Beyond this observation, there is the

question of what shapes the strategy. Lee (2002) suggested that a one-by-one relationship existed between uncertainty and strategy in the supply chain. First, he explained how the supply chain strategy should be adapted to the characteristics of the end-customer demand. This suggestion echoed the call from Fisher (1997), who detailed how the supply chain should be designed to answer the demand, which is often defined by the product type (e.g., innovative, fashionable, or functional). Second, Lee (2002) claimed that the supply chain strategy should also answer to the characteristics of the supply flows. Indeed, some industries are facing supply risks to which the supply chain strategy should respond. In summary, the supply chain strategy has to be aligned with the level of uncertainty from both the supply and the demand sides. By developing this conclusion, Lee (2002) identified four different types of supply chains: efficient supply chains (low supply uncertainty and low demand uncertainty), risk-hedging supply chains (high supply uncertainty and low demand uncertainty), responsive supply chains (low supply uncertainty and high demand uncertainty), and agile supply chains (high supply uncertainty and high demand uncertainty).

Supply chain strategy should be shaped by the uncertainty that it is facing. The four types of supply chains proposed by Lee (2002) are related to distinct levels of supply chain flexibility. As explained by Prater et al. (2001), a core component of agility is flexibility. Consequently, each supply chain has to align its level of flexibility to efficiently absorb its specific changes in demand and supply and, in turn, increase its performance. Empirical results from Ho et al. (2005) and Sun et al. (2009) verified this affirmation. In his model, Ho et al. (2005) included the uncertainty issued from manufacturing (i.e., the third category of uncertainty described by Davis, 1993). This addition is interesting, as it includes the idea of company-based settings. Despite the fact that the strategy should be directed toward achieving bottom-line performance, the situation regarding uncertainty is likely to evolve along the chain. This can be illustrated by changing the location of the customer decoupling point. The customer order decoupling point is the location at which the forecast-driven standard production, mostly serial production of standard components (PUSH), and the demand-driven production (i.e., the commissioned production in response to customer orders or other requirement indicators (PULL)) meet (Gläßer et al., 2009). This leads to the situation of having a hybrid setting with an efficient supply chain strategy upstream of the decoupling point and an agile supply chain strategy downstream (Stratton and Warburton, 2003). Such a strategy at the network level can only be efficient if the possibility exists to coordinate decisions at different managerial levels and time horizons (Simatupang and Sridharan, 2004).

Consequent improvements can be expected from supply chain collaboration. The critical issue of uncertainty is then tackled from both sides. On the one hand, information

sharing supports uncertainty reduction. On the other hand, decision synchronization contributes to efficiently hedging uncertainty. Defining the right strategy for a given network is not trivial. Each strategy impacts the flexibility of the system as well as its inherent uncertainty. Further, as discussed in the previous sections, the dynamics of the flows are also impacted. Consequently, the resulting outcomes of a strategy are difficult to assess. This complexity might help to explain the lack of understanding of the value of collaboration observed by Sahin and Robinson (2002). Moreover, each strategy or improvement is related to investments. For instance, information sharing may require new IT supports. Also, flexibility enablers are known to come at a cost. In order to make wise decisions with regard to which strategy to adopt, the ability to assess the benefits of a given set of practices prior to implementation is necessary. Estimation of the expected benefits also supports the incentive of supply chain partners to collaborate and solve potential conflicts in a sustainable manner.

2.5 Model-based evaluation of the supply chain and decision support

Supply chain performance evaluation is a broad issue in supply chain management that implies the ability to measure the performance of the system. Neely (1995) defined performance measurement as:

“the process of quantifying the efficiency and the effectiveness of action. [...] Effectiveness refers to the extent to which customer requirements are met, while efficiency is a measure of how economically the firm’s resources are utilized when providing a given level of customer satisfaction.” (Neely, 1995)

During the evaluation of the system, qualitative assessments, such as “good,” “adequate,” or “poor,” are imprecise and difficult to compare in an accurate manner (Beamon, 1999). Therefore, quantitative performance measures are generally preferred to qualitative statements. In addition, single performance measures are often considered to be too limited to adequately describe the performance of a system. Supply chains are complex dynamic structures in which any change is likely to induce multiple modifications in the system. The web of causal relationships existing between processes generates trade-offs between parameters; therefore, multiple performance measures represent the only way to identify and manage those dependencies (Beamon, 1999). A review of commonly used supply chain performance measures can be found in Shepherd and Günter (2006). Nevertheless, if there is no doubt that these metrics, or a selection of them, are useful for management activities, it might not be sufficient for decision making. Indeed, many management

decisions require an anticipation of the consequences of such decisions. For instance, investment decisions should be related to some estimation of the return on investment. For this purpose, an overview of the current performance status of the supply chain is not enough. As illustrated by Kleijnen and Smits (2003), managing a system based on a sole observed performance is similar to “driving via the rear mirror”. For wise decision making, it is necessary to look beyond the actual situation and to get ahead of future results. Fortunately, the understanding of supply chain dynamics and in particular the causes and effects relationships related to supply chain performance can support truthful inference on decisions’ consequences, and in this sense, support grounded decision making.

From this perspective, quantitative modeling of complex system is of interest, as it represents an appealing manner of collecting information for decision making (Fishman, 2001). Will et al. (2009) defined quantitative models as those that are

“based on a set of variables that vary over a specific domain, while quantitative and causal relationships have been defined between these variables.” (Will et al., 2009)

The main idea behind this definition is that quantitative models virtually mimic selected aspect of the behavior of a real-world process by reproducing mathematically the causes and effects relationships govern it. By doing so, there is an opportunity not only to gain insight into the process itself, but also to extend upon knowledge by testing “what-if” analyses (i.e., investigate the effect of a distinct management decision) (Law and Kelton, 2000). That is, it offers a unique opportunity to test and evaluate management decisions in a risk-free environment and at a relatively low cost. In supply chain management, modeling methods can be split into two main categories: analytical approach and simulation approach (Chan and Chan, 2005). Analytic models are sets of relationships for which it is possible to obtain exact information about the problem under investigation using mathematical methods, such as algebra, calculus, and probability theory (Law and Kelton, 2000). On the contrary, simulation models do not solve equations in an accurate manner, but rely on software to perform numerical evaluations by imitating the system behavior, generally over time (Kelton et al., 2002). When both categories of methods have merits, the complex interactions existing in the supply chain make it difficult to exploit closed-form analytical solutions (Schodl, 2009). In particular, analytical approaches impede the ability to handle uncertainty (Chan and Chan, 2005).

In the context of the supply chain, analytical solutions are often assumed to be restricted, simplified, and idealized types of problems (Bertrand and Fransoo, 2002). Considering interactions between supply chain partners, analytical models generally focus on optimization based on specific input distributions. They all too often neglect the actual

cause-and-effect relationships existing between processes. For instance, in most production and inventory system studies, lead times are independent from order quantities (i.e., from the workload of the production process). As previously discussed, the assumption of exogenous lead time is generally not realistic in practice (see Section 2.2.2). This characteristic can be found in studies in which the lead time is either fixed (e.g., Chen et al., 2000) or stochastic, but independent of the demand (e.g., Kim et al., 2006). More recently, this issue has been addressed in analytical papers in which authors have relied on queuing theory principles to model the impact of the order pattern on lead time distribution. By doing so, these authors developed inventory/production models, where the lead time is dependent upon the dynamics of the order arrival. In such models, the inventory system influences the production system by initiating orders, and the production system influences the inventory system by completing and delivering orders to the inventory. In contrast to the conventional inventory model, where lead times are defined as exogenous variables, the lead times in production/inventory systems are endogenously controlled by the production system (see Boute, 2007). For instance, Kim (2008) provided evidence that conventional models can fail to provide accurate results when neglecting production/inventory interactions. Example of such studies can be found in Karaesmen et al. (2004).

These models, however, are tied to the assumptions of the queuing theory. In other words, they assume a steady state situation that is generally not realistic in companies. In particular, the ability to adapt to demand (i.e., flexibility) as well as variations in uncertainty might strongly influence the state of the system. In this context, simulation may appear more appropriated. Some authors even suggested that simulation is the only reliable solution for supply chain analysis (Law and Kelton, 2000; Swaminathan et al., 1998). In addition, simulation allows researchers to widen the scope of the analysis, look beyond the goal of optimal solutions (i.e., solutions that are best for a precise set of conditions), and consider robust solutions (i.e., solutions that remain acceptable for a wider range of conditions) (Hopp et al., 2001). Examples of contributions provided by supply chain simulation studies and in the context of the interactions between flexibility and uncertainty can be found in Zhao et al. (2002a). In addition, more details are provided in Chapters 4 and 5.

From a research perspective, the interest in building models as closely as possible to reality (i.e., integrating the relevant cause-and-effect relationships) is of interest as well. Leading researchers in the field of operations management (e.g., Bertrand and Fransoo, 2002; Davis et al., 2007) pointed out that the methodology of quantitative model-driven empirical research offers an opportunity to further advance theory. Quantitative model-based empirical research aims at either verifying the validity of the research models

utilized in quantitative theoretical research or verifying the quality of the solutions obtained from quantitative theoretical research in real-life operational processes (Bertrand and Fransoo, 2002). For instance, one challenge is to test if those analytic contributions, sometimes related to quite “idealized” problem, are useful for real-life systems. As observed by Will et al. (2009), for axiomatic research, relevance (i.e., the validity of the model with regard to real-life) is generally weakly considered. Often, this issue of relevance is addressed by discussing either previous contributions treating similar problems, or broad industrial problems, rather than testing relevance versus empirical observations.

To contribute to this area of research, two main streams can be considered. On the one hand, models can be tested using empirical data, rather than generated “perfect,” sets of data. On the other hand, simple models can be extended to integrate more realistic cause-and-effect relationships, such as the interrelationship between demand patterns and lead time discussed above. These relationships can be examined using both analytical models and empirical studies based on methodologies, such as surveys (e.g., Forza, 2009) and case studies (e.g., Voss, 2009). These relationships should then be integrated into dynamics models in order to provide a holistic evaluation.

Chapter 3

The impact of forecasting on operational performance: mediation effects through flexibility enablers

3.1 Introduction

Forecasting is well known in management to be a strong lever against uncertainty; thus, it has potential to contribute to better performance. In contrast to other uncertainty-hedging possibilities, such as inventory management and capacity management, forecasting is known to act as a direct lever against uncertainty. Therefore, forecasting can contribute to improving performance by directly impacting perceived uncertainty. Literature traditionally considers accuracy as the relevant performance to be evaluated in a forecasting process (Mentzer and Bienstock, 1998; Chase, 1999). When forecast accuracy increases, cost and delivery performance consequently improve, as they are typically correlated with forecast error. Inventory levels and thus related costs, can be reduced; manufacturing systems can be better managed as equipment utilization improves and companies can effectively plan actions to be undertaken in advance (Vollmann et al., 1992; Ritzman and King, 1993; Fisher and Raman, 1996). In turn, manufacturing and production costs decrease. Delivery performance (e.g., order fulfillment and delivery speed/punctuality) also improves because when forecast accuracy is higher, it is more

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probable that products are available when the customer orders them (Enns, 2002; Kalchschmidt et al., 2003).

In contrast, forecast inaccuracy causes major rescheduling and cost difficulties for manufacturing (Ebert and Lee, 1995) and it may impact logistic performance such as delivery timeliness and quality (Kalchschmidt and Zotteri, 2007). On one hand, it is not surprising that several surveys show accuracy as the most important criterion for selecting a forecasting approach (Dalrymple, 1987; Mahmoud et al., 1988); on the other hand, this may explain why some authors have even recommended to eliminate forecasts entirely (Goddard, 1989), especially when forecast accuracy is very difficult to achieve. Forecast accuracy, however, is not important per se, but is important for its impact on operational performance. However, in practice, this relationship is not entirely straightforward (Ritzman and King, 1993; Reiner and Fichtinger, 2009; Kerkkänen et al., 2009). This may be because flexibility somehow substitutes forecast accuracy by absorbing unseen demand, i.e., forecast errors (Zotteri and Kalchschmidt, 2007).

Flexibility is commonly recognized as a key solution to the environmental uncertainty of demand and supply management. Flexibility has been widely studied at the manufacturing level (see, e.g. Slack, 1987; Kara and Kayis, 2004; Koste and Malhotra, 1999; Vokurka and O'Leary-Kelly, 1999, for reviews); recently, there has been expansion of knowledge regarding supply chain flexibility (see Stevenson and Spring, 2007, for a review). However, understanding the relations between flexibility and performance still presents open challenges. On one hand, evidence of the positive impact of flexibility on performance has been provided (e.g., Suarez et al., 1996; Das, 2001; Jack and Raturi, 2002; Hallgren and Olhager, 2009); on the other hand, important knowledge required to understand clearly flexibility and the mechanism of its relationship with performance is still believed to be missing. One explanation for this gap is, of course, the complexity of the flexibility concept, which, for example, still lacks a consensual definition (Zhang et al., 2002).

Due to the broad and multidimensional aspect of the concept, numerous difficulties arise when attempting to encapsulate flexibility as a whole in a single construct. A method of resolving this issue is to focus on the practices and policies applied by a company that contributes to flexibility instead of seeking to quantify the flexibility itself. Factors that generate flexibility are found in literature under several names, such as flexibility enablers (e.g., More and Subash Babu, 2008), internal determinants (e.g., Reichhart and Holweg, 2007) and sources (e.g., Tachizawa and Thomsen, 2007). For instance, lead time compression, based on practices such as setup time reduction, is an enabler of flexibility, as it is known to increase the capacity of coping with uncertainty in demand (Reiner and Trcka, 2004).

Flexibility enablers constitute the internal flexibility of the system, which can be used

to support the systems ability to achieve external flexibility with its environment (Upton, 1994). This distinction between internal and external flexibility separates the capabilities of operations resources from the market requirements; they are thus considered as dual influences that need to be reconciled by operations strategy (Slack and Lewis, 2002). Based on the latter, it can be summarized that some approaches or practices that are applied, constitute flexibility enablers to fulfill customer requirements and to increase customer satisfaction. Furthermore, these approaches also have an impact on cost efficiency. The total success (effectiveness and cost efficiency) of flexibility can only be evaluated by consideration of both aspects (Jammernegg and Reiner, 2007).

The relationship between forecasting and flexibility enablers is evaluated in this work. Previous contributions have often considered these two issues as complementary. When forecasting is rather complex and accuracy is difficult to achieve, flexibility enablers become a powerful tool for improving performance (Goddard, 1989). Instead of spending great efforts in trying to foresee what demand will be in the future, companies choose to increase their ability to react quicker and more efficiently to sudden variations in demand. Conversely, when flexibility enablers are more difficult to extend (typically due to limited resources), companies have to rely more on forecasting capabilities to improve both cost efficiency and effectiveness. However, investments in flexibility enablers are often decided based on the expected forecast accuracy. For this reason, the relationship may be more complex, as interrelations may exist.

A good explanation of this complex relationship is provided by queuing models (see, e.g., Hopp et al., 2001). These models clearly show that waiting times rise with process time, average utilization and variability. We assume that the use of better techniques and information for forecasting will lead to higher forecast accuracy, reduced bias, etc. (see below) and will therefore lead to lower perceived uncertainty, which means that the processes (investments) perform better; i.e., reduced flow time will increase effectiveness.

3.2 Objectives and methodology

The aim of this work is to study the relationship among forecasting, flexibility enablers and operational performance. In particular, this work aims to analyze whether the impact of forecasting on performance is due to the mediating effect of flexibility enablers. To analyze this research question, we considered two different performance measures: cost efficiency and effectiveness. The analytical literature suggests that flexibility enablers and forecasting may affect both performance measures, although little empirical evidence can be found for these relationships. Previous works (see Danese and Kalchschmidt, 2008, for review) showed that the impact of forecasting on performance is due not only to accuracy but also to the forecasting management method itself. In fact, having a structured

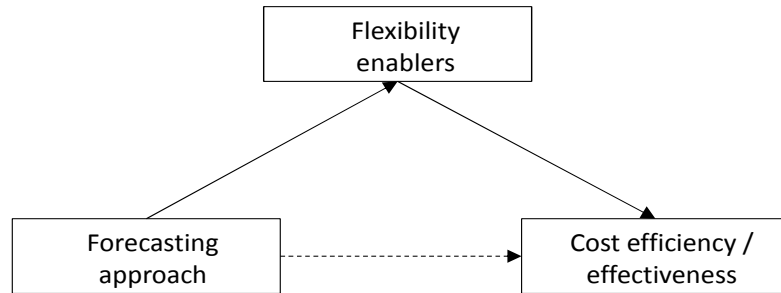


Figure 3.1: Theoretical model.

forecasting process may lead to a better understanding of the context (typically by means of more complex techniques) and to an unbiased forecast (typically obtained through the use of forecasting techniques).

We intended to study whether the relationship between the forecasting method (i.e., extent of investment in forecasting) and operational performance (i.e., cost efficiency and effectiveness) can be moderated by flexibility enablers. The theoretical model we considered is represented in Figure 3.1.

The empirical analysis was based on data collected from the 4th edition of the Global Manufacturing Research Group (GMRG) survey. The GMRG collects information on manufacturing practices in several countries. In particular, a specific questionnaire is designed and shared among researchers belonging to different countries. The questionnaire is translated back and forth by academics in each country and based on this tool, data is collected. This data is centralized by the GMRG and shared with all data gatherers. Sampling is not random and we cannot assume that the data is representative of the country where data has been collected.

In the current data set, 330 companies were considered in six different countries (Austria, Hungary, Italy, Korea, Poland and Switzerland), all of which belong to the manufacturing and assembly industry.

Table 3.1 synthesizes the distribution of the sample in terms of size, while Table 3.2 shows the distribution among the different countries. The sample size shows several medium and large companies; some small companies are also represented in the data set. Table 3.3 provides information on the distribution of the sample with respect to the different industries.

With the aim of analyzing the aforementioned relationships, we first defined the proper items and constructs to measure the considered variables. Based on the GMRG database, we were able to collect information regarding the different variables. The

A copy of the questionnaire can be found at <http://www.gmr.org>.

Table 3.1: Distribution of the sample by size.

Company size	Frequency
Small (less than 50 employees)	21.5%
Medium (50–250)	29.8%
Large (more than 250 employees)	48.7%

Table 3.2: Distribution of the sample by country.

Country	Frequency
Austria	5.2%
Hungary	16.1%
Italy	16.4%
Korea	34.7%
Poland	17.3%
Switzerland	10.3%

reliability of the constructs was tested through confirmative factor analysis and reliability analysis. We then adopted Structural Equation Modeling to identify the moderation effects.

3.3 Empirical analysis

3.3.1 Variables definition

To define the different constructs, we applied a confirmative factor analysis based on the items that, according to current literature, should be influenced by these variables. All items were measured on a seven-point Likert scale, one being not at all and seven being to a great extent.

To evaluate flexibility enablers, we defined two separate constructs of the enablers of flexibility based on previous literature: the layout, or the organization of the plant and the production equipment in the dedicated process (Upton, 1995), and process flow management, or the practices that aim to ease and speed the material flow. Because our goal is to study the impact of flexibility enablers on performance, theoretically, we should have considered flexibility performance. However, it is very difficult to identify flexibility performance that is strictly related to specific practices. For this reason, we decided to evaluate flexibility by means of practices, assuming that a relationship exists between what companies do (i.e., practices) and what they gain (i.e., performance), without involving flexibility. The use of proper layout solutions can influence performance, either through the use of cellular manufacturing systems or by leveraging automation. Consistent with previous literature and to measure the extent of investment on layout,

Table 3.3: Distribution of the sample by industry.

Industry description	US-SIC	Frequency
Food and kindred products	20	2.3%
Textile mill products	22	5.6%
Leather and leather products	31	0.9%
Lumber and wood products, except furniture	24	1.9%
Paper and allied products	26	2.3%
Printing, publishing and allied industries	27	1.4%
Chemicals and allied products	28	2.3%
Rubber and miscellaneous plastics products	30	3.3%
Primary metal industries	33	0.5%
Fabricated metal products, except machinery and transportation equipment	34	18.1%
Industrial and commercial machinery and computer equipment	35	20.0%
Electronic and other electrical equipment and components, except computer equipment	36	12.6%
Measuring, analyzing and controlling instruments; photographic, medical and optical goods; watches and clocks	38	7.4%
Manufacture of motor vehicles, trailers and semi-trailers	37	8.4%
Furniture and fixtures	25	1.9%
Stone, clay, glass and concrete products	32	3.7%
Miscellaneous manufacturing industries	39	7.4%

we considered the extent to which companies have invested in: (1) cellular manufacturing and (2) factory automation. The two items are correlated with each other (the Pearson Correlation index is 0.44 and significant at a 0.01 level). To measure the extent of investment on responsiveness, we considered the extent to which companies have invested in: (1) Just-In-Time activities, (2) manufacturing throughput time reduction, (3) setup time reduction and (4) Total Quality Management. The items are correlated with each other (all Pearson Correlation indexes are above 0.40 and significant at a 0.001 level). Thus, the construct layout and process flow management are defined by averaging the specific items.

We have assessed convergent validity and the one-dimensionality of the defined constructs with a confirmative factor analysis model. The literature recommends using a normed fit index (NFI) and a comparative fit index (CFI) together in assessing the model fit. NFI is 0.98 and CFI is 0.99, which means that the model is acceptable (Hu and Bentler, 1999). In addition, the root mean square error of the approximation (RMSEA) is 0.05, which suggests that the model fit is acceptable. Factor loads are all significant and conform to the lower suggested value of 0.40 (Gefen et al., 2000). Cronbachs Alpha was also measured to verify the reliability of the constructs; constructs are considered reliable if the Alpha value is above the minimum requirement of 0.60 (Nunnally, 1994).

To evaluate how forecasting is managed, we considered two different constructs: the use of structured forecasting techniques and information gathering. The forecasting literature suggests the importance of relying on structured techniques to forecast demand (e.g., Armstrong, 1983; Armstrong et al., 1984; Dalrymple, 1987; Sanders and Manrodt, 1994). Conforming with previous literature and to measure the adoption of structured techniques, we considered the extent to which companies use: (1) quantitative time series models (e.g., exponential smoothing) and (2) quantitative causal models (e.g., regression). The two items are correlated with each other (all Pearson Correlation indexes are above 0.40 and are significant at a 0.01 level).

Proper information gathering is also considered to be a relevant issue in improving forecasting accuracy (e.g., Davis and Mentzer, 2007; Bartezzaghi et al., 1999). In line with what previous studies have shown, data on information used in the forecasting process have been collected regarding the extent to which data on the market evolution is used in forecasting. In particular, we considered the following sources of information: (1) current economic conditions, (2) customer sales plans and (3) market research. The four items are correlated with one another (all Pearson Correlation indexes are above 0.27 and are all significant at a 0.01 level).

Thus, the construct technique and information are defined by averaging the specific items. The NFI is 0.97 and the CFI is 0.99, which means that the model is acceptable. In addition, the RMSEA is 0.03, which suggests that the model fits well. Factor loads are

all significant and Cronbachs Alpha value is above the minimum requirement of 0.60. In the case of information, the Alpha value is 0.531, which is not extremely high; however, we can consider it reliable because the correlation between the items is significant.

Overall, cost efficiency and effectiveness should be considered. Regarding cost efficiency, three items were examined. We asked respondents to provide an evaluation of their performance as compared with their competitors in the following categories, on a seven-point Likert scale (one being far worse than and seven being far better than): (1) direct manufacturing costs, (2) total product costs, and (3) raw material costs. Regarding effectiveness, a similar question was asked for the following: (1) product quality, (2) delivery speed and (3) delivery-as-promised. It can be noted that, as it is difficult to compare performance among companies operating within different contexts, this research focuses on perceptual and relative measures of cost and delivery performance. Thus, the constructs of cost efficiency and effectiveness are defined by averaging the specific items. The NFI is 0.99 and the CFI is 1.00, which means that the model is acceptable. In addition, the RMSEA is 0.00, which suggests that the model fits well. The factor loads are all significant and Cronbachs Alpha value is significantly above the minimum requirement of 0.60. Table 3.4 summarizes the aforementioned information on construct definitions and reliability statistics.

When dealing with the survey data, common method bias (CMB) can affect the statistical results. As suggested by Podsakoff et al. (2003), we checked for this problem by means of confirmatory factor analyzes (CFA) on competing models that increase in complexity (Podsakoff et al., 2003). If method variance is a significant problem, a simple one (e.g., a single-factor model) should fit the data as well as a more complex model (in this case, a six-factor model). The hypothesized model containing six factors gave a better fit of the data than did the simple model (one-factor model: CFI of 0.56 and RMSEA of 0.13; six-factor model: CFI of 0.97 and RMSEA of 0.04). Furthermore, the improved fit of the six-factor model over the simple model was statistically significant: the change in χ^2 was 1117.50, and the change in df was 15 ($p < 0.001$). Thus, the CMB does not appear to be important in our analysis. Previous works using the previous versions of the same dataset have found no significant impact of country and industry on the considered variables, thus we have omitted specific analyzes on these variables (see Wacker and Sprague, 1998; Danese and Kalchschmidt, 2008).

3.3.2 Statistical analysis

To study the mediation effect, we adopted a Structural Equation Modeling (for a review on mediation and moderation, we refer to Little et al. 2007). To verify that a mediation effect exists in a relationship between two variables X and Y through a third variable M,

Table 3.4: Construct definition and reliability statistics.

Construct ^a	Items ^b
Layout (0.600)	Investment in: <ul style="list-style-type: none"> ○ Cellular manufacturing (0.75) ○ Factory automation (0.54)
Process (0.790)	Investment in: <ul style="list-style-type: none"> ○ Just-in-time (0.629) ○ Manufacturing throughput time reduction (0.757) ○ Setup time reduction (0.769) ○ Total quality management (0.639)
Technique (0.672)	Extent to which companies use: <ul style="list-style-type: none"> ○ Quantitative time series models (0.962) ○ Quantitative causal models (0.533)
Information (0.531)	Extent to which companies use: <ul style="list-style-type: none"> ○ Information on current economic conditions (0.455) ○ Customers' sales plans (0.480) ○ Market research (0.662)
Cost efficiency (0.828)	Relative to competitor performance regarding: <ul style="list-style-type: none"> ○ Direct manufacturing costs (0.862) ○ Total product costs (0.875) ○ Raw material costs (0.636)
Effectiveness (0.743)	Relative to competitor performance regarding: <ul style="list-style-type: none"> ○ Product quality (0.424) ○ Delivery speed (0.846) ○ Delivery as promised (0.884)

^a Cronbach's Alpha values are reported in brackets

^b Factor loads are provided in brackets

the necessary conditions are that: i) X is significantly related to M, ii) M is significantly related to Y, and iii) the relationship between X and Y diminishes when M is in the model. We may then have four different situations:

- *Full mediation*: when M is added to the model, the direct relationship between X and Y is not significant and all other relationships are significant;
- *Partial mediation*: when M is added to the model, the direct relationship between X and Y is still significant, but all other relationships are also significant;
- *Inconsistent mediation*: when M is added to the model, the direct relationship between X and Y is significant but with the opposite sign of the estimate, while all other relationships are significant;
- *No mediation*: when M is added to the model, the direct relationship between X and Y is significant and at least one of the other relationships is not significant.

Given our objectives, we built eight different structural equation models (all combinations of the two considered performance measures, the two considered forecasting variables and the two considered flexibility enablers). For each model, we proceeded as follows:

- 1 Verify a correlation between the mediating variables and both forecasting and performance variables;
- 2 Build the direct relationship model between the forecasting variable and performance to determine the existence of a direct relationship;
- 3 Add the mediating variable to the model to identify the type of mediation.

The results of these analyzes are synthesized in Tables 3.5 and 3.6. Table 3.5 provides correlation analyzes among the variables to verify the necessary conditions for mediation; Table 3.6 analyzes the mediation effects; in particular, for each mediating model, we provided the type of mediation effect and an evaluation of both the direct and the indirect effect. In the dataset, some data are missing; thus, the number of companies changes according to the available data. Table 3.6 also provides the number of companies available for each analysis.

Mediation effects were also tested by means of the Wald statistic (Little et al., 2007).

Table 3.5: Correlation analysis for the variables (all correlations are significant with $p < 0.05$).

	Layout	Process	Cost efficiency	Effectiveness
Technique	0.464	0.531	0.210	0.280
Information	0.374	0.422	0.341	0.288
Layout			0.454	0.257
Process			0.331	0.334

Tables 3.5 shows that both forecasting variables and flexibility enablers are correlated to operational performance. This result is consistent with the previous literature (Suarez et al., 1996; Das, 2001; Jack and Raturi, 2002; Hallgren and Olhager, 2009). The correlation analysis also provides evidence that necessary conditions for the mediation effects apply: in fact, both forecasting and performance variables are correlated with flexibility enablers, thereby allowing us to study in detail the mediation effects that are summarized in Table 3.6.

All of the models appear to be reliable and properly fit (all model fit metrics are acceptable). Table 3.6 shows that several mediation effects occur between the variables. In particular, the layout fully mediates the relationship that both the forecasting technique

Table 3.6: Results of mediation analyzes (mediation type: FM Full Mediation, PM Partial Mediation, NM No Mediation, IM Inconsistent Mediation).

Forecast. variable	Mediation variable	Performance variable	Mediat. type	Direct effect	Indirect effect	Total effect	n
Tech.	Layout	Cost efficiency	FM	-0.009	0.214	0.204	307
Tech.	Process	Cost efficiency	FM	0.058	0.152	0.210	300
Tech.	Layout	Effectiveness	NM	0.269	0.061	0.330	258
Tech.	Process	Effectiveness	FM	0.143	0.137	0.280	254
Info.	Layout	Cost efficiency	FM	0.139	0.153	0.292	304
Info.	Process	Cost efficiency	PM	0.276	0.106	0.383	298
Info.	Layout	Effectiveness	PM	0.199	0.072	0.271	256
Info.	Process	Effectiveness	FM	0.180	0.108	0.288	253

All mediation effects are significant with $p < 0.05$. Standardized effects are also provided. The number of companies considered in all analyzes is provided. (NFI > 0.93 ; CFI > 0.95 ; RMSEA < 0.06).

and the information have with cost efficiency. Process flow management also significantly mediates the relationship with both variables and effectiveness. We also identified that layout is not mediating the impact of forecasting techniques on effectiveness and that only a partial mediation effect is found between information and operational performance. In the next section, we discuss these results in greater detail.

3.4 Conclusions

This paper provides interesting results regarding the interaction among forecasting, flexibility enablers and performance (cost efficiency and effectiveness).

Forecasting has a significant impact on effectiveness (the correlation is significant). This result may appear trivial given the large amount of literature devoted to forecasting; however, we argue that strengthening the result obtained from this sample is important for managers because it proves that attention should be devoted to this topic. Understanding how this impact occurs is certainly more challenging. In fact, our analyzes lead us to better understand this relationship. First of all, we provide evidence that there is no mediating effect of layout on effectiveness. This means that better forecasting has no impact on effectiveness due to the better use of layout as a flexibility enabler. Thus, the use of layout as a flexibility enabler does not “translate” better forecasting into better performance. Moreover, the direct effects are high as compared to the total effects (0.269 as compared to 0.330 for technique and 0.199 as compared to 0.271 for information).

Secondly, there is a strong mediating effect of process flow management on effectiveness, meaning that when companies make a better forecast, it results in better process flow management and leads to better effectiveness. Thus, process flow management ex-

plains part of this relationship. Quite interestingly, however, the direct effects are still high (0.143 as compared to 0.280 for technique and 0.180 as compared to 0.288 for information). Thus, there are additional causes of this relationship, which should be analyzed further.

Forecasting has also a significant impact on cost efficiency (the correlation is significant). Again, we argue that this result is relevant for companies because this relationship applies (at least in our sample), regardless of the industry or country studied. We now understand how this effect occurs.

First of all, there is a strong mediating effect of layout on cost efficiency. This means that better forecasting has an impact on cost efficiency due to the better use of layout as a flexibility enabler. In fact, direct effects are irrelevant as compared to the total effects (-0.009 as compared to 0.204 for technique and 0.139 as compared to 0.292 for information). Thus, the layout explains a great deal of this relationship.

Secondly, the mediating effect of process flow management on cost efficiency is not fully consistent. In fact, the relationship between forecasting techniques and cost efficiency is fully explained by process flow management (the direct effects are low: 0.058 as compared to 0.210). However, this is not true for information, where a partial mediating effect occurs (in fact, direct effects are high: 0.276 as compared to 0.383). Thus, there are additional causes of this relationship and the forecasting method is more complex than it appears. Further research should analyze this relationship in greater detail. A structured summary of these findings is presented in Table 3.7.

In general, it appears that the relationship between forecasting and effectiveness is mainly due to process flow management, while the relationship with cost efficiency is mainly due to layout. These results provide interesting evidence for both researchers and practitioners. Research on the impact of forecasting on performance has not devoted much attention to the reasons behind the strength of this relationship. Thus, this work provides some details on the causality of this relationship; however, this should be investigated further. This study also provides companies with a better explanation of how to improve their performance through forecasting. From a managerial perspective, we argue that situations, in which a full mediation effect is found, are interesting because they explain how improvements (at least within the specificity of this study) occur. From another point of view, the partial mediated relationships offer interesting indications. Specifically, information use within forecasting only partially contributes to better performance but it significantly supports companies in being more flexible. In fact, the availability of additional information helps the actors involved in a specific process to make prompt decisions and align different units that manage each separate part of the production process. Improved forecasting, without related process or layout modification, provides only limited performance improvement, i.e. increased cost efficiency as

well as effectiveness.

Table 3.7: Summary and implications of the mediation analyzes results.

Performance variable	Mediation variable	Mediation strength	Implications
Cost efficiency	Layout	Strong	○ Relationship between forecasting and cost efficiency is mainly due to layout.
	Process	Inconsistent	○ Mediating effect of process flow management on cost efficiency is not fully consistent, i.e., technique and information are not sufficient to characterize forecasting and further research is needed to understand this relationship.
Effectiveness	Layout	None	○ No mediating effect of layout on effectiveness, i.e., better forecasting has no impact on effectiveness due to the better use of layout as a flexibility enabler.
	Process	Strong	○ Relationship between forecasting and effectiveness is mainly due to process flow management.

The results also allow us to provide companies with some suggestions on how to increase specific performance measures. In fact, we found that companies wanting to improve cost efficiency and effectiveness should focus on forecasting performance. Moreover, companies that consider cost efficiency critical or that are seeking improvements in cost efficiency should strongly focus on layout (i.e., factory automation). The positive impact of greater forecasting accuracy is reflected directly in cost efficiency via investments in the factory layout, making investments in this area critical. Furthermore, for companies looking for better effectiveness, managing the process flow in a better manner seems to also be important because, again, forecast accuracy directly reflects on better process management and implies improvements in this performance.

This paper thus highlights that according to the performance factors that companies want to improve (and thus their strategic goals), companies should also invest in specific areas of manufacturing (here, process flow management and layout). Overall, we are aware of several limitations of this work and would like to highlight some of them. First, we did not specifically consider any contingent factor that may influence the different variables and relationships described herein. Future works should focus on factors that may change how variables are defined. We argue that general results will not be drastically affected by these variables because, among other reasons, several degrees of freedom are left to companies regarding how they can impact flexibility enablers, i.e., by selecting which practices they can adopt. At any rate, future studies should compare

results among companies belonging to different countries or characterized by different sizes.

Secondly, we did not evaluate the impact of strategic objectives on the relationships considered here; in particular, we identified some effects on performance, but internal processes (i.e., forecasting and flexibility enablers) are strongly affected by companies goals. In the future, this issue should be considered in greater detail. Thirdly, we devoted attention to only two specific flexibility enablers (i.e., process flow management and layout). Several other enablers could have been considered (i.e., information, slack allocation). Future studies will consider more practices so as to extend and (hopefully) more completely define the relationships under investigation. Overall, while our sample is rather numerous, we are conscious that some results may be affected by the specific companies that we have considered, given our research objectives and our model. Thus, future research should replicate these analyzes on different datasets, eventually with focus to specific industries. Lastly, a final limitation is related to the data used to conduct the empirical analysis. The GMRG questionnaire is not designed specifically to study this topic but includes several topics, thus the information collected on flexibility enablers and forecasting process is limited. Besides, the data sampling is not random but should be considered a convenience sample by country.

Chapter 4

Benefits of advance demand information: Exploring the side-effect of the interaction with volume flexibility

4.1 Introduction

Information sharing is acknowledged to be a cornerstone of collaboration within a supply chain and is widely promoted in supply chain management. However, although it is commonly accepted that efficient information sharing can provide superior performance in terms of customer service and total cost, the extent of these improvements is less clear. Indeed, a large body of literature has provided contrasting results (Sahin and Robinson, 2002). Observing these contrasts, Cachon and Fisher (2000) pointed out that the conclusions drawn from one problem environment may not be applicable to another problem with different operational characteristics. A significant number of empirical findings corroborate this statement by suggesting that effective information sharing enhances effective supply chain practices, resulting in higher performance (Zhou and Benton Jr, 2007). In other terms, the specific settings of the network, that is, the practices applied by each echelon of the supply chain, determine the ability of the partners to convert (better) information into (better) performance. Close attention should therefore be given to the interaction between information and supply chain practices.

In this context, the concept of flexibility, i.e., the ability to change or react with little penalty in time, cost, or performance (Upton, 1994), is of interest. Several authors have identified information sharing as a source of supply chain flexibility and that im-

proving information exchange between companies gives partners greater visibility and time to respond to change (see, e.g., Stevenson and Spring, 2009). For instance, information sharing might be particularly relevant to companies that rely on flexibility in their workforce to periodically adjust their capacity. In such settings, information sharing can support better decision making in labor resource planning and could ameliorate the trade-off between efficiency and flexibility. In this study, we investigate the value of information sharing, particularly in the forms of advance demand information and production capacity, and how it can improve the volume flexibility of a manufacturer. We build on the specific characteristics of a real-life supply chain operating in the furniture industry and determine the value of advance demand information from simulation models. This framework allows us to assess the value of different amounts of information. Furthermore, we extend information-sharing policies to information about production capacity to allow co-ordination between order quantities and production capacity. We considered a production/inventory system, that is, the interaction between the inventory control system and the production system explicitly modeled, to capture the dynamic relationship between the order pattern and the lead time. Multiple performance measures obtained from the situation without advance demand information constitute the input for a benchmark analysis, which enables the improvements related to information sharing to be quantified given distinct inventory and production characteristics. It is important to highlight that, beyond the specificity of the situation analyzed in this work, the step-by-step methodology proposed can be replicated and support complete and valuable evaluation for other supply chains, with distinct constraints and process settings. The paper is structured as follows. In Section 4.2, we review some literature on the value of advance demand information and highlight its relationship with volume flexibility. In Section 4.3, we describe the empirical situation investigated in this study and the related supply chain model. In Section 4.4, we present the experimental design of the study. In Section 4.5, we detail and discuss the results obtained from the simulations. Finally, in Section 4.6, we present our conclusions, highlight the limitations of this study and provide some directions for further research.

4.2 Literature review

Advance demand information refers to the particular case in which customers place orders in advance for a future delivery (Özer and Wei, 2004). In other words, the customer accepts a positive lead time for the order, as immediate delivery is not expected. The benefits associated with this practice are intuitive and result from the apparent reduction of uncertainty. However, quantifying these benefits remains an open challenge, as they are closely related to the specificity of the network as well as to its environment

Cachon and Fisher (2000). In particular, it is well known that demand uncertainty is directly connected to the bullwhip effect and thus has a direct impact on supply chain dynamics (see, e.g., Lee et al., 1997). Most of the literature treatments of the value of advance demand information are related to problems of inventory control with advance demand information, and these studies can be split into two general categories based on the underlying supply process: models with an exogenous lead time and models with an endogenous lead time (Gayon et al., 2009). In the first category, the lead time required for inventory replenishment is assumed to be independent of the workload on the production system (i.e., production capacity is assumed to be unlimited). Contributions in this category include studies by Hariharan and Zipkin (1995), Chen (2001), and Gallego and Özer (2001). A review of the literature concerning advance demand information in models with an exogenous lead time can be found in Gallego and Özer (2002). In the second category, the production capacity is assumed to be limited, and replenishment lead times are thus influenced by the pending workload and the resulting congestion issue. Recent contributions in this category can be found in Özer and Wei (2004), Karaesmen et al. (2004), and Wijngaard (2004). Özer and Wei (2004) showed how capacity and inventory can be replaced with advance demand information. Karaesmen et al. (2004) first highlighted that the average utilization of the system is a critical factor in the value of advance demand information. They also suggested that advance demand information loses value in a heavily loaded system. Wijngaard (2004) stressed that flexibility is an important concern when investigating the benefits of advance demand information. The author motivates this statement by explaining that at one extreme, highly flexible production systems do not require advance information because anticipation is unnecessary, highlighting that the value of advance demand information increases as flexibility decreases (when modeled as a reduction of average utilization). At the other extreme, Wijngaard confirmed the statement from Karaesmen et al. (2004) that a heavily loaded system does not benefit much from advance demand information. The impacts of the available capacity and the flexibility of the production system are strongly emphasized in these studies, driving interest in investigating the potential effect of interactions between advance demand information and flexibility. The available capacity and its utilization represent an important concern for companies that generally face cost and efficiency pressures. In this context, volume flexibility, that is, “the ability of a manufacturing system to be operated profitably at different output levels,” (Sethi and Sethi, 1990) is of interest. (Jack and Raturi, 2002) identified slack capacity, inventory buffers, and labor flexibility as the primary sources of short-term volume flexibility in companies. The authors understand slack capacity as the ability to reserve capacity for sudden increases in demand, for instance, by operating on a two-shift basis and reserving the third shift. Inventory buffers refer to excess inventory of both raw material and finished products

maintained to hedge increases in demand. Finally, labor flexibility is obtained from practices such as flexitime, enforced Fridays off and temporary workers who hold near-permanent status (“perma-temps”) (Jack and Raturi, 2002). Intuitively, efficient volume adjustment will benefit from advance demand information, as decision making will be aided by the reduction in uncertainty. The trade-off between efficiency and flexibility could then be positively influenced. Kumar et al. (2008) mentioned that volume flexibility is supported by a strong information system, and Vollmann (2005) highlighted that information sharing between a customer and a supplier helps the manufacturing planning and control system to fulfill demand while minimizing resource use. The positive impact of information on efficiency was also highlighted in Huang et al. (2003). Finally, Kalchschmidt et al. (2010) showed that investments in volume flexibility enablers can improve the benefits induced by better information on forthcoming demand, attesting to the interaction between information and flexibility. Such considerations are crucial for supply chain dynamics. As discussed by Taylor and Fearné (2006) in the context of agri-food supply chains, misalignments of demand and supply are generated by demand amplification (bullwhip effect) along the chain and by a “supply-side effect” in which decision making is driven more by efficiency concerns than by the incentive of producing in line with demand. The interaction between demand information and flexibility can therefore improve processes beyond the traditional bullwhip improvement related to uncertainty reduction (e.g., Lee et al., 1997) by contributing to efficiently aligned production processes. To capture the full value of advance demand information, the impact of a dynamic adjustment to production capacity on the lead time must be considered. From a modeling point of view, this insight implies the need to consider the influence of finite production capacity and then to explicitly model the interaction between the inventory control system and the production system, the so-called production/inventory model (see, e.g., Boute, 2007). To capture the non-trivial interaction between advance demand information and the dependent constrained capacity under specific supply chain characteristics, simulation constitutes an appealing alternative to analytical approaches. Simulation-based contributions related to flexibility and demand information are found in Zhao et al. (2002a), Zhao et al. (2002b), and Chan and Chan (2006). Simulation will allow us to integrate empirical data and to remain closer to the specific supply chain under study. As noted by Huang and Gangopadhyay (2004), it is not feasible to analyze a supply system that will correspond to all industries. Therefore, supply chain evaluation has to be product- and company-specific (Reiner and Trcka, 2004). Finally, it is worth mentioning that the evaluation has to be performed based on multiple supply chain performance measures, as multiple performance measures can reveal any potential trade-offs between the different indicators (Beamon, 1999).

4.3 Case and model description

The supply chain model is developed from the actual situation of a plant belonging to an international company producing industrial polymer solutions. The plant is located in Europe and manufactures large quantities of low-value products intended for the furniture industry. These characteristics of intensive mass-production generate high pressure from low-wage country competitors, and customer loyalty is mainly ensured through on-time deliveries, short lead times, and volume flexibility. Lately, the company has been facing difficulties in satisfying customer demand due to high workloads, efficiency pressure and demand uncertainty. In this context, increased information sharing has been identified as a potential lever of improvement, and discussions have been undertaken with a key customer. In particular, advance demand information, that is, orders sent in advance for delivery in the future, has been considered. In the current situation, the primary customer expects immediate delivery from a distribution center, which holds stocks for this purpose. The distribution center is responsible for handling customer service and for controlling its inventory based on demand forecasts and periodic replenishment orders to a manufacturer. To provide accurate advance demand information, the customer should accept an increase in the lead time, and information exchange should thus come with service or cost improvements. To support decision making, evaluation is required to quantify the benefits related to advance demand information. In this study, the focus will be on improvements related to one- and two-week advance demand information for a selected relevant product ordered regularly by the key customer. Furthermore, we consider the case in which, once this is efficiently communicated to the manufacturer, demand information enables improvement in the manufacturing planning, allowing for greater flexibility and efficiency in production (see section 4.2). In the case under study, the manufacturer is able to influence the slack capacity and the workforce to keep the utilization level reasonably high. This dependency between demand and capacity is evident in Figure 4.1.

4.3.1 Production/inventory model

In the case under study, the distribution center aims to fulfill periodic orders from the customer directly from its on-hand inventory. At the beginning of each period t , the distribution center checks its inventory position to determine how much to order based on the selected replenishment policy. The quantity ordered at the end of period t will be received at time $t + l_t$, where l_t is the observed lead time associated with this order. A random customer demand, D_t , is observed at the end of the period t and is fulfilled through on-hand inventory. Any unfulfilled demand is backlogged. In accordance with the realistic setting of the case, we consider the lead time to be dependent on both the

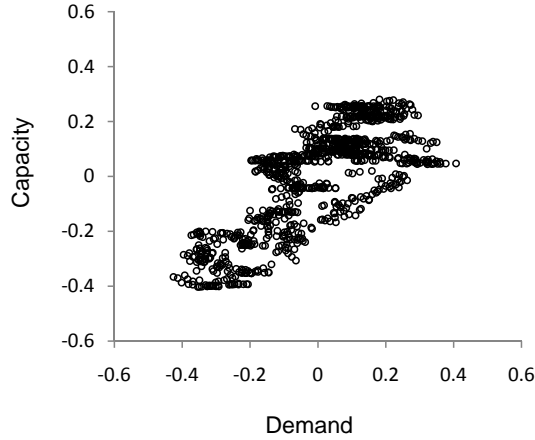


Figure 4.1: Plot of standardized smoothed total demand versus standardized smoothed total available capacity.

production workload and the available production capacity of the manufacturer. The lead time related to each order is therefore equal to the time necessary to process the workload from the earlier orders (i.e., the quantity related to orders waiting to be processed) plus the quantity of the actual order given the production capacity available in the upcoming periods. Formally, l_t is then equal to the smallest amount of time l that satisfies

$$\sum_{i=1}^l C_{t+i} \geq b_t + n_t Q, \quad l \in \mathbb{N}^*, \quad (4.1)$$

where b_t is the workload related to pending orders at time t , C_{t+i} is the available production capacity in period $t+i$ and $n_t Q$ is the order quantity at time t restricted to a discrete number n of standard batches of size Q . Equ. 4.1 allows the capacity to be adjusted in each period.

The distribution center behaves in the original situation as an independent entity and replenishes its inventory based on demand forecasts and on a periodic order-up-to policy. The order-up-to point, S_t , is computed in the classical manner (e.g., Silver et al., 1998) as

$$S_t = (R + L)D_{R+L} + ss, \quad (4.2)$$

where D_{R+L} is the forecast (or expected) demand over a review period, R plus a replenishment lead time L and ss is the safety stock. In this study, L and ss are based on heuristics from the company and considered to be fixed quantities. In detail, L is the desired lead time, and ss is based on a selected fixed proportion of average weekly demand. From Equ. 4.2, the quantity n_t , that is, the order quantity expressed as a multiple of the standard batch size, is straightforward and can be formalized as the minimum integer n

that satisfies the equation:

$$nQ \geq \Delta_t, \quad n \in \mathbb{N}, \quad (4.3)$$

where Δ_t is the discrepancy between the order-up-to point S_t and the inventory position, described as

$$\Delta_t = S_t - I_t + O_t - B_t, \quad (4.4)$$

where I_t is the on-hand inventory, O_t is the on-order inventory and B_t is the customer order backlog.

4.3.2 Demand and capacity model

In this study, we analyzed three years of the weekly demand for a selected product as well as three years of the total available capacity of the plant. This analysis confirmed the ability of the manufacturer to adjust its production capacity based on the demand (see Figure 4.1), highlighting the need to assess the potential impact of advance demand information on production capacity. To simulate this impact, datasets were generated from the empirical information on both demand and capacity. These datasets served to enable simulation replications of the situation. First, demand datasets for the product under study were generated based on the general weekly pattern of the demand, which was extracted using a moving average. Second, an error term from a normal distribution was added to each period to model variability between the datasets. The expected mean of the error term was zero and its variance was visually selected to match the volatility of the original time series. Second, weekly capacity time series were generated. The same procedure was followed for the available capacity: the general pattern was identified based on moving average, and error terms were added to generate multiple datasets. The error terms were again based on a centered normal distribution, and the variance was selected based on visual observation. The above information enabled an evaluation of the benefits provided by advance demand information. The next section details the evaluation procedure and the policies of information sharing considered in this study.

4.4 Experimental design

This section first describes the advance demand information policies and then the exchange of capacity information that will be evaluated in this study. Finally, the performance measures and the evaluation procedure will be described.

4.4.1 Demand information

Discussion with the customers showed that advance demand for either one or two weeks could be considered. In other terms, the customer could agree to provide fixed orders either one or two weeks in advance to the distribution center. In the actual situation, the distribution center is replenishing its inventory based on forecasted demand. It uses simple exponential smoothing to assess the demand for a horizon of 2 weeks. Assuming that the two-week horizon remains unchanged, three policies were developed:

- *No Demand Information (NDI)*. No advance demand information is provided; that is, the distribution center is relying on forecasts for the entire demand horizon, as it does in reality.
- *Limited Demand Information (LDI)*. One week of demand information is provided in advance by the customer. The second week of the horizon remains estimated based on forecasts.
- *Extended Demand Information (EDI)*. Advance demand information for both weeks is provided by the customer.

Intuitively, the reduction in uncertainty will be proportional to the amount of advance demand information. The reduction in uncertainty can be quantified by using the accuracy of the forecast horizon as a measure for the perceived demand uncertainty. Table 4.1 summarizes the three policies and presents an estimation of the average accuracy of the expected demand. The average accuracies were computed using the mean absolute percentage error (MAPE).

Table 4.1: Definition and details of the advance demand information policies used in the study.

Advance demand information	Types of advance information		Error (MAPE)
	Week 1	Week 2	
No demand information	Forecast	Forecast	20.92%
Limited Demand information	Advance order	Forecast	13.15%
Extended Demand information	Advance order	Advance order	0.00%

4.4.2 Capacity information

Information sharing is not restricted to demand information. Upstream information such as the suppliers' capacity is also relevant to inventory management. Capacity information provides the distribution center with an opportunity to limit its order quantity based on

the available production capacity at the manufacturer. Federgruen and Zipkin (1986) showed that, in a periodic replenishment system, it is optimal to order the minimum between the necessary quantity and the available capacity of the supplier. Therefore, the distribution center should not order more than the quantity the supplier is able to produce within the replenishment period, thus aligning its replenishment requirements with the supplier's capacity. The maximum order quantity at time t , n_t^* , should therefore be constrained to the number of finished batches that can be produced within the period, such as

$$n_t^* = \left\lfloor \frac{C_t - b_t}{Q} \right\rfloor, \quad (4.5)$$

where C_t is the expected capacity for period t . Interestingly, the previous rules provide at the same time a workload control mechanism for the supplier, preventing overload (congestion) and its known negative effects on the lead time. Therefore, three capacity information exchange policies were considered:

- *No Capacity Information (NCI)*. No capacity information is provided by the manufacturer, and the distribution center freely determines the quantity to order.
- *Inaccurate Capacity Information (ICI)*. The manufacturer provides capacity information, and the distribution center constrains its order based on that information to align its requirement with the manufacturer's capacity. However, the information is not reliable, as the manufacturer under- or overestimates its forthcoming capacity. Formally, we modeled the capacity information inaccuracy by multiplying the real capacity at time t by an error term based on a triangular distribution of the form $T(0.9, 1.0, 1.1)$.
- *Accurate Capacity Information (ACI)*. The manufacturer provides accurate capacity information, and the distribution center constrains its order based on this information.

In the case of aligned replenishment (i.e., capacity information is exchanged), the order size at time t , n_t , is constrained so that $n_t \leq n_t^*$.

4.4.3 Performance measurement

To assess the value of advance demand information, multiple measures were used to evaluate the supply chain performance. First, the customer service level *CSL*, defined as the percentage of orders fulfilled entirely from on-hand inventory, was measured. This measure is of central interest, as the timeliness of deliveries is of primary importance to the customer. Second, the average on-hand inventory, *OHI*, was considered. Influences

on the supply chain dynamics were monitored by measuring the variabilities of the order size, σ_{ORD} , the replenishment lead time, σ_{LDT} , and the average on-hand inventory, σ_{OHI} . As discussed in the previous sections, these parameters are directly related to potential improvements and are important in evaluating the benefits of information sharing.

The policies were evaluated using simulations. Each scenario was evaluated based on 100 replications of 156 periods. The performance measurements were restricted to the final 146 periods to limit any transient effects at the start. First, the scenario without any information sharing, that is, the case that corresponds to the actual supply chain under study, was evaluated. Then the alternative strategies with information sharing were evaluated, and the results were benchmarked against the initial scenario to quantify the improvements. In particular, we tested the scenarios with one week (LDI) and two weeks (EDI) of advance demand information together with the three policies of capacity information sharing (i.e., NCI, ICI and ACI). Therefore, we analyzed 6 distinct alternatives. In each alternative scenario, we allow the initially available capacity to increase from 0% to 40%. The case of a 0% increase corresponds to the situation in which the volume flexibility of the manufacturer is independent from the advance demand information obtained from the customer (the manufacturer's capacity remains unchanged). However, as discussed above, this relationship is unrealistic in our setting, and we allowed the volume flexibility to increase. We modeled an increase in volume flexibility by increasing the production capacity, similar to the method used in Wijngaard (2004). It might seem unrealistic to expect a 40% increase in capacity from advance demand information, and it probably is unrealistic, but this large increase is interesting from a research point of view, as it increases the study's ability to capture patterns in the dynamic impact of flexibility. The results are presented in the next section.

4.5 Results

The outputs of the simulation experiments, that is, the performance measures obtained from each scenario, were examined, and the results are presented in Figure 4.2. In this figure, each graph presents the improvement produced by the limited (LDI) and extended (EDI) advance demand information policies (represented by the dashed and straight lines, respectively, in Fig. 4.2) for each capacity information situation (in rows in Fig. 4.2) and each specific performance measure (in columns in Fig. 4.2). The improvements are quantified as percentages of the results obtained from the initial situation, that is, the case without advance demand information, and the impact of each policy on volume flexibility is highlighted by the increase in capacity expressed as a percentage of the initial capacity.

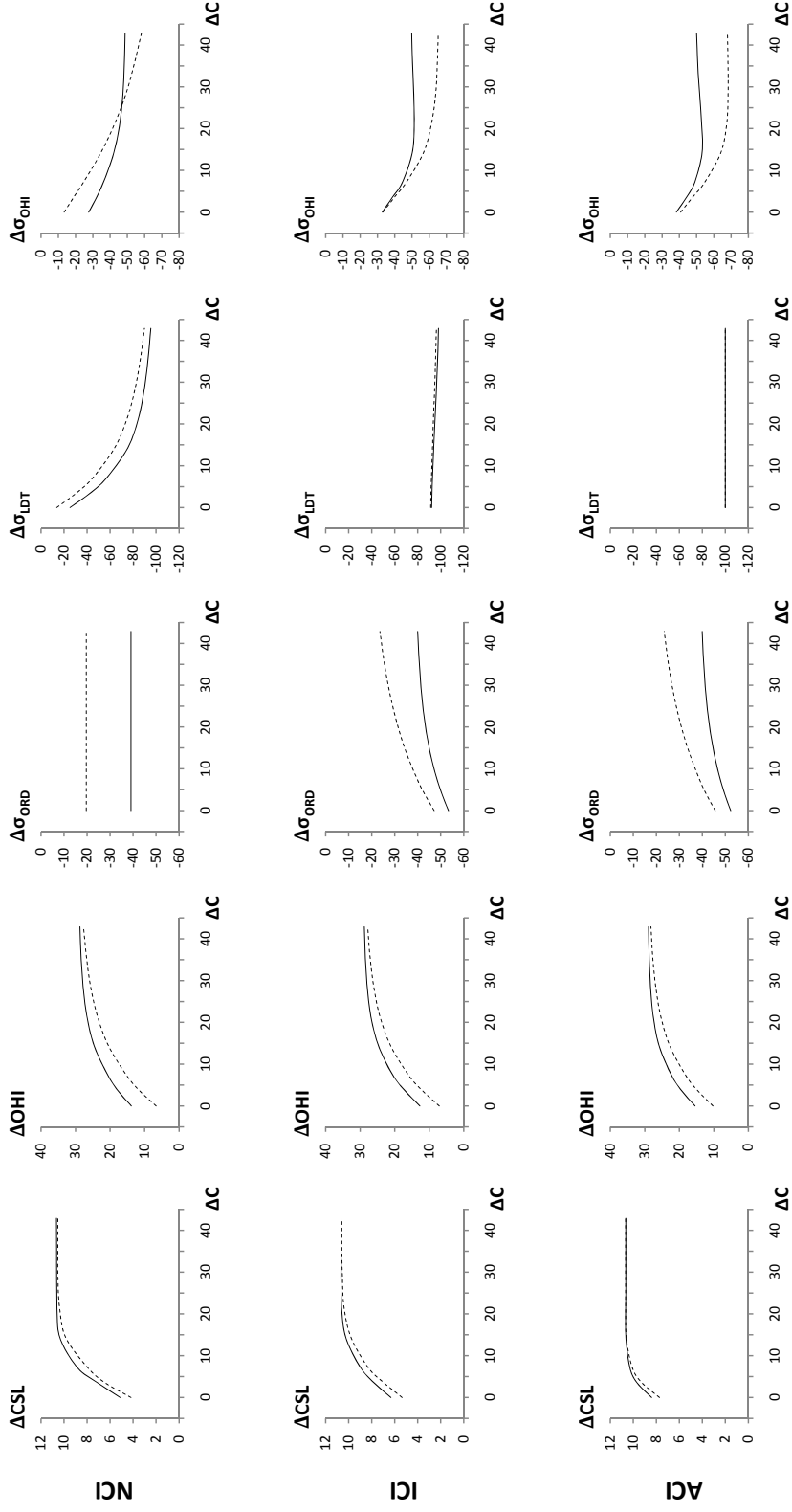


Figure 4.2: Performance improvements presented as percentages of the results obtained in the initial situation. Each graph presents the improvement related to the limited (LDI) and the extended (EDI) advance demand information policies (represented by the dashed and straight lines, respectively) for a given capacity information policy (in the rows) and for a specific performance measure (in the columns).

Benefits without capacity information exchange (NCI) We first consider the situation without any interaction with volume flexibility ($\Delta C = 0$). We observe that important changes in all performance measures are induced by advance demand information. However, these changes are not always positive. If a large improvement in the customer service level (CSL) is observed, the performance related to the average on-hand inventory (OHI) decreases. The reasons that advance demand information leads to more on-hand inventory are that stock-out is strongly reduced (less uncertainty in demand) and that the improvement in the lead time is not taken into account in the inventory policy (i.e., the heuristics are identical for each scenario despite any lead time improvement). The improvement in the lead time, in particular σ_{LDT} , is related to the reduced variability of the order size. As expected, σ_{ORD} is strongly reduced by advance demand information (see, e.g., Lee et al., 1997). The variability of the on-hand inventory, σ_{OHI} , is also reduced due to the improvement in the lead time. In general, we note that improvements are larger for the extended demand information policy (EDI), but these improvements are realized to a large extent with only a single week of demand information (LDI).

Furthermore, we consider the benefits of advance demand information when this information can produce an improvement in volume flexibility ($\Delta C > 0$). We observe that advance demand information in this situation allows further improvements in the customer service level (CSL). However, the average on-hand inventory, (OHI), increases due to further improvements in the lead time, σ_{LDT} , that are not integrated by the inventory policy. The variability in the order pattern is not affected, as the inventory policy is not influenced by information exchange (i.e., L and ss are fixed). The variability in the on-hand inventory, σ_{OHI} , is interesting. The improvement is strengthened by the increased capacity; however, this improvement is stronger for LDI than for EDI when the capacity increase is large. This phenomena results because the improvement in the lead time does not continue to increase when flexibility is high and also because the highly reliable lead time (i.e., high manufacturing flexibility) and the smoother demand pattern (i.e., smaller σ_{ORD}) enabled by increased demand information inversely affect the variability of the on-hand inventory, σ_{OHI} . This inverse relationship between a smooth replenishment order pattern and smooth on-hand inventory trending has been discussed in detail by Disney and Towill (2003).

Benefits with capacity information exchange (ICI and ACI) In this section, we studied the case in which the distribution center limits its order quantity based on the capacity information it receives from the manufacturer. We first consider the situation without interaction with volume flexibility ($\Delta C = 0$). In general, it can be observed that the capacity information magnifies the improvements observed in the NIC case. This is particularly obvious regarding σ_{LDT} . Additionally, stronger improvements are observed in the customer service level (CSL) and the variance in the order size (σ_{ORD}). However,

in the ICS case, no difference is observed in the performance measures related to the on-hand inventory (OHI and σ_{OHI}). It is interesting to note that the constraint on the order size contributes to a reduction in σ_{ORD} .

Further, we consider the benefits of advance demand information when it is related to an improvement in volume flexibility ($\Delta C > 0$). The general pattern of the impact of flexibility regarding the customer service level (CSL), the on-hand inventory (OHI) and the inventory variance (σ_{OHI}) are similar to the case without capacity information sharing (NIC). The constraint on the order size leads to a large improvement in the lead-time variability σ_{LDT} , with the lead time becoming perfectly reliable in the case of accurate information (ACI). Additionally, it is worth mentioning that, with the increase in capacity, the smoothing effect on σ_{ORD} observed with ($\Delta C = 0$) disappears, leading to the same variability as in the unconstrained scenarios. Finally, it has to be highlighted that, first, the benefits from advance demand information tends to stabilize with increased capacity and second, in this setting, most of the benefits are achieved from a single week of advance demand information. Moreover, these results confirm the strong impact of the relationship between advance demand information and volume flexibility (modeled as an increase in capacity).

4.6 Conclusion and future research

This study investigated the value of advance demand information given specific production and inventory management constraints. In particular, we assessed the impact of the potential link between advance demand information and volume flexibility. Using simulation experiments based on empirical settings, we showed that the value of advance demand information is highly dependent on operational constraints as well as on the quantity of information that is provided. The general findings are in accordance with previous findings that a heavily loaded system struggles to benefit from advance demand information (Karaesmen et al., 2004) and that a highly flexible system attenuates the value of advance demand information (Wijngaard, 2004). However, further insights can be gleaned from our results. In particular, we showed that most of the benefits are achieved with only a single period of advance demand information. Additionally, the benefits of advance demand information are strongly influenced by volume flexibility, and the strongest influence is observed with a capacity increase of only a few percentage points. This study contributes to the literature in the sense that it demonstrates the necessity of complete integration of the dynamic relationship to assess the benefits of advance demand information. In particular, the highly realistic interaction between the manufacturer's volume flexibility and the amount of information provided is likely to strongly influence the resulting improvements, even if this interaction induces only a small

increase in the available capacity. When evaluating a supply chain, great care should be put into identifying all of the changes induced by an alternative strategy. Further, it is interesting to consider realistic situations using suboptimal policies, as it highlights some counterintuitive results that are not considered in state-of-the-art policies. As highlighted by Cachon and Fisher (2000), the improvements resulting from information sharing are closely related to the operational characteristics of the system.

An important contribution from this work is also to propose and to illustrate a method to analyze and quantify the value of advance demand information for specific real-life supply chain using simulation. The step-by-step approach proposed in this work, consisting in studying the relevant dynamic relationship and in modeling them to ensure the behavior of the system is preserved, is not limited to the situation studied in this work. This method can be replicated in distinct setting to allow for a more accurate decision making.

When the methodology is not, these results of the study remains however specific to the case considered. Nevertheless, they are believe to provide some interesting insights into possible causes for unrealized benefits from improvements in advance demand information. Extending this work to different empirical settings, that is, based on distinct supply chain characteristics, would strengthen the contribution of this study. One further research direction is to analyze in detail and quantify the impact of advance demand information on the volume flexibility of the manufacturer. This knowledge will allow better insights into the benefits related to demand information and enable a better understanding of improvements in the specific cost structure of a given system. Additionally, an assessment of the lead-time parameters required by traditional inventory policies, in terms of the procedure of approximation and the frequency of updates, seems to be critical to fully realizing the benefits of improved demand information and enhancing the integration of production and inventory.

Chapter 5

Inventory Control with Seasonal Demand: The Trade-off between Safety Stock Variability and Accuracy

5.1 Introduction

To satisfy demand in a sustainable way, supply chain processes must be prepared to cope with variable and only partially predictable supply and demand. In inventory management, a common strategy to hedge these uncertainties is to constitute safety stocks. This approach is used extensively in practice, and numerous procedures have been proposed to optimize the inventory level regarding key parameters such as target service level, variability of the demand, and variability of the replenishment lead time. However, a critical pitfall of these procedures is that they assume both the demand and the lead time to be independent and identically distributed variables. Unfortunately, considering empirical data, these assumptions are not always fulfilled, leading to inappropriate inventory levels and inaccurate service levels (Snyder et al., 2002).

A well-known driver of non-constant demand variance is seasonality. For seasonal products, the means and the standard deviations of in- and out-season periods are very likely to differ (Brown, 1959). Figure 5.1 illustrates this phenomenon with the weekly sales figures of a seasonal product from the retail industry. It can be observed that the demand moments for the in-season periods (from mid-October to mid-January) are clearly different from those for the out-season periods.

Seasonal changes in demand levels are commonly predicted from seasonal-sensitive

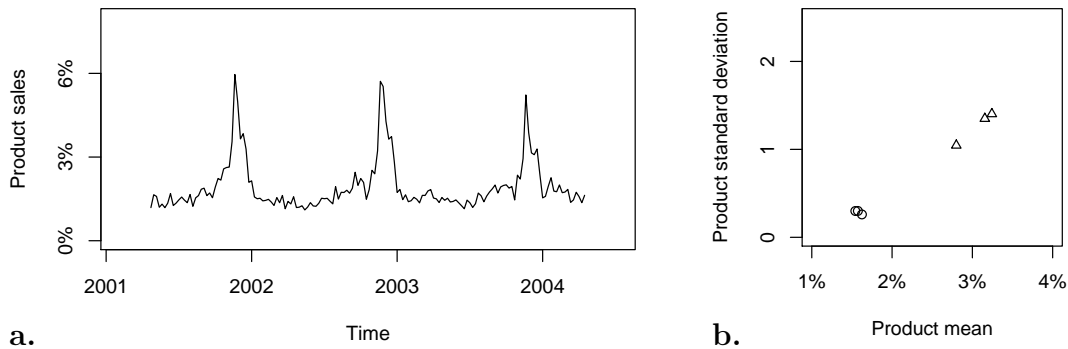


Figure 5.1: (a) Weekly sales figures of a seasonal product from the retail industry. Sales data extends from May 2001 to May 2005 and is expressed in percentages of the average sales per year. (b) The means and standard deviations of the in-season demand (triangles) are clearly bigger than for out-season periods (circles).

forecasting methods, such as the seasonal exponential smoothing method (Mentzer and Moon, 2005). However, the seasonal variability of the demand standard deviation has received considerably less attention and is often neglected. Traditionally, the estimation of the standard deviation of the demand is assessed directly from sets of historical demand data gathered during the last few years and fails to capture the seasonal variability of this parameter. Consequently, this overestimates demand variability during out-season periods and underestimates it during peak periods. As highlighted by Snyder et al. (2002), in-season underestimations of inventory levels are highly negative as they occur during the most profitable period. Integrating seasonal variations of the standard deviation of the demand in inventory management models is therefore of interest, and several authors have recently proposed methods fulfilling that objective (Snyder et al., 2002; Herrin, 2005; Mattsson, 2010). However, integrating this seasonality will by definition result in more variable estimates of the demand standard deviation. This extra variability is likely to pass to the replenishment order variance and then increase the bullwhip effect. Consequently, the negative impact of the resulting increase of variability will potentially cancel out the benefits of more accurate estimates.

For this study, we used a two-stage supply chain simulation model to evaluate the benefits of forecasting the standard deviation of the demand and to evidence a potential trade-off between the variability and the accuracy of this parameter. The experiment is built on empirical demand and shows the importance of a holistic and dynamic evaluation of the processes when considering changes that affect the supply chain dynamics.

The paper is structured as follows. Section 5.2 discusses the theoretical background of the research, focusing on the dynamic aspect of the supply chain. Section 5.3 details the experiment. Section 5.4 provides a numerical illustration of the impact of supply chain

dynamics when evaluating practices related to the variability of the system. Finally, section 5.5 develops conclusions, details the limitation of this study, and discusses further research.

5.2 Literature review

Estimation of the lead time demand is a cornerstone of inventory management and implies the forecasting of the level of demand and its variability (see e.g., Silver et al., 1998, for a comprehensive review on inventory models). Forecasting the demand level itself is widely discussed in the literature and commonly applied in practice. For instance, (Mentzer and Moon, 2005) identified 70 demand forecasting procedures based on time series techniques alone. But forecasting of the standard deviation of the demand has received considerably less attention. Traditionally, the standard deviation of the demand is estimated from direct measurement of historical demand observed during the last few years. Alternatively, some authors have proposed to use the relationship with the mean of the demand to predict the variance (Boylan and Johnston, 1996). The relation between the mean and the variance of random demand variations was first identified by Brown (1959), who stated that the standard deviation of demand is likely to be nearly proportional to the total annual usage, or to the average monthly usage. Later, several authors characterized this relationship, allowing for distinct forms of dependency such as linear, power form (Brown, 1959), or quadratic (Burgin and Wild, 1967). This topic is of particular interest in the context of seasonal demand where the demand level as well as the demand variance are likely to present non-stationary patterns (see Figure 5.1 for an illustration of this statement). Forecasting is then of main importance to anticipate the changes in demand level as well as in demand variance. However, despite the commonness of seasonality, few studies have tackled the problem of forecasting the standard deviation for seasonal random variations (Mattsson, 2010).

In recent literature, Herrin (2005) proposed a method where the standard deviation of the demand for a given period is estimated from the demand during the last years at the same period. (Mattsson, 2010) forecasted the standard deviation of the demand during lead time based on the forecasted demand level and information on the last year's de-seasonalized demand. This method is based on the power form of the variance law where the power coefficient must be defined. The author mentioned a set of heuristics from van Hees and Monhemius (1972) to identify the relevant coefficient. Snyder et al. (2002) used state space models for exponential smoothing methods with a single source of error together with a bootstrap approach to estimate the variance of the error of the forecasted lead time demand. In this last case, the authors estimated the standard deviation of the forecast error instead of the standard deviation of the demand itself, but

the aim of the research was the same, i.e., improving the inventory control by integrating non-constant variance resulting from seasonal demand. According to Chen et al. (2000), there exists a simple relationship between the two quantities, i.e. the standard deviation of the forecast error and the one of the demand. However, the error of the forecasted demand during lead time is more appropriated in safety stock calculation as it provides a more conservative inventory policy because the standard deviation of the error of the forecast captures the demand uncertainty plus the uncertainty related to the estimation of the demand when the standard deviation of the demand captures the uncertainty of the demand (Chen et al., 2000).

Despite being integrated into distinct inventory policies with different supply chain settings, a common point of the prediction methods presented above is that they always succeed, in their respective study, to improve the inventory control and to provide superior service level compared to the case where inventory levels were assessed without consideration of the non-constant variance of the demand. Nevertheless, a critical point of these evaluations is that they were performed without considering the impact of the method on the variability of the system. Traditional methods to assess the standard deviation of the demand during lead time, such as those based on direct measurement of historical data, tend to smooth the value of the parameter as in- and out- season demand figures are merged in the historical dataset used. On the other hand, the prediction methods integrate the non-constant nature of the variance of the demand and provide therefore more variable estimates. It is clear that the extra variability will echo the order quantity (through the inventory policy) and potentially influence the dynamic of the system.

Supply chain dynamics is a tremendous issue in operations management. Inspired by the work of Forrester and Wright (see e.g., Forrester and Wright, 1961), numerous authors have contributed to the understanding of the dynamic relationships existing between supply chain partners (see e.g., Sterman, 2000). In this context, the bullwhip effect (the demand amplification along the supply chain from customer to raw material suppliers) is of main interest. This phenomenon is known to lead to negative supply chain performance as it exacerbates the supply chain costs (stock holding, backlog, late delivery, or under/over resource utilization) (Huang et al., 2003). Lee et al. (1997) provided a detailed description of the bullwhip effect and identified among others causes the rational update of management parameters-such as forecast values or inventory target level-as an important driver of the bullwhip effect. The aforementioned cause is closely related to this study as the prediction methods might lead to a bigger update of the target inventory level due to the increased variability of the demand moments estimation or alternatively the subjects of forecast error. Beyond the dynamic effects themselves, it is necessary to integrate their impact into system performance. In particular, more

variability in the order pattern can potentially affect the lead time distribution. As summarized by Boute et al. (2007), when supply lead times are generated by a finite-capacity production system, the variability in demand has a direct impact on the variability of the lead times because demand variability determines the arrival pattern of production orders and the backlog. In addition, large orders require longer production time (and consequently replenishment time), causing longer lead time, which induces larger order size. This impacts the demand during lead time and consequently influences the inventory distribution. Benjaafar et al. (2005) noted that treating production systems and inventory systems as independent units is realistic under limited circumstances, such as when inventory and production are decoupled through large inventory buffers at the production facility or at subsequent stages of the supply chain (when a local retailer is replenished from the large regional warehouse). It may also be reasonable when the inventory and production systems belong to separate entities, with the owner of the production system guaranteeing a fixed delivery date. Similarly, it might be justified when, for instance, transportation lead times are significantly longer than manufacturing lead times. However, for most of integrated systems, these assumptions rarely hold. Consequently, distributors and retailers can be immediately affected by congestion and delays on the factory. In this context, production/inventory models (where the interaction between the systems is explicitly modeled) are of particular interest. In such models, the inventory system influences the production system by initiating orders, and the production system influences the inventory system by completing and delivering orders to inventory. In contrast to the conventional inventory model, where lead times are defined as exogenous variables, the lead times in production/inventory systems are endogenously controlled by the production system (Boute et al., 2007). For instance, Kim (2008) provided evidence as to how conventional models can fail to provide accurate results when neglecting production/inventory interactions. Also, production/inventory systems are necessary to capture existing trade-off in supply chain dynamics as with, for instance, the relationship between replenishment order pattern and on-hand inventory pattern (Disney and Towill, 2003).

Finally, it is noteworthy that the evaluation must be performed based on multiple supply chain performance measures. As observed by Beamon (1999), multiple performance measures are required to highlight potential trade-offs between indicators. In addition, Reiner and Fichtinger (2009) showed that the bullwhip effect is an important but not the only performance measure that should be used to evaluate process improvements. Therefore, this study considers the variability of the system through the variances of the on-hand inventory, of the retailer order, and of the lead time. It also looks for the efficiency as well as the effectiveness of the supply chain by analyzing the average on-hand inventory and the customer service level (Reiner, 2005).

5.3 Study Description

To illustrate the need for integrating the impact of the dynamics into the performance evaluation of supply chain practice improvements, this study focuses on the settings of a single seasonal product and details the interactions between a manufacturer, a distribution center, and the customer (the network of retailers). It uses a simulation model to assess the impact of the dependency between the order pattern and the lead time on the performance evaluation of an inventory model using either a prediction or a traditional method to compute the standard deviation of the forecast error during lead time.

5.3.1 Seasonal Demand

Three years of weekly sales for the seasonal product were analyzed and is presented in Figure 5.1. As observed in the introduction, both the mean and the standard deviation of the sales of this product are dependent on the period (in- or out-season). The assumption of constant variance is therefore not verified, and the estimation of the required safety stock to achieve a target service level is no longer straightforward. To study the dynamics of this issue for a relevant number of periods, weekly sales data were generated presenting the same characteristics as the empirical sample. This study modeled the demand for each week from normal distributions with specific means, μ_p , and standard deviations, σ_p , where p is the index of the week. The study also assumes these parameters to be linearly dependant. This assumption of a linear relationship seems reasonable when observing the second part of Figure 5.1. In addition, as explained by Mattsson (2010), it is correct to assume a linear relationship between the standard deviation and the mean of the demand if the changes in demand are related to the size of the orders and not to the number of orders. This last statement corroborates this study's illustration settings as the number of customers (the number of retailers of the network) is constant, and each is ordering on a periodic basis. Therefore, σ_p is expressed as a linear function of μ_p :

$$\sigma_p = \alpha\mu_p + \beta, \quad (5.1)$$

where α and β are constants defining respectively the slope and the intercept of the relationship. The estimation was performed using linear regression, where $\alpha = 0.13$ and $\beta = -97$ (both parameters were significant with $p < 0.001$). The generated sales data reproduces satisfactorily the pattern of the empirical sampling. First, the periodic behavior of the generated data is visually similar to the empirical demand. Second, the relationship between the mean and the standard deviation of the in- and out-season period is preserved. Figure 5.2 shows a sample of the generated data as well as the resulting relationship between per period means and standard deviations.

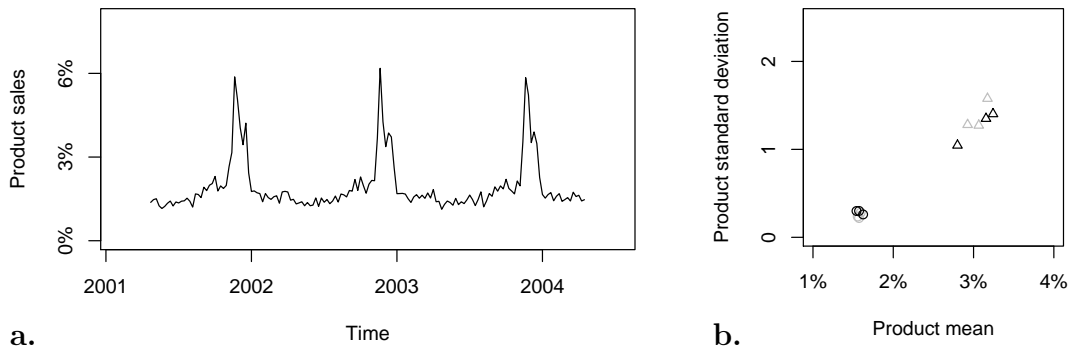


Figure 5.2: (a) Example of simulated weekly sales figures of a seasonal product based on the empirical data presented in Figure 5.1. (b) The means and standard deviations of the in-season demand (black triangles) and out-season periods (black circles). In gray is a reproduction of the per period first two moments of the empirical demand.

5.3.2 Supply Chain Model

This study models a two-stage supply chain based on the actual situation of a distribution center dedicated to a retail network in Europe. The distribution center aims at fulfilling periodic orders from the retailers directly from its on-hand inventory and uses an order-up-to inventory policy to periodically replenish its inventory. At the end of each period, the distribution center checks its inventory position and determines how much to order based on its replenishment policy. The quantity ordered in period t , Q_t , will be received at time $t + l_t$, where l_t is the observed lead time associated with this order. Retailers aggregated demand, D_t , which is observed at the end of the period t and fulfilled through on-hand inventory. Any unfulfilled demand is backlogged.

This study considers a model integrating the dependency between the order quantity and the lead time. The lead time at time t , l_t , is therefore formally defined as

$$l_t = f(Q_t), \quad (5.2)$$

where $f(Q_t)$ is a function of the order quantity at time t , Q_t , selected to model the relationship between the order workload and the lead time. The lead time is therefore endogenously determined by the replenishment order which enables the development of potential dynamic impact between the inventory system and the production system. More details regarding this dependency will be provided in the illustration presented later. The order quantity to replenish the inventory of the distribution center is based on an order-up-to inventory policy (see e.g., Silver et al., 1998), where the order-up-to point S_t is periodically computed from the observed lead time demand as

$$S_t = \hat{D}_{L_t} + z\hat{\sigma}_{L_t}, \quad (5.3)$$

where \hat{D}_{L_t} is an estimate of the mean of the L period demand; $\hat{\sigma}_{L_t}$ is an estimate of the standard deviation of the demand over L periods; and z is the safety factor. Note that L is defined here as the replenishment lead time period (the lead time plus the length of the review period). The distribution center assesses the demand during lead time from retailers based on historical data. It uses seasonal exponential smoothing (Winters, 1960) to predict the aggregated demand up to the necessary horizon. Knowing that the distribution center faces seasonal demand with non-constant variance, an interesting step is in assessing the standard deviation of the demand during lead time. This study uses the classical equation originally developed by Hadley and Whitin (1963), which takes into account both the variability of the lead time and the variability of the demand:

$$\hat{\sigma}_{L_t} = \sqrt{\hat{\sigma}_{e_t}^2 + \hat{\sigma}_{l_t}\hat{\mu}_t^2}, \quad (5.4)$$

where $\hat{\mu}_t$ is an estimate of the demand mean; $\hat{\sigma}_{l_t}$ is an estimate of the lead time standard deviation; and $\hat{\sigma}_{e_t}$ is an estimate of the standard deviation of the forecast error during lead time. Note that the standard deviation of the lead time demand $\hat{\sigma}_{L_t}$ is replaced by the standard deviation of the forecasting error during lead time $\hat{\sigma}_{e_t}$ as in Fichtinger et al. (2009). As explained by Chen et al. (2000), this modification is more appropriate as σ_{e_t} captures the demand error uncertainty related to the estimation of the demand plus the uncertainty of the demand. Moreover, there exists a simple relationship between these quantities, i. e. $\sigma_{e_t} = c\sigma_{L_t}$, for $c \geq 1$.

To evaluate the impact of the supply chain dynamics regarding the introduction of a prediction method to estimate the standard deviation of the forecasted error during lead time, two methods are considered to assess the standard deviation of the forthcoming forecast error during lead time (the traditional and the prediction methods). These methods are detailed below.

- *Traditional method.* This method consists of estimating σ_{e_t} based on historical data. Formally, the standard deviation is calculated from the vector of the past errors for a given period. In this illustration, this estimation is based on the errors realized in the last three years.
- *Prediction method.* This method consists of estimating σ_{e_t} based on the method from Mattsson (2010). This method is originally for the standard deviation of the demand during lead time; however, based on the simple relationship existing between the two quantities, $\sigma_{e_t} = c\sigma_{L_t}$ (Chen et al., 2000), it is possible to convert it into a prediction method for σ_{e_t} . The method can be written as

$$\hat{\sigma}_{e_t} = c \cdot \left(\frac{\hat{D}_{L_t}}{\hat{D}_{L_y}} \right) \cdot \hat{\sigma}_{L_y}, \quad (5.5)$$

where \hat{D}_{L_y} and $\hat{\sigma}_{L_y}$ are respective estimates of the average demand during lead time last year and of the standard deviation of the de-seasonalized demand last year. The constant c is estimated as the ratio of the standard deviation of the historical forecast errors during lead time and the average of the historical predicted standard deviation of the demand, both estimated on a three-year history. The performance of the system is assessed based on a selection of performance measures.

First, the customer service level is evaluated as the percentage of period per year facing stock out. Also, for further insight into the performance of the system, a per period service level is computed, creating the distinction between the in- and out-season periods.

Second, the yearly average on-hand inventory at the distribution center is considered. While the on-hand inventory can be seen as a proxy for inventory related to costs (such as holding cost), the service level refers to the ability of the distribution center to satisfy its customers, the retailers. In addition, this performance evaluation includes performance measures related to the dynamics of the supply chain. The variability of the quantities ordered by the distribution center for the supplier is measured, as is the variability of the on-hand inventory at the distribution center. Both variability measures are assessed on a yearly basis. Finally, the first two moments of the lead time are assessed to complete the overview of the variability of the flows between the supplier and the distribution center.

5.4 Illustration

First, the difference induced by the two methods of assessment of the forecast error during lead time is illustrated. Second, the performance of these methods is evaluated, taking into account the dynamics of the supply chain. This study modeled the lead time as linearly dependent from the order quantity. Formally, l_t is modeled as a random variable, normally distributed with mean μ_{λ_t} defined as

$$\mu_{\lambda_t} = \delta \left(\frac{Q_t - \bar{Q}_t}{\bar{Q}_t} \right), \quad (5.6)$$

where \bar{Q}_t is the average order quantity, and δ is a constant defining the strength of the relationship between the lead time and the deviation of the order quantity Q_t from its average \bar{Q}_t . Therefore, the link between the order quantity and the lead time is triggered by the deviation of the order quantity Q_t from its long-term average. The standard deviation of the lead time random variable is set as a constant. We use a linear

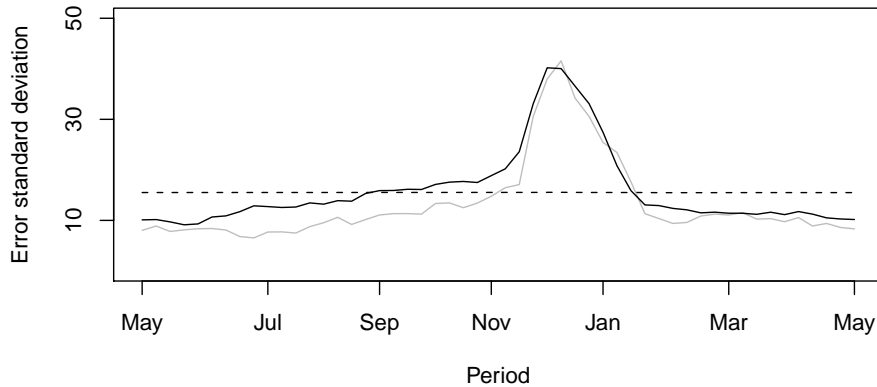


Figure 5.3: Estimations of the per period average forecast error during lead time for a fixed lead time of 2 based on direct evaluation from the simulated data (gray line), on the traditional method (dashed line), and on the selected prediction method (black line).

relationship instead of the exponential relationship between workload and lead time (Suri, 1998) to avoid the strong assumption regarding the supplier capacity (empirical data according to the capacity of the supplier was not available). The relationship established in this study preserves the nature of an endogenous production/inventory model despite the fact that the capacity of the supplier is not explicitly modeled. The model is developed under Matlab Simulink v7.8 (The Mathworks, 2010), and the verification of the model has been realized through a careful step by step control of the behavior of the model. In addition, the model is validated by confirming that when fed with i.i.d normally distributed inputs for both the lead time and the demand (when demand and lead time were exogenous i.i.d normal variables), the model provided results in accordance with the theory.

To visualize the differences induced by the two methods, the average forecast error (based on the seasonal exponential smoothing method) during lead time is assessed for a fixed lead time of two weeks. This computation is performed using 100 years of seasonal demand generated based on the model presented in section 5.3.2. In addition, taking advantage of this amount of data allows a comparison of the later results with an empirical estimation of the realized per period average forecast error during lead time for the same fixed lead time of two weeks. The results of this evaluation are presented in Figure 5.3.

As seen in Figure 5.3, the direct estimation from the simulated data presents a clear pattern, attesting to the conservation of the non-constant variance of the demand in the variance of the error of the forecasted demand during lead time. Second, the two methods proposed above to assess σ_{et} lead to clearly distinct estimations. The traditional method provides a stable estimation that by turns over- and under-estimate the true variability. On the other hand, the prediction method gives highly variable estimations of remarkable

accuracy. This first result is in accordance with the expectation presented in section 5.2 (accuracy is related to variability, and therefore to potential negative consequences on the system performance).

Next, the performance of these methods are evaluated, taking into account the dynamics of the supply chain described above. The supply chain processes for 100 year-cycles for distinct δ values between 0.0 and 1.0 are simulated (from a lead time independent of the order quantity to a strongly dependent lead time). For this illustration, the standard deviation of the random lead time variable is fixed at 0.2, and the desired service level is set at 98%. Figure 5.2 presents the results obtained for both methods in terms of order quantity standard deviation, lead time standard deviation, service level, and average on-hand inventory. All the results present the average of the yearly results for the 100 year-cycles.

First, the variance of the order quantity is, as expected, higher when orders are generated from the prediction method (Figure 5.4a). This is coherent with the results presented in Figure 5.3, as safety stock suffers more fluctuations when computed using the prediction of the standard deviation of the demand during lead time. This difference in variance is strongly significant under all δ values (Wilcoxon test, p-value < 0.001).

Next, lead time variability increases with regard to the strength of the relationship between the order quantity and the lead time. Again, this result is in accordance with expectations because the amount of order variability “transmitted” to the lead time is proportional to the strength of the coefficient δ . The variability of the lead time increases faster when using the prediction methods, inducing, for high δ , significant differences in between the two methods (Wilcoxon test, p-value < 0.01 for $\delta \geq 0.6$) (Figure 5.4b). This resulting extra variability in the lead time obtained with the prediction method is in accordance with the literature review.

As hypothesized above, this has an impact on the service level. As evident in Figure 5.4c, the improvement issued from the prediction method when lead time is weakly related to the order quantity, vanishes when δ gets stronger. This decrease in service level is analyzed further below. Finally, Figure 5.4d shows that the two methods provide different average on-hand inventories. The prediction methods lead to more inventory than the traditional methods, and this difference increases with δ .

Table 5.1 presents the complete results for all the performance measures obtained for δ equals 0.0, 0.5, and 1.0. Starting with $\delta = 0.0$, it can be observed that the average yearly service levels outperform the target service level of 98% for both methods. These results might seem surprising as one could have expected seasonality to degrade the service level and not improve it. However, as shown in Figure 5.3, both methods underestimate the standard deviation of the forecast error during lead time for most of the periods. Underestimations only occur during the in-season period, as expected by Snyder et al.

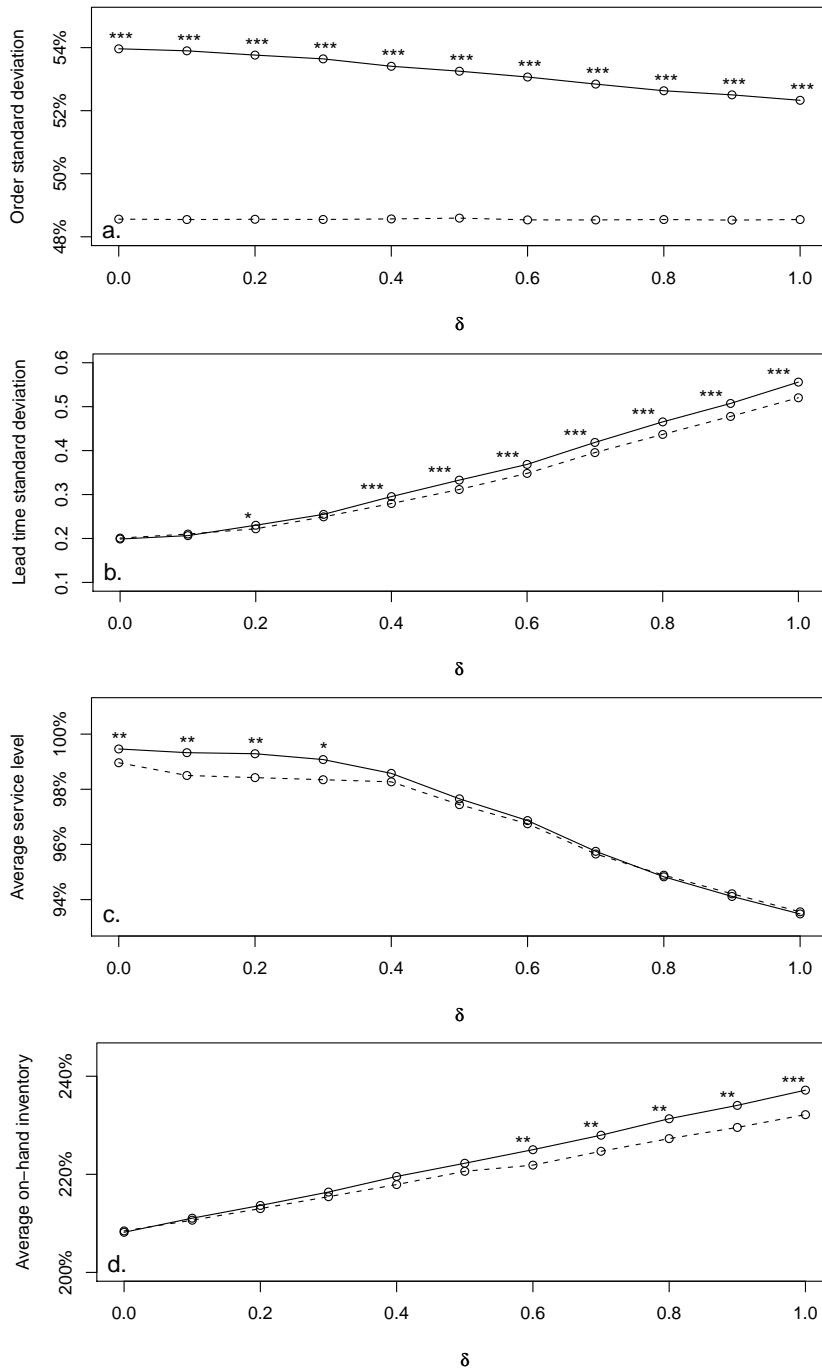


Figure 5.4: Performance results for the traditional method (dashed line) and the prediction method (black line) regarding δ for the standard deviation of the order quantity (a); the standard deviation of the lead time (b); the average of the service level (c); and the average on-hand inventory level (d). All the performances are expressed as averages of the yearly results and quantities are expressed in percentages of the average demand. Significance of the difference between the two methods is established based on Wilcoxon test with $*p \leq 0.05$; $**p \leq 0.01$ and $***p \leq 0.001$.

(2002). This observation is in accordance with the service levels obtained for the in- and out-season periods. When the traditional method failed to maintain the target service level during in-seasons (due to the strong underestimation of σ_{e_t}), the prediction method succeeded in maintaining it. This observation is in accordance with theory, and the results confirm that the prediction method proposed by Mattsson (2010) indeed provides better performance when lead time is independent of the order quantity. The results obtained for the other performances measures with $\delta = 0.0$ are similar for the two methods, with the exception of the variability of the order quantity as discussed above, and also the variability of the on-hand inventory.

Next, the detailed results for $\delta = 0.5$ and 1.0 are considered. In these cases, the lead time is endogenously influenced by the order quantity. This can be observed by looking at the lead time standard deviation. The variability of the lead time is increasing with δ , and that phenomenon is stronger for the prediction method results (due to its induced higher order variance). This has a direct influence on the service level. The decrease in service level is related to the increase of the strength of the relationship between order quantity and lead time—to δ . The stronger the coefficient, the lower the performance. This is triggered by the in-season service level. In addition, the service level decreases faster for the prediction method than when using the traditional method. With a δ of 0.5 , the service level obtained with the prediction method is similar to the one obtained from the traditional method. This is true as well for $\delta = 1.0$, but in this case, the prediction method fails to provide a better service level despite average on-hand inventory being significantly higher. Therefore, with respect to this study, the relationship between order quantity and lead time is leveraging a trade-off between the accuracy of the standard deviation of the demand during lead time used to control inventory and the resulting order variability induced.

5.5 Conclusion and Further Research

This study first illustrates the increase variability of the system induced by using a prediction method to estimate the standard deviation of the lead time forecast error. Although the traditional method tends by nature to provide more stable but inaccurate estimations, the prediction method leads to more accuracy, but also to more variability. Second, this study provides evidences on the lack of impact from the extra order variability when considering an evaluation model that decouples the production and the inventory processes. In this case (lead time independent from the order quantity), the results are in accordance with the results obtained in the literature Snyder et al. (2002); Herrin (2005); Mattsson (2010), i. e., forecasting the variability allows for a better inventory control. However, as stated by Benjaafar et al. (2005), for most integrated systems, the assump-

Table 5.1: Detailed of the performance results for δ values of 0.0, 0.5 and 1.0. Results are summarized based on per year outputs averages. Inventory and order quantities are expressed as percentages of the average sales per period.

Parameter	Traditional method			Prediction method		
	Min.	Avg.(Std.)	Max.	Min.	Avg.(Std.)	Max.
$\delta = 0.00$						
Avg. lead time	1.94	2.00 (0.03)	2.06	1.94	2.00 (0.03)	2.08
Std. lead time	0.15	0.20 (0.02)	0.24	0.15	0.20 (0.02)	0.27
Avg. on-hand inv.	196.50	208.46 (4.02)	215.98	197.11	208.18 (4.39)	219.04
Std. on-hand inv.	82.92	103.34 (8.13)	122.82	96.73	109.63 (11.71)	164.87
Avg. order qty	97.17	100.02 (1.44)	104.89	96.61	100.02 (1.49)	105.34
Std. order qty	40.93	48.56 (3.63)	65.41	43.00	53.96 (6.61)	83.57
Service level	94.23	98.96 (1.40)	100.00	94.23	99.46 (1.13)	100.00
Service level Out	97.50	99.98 (0.25)	100.00	95.00	99.90 (0.61)	100.00
Service level In	75.00	95.58 (5.86)	100.00	75.00	98.00 (4.60)	100.00
$\delta = 0.50$						
Avg. lead time	1.93	2.01 (0.03)	2.07	1.92	2.00 (0.03)	2.07
Std. lead time	0.24	0.31 (0.03)	0.38	0.25	0.33 (0.04)	0.43
Avg. on-hand inv.	206.68	220.61 (6.13)	237.86	208.38	222.26 (6.51)	240.87
Std. on-hand inv.	120.19	143.32 (11.82)	181.89	126.26	155.27 (17.58)	235.67
Avg. order qty	97.02	100.02 (1.46)	105.02	96.85	100.02 (1.46)	105.23
Std. order qty	41.18	48.59 (3.64)	65.22	42.25	53.25 (6.31)	81.17
Service level	90.38	97.44 (2.43)	100.00	92.31	97.65 (1.89)	100.00
Service level Out	100.00	100.00 (0.00)	100.00	100.00	100.00 (0.00)	100.00
Service level In	58.33	88.92 (10.53)	100.00	66.67	89.83 (8.17)	100.00
$\delta = 1.00$						
Avg. lead time	1.93	2.00 (0.03)	2.09	1.93	2.00 (0.03)	2.09
Std. lead time	0.44	0.52 (0.04)	0.63	0.46	0.56 (0.06)	0.76
Avg. on-hand inv.	214.24	232.17 (8.21)	256.12	217.39	237.17 (10.29)	278.52
Std. on-hand inv.	153.59	184.50 (16.54)	230.08	149.67	197.49 (23.65)	291.14
Avg. order qty	96.94	100.02 (1.47)	105.08	96.80	100.02 (1.48)	105.12
Std. order qty	41.02	48.55 (3.65)	65.26	41.64	52.33 (5.92)	79.53
Service level	88.46	93.56 (2.00)	98.08	88.46	93.48 (2.06)	98.08
Service level Out	100.00	100.00 (0.00)	100.00	100.00	100.00 (0.00)	100.00
Service level In	50.00	72.08 (8.65)	91.67	50.00	71.75 (8.93)	91.67

tions of independence between production and inventory systems rarely hold in reality. Therefore, this analysis is extended by integrating a linear dependency between order pattern and the lead time. This relationship enables the integration of effects such as for instance the production time related to the order quantity and potential backlog at the supplier. These phenomena are common and, to be avoided, substantial investments in flexibility are required. The results obtained with the enhanced model evidenced the trade-off between accuracy and variability in assessing the inventory level when the dependency between the order pattern and the lead time is explicitly modeled. In this setting, the negative impact of the extra variability induced by the forecasted estimation of the lead time forecast error are likely to overshoot the benefits of the improved accuracy. This phenomenon might have strong implication for the discrepancies sometimes existing between expected improvements (estimated from incomplete simulation or analytical models) and the realized performance in practice. We believe this is of interest for practitioners at the time of considering implementing a standard deviation forecast method in their inventory policy.

A clear limitation of this study is that it relies on a single demand pattern. The generalization of seasonal products is therefore not allowed. However, by analyzing the impact on the dynamics as well as on the performance itself, this study evidences a general phenomenon. In addition, the literature generally considers an exponential relationship between the variance of the order quantity and the lead time. This exponential behavior is easily evidenced based on queuing theory (Hopp et al., 2001). However, implementing such exponential pattern in this model would imply difficult assumptions, in particular concerning the capacity constraints of the supplier. The linear relationship enables a more generic model and at the same time is sufficient to illustrate this study's statement. Models including an exponential relationship would exacerbate the negative impact of increased order variability, leading in the end to similar conclusions.

Finally, it is obvious that prediction methods offer great opportunities for improvement, and further research should aim at combining these methods with other practices in order to dampen the induced extra variability. In this context, techniques to anticipate the in-season safety stock increase might be of interest.

Chapter 6

Conclusion

The overall objective of the thesis was to extend the understanding of the dynamic relationships between uncertainty, flexibility, and performance in the supply chain. Little consideration has been given in the literature to the mechanisms underlying supply chain flexibility. To contribute to this issue, the aim of this dissertation was to investigate the interactions between practices enabling flexibility and consider their relationships to uncertainty and performance. Further, This work sought to take advantage of the knowledge developed to explore potential benefits from the modeling point of view. Offering better evaluation tools to test and challenge existing theory as well as proposing to practitioners better model-based decision support are obvious assets from improved supply chain models.

It is clear from the literature underlying this research work that supply chain dynamics studies require to further integrate the specific characteristics of the network under study and to better understand their impact on the dynamics and the performance of the system. In particular, it stressed the necessity for deeper understanding of the interaction between flexibility enablers and uncertainty in order to strengthen the knowledge of supply chain dynamics. This knowledge is needed to develop more realistic supply chain models that will provide better decision support.

Based on the analysis of survey data, the first study directly contributed to this understanding by providing evidence of interactions between specific supply chain flexibility enablers. The analysis of the interaction between forecasting, flexibility enablers and performance provided interesting insights on their relationships. After confirming the positive influence of forecasting on both effectiveness and cost efficiency, this study analyzed how these relationships develop. It showed that the relationship between forecasting and effectiveness is mainly due to process flow management, while the relationship with cost efficiency is mainly due to layout. Therefore, this study not only provided

evidence of the existing relationships between forecasting and performance, but it also provided as well some insights on the causality of this relationship. In particular, the study showed that the availability of additional information helps the actors involved in a specific process to make prompt decisions and align different units that manage each separate part of the production process. The performance improvements (i.e., increased cost efficiency as well as effectiveness) related to improved forecasting can then be magnified by process or layout modifications. The latter can therefore be seen as a motivation for the other studies because it highlights that the impact from uncertainty reduction is not fully direct, but tempered or magnified by the specific operational characteristics of supply networks. Such interactions should therefore be integrated into evaluation models in order to provide accurate insights on the system under consideration.

The latter is confirmed based on simulation studies. First, the study presented in Chapter 4 showed that, for the specific settings of the study, the benefits from the uncertainty reduction provided by advance demand information are strongly influenced by the production and inventory management constraints engaged in the supply network. In general, the extent to which uncertainty is reduced is of importance; however, this importance depends on the operational characteristics of the network. In particular, the value of advance demand information is magnified by the realistic situation where uncertainty reduction enables the manufacturer to improve the alignment of its production capacity with the forthcoming demand. Also, the value of the advance demand information is dependent on the policy regulating the interaction between the distribution center and the manufacturer. All these interactions combine to determine the ability of the supply chain to satisfy demand in an effective and efficient manner and are therefore of critical importance to support decision making.

Next, the study presented in Chapter 5 of this research work demonstrated the potential trade-off existing between safety stock accuracy and safety stock variability in inventory control with seasonal demand. This chapter showed how the improvement achieved in adapting the safety stock to the fluctuation of the variability of the perceived uncertainty (i.e., the non-constant variability of the forecast error) is balanced by the resulting increase in replenishment order variability. Further, this study demonstrated that this dynamic dependency can only be captured if the relationship between the capacitated production system and the inventory system is explicitly modeled (i.e., the lead time is endogenous).

From a research perspective, these findings contribute to the understanding of supply chain dynamics, and in a general manner, emphasize the importance of these dynamics on supply chain performance. In line with the theory presented in the literature review, the results obtained in this dissertation confirm the importance of companies' specificities

on the network behavior. In particular, the capabilities provided by each member of the supply chain determine the level of variability in the system and its performance. This observation might help to explain the contrasting results provided by similar supply chain improvements, but in networks that are composed of different operational characteristics (Cachon and Fisher, 2000). Moreover, this work suggests that the specificity of a network is not only conferred by its capabilities, but also by the interaction between these capabilities. The evidence from the first study (based on survey data) clearly suggests that the improvements related to forecasting improvement are not direct but instead are modulated by the flexibility enablers engaged by companies. Consequently, when evaluating a supply chain, great care should be given to its specific characteristics (i.e. flexibility enablers).

Quantifying the potential benefits of new practices in a supply network accurately and in advance is highly relevant for decision support. In this context, model-based evaluation constitutes a privileged tool for decision support. It enables to test distinct decision alternatives in a risk-free environment and, to build on that knowledge in an effort to select the best option. However, valuable decision support can only be delivered by reliable models. This means that the evaluation should be based on models that are realistic enough to provide meaningful insight into the expected performance or behavior of the system.

The findings of this dissertation highlight the necessity to rely on integrated production and inventory models. The assumption that the production system is independent from the inventory system is generally unrealistic, and this research work indicated the mistaken results that can be obtained when neglecting this dependency. In addition, this research work notes that the interaction between the inventory and production systems is potentially dynamic. Production facilities are potentially able to adjust their capacity on the demand (or on the expected demand). These adjustments are dependent on the company's level of flexibility, or the flexibility resulting from its flexibility enablers as well as from its interaction, as well as on the degree of uncertainty that is faced. The impact of these parameters on the performance of the system has been shown to be important, and these interactions should therefore be integrated in the evaluation. Despite its challenges, this complexity should not be altered for over-simplified models to avoid potential mistaken results (Chapters 4 and 5).

The results from Chapters 4 and 5 are clearly difficult to extend beyond the specific settings considered in each study. However, these findings put some perspective to the contributions issued from stereotypical ("idealized") supply chain evaluation problems that are provided in the literature. While these general models offer insight into general behavior that potentially occurs in reality, the related performance evaluation might

seem questionable, especially considering the simplification of the dynamic relationships. Indeed, the strong influence observed in this research work that was generated from interactions between flexibility enablers suggest that these relationships should, in any case, be neglected. By opposition to the specificity of the results from these studies, the methodology presented in chapter 4 and 5 can be generalized. Indeed, analyzing the key interaction in a system and then integrating them properly in the supply chain model as illustrated in this work is of key importance and the illustration provided in the modeling studies clearly support this statement. From these perspective, this studies propose examples of a step-by-step methodology to properly investigate a system and derive an appropriate model.

This research work also suggest some managerial implications. First, the interest of forecasting was confirmed as a valuable practice to support performance in terms of effectiveness and cost efficiency. However, evidence was provided that the benefits related to forecasting can be improved by suitable investments in flexibility enablers. This observation is not straightforward and is extended with suggestions on where to invest based on the target performance improvement. Therefore, companies that are seeking cost efficiency improvements should focus on layout, while companies that are looking for increased effectiveness should invest in better managing the process flow (Chapter 3). Second, model-based evaluation also offers attractive possibility in practice. Predictions on the potential outcomes of a supply chain strategy can support decision making and serve as an incentive to partners for increased supply chain collaboration. However, despite the attractiveness of supply chain modeling, this work highlights that great care should be taken when simplifying the dynamic of the system. Mistaken results and therefore erroneous decisions can occur from models that present incomplete dynamic interactions. From this perspective, the methodology developed and illustrated in chapter 4 and 5 constitute a valuable source of inspiration to address supply chain evaluation issues.

Finally, exploring the relationships underlying those between supply chain partners and supply chain characteristics is required in order to extend knowledge on supply chain dynamics. This knowledge is needed to move models closer to reality and to shrink the gap between theory and practice.

6.1 Further research

While the interaction between forecasting and specific flexibility enablers have been identified as a general relationship in supply chain, the method of defining the strength of that interaction for a given company remains to be worked out. Indeed, in order to

accurately transfer this knowledge into a model relationship, better insights should be available. Still considering the accuracy of the modeled relationships, the influence of additional flexibility enablers should be evaluated to verify that key interactions have not been omitted.

A future research opportunity would be to extend the models to capture the dependency between workload and lead time in a more detailed manner. In this context, clearing functions (Pahl et al., 2007) might be of interest. These functions, which capture the specific relationship between the process workload and the lead time for given operational characteristics, can be defined via either mathematical formulation or fitted on empirical information.

Finally, an interesting addition to this research would be to consider a setting where the available demand and capacity information are used to make the production workload more effective by balancing exceeding order quantity on a lower utilized period. Intuitively, such a policy would further relax the trade of between flexibility and effectiveness and would augment the value of information sharing.

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Bibliography

- Armstrong, J. (1983). Relative accuracy of judgmental and extrapolative methods in forecasting annual earnings. *Journal of Forecasting* 2, 437–447.
- Armstrong, J., R. Ayres, C. Christ, and J. Ord (1984). Forecasting by Extrapolation: Conclusions from 25 Years of Research [with Comment and Reply]. *Interfaces* 14(6), 52–66.
- Baganha, M. and M. Cohen (1998). The stabilizing effect of inventory in supply chains. *Operations Research* 46(3), 72–83.
- Bartezzaghi, E., R. Verganti, and G. Zotteri (1999). A simulation framework for forecasting uncertain lumpy demand. *International Journal of Production Economics* 59(1-3), 499–510.
- Beamon, B. (1999). Measuring supply chain performance. *International Journal of Operations & Production Management* 19(3), 275–292.
- Benjaafar, S., W. Cooper, and J. Kim (2005). On the benefits of pooling in production-inventory systems. *Management Science* 51(4), 548–565.
- Bertrand, J. and J. Fransoo (2002). Operations management research methodologies using quantitative modeling. *International Journal of Operations & Production Management* 22(2), 241–264.
- Billington, C., G. Callioni, B. Crane, J. Ruark, J. Rapp, T. White, and S. Willems (2004). Accelerating the profitability of Hewlett-Packard’s supply chains. *Interfaces* 34(1), 59–72.
- Boute, R. (2007). Impact of replenishment rules with endogenous lead times on supply chain performance. *4OR: A Quarterly Journal of Operations Research* 5(3), 261–264.
- Boute, R. N., S. M. Disney, M. R. Lambrecht, and B. Van Houdt (2007). An integrated production and inventory model to dampen upstream demand variability in the supply chain. *European Journal of Operational Research* 178(1), 121–142.

- Boyer, K. and G. Leong (1996). Manufacturing flexibility at the plant level. *Omega* 24(5), 495–510.
- Boylan, I. and F. Johnston (1996). Variance laws for inventory management. *International Journal of Production Economics* 45(1-3), 343–352.
- Brown, R. (1959). *Statistical forecasting for inventory control*. McGraw-Hill New York.
- Burgin, T. and A. Wild (1967). Stock control-experience and usable theory. *OR* 18(1), 35–52.
- Cachon, G. and M. Fisher (2000). Supply chain inventory management and the value of shared information. *Management science* 46(8), 1032–1048.
- Chan, F. and H. Chan (2005). The future trend on system-wide modelling in supply chain studies. *The International Journal of Advanced Manufacturing Technology* 25(7), 820–832.
- Chan, F. and H. Chan (2006). A simulation study with quantity flexibility in a supply chain subjected to uncertainties. *International Journal of Computer Integrated Manufacturing* 19(2), 148–160.
- Chase, C. (1999). Sales forecasting at the dawn of the new millennium? *Journal of Business Forecasting Methods and Systems* 18, 2–5.
- Chen, F. (2001). Market segmentation, advanced demand information, and supply chain performance. *Manufacturing & Service Operations Management* 3(1), 53–67.
- Chen, F., J. Ryan, and D. Simchi-Levi (2000). The impact of exponential smoothing forecasts on the bullwhip effect. *Naval Research Logistics* 47(4), 271–286.
- Chopra, S. and P. Meindl (2001). *Supply chain management*. Prentice Hall: Upper Saddle River, NJ.
- Christopher, M. (1998). Logistics and supply chain management: Strategies for reducing cost and improving service. london. *Financial Times Pitman Publishing: London*.
- Dalrymple, D. (1987). Sales forecasting practices: Results from a United States survey. *International Journal of Forecasting* 3(3-4), 379–391.
- Danese, P. and M. Kalchschmidt (2008). The Impact of Forecasting on Performances: Is Accuracy the Only Matter? In *Proceeding of the 15th Working Seminar on Production Economics, Innsbruck*, pp. 153–166.

- Das, A. (2001). Towards theory building in manufacturing flexibility. *International journal of production research* 39(18), 4153–4177.
- Davis, D. and J. Mentzer (2007). Organizational factors in sales forecasting management. *International Journal of Forecasting* 23(3), 475–495.
- Davis, J., K. Eisenhardt, and C. Bingham (2007). Developing theory through simulation methods. *Academy of Management Review* 32(2), 480.
- Davis, T. (1993). Effective supply chain management. *Management Review* 8, 35–46.
- Dejonckheere, J., S. Disney, M. Lambrecht, and D. Towill (2003). Measuring and avoiding the bullwhip effect: A control theoretic approach. *European Journal of Operational Research* 147(3), 567–590.
- Disney, S. and D. Towill (2003). The effect of vendor managed inventory (VMI) dynamics on the Bullwhip Effect in supply chains. *International journal of production economics* 85(2), 199–215.
- Ebert, R. and T. Lee (1995). Production loss functions and subjective assessments of forecast errors: untapped sources for effective master production scheduling. *International Journal of Production Research* 33(1), 137–159.
- Enns, S. (2002). MRP performance effects due to forecast bias and demand uncertainty. *European Journal of Operational Research* 138(1), 87–102.
- Federgruen, A. and P. Zipkin (1986). An inventory model with limited production capacity and uncertain demands I. The average-cost criterion. *Mathematics of Operations Research* 11(2), 193–207.
- Ferdows, K., M. Lewis, and J. Machuca (2004). The 21st-Century Supply Chain-Rapid-fire fulfillment. *Harvard Business Review* 82(11), 104–110.
- Fichtinger, J., Y. Nieto, and G. Reiner (2009). A Dynamic Forecasting and Inventory Management Evaluation Approach. In G. Reiner (Ed.), *Rapid modelling for increasing competitiveness: tools and mindset*, pp. 65–78. Springer: London.
- Fisher, M. (1997). What is the right supply chain for your product? *Harvard Business Review* 75(2), 105–116.
- Fisher, M. and A. Raman (1996). Reducing the cost of demand uncertainty through accurate response to early sales. *Operations Research* 44(1), 87–99.
- Fishman, G. (2001). *Discrete-event simulation: modeling, programming, and analysis*. Springer Verlag: New York, NY.

- Forrester, J. (1958). Industrial dynamics: a major breakthrough for decision makers. *Harvard business review* 36(4), 37–66.
- Forrester, J. and J. Wright (1961). *Industrial dynamics*. MIT press Cambridge, MA.
- Forza, C. (2009). Surveys. In C. Karlsson (Ed.), *Researching Operations Management*, pp. 84–161. Routledge: New York.
- Gallego, G. and Ö. Özer (2001). Integrating replenishment decisions with advance demand information. *Management Science* 47(10), 1344–1360.
- Gallego, G. and Ö. Özer (2002). Optimal use of demand information in supply chain management. In J. Song and D. Yao (Eds.), *Rapid modelling for increasing competitiveness: tools and mindset*, pp. 116–160. Kluwer Academic: Norwell, MA.
- Gayon, J., S. Benjaafar, and F. de Véricourt (2009). Using imperfect advance demand information in production-inventory systems with multiple customer classes. *Manufacturing & Service Operations Management* 11(1), 128–143.
- Gefen, D., D. Straub, and M. Boudreau (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems* 4(1), 1–78.
- Gläßer, D., Y. Nieto, and G. Reiner (2009). Performance Evaluation of Process Strategies Focussing on Lead Time Reduction Illustrated with an Existing Polymer Supply Chain. In G. Reiner (Ed.), *Rapid modelling for increasing competitiveness: tools and mindset*, pp. 79–90. Springer: London.
- Goddard, W. (1989). Lets scrap forecasting. *Modern Materials Handling* 39, 39.
- Gribble, S. (2001). Robustness in complex systems. In *8th Workshop on Hot Topics in Operating Systems*, pp. 21–26. Published by the IEEE Computer Society.
- Hadley, G. and T. Whitin (1963). *Analysis of inventory systems*. Prentice Hall: Englewood Cliffs, NJ.
- Hallgren, M. and J. Olhager (2009). Flexibility configurations: Empirical analysis of volume and product mix flexibility. *Omega* 37(4), 746–756.
- Hariharan, R. and P. Zipkin (1995). Customer-order information, leadtimes, and inventories. *Management Science* 41(10), 1599–1607.
- Herrin, R. (2005). How to calculate safety stocks for highly seasonal products. *Journal of Business Forecasting Methods and Systems* 24(2), 6.

- Ho, C., Y. Tai, Y. Tai, and Y. Chi (2005). A structural approach to measuring uncertainty in supply chains. *International Journal of Electronic Commerce* 9(3), 91–114.
- Holweg, M., S. Disney, J. Holmström, and J. Småros (2005). Supply Chain Collaboration:: Making Sense of the Strategy Continuum. *European management journal* 23(2), 170–181.
- Hopp, W., M. Spearman, and B. Sarker (2001). *Factory physics: foundations of manufacturing management*. Irwin/McGraw-Hill: Burr Ridge, IL.
- Hu, L. and P. Bentler (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal* 6(1), 1–55.
- Huang, G., J. Lau, and K. Mak (2003). The impacts of sharing production information on supply chain dynamics: a review of the literature. *International Journal of Production Research* 41(7), 1483–1517.
- Huang, Z. and A. Gangopadhyay (2004). A simulation study of supply chain management to measure the impact of information sharing. *Information Resources Management Journal* 17(3), 20–31.
- Jack, E. and A. Raturi (2002). Sources of volume flexibility and their impact on performance. *Journal of Operations Management* 20(5), 519–548.
- Jammernegg, W. and G. Reiner (2007). Performance improvement of supply chain processes by coordinated inventory and capacity management. *International Journal of Production Economics* 108(1-2), 183–190.
- Kalchschmidt, M., Y. Nieto, and G. Reiner (2009). Managing Demand Through the Enablers of Flexibility: The Impact of Forecasting and Process Flow Management. In G. Reiner (Ed.), *Rapid modelling for increasing competitiveness: tools and mindset*, pp. 265–276. Springer: London.
- Kalchschmidt, M., Y. Nieto, and G. Reiner (2010). The impact of forecasting on operational performance: Mediation effects through flexibility enablers. *Operations Management Research* 3(3–4), 129–137.
- Kalchschmidt, M. and G. Zotteri (2007). Forecasting practices: empirical evidence and a framework for research. *International Journal of Production Economics* 108, 84–99.
- Kalchschmidt, M., G. Zotteri, and R. Verganti (2003). Inventory management in a multi-echelon spare parts supply chain. *International journal of production economics* 81, 397–413.

- Kara, S. and B. Kayis (2004). Manufacturing flexibility and variability: an overview. *Journal of Manufacturing Technology Management* 15, 466–478.
- Karaesmen, F., G. Liberopoulos, and Y. Dallery (2004). The value of advance demand information in production/inventory systems. *Annals of Operations Research* 126(1), 135–157.
- Kelton, W., R. Sadowski, and D. Sadowski (2002). *Simulation with ARENA*. McGraw-Hill: Boston, MA.
- Kerkkänen, A., J. Korpela, and J. Huiskonen (2009). Demand forecasting errors in industrial context: Measurement and impacts. *International Journal of Production Economics* 118(1), 43–48.
- Kim, J. (2008). The (Q, r) Inventory Policy in Production-Inventory Systems. In *Proceedings of SKISE Fall Conference*.
- Kim, J., D. Chatfield, T. Harrison, and J. Hayya (2006). Quantifying the bullwhip effect in a supply chain with stochastic lead time. *European Journal of operational research* 173(2), 617–636.
- Klassen, R. and L. Menor (2007). The process management triangle: An empirical investigation of process trade-offs. *Journal of Operations Management* 25(5), 1015–1034.
- Kleijnen, J. and M. Smits (2003). Performance metrics in supply chain management. *Journal of the Operational Research Society* 54(5), 507–514.
- Kleinrock, L. and R. Gail (1976). *Queueing systems*, Volume 2. Wiley: New York, NY.
- Koste, L. and M. Malhotra (1999). A theoretical framework for analyzing the dimensions of manufacturing flexibility. *Journal of Operations Management* 18(1), 75–93.
- Krajewski, L., J. Wei, and L. Tang (2005). Responding to schedule changes in build-to-order supply chains. *Journal of Operations Management* 23(5), 452–469.
- Kumar, P., R. Shankar, and S. Yadav (2008). Flexibility in global supply chain: modeling the enablers. *Journal of Modelling in Management* 3(3), 277–297.
- Lapide, L. (2001). New developments in business forecasting. *Journal of Business Forecasting Methods and Systems* 20(4), 11–13.
- Law, A. and W. Kelton (2000). *Simulation modeling and analysis* (3 ed.). McGraw Hill: New York, NY.

- Lee, H. (2000). Creating value through supply chain integration. *Supply Chain Management Review* 4(4), 30–36.
- Lee, H. (2002). Aligning supply chain strategies with product uncertainties. *California management review* 44(3), 105–119.
- Lee, H. and C. Billington (1995). The evolution of supply-chain-management models and practice at Hewlett-Packard. *Interfaces* 25(5), 42–63.
- Lee, H., V. Padmanabhan, and S. Whang (1997). Information distortion in a supply chain: the bullwhip effect. *Management science* 43(4), 546–558.
- Lee, H. and M. Wolfe (2003). Supply chain security without tears. *Supply Chain Management Review* 7(1), 12–20.
- Little, T., N. Card, J. Bovaird, K. Preacher, and C. Crandall (2007). *Structural equation modeling of mediation and moderation with contextual factors*. Lawrence Erlbaum: Mahwah, NJ.
- Mahmoud, E., G. Rice, and N. Malhotra (1988). Emerging issues in sales forecasting and decision support systems. *Journal of the Academy of Marketing Science* 16(3), 47–61.
- Mason-Jones, R., B. Naylor, and D. Towill (2000). Engineering the leagile supply chain. *International Journal of Agile Management Systems* 2(1), 54–61.
- Mason-Jones, R. and D. Towill (1998). Shrinking the supply chain uncertainty circle. *IOM Control* 24(7), 17–22.
- Mattsson, S.-A. (2010). Inventory control in environments with seasonal demand. *Operations Management Research*. In press.
- Meadows, D. (1982). Whole earth models and systems. *CoEvolution Quarterly* 34, 98–108.
- Mentzer, J. and C. Bienstock (1998). *Sales forecasting management*. Sage: Beverley Hills, CA.
- Mentzer, J. and M. Moon (2005). *Sales forecasting management: a demand management approach*. Sage Publications Inc: Thousand Oaks, CA.
- More, D. and A. Subash Babu (2008). Perspectives, practices and future of supply chain flexibility. *International Journal of Business Excellence* 1(3), 302–336.
- Neely, A. (1995). Performance measurement system design: theory and practice. *International Journal of Operations and Production Management* 15(4), 80–116.

- Nunnally, J. (1994). *Psychometric Theory*. McGraw-Hill Inc: New York, NY.
- Özer, Ö. (2006). Inventory management: information, coordination and rationality. In K. Kempf, P. Keskinocak, and R. Uzsoy (Eds.), *Handbook of Production Planning*. Springer: New York, NY.
- Özer, Ö. and W. Wei (2004). Inventory control with limited capacity and advance demand information. *Operations Research* 52(6), 988–1000.
- Pahl, J., S. Voß, and D. Woodruff (2007). Production planning with load dependent lead times: an update of research. *Annals of Operations Research* 153(1), 297–345.
- Podsakoff, P., S. MacKenzie, J. Lee, and N. Podsakoff (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of applied psychology* 88(5), 879–903.
- Prater, E., M. Biehl, and M. Smith (2001). International supply chain agility-Tradeoffs between flexibility and uncertainty. *International Journal of Operations & Production Management* 21(5/6), 823–839.
- Reichhart, A. and M. Holweg (2007). Creating the customer-responsive supply chain: a reconciliation of concepts. *International Journal of Operations & Production Management* 27(11), 1144–1172.
- Reiner, G. (2005). Customer-oriented improvement and evaluation of supply chain processes supported by simulation models. *International Journal of Production Economics* 96(3), 381–395.
- Reiner, G. and J. Fichtinger (2009). Demand forecasting for supply processes in consideration of pricing and market information. *International Journal of Production Economics* 118(1), 55–62.
- Reiner, G. and M. Trcka (2004). Customized supply chain design: Problems and alternatives for a production company in the food industry. A simulation based analysis. *International Journal of Production Economics* 89(2), 217–229.
- Ritzman, L. and B. King (1993). The relative significance of forecast errors in multistage manufacturing. *Journal of Operations Management* 11(1), 51–65.
- Sabri, E. and B. Beamon (2000). A multi-objective approach to simultaneous strategic and operational planning in supply chain design. *Omega* 28(5), 581–598.
- Sahay, B. (2003). Supply chain collaboration: the key to value creation. *Work Study* 52(2), 76–83.

- Sahin, F. and E. Robinson (2002). Flow coordination and information sharing in supply chains: review, implications, and directions for future research. *Decision Sciences* 33(4), 505–536.
- Sanders, N. and K. Manrodt (1994). Forecasting practices in US corporations: survey results. *Interfaces* 24(2), 92–100.
- Schodl, R. (2009). The Best of Both Worlds-Integrated Application of Analytic Methods and Simulation in Supply Chain Management. In G. Reiner (Ed.), *Rapid modelling for increasing competitiveness: tools and mindset*, pp. 155–162. Springer: London.
- Selcuk, B., J. Fransoo, and A. De Kok (2006). The effect of updating lead times on the performance of hierarchical planning systems. *International Journal of Production Economics* 104(2), 427–440.
- Sethi, A. and S. Sethi (1990). Flexibility in manufacturing: a survey. *International Journal of Flexible Manufacturing Systems* 2(4), 289–328.
- Shepherd, C. and H. Günter (2006). Measuring supply chain performance: Current research and future directions. *International Journal of Productivity and Performance Management* 55(3/4), 242–258.
- Silver, E., D. Pyke, and R. Peterson (1998). *Inventory management and production planning and scheduling* (3rd edition ed.). Wiley: New York, NY.
- Simatupang, T. and R. Sridharan (2004). A benchmarking scheme for supply chain collaboration. *Benchmarking: An International Journal* 11(1), 9–30.
- Slack, N. (1987). *Manufacturing systems flexibility: ten empirical observations*. Templeton College, The Oxford Centre for Management Studies.
- Slack, N. (2005). The flexibility of manufacturing systems. *International Journal of Operations and Production Management* 25(12), 1190.
- Slack, N. and M. Lewis (2002). *Operations strategy*. Financial Times/Prentice Hall.
- Snyder, R., A. Koehler, and J. Ord (2002). Forecasting for inventory control with exponential smoothing. *International Journal of Forecasting* 18(1), 5–18.
- Sterman, J. (1989). Misperceptions of feedback in dynamic decision making. *Organizational behavior and human decision processes* 43(3), 301–335.
- Sterman, J. (2000). *Business dynamics: Systems thinking and modeling for a complex world with CD-ROM*. Irwin/McGraw-Hill: New York, NY.

- Stevenson, M. and M. Spring (2007). Flexibility from a supply chain perspective: definition and review. *International Journal of Operations & Production Management* 27(7), 685–713.
- Stevenson, M. and M. Spring (2009). Supply chain flexibility: an inter-firm empirical study. *International Journal of Operations & Production Management* 29(9), 946–971.
- Stratton, R. and R. Warburton (2003). The strategic integration of agile and lean supply. *International Journal of Production Economics* 85(2), 183–198.
- Suarez, F., M. Cusumano, and C. Fine (1996). An empirical study of manufacturing flexibility in printed circuit board assembly. *Operations Research* 44(1), 223–240.
- Sun, S., M. Hsu, and W. Hwang (2009). The impact of alignment between supply chain strategy and environmental uncertainty on SCM performance. *Supply Chain Management: An International Journal* 14(3), 201–212.
- Suri, R. (1998). *Quick response manufacturing: a companywide approach to reducing lead times*. Productivity Press: New York, NY.
- Swamidass, P. and W. Newell (1987). Manufacturing strategy, environmental uncertainty and performance: a path analytic model. *Management Science*, 509–524.
- Swaminathan, J., S. Smith, and N. Sadeh (1998). Modeling Supply Chain Dynamics: A Multiagent Approach. *Decision Sciences* 29(3), 607–632.
- Tachizawa, E. and C. Thomsen (2007). Drivers and sources of supply flexibility: an exploratory study. *International Journal of Operations & Production Management* 27(10), 1115–1136.
- Taylor, D. and A. Fearne (2006). Towards a framework for improvement in the management of demand in agri-food supply chains. *Supply Chain Management: An International Journal* 11(5), 379–384.
- The Mathworks (2010). MATLAB Product Family. <http://www.mathworks.com>. Retrieve October 2010.
- Upton, D. (1994). The management of manufacturing flexibility. *California management review* 36, 72–100.
- Upton, D. (1995). What really makes factories flexible? *Harvard Business Review* 73, 74–84.

- Van der Vorst, J. and A. Beulens (2002). Identifying sources of uncertainty to generate supply chain redesign strategies. *International Journal of Physical Distribution & Logistics Management* 32(6), 409–430.
- van Hees, R. and W. Monhemius (1972). *An introduction to production and inventory control*. MacMillan.
- Vokurka, R. and S. O’Leary-Kelly (1999). A review of empirical research on manufacturing flexibility. *Journal of Operations Management* 18(4), 485–501.
- Vollmann, T. (2005). *Manufacturing planning and control for supply chain management*. Irwin/McGraw Hill: New York, NY.
- Vollmann, T., W. Berry, and D. Whybark (1992). *Manufacturing planning and control systems*. Irwin Professional Publishing: Homewood, IL.
- Voss, C. (2009). Case Research in Operations Management. In C. Karlsson (Ed.), *Researching Operations Management*, pp. 162–195. Routledge: New York.
- Wacker, J. and L. Sprague (1998). Forecasting accuracy: Comparing relative effectiveness of practices between seven developed countries. *Journal of Operations Management* 16, 271–290.
- Wijngaard, J. (2004). The effect of foreknowledge of demand in case of a restricted capacity: the single-stage, single-product case. *European Journal of Operational Research* 159(1), 95–109.
- Will, J., M. Bertrand, and J. Fransoo (2009). Modelling and Simulation. In C. Karlsson (Ed.), *Researching Operations Management*, pp. 265–306. Routledge: New York.
- Winters, P. (1960). Forecasting sales by exponentially weighted moving averages. *Management Science*, 324–342.
- Zhang, Q., M. Vonderembse, and J. Lim (2002). Value chain flexibility: a dichotomy of competence and capability. *International Journal of Production Research* 40(3), 561–583.
- Zhao, X., J. Xie, and J. Leung (2002a). The impact of forecasting model selection on the value of information sharing in a supply chain. *European Journal of Operational Research* 142(2), 321–344.
- Zhao, X., J. Xie, and W. Zhang (2002b). The impact of information sharing and ordering co-ordination on supply chain performance. *Supply Chain Management: an international journal* 7(1), 24–40.

- Zhou, H. and W. Benton Jr (2007). Supply chain practice and information sharing. *Journal of Operations Management* 25(6), 1348–1365.
- Zotteri, G. and M. Kalchschmidt (2007). Forecasting practices: Empirical evidence and a framework for research. *International Journal of Production Economics* 108(1-2), 84–99.

