A coordination mechanism for supply chains with capacity expansions and order-dependent lead times

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Abstract

This paper considers a supply chain consisting of a retailer for short life cycle products facing stochastic customer demand and a manufacturer that initiates production upon receipt of retail orders. Departing from the common view of the newsvendor problem, we assume that the delivery lead time is not fixed, but that both the retailer and the manufacturer have the option to shorten it. Shorter lead times enable the retailer to place orders closer to the start of the selling season where additional information on customer preferences has become available, reducing demand uncertainty. In the work at hand, lead time is assumed to depend on the order quantity, on the supplier's production capacity, and a fixed transportation delay. This paper proposes a model for determining the optimal order quantity and production capacity in centralized and decentralized settings. For the uncoordinated case, we show that if the retailer's ability to gather and analyze additional demand information is revealed to the manufacturer, the arising information asymmetry between the two parties can aggravate the double marginalization effect and, in turn, erode supply chain efficiency. In a coordinated supply chain, however, both parties have an incentive to align both order quantity and investments in lead time reduction. To coordinate the decentralized supply chain, we propose a buy-back contract that helps to leverage supply chain profitability. We conclude with an outlook on future research opportunities.

Keywords: Supply chain management; newsvendor model; order-dependent lead times; capacity expansion; coordination mechanism

1. Introduction

Lead times are considered an important factor in global competition (e.g., Tersine and Hummingbird, 1995; de Treville et al., 2004; Nguyen and Wright, 2015; Ghaderi et al., 2016). In the apparel industry, for example, lead times play an especially critical role due to short selling seasons that often allow retailers to place orders only once before the start of the selling season. In such a situation, long lead times oblige the retailer to order long before the start of the selling season where accurate information on future customer demand is often not available. This imposes a significant risk of ordering an over- or undersized quantity on the retailer. The international fashion retailer H&M, for example, has recently been reported to suffer from excess inventory that forced the company to reduce prices massively to clear out unsold goods. Long order lead times and a misassessment of customer preferences have been identified as the main causes of this development (Chaudhuri, 2018; Paton, 2018). Shorter lead times, however, would enable the retailer to place orders closer to the actual realization of customer demand, where more information on customer demand is available and where future requirements can be forecasted more accurately. As a consequence, companies have made various efforts to reduce information lead times and supply lead times, with examples including the use of electronic data interchange, the rationalization of logistics processes, or improved manufacturing methods (see, e.g., Fisher and Raman, 1996; de Treville et al., 2004).

The work at hand studies the influence of controllable lead times on the production, pricing and ordering decision of a retailer and its supplier for a fashionable product. Acknowledging that the lead time of a product usually consists of a variety of components in practice, such as setup time, processing time, or queuing time (cf. Tersine and Hummingbird, 1995), we investigate the case where the delivery lead time depends both on the order quantity of the retailer and on the production capacity of the manufacturer (supplier) of the product, as well as on a fixed transportation delay. Thus, both, the retailer and the manufacturer are able to reduce lead times by either adjusting the retailer's order quantity or the manufacturer's production capacity. While shorter lead times enable the retailer to collect additional information about customer demand before placing the order, we take account of the fact that a reduction in demand uncertainty presupposes adequate information collection and processing capabilities at the retailer as well. By comparing a centrally coordinated supply chain to the decentralized case with the manufacturer acting as the Stackelberg leader, we gain insights into the manufacturer's and the retailer's incentives to reduce lead times and the coordination mechanisms required to attain supply chain supply chain efficiency. Prior research has shown that the manufacturer may have strong disincentives to reduce lead times as this could reduce demand uncertainty faced by the retailer which, in turn, may lead to lower order quantities at the retail level and reduced profit for the manufacturer (e.g., Kraiselburd et al., 2010). In this paper, we investigate the interdependencies that exist between the retailer's and the manufacturer's decisions and propose a contract that coordinates the system and that ensures that the supply chain reaches its maximum expected profit.

The objectives of the paper are threefold:

I. Develop an inventory control framework that models the linkage between order quantity and timing decisions in supply chains. This framework integrates possible investments into the manufacturer's production capacity and the retailer's ability to gather and analyze demand information.

II. Highlight the potential benefits from reducing lead times and delaying the ordering decision that enables the retailer to collect and analyze additional demand information and to assess demand more accurately.

III. Illustrate how collecting additional demand information impacts on the expected profit of manufacturer and retailer in order to investigate each parties' incentives to cooperate as well as the efficiency of buy-back contracts in coordinating the supply chain.

In order to address these objectives, we introduce three distinct scenarios. In the centralized scenario, we highlight the benefits of delaying the ordering decision. We show that an optimal investment level, both for the production capacity and the information processing capability, exists that maximizes the payoff from reducing lead times. In the decentralized uncoordinated scenario, we show that the two supply chain actors may have conflicting positions depending on the level of information sharing as well as the investments into the production capacity and demand learning capability. This conflict of interest could lead to a situation in which the retailer decides not to disclose demand information to the manufacturer, who, in turn, would not invest in additional production capacity. This causes long lead times and a reduction of the supply chain profitability. In the decentralized coordinated scenario, we propose a buy back mechanism that results in a win-win situation for both players in which the order quantity as well as the investments are jointly coordinated.

The remainder of the paper is organized as follows: Section 2 reviews the related literature and differentiates the work at hand from earlier publications. Section 3 outlines the assumptions and definitions that will be used in the remaining parts of the paper, and Section 4 then introduces models for the centralized and decentralized supply chains. Section 5 concludes the paper and provides managerial insights as well as suggestions for future research.

2. Literature review

This section reviews a selection of earlier publications that are related to the models proposed in this paper, and pays particular attention to newsvendor models that consider multiple ordering opportunities associated with alternative lead times, inventory control models that consider variable lead times, and coordination in single-period models that take account of investment decisions.

It has been recognized early that gathering additional demand information prior to the selling season facilitated by shortened order lead times provides a valuable opportunity for retailers to reduce uncertainty while increasing expected profits. In the literature, quick response systems (QRS) that allow the retailer to order more than once before the start of a selling season or to update orders once they have been placed have attracted some attention. Fisher and Raman (1996), for example, studied a QRS with two selling periods. In this case, the retailer places an initial order before the start of the first selling period, then observes demand in the first selling season, and then orders for the second period. A comparison of the QRS to the classical newsvendor model showed that two ordering opportunities may significantly reduce expected total cost. Donohue (2000) studied a two-stage supply chain with a newsvendor-type retailer and a manufacturer having access to two production modes, one providing short and the other one providing long lead times. The quick response production mode was assumed more expensive than the slow one. The author proposed a model that supports the retailer in finding optimal order quantities for both production modes under the assumption that the demand forecast is more accurate for the fast production mode that allows the retailer some additional time to collect further demand information. The author also proposed a contract to coordinate the channel. Similarly, Choi et al. (2004) and Wang et al. (2012) investigated situations where a retailer faces multiple ordering opportunities, each associated with an ordering cost that decreases in the lead time. Placing the order late would enable the retailer to collect further demand information and to use this information for updating the demand distribution of the product, albeit at the expense of higher ordering costs. Wang et al. (2014) investigated the case of two ordering opportunities for two competing retailers that sell a substitutable product. Both ordering opportunities were assumed to result in the same cost. The first one, however, enables both retailers to make a credible early commitment. The analysis revealed that an early commitment is especially beneficial in case demand uncertainty is low or competition intense. Serel (2009) studied another QRS with two ordering opportunities. After the initial order has been placed, the retailer collects additional market information to update the demand forecast before placing the second order. In addition, the author assumed that the selling price of the second order is unknown, such that the decision maker has to balance the advantage of late orders with the risk of a price increase. In a second version of the model, the author assumed that the first order may be cancelled partially or completely after updating the demand forecast. Kraiselburd et al. (2010) studied the case of a two-stage supply chain where a supplier has the opportunity to reduce lead times to zero free of cost, and where the retailer, in turn, has the option to increase demand at an investment. Reducing lead times to zero would enable the retailer to observe the realization of the uncertain demand before ordering and receiving the products, which would imply that all uncertainty is removed at the time the retailer decides on the order quantity. The authors investigated under which conditions the supplier should reduce lead times, and showed that in some cases, the supplier prefers not to shorten lead time to set an incentive to the retailer to stimulate demand and to increase its order quantity due to the presence of some uncertainty. More recently, Yang et al. (2015) explored the impact of QRS for various supply chain structures with strategic customer behavior. In this setting, the retailer places an initial order for a given wholesale price before the start of the selling season. Until the beginning of the selling season when more demand information is gathered, the retailer with quick response capability observes the accurate demand and has the option to submit a second order at an increased wholesale price. It was shown that the value of QRS is higher in centralized systems if the extra cost of quick response is relatively low, and that it is higher in decentralized systems if the extra cost of quick response is high.

Another stream of research that is relevant to this paper considers periodic or continuous inventory control models and assumes that manufacturing and transportation lead times can be shortened. Lower lead times enable the buying company to reduce safety stocks that have to be kept in the system, and hence the system's expected total cost. Some authors also assumed that lead time influences the customer's buying decision, such that shorter lead times result in an increase in customer demand (e.g., Nguyen and Wright, 2015; Modak and Kelle, 2019). One of the first papers that studied lead time reduction in an inventory control model is the one of Liao and Shyu (1991), who used a piecewise linear crashing cost function to model the relationship between lead time crashing cost and lead time length. For a given lot size and normally distributed demand, they calculated an optimal lead time and showed that reducing lead time may result in lower expected total costs. This paper was extended by Ben-Daya and Raouf (1994), who treated both lead time and order quantity as decision variables, and by Chandra and Grabis (2008), who assumed a lead time-dependent procurement cost. Other works in this area are those of Hoque (2007), Jha and Shanker (2009), and Srinivas and Rao (2010). Some authors also considered the case where the lead time length varies with the order quantity. Kim and Benton (1995), for instance, assumed that the production lead time is a linear function of the lot size, and that a queuing factor has to be considered to account for the time a lot spends in queues or materials handling processes. Ben-Daya and Hariga (2004) studied the case of a supply chain consisting of a single supplier and a single buyer and assumed that lead time varies linearly with the lot size and that demand during lead time is stochastic and normally distributed. The authors showed that under lot size-dependent lead times, order quantities are usually smaller than in case of the classical (R, q) inventory model. The work of Ben-Daya and Hariga (2004) was extended by Glock (2012), who took account of different measures for reducing lead times, namely increasing the production rate, reducing the order quantity, or crashing the queuing factor. Extensions of these works that took account of different types of stockout cost, raw material procurement or other demand distributions are those of AlDurgham et al. (2017), Hossain et al. (2017) and Braglia et al. (2018), for example.

Works that studied production capacity decisions at the newsvendor or the newsvendor's supplier often assumed that the production capacity introduces a constraint into the model that limits the newsvendor's order quantity to some value. Chen et al. (2010), for example, studied a supplier-retailer supply chain where the supplier decides on the production capacity in the first step, and where the retailer places the order after a demand update in the second step. The authors proposed a risk and profit sharing contract to coordinate the channel. Serel (2014) studied a multi-item newsvendor model where the production capacity at the supplier is uncertain. To avoid supply shortages, the newsvendor can reserve a certain amount of capacity in a first step at a fixed cost per unit capacity reserved. The reservation guarantees that the capacity is available afterwards when the newsvendor has to decide on its order quantity. The capacity beyond the reserved amount would still be uncertain, though. Mohammadivojdan and Geunes (2018) investigated a newsvendor facing multiple capacity-constrained suppliers each offering an individual discount scheme to the newsvendor. In this case, the challenge for the newsvendor is to select the right set of suppliers and to benefit from the discount schemes without increasing the overstock risk too much. Bicer and Seifert (2017) studied a newsvendor model with multiple ordering opportunities and a capacity constraint. For each ordering opportunity, the newsvendor can update the demand forecast, which leads to a lower demand uncertainty as the selling season approaches. The forecast update thus sets an incentive to postpone the ordering decision, while the capacity constraint induces the newsvendor to order early to avoid that the constraint interferes with the ordering decision in a later sub-period. The authors showed that especially in cases where lead times are long, the newsvendor can increase its expected profit by increasing the production capacity.

The work at hand extends the literature on the coordination of two-echelon supply chains in two respects. First, it assumes that the delivery lead time depends on the order quantity, such that higher order quantities force the retailer to place the order earlier. As in prior research, we assume that shortening lead time reduces demand uncertainty (see, e.g., Özer et al., 2007; Wang et al., 2012). In contrast to earlier works that assumed that the retailer faces a finite set of ordering opportunities, this paper considers the case where the lead time is a continuous function of the retailer's order quantity (see, for the latter assumption, also Kim and Benton (1995) and Ben-Daya and Hariga (2004)). The order quantity decision, therefore, directly impacts the lead time and the chance to collect additional demand information closer to the start of the selling season. We also assume that the retailer may improve its capability to assess future customer demand, for example by initiating some marketing-type expenditure or by investing in data processing facilities. The higher the retailer's information collection and processing capability, the better is he/she able to assess future demand variability. The proposed approach also takes account of the fact that in a make-to-order environment, the order processing time at the manufacturer usually directly depends on the production quantity, such that processing a smaller lot enables the manufacturer to initiate the shipment earlier. Secondly, this paper assumes that the manufacturer may adjust its production capacity to speed up or slow down the production process. Controllable production capacities have frequently been investigated in the context of different inventory control problems (e.g., Khouja, 1995; Glock, 2011), but they have not attracted much attention in a newsvendor setting yet, and earlier works in this area were subject to quite restrictive assumptions (e.g., varying the production capacity is free of cost, or there are only two possible capacity levels). In the setting analyzed in this paper, we assume that the manufacturer controls the production capacity, while the retailer decides on how much to order at the manufacturer. The scenario investigated here enables us to analyze the incentives of the two parties to shorten lead times and to reduce demand uncertainty. In addition, a contract is proposed that coordinates the supply chain to maximize the expected total profit.

3. Supply chain setting and assumptions

This paper considers a two-echelon supply chain consisting of a retailer of a short life cycle product that faces a stochastic consumer demand and a manufacturer that initiates production upon the receipt of retail orders. Supply lead times between the manufacturer and the retailer depend on the retailer's order quantity, the manufacturer's production capacity (production rate) and a transportation delay. In such a make-to-order scenario, reducing order quantities and transportation delays or providing higher production capacities evidently reduces supply lead times. This, in turn, enables the retailer to observe additional demand information prior to the upcoming selling season, for example, by analyzing pre-season sales of related products or fashion trends in social media, which would improve the quality of consumer demand forecasts and reduce uncertainty. In case the retailer's ability to gather and analyze additional demand information is not revealed to the manufacturer, the arising information asymmetry between the two parties aggravates the double marginalization effect in uncoordinated supply chains and, in turn, erodes supply chain efficiency. In a coordinated supply chain, however, both parties not only have an incentive to align quantity decisions, but also investments into the production capacity and the capability to process pre-season demand information. The focus of the paper is thus on examining supply chain coordination in the presence of strategic investments for reducing demand uncertainty controlled by the manufacturer and the retailer subject to asymmetric information about the outcome of such investments.

The notation used throughout this paper is summarized as follows:

α	variable cost for one unit of production capacity
β	variable cost for the ability to gather and process additional demand information
B_i	buyback price per unit offered by the manufacturer in scenario i
C	production cost per unit for the manufacturer
k	scaling parameter for the ability to gather and process additional demand information with $k > 0$
$L(Q)$	quantity-dependent manufacturing and transportation lead time
μ	mean demand
R	retail price per unit charged to consumers
p	production capacity (or production rate) of the manufacturer in units per unit of time
Q_i	retailer's order quantity placed at the manufacturer in scenario i
σ	standard deviation of customer demand

τ	fixed transportation component of the lead time
V	salvage value per unit after the selling season
W_i	wholesale price per unit charged to the retailer in scenario i
x	random demand in the selling period with $f_x(\cdot), F_x(\cdot)$ as pdf and cdf of x

We use the hat operator, $\widehat{\ }$, to denote estimated values. Further, the indices C, DU and DC refer to the centralized (C), the decentralized uncoordinated (DU) and the decentralized coordinated (DC) scenarios. Additional nomenclature will be introduced where required.

The manufacturer is assumed the Stackelberg leader in this setting who anticipates the reaction of the retailer to the wholesale price and who initiates production at the capacity level p upon receipt of the order. Providing a capacity level p causes a variable unit capacity cost α at the manufacturer. Given the manufacturer's pricing decision, the retailer places a single order prior to the start of the selling period and is not able to release additional orders or cancel the existing order before or during the selling period. The order can be placed $L^{earliest}$ days before the start of the selling season at the earliest, or be delayed and placed $L(Q)$ days prior to the start of the selling season to improve the retailer's knowledge about the demand distribution (note that $L^{earliest}$ corresponds to the earliest point in time at which the retailer can commit to order quantities). In the fashion industry, for example, retailers can commonly place initial orders following big trade shows between 3 to 6 months prior to the selling season depending on the manufacturer's capacities (cf. Sen, 2008). Once production has been completed, the order is shipped to the retailer causing a fixed transportation delay of τ days. The effective lead time $L(Q) \leq L^{earliest}$ can hence be described as a function of the capacity level p, the order quantity Q, and the fixed transportation duration τ (for a more detailed discussion, please be referred to Kim and Benton (1995) or Ben-Daya and Hariga (2004)):

$$L(Q) = Q/p + \tau \tag{1}$$

During the selling season, a normally distributed demand with average μ and standard deviation σ occurs. For items sold during the selling season, the retailer earns a unit revenue R, and the remaining items can be sold at a discount price V at the end of the season or returned to the manufacturer at a price of $V + B_i$ in case a buyback contract exists.

If the ordering decision is made $L(Q) \leq L^{earliest}$ days before the start of the selling season, presupposing higher production capacities and/or lower order quantities, the retailer is able to gather and analyze additional information about the future consumer demand in order to revise his/her forecasts. The evolution of forecasts over time can be considered as a special case of the martingale method of forecast evolution (MMFE) according to which successive forecasts of the demand are supposed to form a Martingale process (cf. Hausman, 1969; Heath and Jackson, 1994; Graves et al., 1998). Given that the consumer demand is a random variable and realized at the start of the selling season, we can assume that market signals gradually unveiled during the lead time will improve the demand forecast. This forecast process can be modelled as an additive or a multiplicative MMFE. For the additive model, the forecast adjustments at time $t \in \{1, \ldots, T\}$ given as $\varepsilon_t = x_t - x_{t-1}$, where x_t is the demand in period t, are independent and normally distributed with mean 0 and variance σ_t^2, whereas for the multiplicative model, the forecast adjustments at time $t \in \{1, \ldots, T\}$ is given as $\varepsilon_t = log(x_t) - log(x_{t-1})$, again normally distributed with mean $-\sigma_t^2/2$ and variance σ_t^2 (Heath and Jackson, 1994). Let y_n be the (mean-adjusted) cumulative forecast adjustment, then the estimated demand after observing y_n under additive (multiplicative) MMFE is normal (log-normal) with parameters $(\mu + y_n, \hat{\sigma}_n^2)$ and $\hat{\sigma}_n^2 = \sum_{t=n+1}^{T} \sigma_t^2$ representing the residual uncertainty after time n. Hence, $\hat{\sigma}_n^2$ decreases in time, which captures one of the core characteristics of the demand forecasting process stating that forecasts become more accurate with shortening forecast horizon. In addition, due to the relationship between $\hat{\sigma}_n^2$ and t, uncertainty diminishes linearly over time (Graves et al., 1998). This linear reduction in uncertainty under the additive (multiplicative) MMFE is equivalent to a demand forecast evolving according to a Brownian (geometric Brownian) motion.

Consequently, it is assumed in the following that perfect knowledge of the consumer demand variance as faced by the retailer, σ^2, can only be achieved just at the start of the selling season (i.e., for a perfect just-in-time case obtained if p tends to infinity and τ is equal to zero). With increasing temporal distance to the selling season, the estimated variance of consumer demand, $\hat{\sigma}^2$, is assumed to deviate from the actual value of σ^2 by the factor $kL(Q)$ following a linear relationship:

$$\hat{\sigma}^2(Q) = kL(Q) + \sigma^2 \tag{2}$$

where $k > 0$ is a scaling parameter measuring the retailer's ability to gather and analyze additional information about the demand variance over time. A lower value of k corresponds to enhanced abilities in assessing the actual demand variance over time. In practice, k could be decreased by investing in marketing analytics or social media investigations, wherefore it is assumed in the following that the retailer faces a unit cost β linear in $\frac{1}{k}$ to capture this investment opportunity.

Consequently, at the time an order is placed, the retailer is not accurately aware of the actual moments of the demand distribution N with mean μ and standard deviation σ, and instead considers an estimated normally distributed demand $\widehat{N}(Q)$ with mean $\hat{\mu} = \mu$ and standard deviation $\hat{\sigma}(Q) = \sqrt{kL(Q) + \sigma^2}$. In the following, $\hat{f}(x, Q)$ and $\hat{F}(x, Q)$ refer to the PDF and CDF associated with $\widehat{N}(Q)$ given as:

$$\hat{f}(x, Q) = \frac{1}{\hat{\sigma}(Q)\sqrt{2\pi}} e^{-\frac{1}{2}\left[\frac{x-\mu}{\hat{\sigma}(Q)}\right]^2} \tag{3}$$

$$\hat{F}(y, Q) = \int_{-\infty}^{y} \hat{f}(x, Q) dx \tag{4}$$

When an ordering decision is made $L^{earliest}$ units of time prior to the start of the selling season, the retailer is subject to the worst information about the demand variability and has to rely on an estimation of the demand distribution $\widehat{N}^{earliest}$ with average $\hat{\mu} = \mu$ and standard deviation $\hat{\sigma} = \sqrt{kL^{earliest} + \sigma^2}$. By delaying the ordering decision, and hence ordering $L(Q)$ days before the start of the selling season instead of $L^{earliest}$ days before the start of the selling season with $L(Q) < L^{earliest}$, the retailer improves his/her knowledge about the moments of the demand distribution and consequently decreases the estimated variance until facing the actual distribution at the start of the selling season. The imparted bounds on the lead time $\tau \leq L(Q) \leq L^{earliest}$ limit the values the estimated standard deviation of demand may adopt, i.e. $\sqrt{k\tau + \sigma^2} < \hat{\sigma}(Q) \leq \sqrt{kL^{earliest} + \sigma^2}$. The definition of an upper bound on $L(Q)$ is also equivalent to specifying a lower bound on the production capacity p for a given order quantity. If an order is placed $L^{earliest}$ units of time prior to the start of the selling season, which would be associated with the maximum value of the estimated standard deviation $\hat{\sigma}^{max} = \sqrt{kL^{earliest} + \sigma^2}$, the optimal order quantity, $Q^{earliest}$, is nothing else than the classical newsvendor order quantity solving $\widehat{F}^{earliest}\left(Q^{earliest}\right) = \frac{R-C}{R-V}$ obtained for the estimated demand distribution $\widehat{N}^{earliest}$. Such an order quantity needs a minimum production capacity $p^{min} = \frac{Q^{earliest}}{L^{earliest} - \tau}$ in order to be delivered to the retailer at the start of the selling season.

4. Model development

4.1. Centralized supply chain

First, we consider the benchmark scenario of a centralized supply chain that aims on maximizing the supply chain's expected total profit. The expected total profit function in this case is the same as in the classical newsvendor model with two notable exceptions. The standard deviation of the consumer demand is a function of the order quantity Q which determines the point in time when the ordering decision is made and thus the uncertainty faced. Furthermore, investment costs for the manufacturer's production capacity and the retailer's demand analysis capability are considered. In the centralized case, if both parties know the accurate value of the demand distribution N as revealed at the beginning of the selling season, the actual expected profit as a function of the order quantity Q can be written as:

$$\pi_C(Q) = (R - C)\mu - (R - C)\int_{x=Q}^{+\infty}(x - Q)f(x)dx - (C - V)\int_{x=0}^{Q}(Q - x)f(x)dx - \alpha p - \frac{\beta}{k} \qquad (5)$$

The first part of $\pi_C(Q)$ equals the well-known newsvendor expected profit function considering expected revenues reduced by expected overage and underage costs, which is complemented by the investment for providing the production rate, αp, and the investment required to enhance the retailer's capability to gather and analyze additional information, $\frac{\beta}{k}$. In the case of perfect knowledge of the consumer demand distribution, both parties would agree on ordering the quantity Q^* that maximizes the expected profit for the actual distribution N. Such a quantity is nothing else than the classical newsvendor order quantity associated with the distribution N and solving $F(Q^*) = \frac{R-C}{R-V}$. However, since the ordering and production decision is made $L(Q)$ days before the start of the selling season, the actual demand variance is unknown at that time and has to be estimated as $\hat{\sigma}^2(Q)$, wherefore the relevant expected profit function for the supply chain becomes:

$$\hat{\pi}_C(Q) = (R-C)\mu - (R-C)\int_{x=Q}^{+\infty}(x-Q)\hat{f}(x,Q)dx - (C-V)\int_{x=0}^{Q}(Q-x)\hat{f}(x,Q)dx - \alpha p - \frac{\beta}{k} \quad (6)$$

In this case, both parties would agree on ordering the quantity Q_C^* that maximizes the expected profit based on the estimated demand distribution at the time the decision is made, $\widehat{N}(Q)$. The actual expected profit realized by the supply chain is consequently given as:

$$\pi_C^* = \pi_C(Q_C^*) \quad (7)$$

Thus, the relative benefit of shortening the lead time from $L^{earliest}$ to $L(Q_C^*)$ can be calculated as:

$$Benefit_C^L = \frac{\pi_C(Q_C^*) - \pi_C(Q^{earliest})}{\pi_C(Q^{earliest})} \quad (8)$$

The following proposition enables finding the optimal order quantity for the centralized case.

Proposition 1.

For a given manufacturing capacity p, the optimal order quantity in the centralized case solves the first derivative condition satisfying:

$$(R-V)\left[\hat{F}(Q_C^*, Q_C^*) + \hat{\sigma}(Q_C^*)\frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_C^*)\hat{f}(Q_C^*, Q_C^*)\right] = (R-C) \quad (9)$$

- *If $k - 4\sigma^2p^2 - 4kp(\mu + p\tau) < 0$, the expected profit function $\hat{\pi}_C(Q)$ is concave and the first derivative condition has one unique solution.*
- *If $k - 4\sigma^2p^2 - 4kp(\mu + p\tau) \geq 0$, the expected profit function $\hat{\pi}_C(Q)$ is not concave. The first derivative condition, however, has at minimum one solution and at maximum two solutions. For the latter case, the choice of the optimal order quantity depends on the sign of $(R-V)\left[\hat{F}(0,0) + \hat{\sigma}(0)\frac{\partial\hat{\sigma}(Q)}{\partial Q}(0)\hat{f}(0,0)\right] - (R-C)$:*
    - *If the sign is positive, the smallest solution maximizes the expected profit.*
    - *Otherwise, the largest solution maximizes the expected profit.*

The proof of Proposition 1 is provided in Appendix A.

Given this result, it is worth mentioning that in case the standard deviation of demand is independent of the order quantity Q, i.e., $\frac{\partial\hat{\sigma}(Q)}{\partial Q} = 0$, the optimal order quantity obtained by Proposition 1 corresponds to the classical newsvendor solution. Even if we assume a linear relationship between the variance of demand and $L(Q)$ (i.e., $\hat{\sigma}(Q) = \sqrt{kL(Q) + \sigma^2}$ with $L(Q) = \frac{Q}{p} + \tau$), the optimal order quantity obtained by Proposition 1 remains valid for each convex function $\hat{\sigma}(Q)$. As mentioned earlier, the optimal solution obtained by Proposition 1 is valid under the condition that negative demands can be neglected as a result of the parameter configuration. By setting a value for $L^{earliest}$, the standard deviation $\hat{\sigma}(Q)$ is bounded by an upper value of $\sigma^{max} = \sqrt{kL^{earliest} + \sigma^2}$.

In the following, we consider a numerical example of a normally distributed consumer demand with mean $\mu = 100$ and an actual standard deviation $\sigma = 5$. An ordering decision could be made no earlier than 182 days (6 months) before the start of the selling season (see Sen, 2008). We set the fixed transportation duration to $\tau = 30$ days (see Arikan et al., 2014), successively increase the production capacity from $p^{min} = Q^{earliest} / (L^{earliest} - \tau)$ to 10 units/day and consider two values for the retailer's information processing capability before the selling season, namely $k = \{5,10\}$. We set the unit selling price to $R = 50$ and the unit discount price to $V = 5$ and consider two possible values of the production cost $C = \{10,45\}$. The former (latter) value models a high (low) margin product where underage costs are more (less) important than overage costs. We also consider three possible values of the unit cost associated with providing the production rate $\alpha = \{0,1,5\}$ and three possible values for the capability investment cost $\beta = \{0,100,300\}$.

Figure 1 illustrates the evolution of the optimal order quantity for an increasing production capacity p and for the different values of k, and Figure 2 illustrates the associated production and transportation lead time. The behavior of Q_C^* can be explained as follows. As in the classical newsvendor problem, the order quantity increases (decreases) with the standard deviation of demand for high (low) margin products as underage (overage) cost is more important than overage (underage) cost. As shown in Figure 2, an increase in p leads to a reduction in lead time and the estimated standard deviation of demand which, in turn, leads to a decreasing (increasing) optimal order quantity for a high (low) margin product. The relative benefit resulting from shortened lead times is illustrated in Figure 3 (Figure 4) for the high (low) margin product.

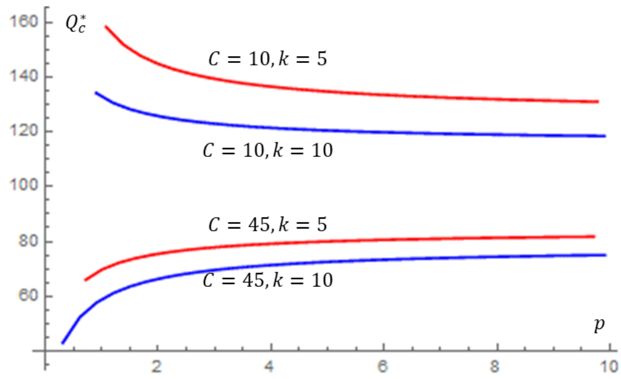

Figure 1: Optimal order quantity for alternative p-values

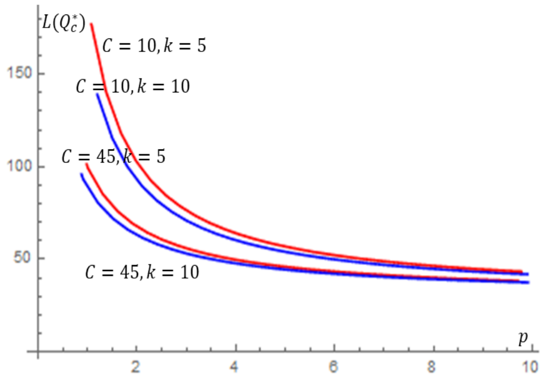

Figure 2: Optimal order lead time for alternative p-values

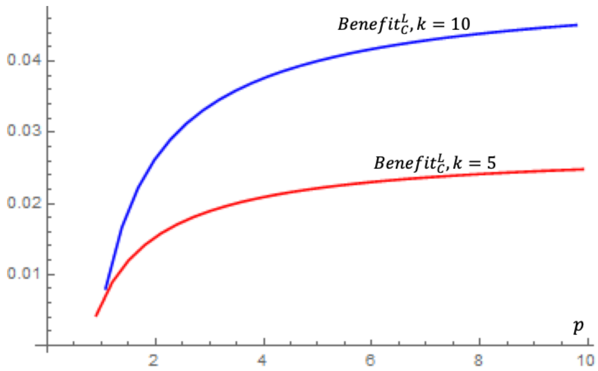

Figure 3: Benefit of postponing the order decision for perfect demand knowledge: C=10 (high-margin setting)

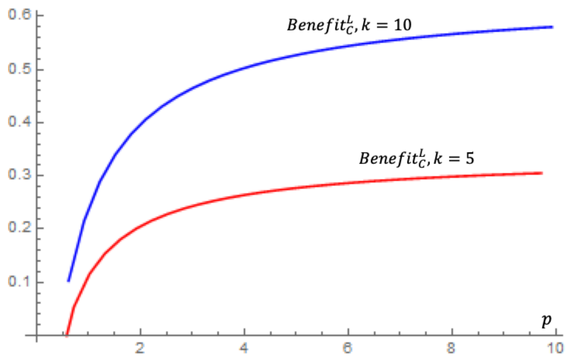

Figure 4:Benefit of postponing the order decision for perfect demand knowledge: C=45 (low-margin setting)

Figure 2 further shows that a higher information processing capability (lower values of k) leads to slightly increasing lead times. Obviously, if the retailer is able to process demand information well even though the lead time is long, there is less pressure to shorten lead times than in a scenario where k adopts high values. This also leads to higher order quantities for lower k-values, as there is less pressure on the retailer to shorten lead time by ordering less. Reducing lead times and thus enabling the retailer to gather additional demand information is clearly beneficial for the centralized supply chain as illustrated in Figures 3 and 4; this is especially the case in situations where the information processing capability of the retailer is low (high values of k), as the only way to improve demand information sufficiently are shorter lead times in this case. If the production capacity is set to p_{min}, there is still a benefit due to the adjustment of the information processing capability in the centralized scenario. The influence of k on the relative benefit of shortening lead times again depends on the product margin (high- vs. low-margin product). It is worthwhile to notice that the benefits that result from postponing the ordering decision and gathering additional demand information are higher for the low-margin product than for the high-margin setting (compare Figures 3 and 4). For the low-margin product, the cost of overstocking are higher than the cost of understocking; the decreased risk of overstocking that results from postponing the order therefore benefits the low-margin product more than the high-margin product.

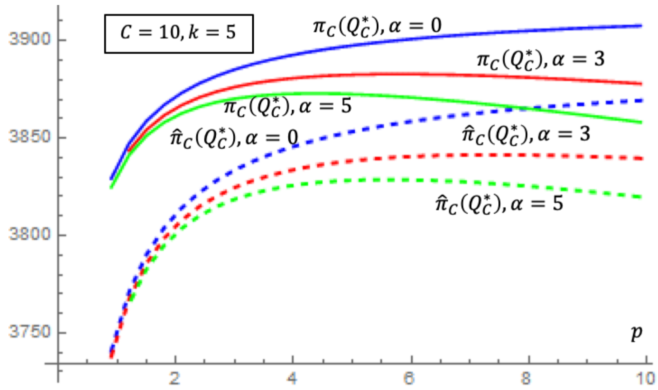

Figure 5: Optimal estimated (dashed) and actual (solid) expected profit: C=10, k=5, $\beta = 0$ (high-margin setting)

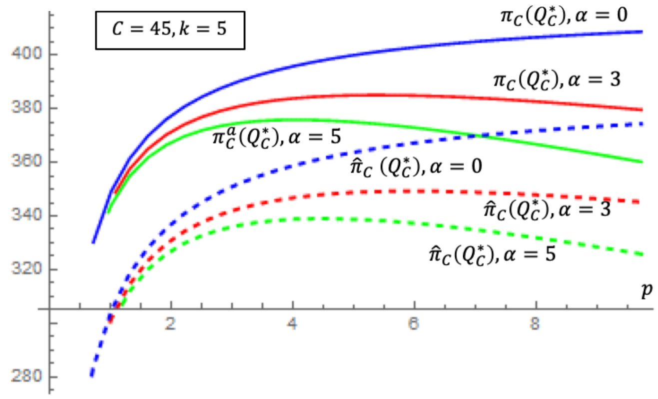

Figure 6:Optimal estimated (dashed) and actual (solid) expected profit: C=45, k=5, $\beta = 0$ (low-margin setting)

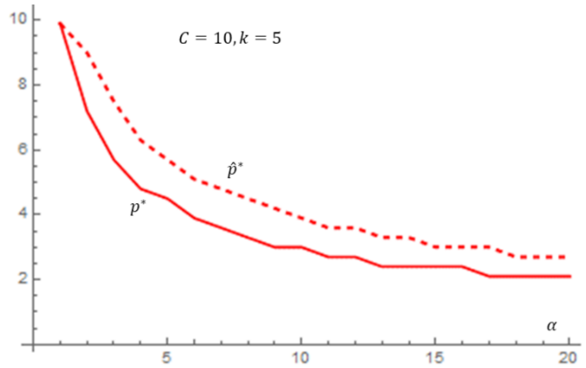

Figure 7: Optimal estimated (dashed) and actual (solid) production rate : C=10, k=5, $\beta = 0$ (high-margin setting)

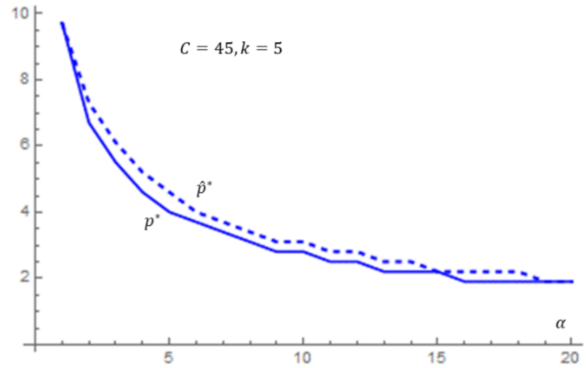

Figure 8:Optimal estimated (dashed) and actual (solid) production rate: C=45, k=5, $\beta = 0$ (low-margin setting)

The expected profit estimated when ordering, $\hat{\pi}_C(Q_C^*)$, as well as the actual expected profit achieved in case of perfect knowledge of the demand variance, $\pi_C(Q_C^*)$, are illustrated in Figures 5 (for the high-margin setting) and 6 (for the low-margin setting), and the evolution of $\hat{p}^*$ and $p^*$with increasing values of α is illustrated in Figures 7 and 8 for the high- and low-margin setting. It is interesting to note that the estimated expected profit underestimates the actual expected profit. The result is that the manufacturer tends to select a production capacity that is larger than the one s/he would select if the standard deviation of demand was accurately known. The incentive to invest in higher production capacities when demand uncertainty is overestimated can be explained by the higher marginal value of the investment at a higher perceived level of uncertainty. As similar effect can be observed in the electronics industry in which OEMs have an incentive not to share true forecasts of the demand variability in order to shift risks to contract manufacturers that will have to build higher capacities in advance to receiving the actual orders. This effect is also illustrated in Figures 7 and 8, which leads to a loss in expected profit. Both estimated and actual expected profit increase for higher values of the production capacity p if increasing p is free of cost ($\alpha = 0$). In the case where $\alpha > 0$, an increasing manufacturing capacity provides more flexibility to take advantage of lead time reductions by postponing the ordering decision, but it entails investment cost for the supply chain. For this reason, when $\alpha > 0$, there is an optimal value of the production capacity, calculated $\hat{p}^*$ and actual p^*, that optimizes the trade-off between the positive effect of lead time reductions and the cost associated with increasing capacities. As can be seen, higher values of α induce a lower production capacity to avoid high investment cost.

4.2. Decentralized uncoordinated supply chain

In the following, we analyze the decentralized uncoordinated scenario and assume that the manufacturer and the retailer are two independently owned and managed firms. Both parties aim to maximize their own expected profit and do not coordinate their decisions. In this case, the manufacturer decides on the unit wholesale price W_{DU} and the production capacity p and, after observing both values, the retailer decides on his/her order quantity Q_{DU} and his/her scaling parameter k. The retailer's objective function is the same as the one in the centralized scenario with the exception that the retailer now pays a wholesale price W_{DU} to the manufacturer, whose unit production cost is still C. The cost for the capacity investment is carried by the manufacturer. The estimated expected profit for the retailer in this case becomes:

$$\hat{\pi}_{DU}^{R}(Q) = (R - W_{DU})\mu - (R - W_{DU}) \int_{x=Q}^{+\infty} (x - Q)\hat{f}(x,Q)dx - (W_{DU} - V) \int_{x=0}^{Q} (Q - x)\hat{f}(x,Q)dx - \frac{\beta}{k} \tag{10}$$

The actual expected profit is again calculated based on the actual demand distribution as in the centralized case:

$$\pi_{DU}^{R}(Q) = (R - W_{DU})\mu - (R - W_{DU}) \int_{x=Q}^{+\infty} (x - Q)f(x)dx - (W_{DU} - V) \int_{x=0}^{Q} (Q - x)f(x)dx - \frac{\beta}{k} \tag{11}$$

The manufacturer, who is assumed the Stackelberg leader in this setting, anticipates the reaction of the retailer to his/her decision on the wholesale price W_{DU} and the production capacity p and considers this reaction in optimizing his/her decision variables. For the manufacturer, there are two possible ways to link W_{DU} to Q_{DU} depending on his/her awareness of the retailer's ordering strategy:

- *Perfect Information (PI) case*: The manufacturer is fully aware of the retailer's strategy and has perfect information about the information processing capability parameter k as well as the relationship between lead time $L(Q)$ and the standard deviation of consumer demand.

- *No Information (NI) case*: There is asymmetric information about the estimated demand variance. The manufacturer has to make his/her decision $L^{earliest}$ days before the start of the selling season, and consequently assumes the worst estimation of the demand distribution $\widehat{N}^{earliest}$ with mean μ and standard deviation $\hat{\sigma}^{max}$. We assume in the following that $\mu, \hat{\sigma}^{max}$ as well as the retail and discount prices are known to the manufacturer, and that the manufacturer only lacks information on the improved estimate of the demand variance when the retailer delays the order from $L^{earliest}$ to $L(Q)$.

The perfect information case can be found in practice when the retailer either deliberately shares obtained demand information with the manufacturer or the manufacturer estimates the demand parameter accurately over time based on other information available. Under the Collaborative Planning, Forecasting and Replenishment (CPFR) standards established by the Voluntary Interindustry Commerce Solutions (VICS) Association, for example, several global retailers and their suppliers have realized substantial benefits from integrating their inventory planning, forecasting and replenishment processes and from sharing information, developing joint forecasts and jointly crafting replenishment plans. Although CPFR implementations have turned out to be quite complex in practice due to the exchange of large amounts of forecasting-related data, the integration of different functional areas from multiple firms and the consideration of various other factors such as promotions, substantial benefits of sharing information with the supply chain have been reported (see Yao et al., 2013). In contrast, the no information scenario refers to the case where no information about demand is shared between the retailer and the manufacturer. Thus, the manufacturer has only poor information about the actual demand and assumes the worst estimation of the demand distribution. This scenario can also be frequently observed in practice.

As was shown in the analysis of the centralized scenario, the estimated expected profit is maximized for an optimal order quantity solving (note that we use the results of the centralized scenario by replacing C by W_{DU}):

$$(R-V)\left[\hat{F}(Q_{DU}^*, Q_{DU}^*) + \hat{\sigma}(Q_{DU}^*)\frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_{DU}^*)\hat{f}(Q_{DU}^*, Q_{DU}^*)\right] = (R - W_{DU}) \quad (12)$$

Under the *PI* scenario, the function linking the order quantity to the wholesale price is deterministic as far as the manufacturer is concerned:

$$W_{DU}^{PI} = R - (R-V)\left[\hat{F}(Q_{DU}, Q_{DU}) + \hat{\sigma}(Q_{DU})\frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_{DU})\hat{f}(Q_{DU}, Q_{DU})\right] \quad (13)$$

The *NI* scenario can be seen as a special case of the *PI* scenario considering the $\widehat{N}^{earliest}$ demand distribution and ignoring the linkage between $\hat{\sigma}$ and Q_{DU}:

$$W_{DU}^{NI} = R - (R-V)\left[\hat{F}^{earliest}(Q_{DU})\right] \quad (14)$$

The manufacturer's decision in this case is to choose the wholesale price W_{DU}^{j} $(j = PI, NI)$ that maximizes its own expected profit $\pi_{DU}^{M,j}(Q_{DU})$:

$$\pi_{DU}^{M,j}(Q_{DU}) = \left(W_{DU}^{j} - C\right)Q_{DU} - \alpha p \quad (15)$$

Proposition 2.

In the Perfect Information (PI used as superscript) scenario:

1. *The optimal order quantity of the retailer has to satisfy:*

$$\left[\hat{F}(Q_{DU}^{PI*}, Q_{DU}^{PI*}) + \hat{\sigma}(Q_{DU}^{PI*})\frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_{DU}^{PI*})\hat{f}(Q_{DU}^{PI*}, Q_{DU}^{PI*}) + \left[\left\{1 - \frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_{DU}^{PI*})\frac{QPI_{DU}^{*} - \mu}{\sigma(Q_{DU}^{PI*})}\right\}^2 - \left\{\frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_{DU}^{PI*})\right\}^2\right] Q_{DU}^{PI*}\hat{f}(Q_{DU}^{PI*}, Q_{DU}^{PI*})\right] = \frac{R-C}{R-V} \quad (16)$$

2. *The corresponding optimal wholesale price is:*

$$W_{DU}^{PI*} = C + (R - V)\left\{1 - \frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_{DU}^{PI*})\frac{Q_{DU}^{PI*} - \mu}{\hat{\sigma}(Q_{DU}^{*})}\right\}^2 Q_{DU}^{PI*}\hat{f}(Q_{DU}^{PI*}, Q_{DU}^{PI*}) \quad (17)$$

3. *The optimal expected profit for the manufacturer is:*

$$\pi_{DU}^{M,PI*} = (R - V)\left\{1 - \frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_{DU}^{PI*})\frac{Q_{DU}^{PI*} - \mu}{\hat{\sigma}(Q_{DU}^{PI*})}\right\}^2 {Q_{DU}^{PI*}}^2\hat{f}(Q_{DU}^{PI*}, Q_{DU}^{PI*}) \quad (18)$$

4. *The optimal actual expected profit for the retailer is:*

$$\pi_{DU}^{R,PI*} = \pi_{DU}^{R}\left(Q_{DU}^{PI,*}\right) \quad (19)$$

The No Information scenario (NI used as subscript) is obtained from the above by replacing in the last four results $\hat{F}(Q_{DU}^{PI*}, Q_{DU}^{PI*})$ by $F^{earliest}\left(Q_{DU}^{NI^*}\right)$, $\hat{f}(Q_{DU}^{PI*}, Q_{DU}^{PI*})$ by $f^{earliest}\left(Q_{DU}^{NI^*}\right)$ and by setting $\frac{\partial\hat{\sigma}(Q)}{\partial Q}(.) = 0$.

The proof of Proposition 2 is provided in Appendix B.

In the following, we consider the same numerical example as in the centralized scenario (i.e., $\mu = 100, \sigma = 5$, $k = \{5,10\}$, $C = 10$, $R = 50$, and $V = 5$). Figures 9 and 10 illustrate the relationship between the optimal order quantity and the unit wholesale price for two different levels of information processing capabilities $k = 5$ and $k = 10$. The connection between the order quantity and the wholesale price reveals the reaction of the retailer to a given wholesale price set by the manufacturer. It can be observed that the obtained results are quite sensitive to changes in the retailer's information processing capability as compared to changes in the manufacturer's production capacity. As illustrated in Figures 9 and 10, the order of the three curves (NI and PI with $p = 2$ and $p = 10$) changes if the retailer's information processing capability improves (i.e., k decreases from $k = 10$ (Figure 10) to $k = 5$ (Figure 9)). This shows that in the PI case, if the retailer improves its information processing capability, the manufacturer takes advantage by increasing its wholesale price, rendering this setting less attractive to the retailer.

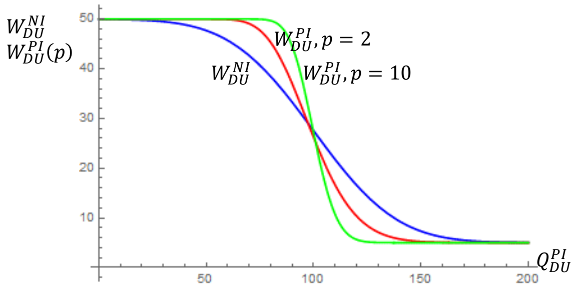

Figure 9: Link between the wholesale price and the order quantity for the DU scenario, k=5

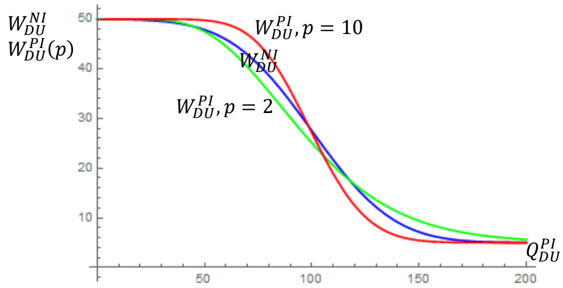

Figure 10: Link between the wholesale price and the order quantity for the DU scenario, k=10

As a result, the attractiveness of the NI and the PI scenarios to both the retailer and the manufacturer is strongly linked to the two variables k and p. Given that k is determined by the retailer and p is chosen by the manufacturer, it is necessary to investigate in which scenario of information sharing both supply chain parties are better off.

Acting as the Stackelberg leader, the manufacturer proposes a unit wholesale price closer to R than to V, which makes the overage cost more important than the underage cost for the retailer (this entails that the ratio of underage cost to the sum of overage and underage costs is less than 0.5). The optimal order quantity is lower than the demand average, and its behavior with increasing p is similar to the low margin setting discussed in the centralized scenario (cf. Figure 12). Under the No Information case, the manufacturer proposes a fixed unit wholesale price (independent of p and k), where the calculation of the wholesale price is identical to the classical wholesale contract problem with $\widehat{N}^{earliest}$ as the demand distribution (cf. Figure 13).

It is worthwhile to notice that $\widehat{N}^{earliest}$ depends directedly on the maximum value of the estimated standard deviation $\hat{\sigma}^{max} = \sqrt{kL^{earliest} + \sigma^2}$. Under the NI case, the retailer does not share any obtained demand information with the manufacturer. The latter proposes a wholesale price W_{DU}^{NI*} based on his/her own estimate of $\hat{\sigma}^{max}$ under the NI scenario. A mismatch between the manufacturer's $\hat{\sigma}^{max}$ estimate and the retailer's demand processing capability can lead to a conflicting choice of the decision variables or to a mutual agreement on whether or not to reduce the lead time. Based on these observations, we can define four regions based on the manufacturer's estimate of $\hat{\sigma}^{max}$ and the retailer's information processing capability k.

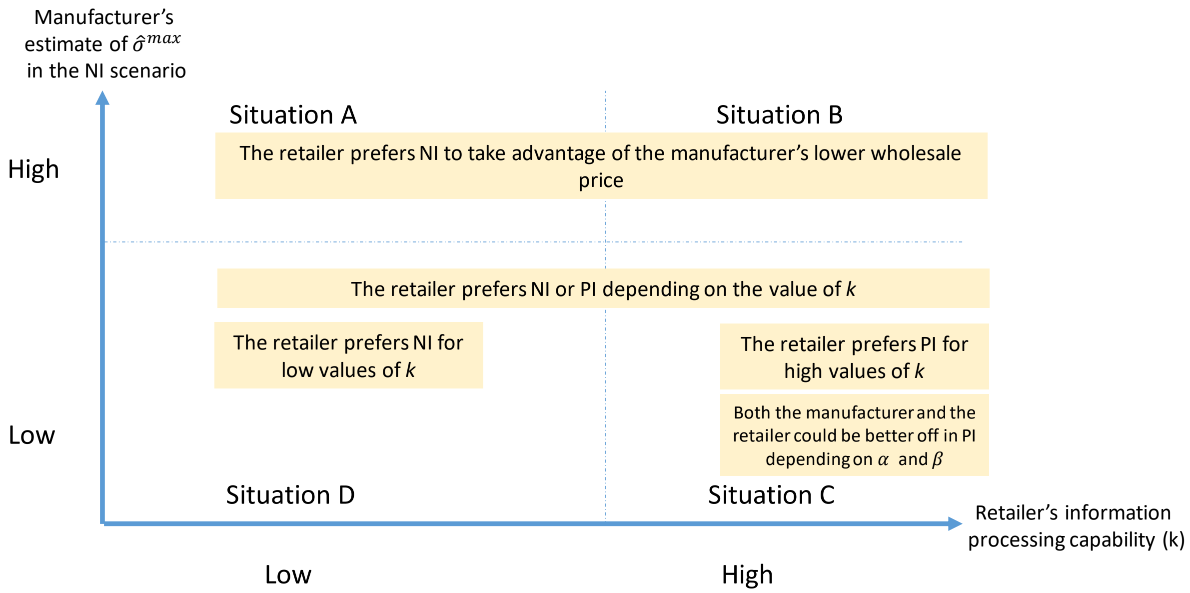

Figure 11: The supply chain actors' preference for the PI and the NI scenario depending on k and $\hat{\sigma}^{max}$

Assuming an actual demand standard deviation $\sigma = 5$, Figures 12 to 17 illustrate four different situations where the manufacturer sets the NI wholesale price based on two estimates of $\hat{\sigma}^{max}$ ($\hat{\sigma}^{max} = 30$ for situations A and B and $\hat{\sigma}^{max} = 15$ for situations C and D), whereas the retailer sets the information processing capability to $k = 1$ in situations A and D and to $k = 5$ in situations B and C. Given these values of k, the retailer is able to estimate $\hat{\sigma}^{max} = \sqrt{kL^{earliest} + \sigma^2}$ as 14.40 for $k = 1$ (and as 30.60 for $k = 5$, respectively) based on an $L^{earliest}$ equal to six months. As a result, the manufacturer's and the retailer's estimates of $\hat{\sigma}^{max}$ are close in situations B and D and (oppositely) different in situations A and C ($\hat{\sigma}^{max}$ is overestimated by the manufacturer in situation A and underestimated in situation C and vice versa for the retailer). Note that under the NI scenario, the manufacturer has no incentive to invest in the production capacity and sets its production capacity to its minimum value $p^{min} = \frac{Q_{DU}^{NI*}}{L^{earliest} - \tau}$. For this reason, the NI illustrations in Figures 12 to 17 are represented by a point marker at p^{min}.

In situations A and B, the manufacturer overestimates $\hat{\sigma}^{max}$ and consequently proposes a low W_{DU}^{NI*} in the NI scenario (Figure 13). The retailers takes advantage of such a proposal and would prefer the NI scenario if the manufacturer overestimated $\hat{\sigma}^{max}$. Not sharing obtained demand information with the manufacturer (NI) and investing in k (a low k as in situation A) would be the best strategy for the retailer in this case. The retailer could then take advantage of both the lower wholesale price and the reduced demand uncertainty. Even if additional demand information is not shared with him/her, the manufacturer would still prefer the retailer to invest in his/her demand processing capabilities (c.f. $\pi_{DU}^{M,NI*}$, situation A, and $\pi_{DU}^{M,NI*}$, situation B, in Figure 14). This can be explained by the higher order quantity of the retailer in situation A compared to situation B as illustrated in Figure 12 (please recall the explanation we provided in Figure 1 on the rationale behind a higher order quantity for a lower k). As a result, delaying the order to acquire additional demand information is beneficial for both firms even when the manufacturer overestimates $\hat{\sigma}^{max}$ and the retailer decides to not share any obtained information (the NI scenario).

However, the results are entirely different when the manufacturer underestimates $\hat{\sigma}^{max}$ (situations C and D). The wholesale price W_{DU}^{NI*} proposed in the NI scenario could be lower or higher than his/her proposal of W_{DU}^{PI*} in the PI scenario depending on the value of k set by the retailer. If $\beta = 0$ (Figures 12 to 17 are drawn for $\beta = 0$ and $\alpha = 10$), the retailer would prefer the PI scenario over the NI scenario as he/she would be better off by investing less into information processing capabilities (i.e., by selecting a high k-value) in order to profit from a lower wholesale price (W_{DU}^{PI*} under situation C is lower than the one offered under situation D). The manufacturer is, in contrast, is better off in situation D if the retailer decides to share demand information (Figure 14) as he/she can benefit from the most accurate level of demand information (i.e., low value of k) which is shared by the retailer. This obvious conflict of interest is also influenced by the cost of capacity investments α as the manufacturer moves from the lowest production rate p^{min} (under the NI scenario) to a higher production rate (under the PI scenario) which could be optimized as illustrated in Figure 14 for the PI curves (i.e., there is a best value of p^* which maximizes the manufacturer's profit). In addition, the decision of the retailer to move or not to move from the NI scenario to the PI scenario strongly depends on the value of k as shown in Figure 15. In situation D, the retailer should rather stay in the NI scenario and move to the PI scenario under situation C. By moving to the PI scenario, he/she can benefit or loose from acquiring additional demand information depending on the level of capacity p^* set by the manufacturer. The profit of the retailer in the PI scenario in situation C decreases with p and can drop below his/her profit in the NI scenario depending on the problem parameters.

For all situations, it is worthwhile to notice that the expected supply chain profit (i.e., the sum of the retailer's and the manufacturer's expected profits) is higher when the market insights are shared (see Figure 16). To assess the performance of the supply chain under the decentralized uncoordinated (DU) scenario, we define the supply chain efficiency as the expected profit of the supply chain in the DU scenario divided by the expected profit under the centralized (C) scenario ($Eff^j = \frac{\pi_{DU}^{R,j} + \pi_{DU}^{M,j}}{\pi_C(Q_C^*)}, j = PI, NI$). As illustrated in Figure 16, there is a significant difference between the expected supply chain profit under the NI and PI scenarios. Contradictorily, the supply chain efficiency is better in the NI scenario (cf. Figure 17) except for situation C. This is due to the double marginalization effect which is stronger if the manufacturer is aware of the retailer's ability to collect and analyze additional information. In this case, the manufacturer increases the wholesale price, which leads to a lower order quantity on the retailer's side and consequently a higher double marginalization effect (see also Figure 12).

We note that the somewhat counterintuitive result that lead times are not shortened by increasing the production capacity in the uncoordinated case is caused by the fact that the manufacturer is assumed the Stackelberg leader in our model. The manufacturer would only be willing to shorten lead time if he/she is aware of the impact of shorter lead times on the retailer's order behavior. As the manufacturer would, at the same time, extract profit from the retailer by increasing the wholesale price, the retailer is better off by not sharing any information, inducing the manufacturer to select the lowest possible production capacity.

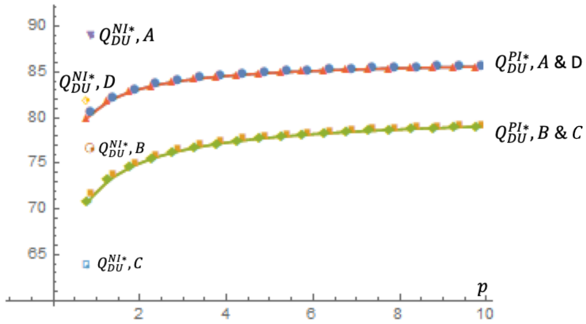

Figure 12: Optimal order quantity for the DU scenario, α=5, $\beta = 0$

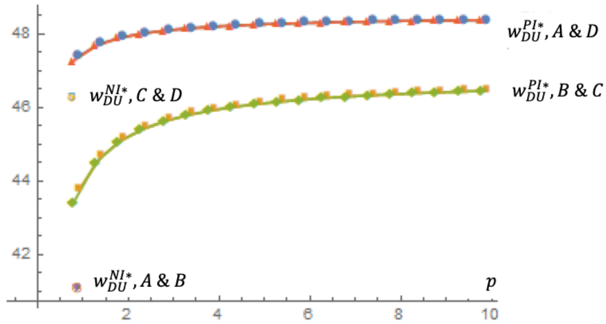

Figure 13: Optimal wholesale price for the DU scenario, α=5, $\beta = 0$

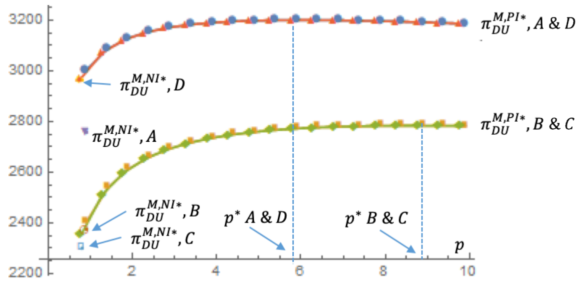

Figure 14: Optimal expected profit for the manufacturer, α=10

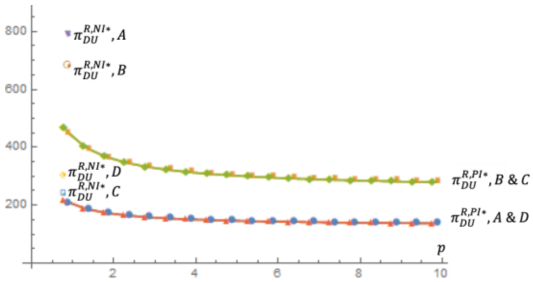

Figure 15: Optimal expected profit for the retailer, α=10

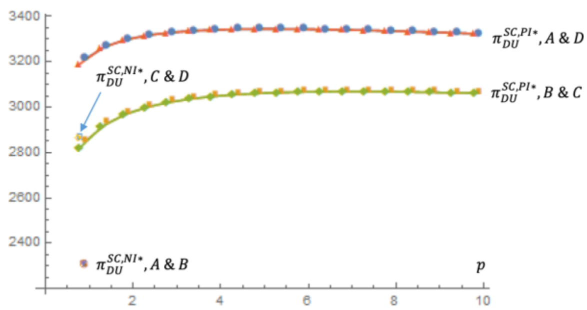

Figure 16: Optimal expected profit for the supply chain, k=10, α=10

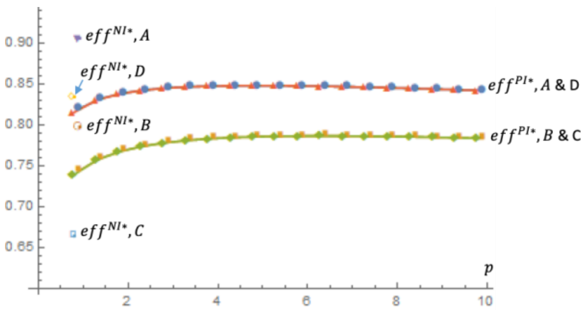

Figure 17: Supply chain efficiency for k=5 and k=10

As mentioned earlier, the retailer would be better off for lower values of k under the NI case. In such a situation, the best solution for the manufacturer is not to invest in p and to only offer p^{min} as a production capacity. However, an increase in the information processing capability (i.e., lower values of k) comes at the expense of additional investments cost. For different values of β, Figure 18 illustrates the existence of a best value of k trading off the benefit of reduced demand uncertainty and the investment needed to lower k under the NI case. As discussed in the centralized scenario, the retailer optimizes his/her decisions based on the estimated expected profit function. However, his/her actual performance is measured by the actual expected profit function involving the actual expected demand distribution. Consequently, the best k chosen by the retailer under the NI case is suboptimal compared to the case where the ordering decision is postponed until the start of the selling season.

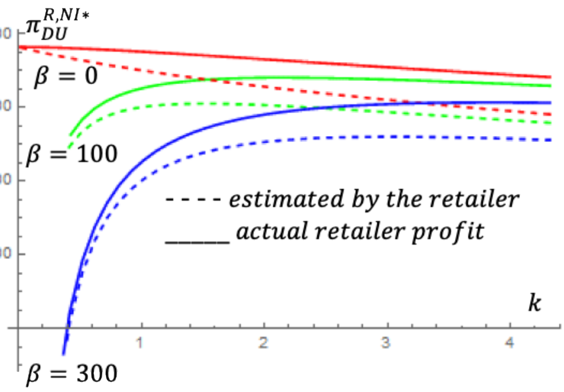

Figure 18: Best k for the retailer - NI case

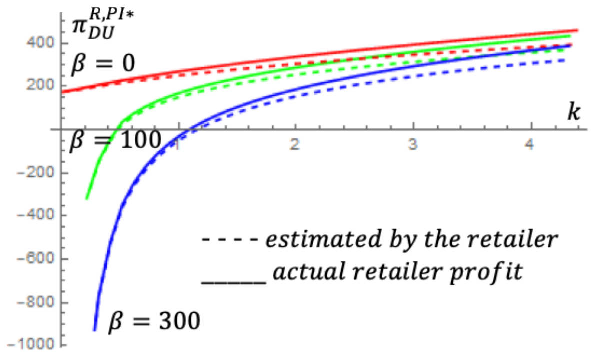

Figure 19: Best k for the retailer - PI case

If the retailer is offered the lowest production capacity p^{min} in the PI scenario, s/he is, in contrast, better off with the highest value of k that helps to take advantage of the lower wholesale price offered by the manufacturer in such a situation (cf. Figure 19). In the PI scenario, the cost of adjusting the production capacity paid by the manufacturer and the cost of the investment information processing capabilities paid by the retailer lead to conflicting best values for these two variables as shown in Figures 20 and 21. The supply chain would choose a best tuple (p, k) minimizing the double marginalization effect (cf. Figure 22). Figure 23 shows that the supply chain efficiency would suffer from the choices made by both supply chain players individually. Despite the conflicting decisions concerning p and k, coordinating the supply chain aims to tackle the double marginalization effect and to arrive at a win-win situation for both the manufacturer and the retailer. The next section will propose a coordination mechanism aiming to bring back the expected supply chain profit to the value realized in the centralized scenario.

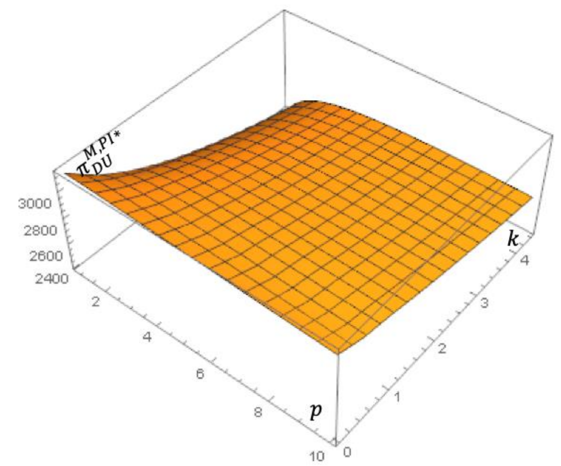

Figure 20: Optimal expected profit of the supplier as a function of p and k, $\alpha = 10$ and $\beta = 100$

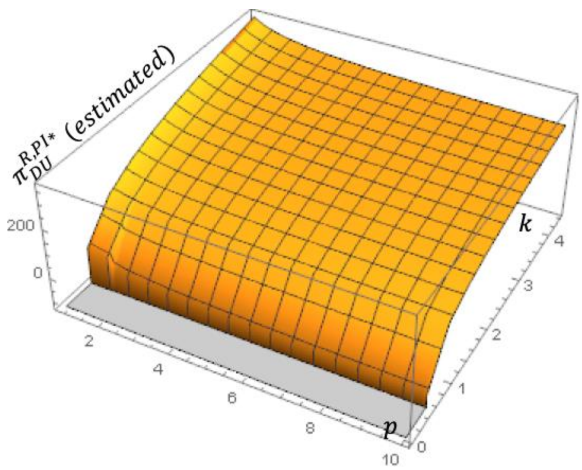

Figure 21: Optimal expected profit of the retailer as a function of p and k, $\alpha = 10$ and $\beta = 100$

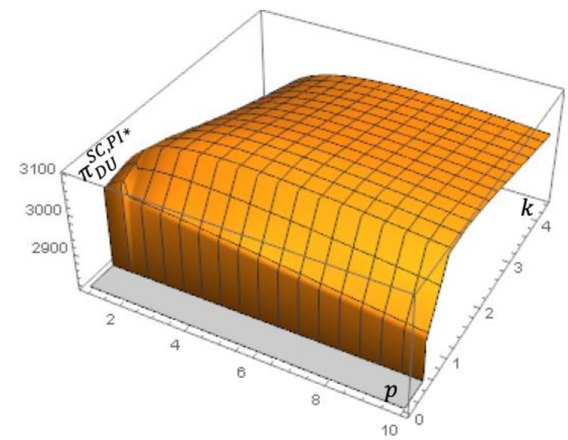

Figure 22: Optimal expected profit of the supply chain as a function of p and k, $\alpha = 10$ and $\beta = 100$

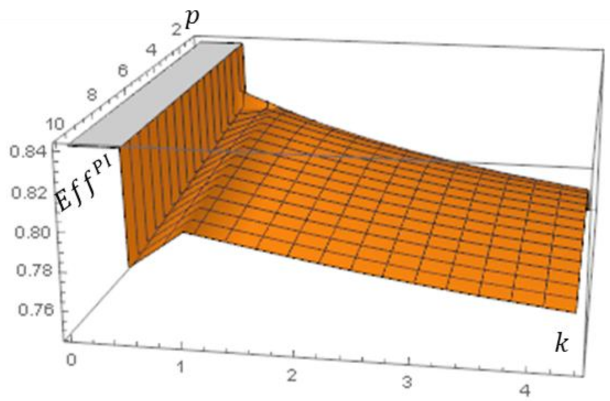

Figure 23: Supply chain efficiency as a function of p and k, $\alpha = 10$ and $\beta = 100$

4.3. Decentralized coordinated supply chain

For the two-stage newsvendor problem, different contracts have been proposed to improve the performance of the supply chain. In a classical buy-back contract, the retailer pays a wholesale price W_{DC} per unit ordered, but can return the excess order quantity at a partial refund B_{DC} at the end of the selling season (Pasternack, 1985). The refund cost is modeled as an extra unit margin for each discounted product to avoid returning it back to the supplier and paying extra reverse logistics costs. The retailer's estimated expected profit function in the decentralized coordinated case is similar to the decentralized uncoordinated scenario except that the unit salvage cost, V, is replaced by $V + B_{DC}$:

$$\pi_{DC}^{R}(Q_{DC}) = (R - W_{DC})\mu - (R - W_{DC}) \int_{x=Q_{DC}}^{+\infty} (x - Q_{DC}) \hat{f}(x, Q_{DC}) dx - (W_{DC} - V - B_{DC}) \int_{x=0}^{Q_{DC}} (Q_{DC} - x) \hat{f}(x, Q_{DC}) dx - \frac{\beta}{k} \quad (20)$$

For a given tuple (W_{DC}, B_{DC}), the optimal order quantity maximizing the retailer's expected profit is given by:

$$(R - V - B_{DC})\left[\hat{F}(Q_{DC}, Q_{DC}) + \sigma(Q_{DC})\frac{\partial\sigma(Q)}{\partial Q}(Q_{DC})\hat{f}(Q_{DC}, Q_{DC})\right] = (R - W_{DC}) \tag{21}$$

For each unsold item, the manufacturer now compensates the retailer with the unit buyback cost, wherefore the manufacturer's estimated expected profit becomes:

$$\pi_{DC}^{M}(Q_{DC}) = (W_{DC} - C)Q_{DC} - B_{DC}\int_{x=0}^{Q_{DC}}(Q_{DC} - x)\hat{f}(x, Q_{DC})dx - \alpha p \tag{22}$$

The manufacturer's problem in this case is to find the best tuple (W_{DC}, B_{DC}) and the associated order quantity Q_{DC} maximizing his/her expected profit and coordinating the supply chain. We first assume that B_{DC} is fixed, and derive the value of W_{DC}^{*} that indicates the optimal order quantity for the manufacturer (resulting from the optimization of $\pi_{DC}^{M}(Q_{DC})$) that is equal to the retailer's (maximizing $\pi_{DC}^{R}(Q_{DC})$).

Proposition 3.

The supply chain is coordinated by the tuple (B_{DC}^{*}, W_{DC}^{*}) solving the following:

$$W_{DC}^{*} = C + B_{DC}^{*} * \left[\hat{F}(Q_{DC}^{*}, Q_{DC}^{*}) + \hat{\sigma}(Q_{DC}^{*})\frac{\partial\hat{\sigma}}{\partial Q}(Q_{DC}^{*})\hat{f}(Q_{DC}^{*}, Q_{DC}^{*})\right] \tag{23}$$

Where: Q_{DC}^{*} verifies:

$$(R - V)\left[\hat{F}(Q_{DC}^{*}, Q_{DC}^{*}) + \hat{\sigma}(Q_{DC}^{*})\frac{\partial\hat{\sigma}(Q)}{\partial Q}(Q_{DC}^{*})\hat{f}(Q_{DC}^{*}, Q_{DC}^{*})\right] = (R - C) \tag{24}$$

Proof.

By using the equation linking B_{DC}^{*} and W_{DC}^{*}, the optimal order quantity maximizing the manufacturer's expected profit coincides with the optimal order quantity of the centralized case. ■

Continuing the numerical example (for $\alpha = 10$ and $\beta = 100$), the supply chain is better off with a production capacity of $p = 3.60$ and an information processing capability of $k = 4.60$. For this set of p and k, the supply chain profit under the centralized scenario is equal to 3726 as illustrated in Figure 25. Without coordination, under the decentralized uncoordinated scenario and given these values of p and k, the retailer realizes an expected profit of 286.97 and the manufacturer of 2744.98. As a result, the total supply chain profit without coordination equals 3031.95. The coordination mechanism permits the supply chain to attain the highest possible expected profit of 3726 (as realized under the centralized case). The refund B_{DC} controls how much the two parties benefit from the cooperation. For higher values of B_{DC}, the manufacturer receives a higher share of the profit due to an increase in the wholesale price (cf. Figure 24). For lower values of B_{DC}, the manufacturer selects a lower wholesale price and hence transfers a larger share of the supply chain profit to the retailer. Based on the chosen tuple (B_{DC}^*, W_{DC}^*), the two supply chain actors consequently share the whole supply chain profit. As illustrated in Figure 25 and based on the expected profits that the two supply chain parties make in the case of no coordination, there exists a range of tuples (B_{DC}^*, W_{DC}^*) that benefit manufacturer and retailer and enable both of them to improve their respective positions thanks to the coordination mechanism.

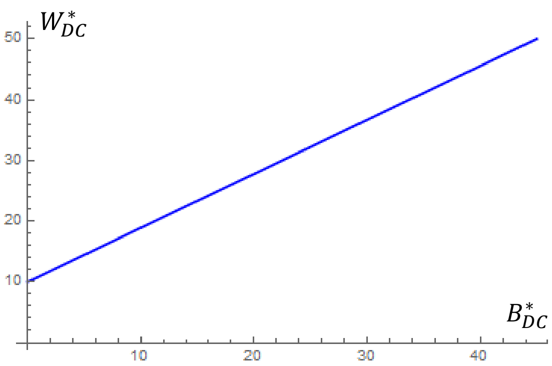

Figure 24: Tuple (B_{DC}^*, W_{DC}^*) coordinating the supply chain, $\alpha = 10$ and $\beta = 100$

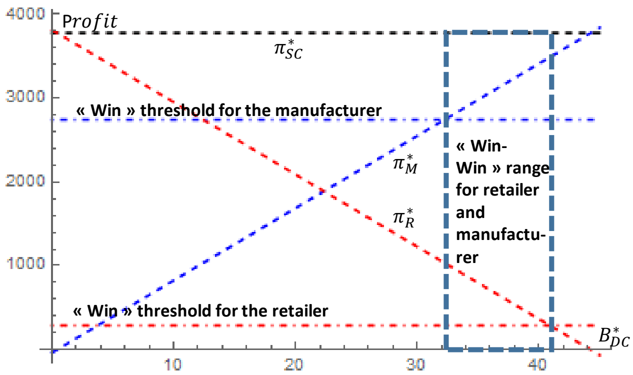

Figure 25: Supply chain, retailer and manufacturer expected profits as a function of B_{DC}^*, $\alpha = 10$ and $\beta = 100$

5. Conclusion

In this paper, we modelled a decentralized supply chain with an order quantity and investment-dependent lead time. The lead time can be shortened by i) a supply-side investment enabling a higher production capacity, and/or ii) a reduction in the order quantity. We further considered a demand-side investment enabling a higher capability to collect information about future demand inducing a decrease in demand variability.

We first considered a centralized scenario and demonstrated the positive benefit of postponing the ordering decision. Our results indicate that from a supply chain point of view, shorter lead times always improve the expected supply chain profit. We thus confirm earlier research on continuous inventory models (e.g., Hoque, 2007; Ben-Daya and Hariga, 2004; Glock, 2012) that showed that supply chains usually benefit from shorter lead times, with the extent of the lead time reduction depending on the supply chain actors' cost and performance parameters. We also showed that optimal investment levels into both the production capacity and the demand information processing capability exist that maximize the benefit of delaying the order. In addition, our results revealed a trade-off between the investment into the demand information processing capability and the effort made to shorten the lead time. If the supply chain can easily improve its capability to process demand information, it is beneficial to accept longer lead times and to invest into demand information processing (and vice versa). This substitution effect between the ability to gather and process demand information and the efforts made in reduced lead times that enable a generally lower level of demand uncertainty has not been studied in the literature so far. In fact, increased forecasting abilities due to improved knowledge or technological progress can enable retailers to benefit from off-shoring with necessarily being affected by the increase in demand uncertainty due to increased lead times.

For the decentralized uncoordinated supply chain, we showed that the two supply chain actors may not always be interested in shorter lead times; their interest in a postponement of the order depends on the level of information sharing and the levels of investments into the production capacity and the demand information processing capability. If the retailer's information processing capability is high or inexpensive to improve, he/she has no incentive to share improved demand information with the manufacturer to avoid that the manufacturer increases the wholesale price. The manufacturer, in this case, has no incentive to shorten lead times, and consequently selects the lowest possible production capacity. If the retailer shares the improved demand information in contrast, then the manufacturer has an incentive to shorten lead time as well. The retailer generally benefits from shorter lead times, but is not always willing to accept the higher wholesale price that the manufacturer charges when shortening lead time. The best strategy for each actor was detailed, and we showed that the supply chain efficiency suffers from these potentially conflicting strategies. The decision about whether or not to shorten lead time was found to be very sensitive to the investment costs as well as the unit overage and unit underage penalties. Controlling these costs is hence of high importance in a practical application. This paper complements the work of Kraiselburd et al. (2010), who had shown that the manufacturer may not be interested in shorter lead times if higher demand uncertainty induces the retailer to order more. We extended their work by considering more than two lead time options, lead time reduction cost, and a demand information processing capability.

To coordinate the supply chain and to avoid a loss in supply chain profit resulting from the manufacturer's and the retailer's conflict of interest, a buyback contract was proposed. In addition to solving the double marginalization problem that has frequently been associated with these kinds of contracts, we showed that the contract also leads to an optimal investment into the production capacity and the demand information processing capability.

Our framework contributes to the literature by assuming a continuous relationship between lead time and order quantity. This relationship was motivated by the martingale method of forecast evolution, and it led to a simple formulation that we integrated in a mathematically tractable manner into the decentralized newsvendor problem. The developed framework permits to link the logistics and marketing interfaces by trading off the logistics cost, the production capacity and the marketing-type expenditure to improve the forecasting exercise. The framework is applicable in many practical situations in the fashion/high tech sector where social media and marketing surveys are solicited before the launch of new products to improve the quality of consumer demand forecasts and to reduce uncertainty. Postponing the ordering decision, if the supplier's production capacity permits it, enables to collect more information about the demand and to improve supply chain performance considerably. The paper provided managerial insights into the strategy for each supply chain actor and their implications on the ordering as well as the investment decisions.

A natural extension of the developed models would be to consider investments in transportation lead time reductions. Today, companies can often choose between alternative transportation modes and transport service providers and may hence trade off shorter transportation time against higher transportation cost. Depending on the sourcing strategy, transportation lead times can account for a significant fraction of the overall lead times, and selecting the best mode of transportation may enable the retailer to reduce transportation-related delays as well. Air shipments, for example, usually have a short and rather predictable lead time as compared to sea freight, but at the expense of higher transportation cost (cf. Arikan et al, 2014). As the proposed models revealed a trade-off between profit maximization and uncertainty reduction, it would also be interesting to consider different risk perceptions of the retailer in this setting by including risk aversion or other behavioral aspects (cf. Arikan and Fichtinger, 2017).

Appendix A: Proof of Proposition 1

Making use of the Leibniz rule, the first derivative of the expected profit function (6) can be written as:

$$\frac{\partial \hat{\pi}_C(Q)}{\partial Q} = -(R-C)\int_{x=Q}^{+\infty}\left[-\hat{f}(x,Q)+(x-Q)\frac{\partial \hat{f}(x,Q)}{\partial Q}\right]dx-(C-V)\int_{x=0}^{Q}\left[\hat{f}(x,Q)+(Q-x)\frac{\partial \hat{f}(x,Q)}{\partial Q}\right]dx \qquad \text{(A-1)}$$

In addition, the first derivative of the *pdf* with respect to Q leads to:

$$\frac{\partial \hat{f}(x,Q)}{\partial Q} = -\frac{\partial \hat{\sigma}(Q)}{\partial Q}\frac{1}{\hat{\sigma}(Q)}\left[1-\left(\frac{x-\mu}{\hat{\sigma}(Q)}\right)^2\right]\hat{f}(x,Q) \qquad \text{(A-2)}$$

Using the fact that the second derivative of the *pdf* with respect to x is given as:

$$\frac{\partial^2 \hat{f}(x,Q)}{\partial^2 x} = -\frac{1}{\hat{\sigma}(Q)^2}\left[1-\left(\frac{x-\mu}{\hat{\sigma}(Q)}\right)^2\right]\hat{f}(x,Q) \qquad \text{(A-3)}$$

The first derivative of the *pdf* with respect to Q can be rewritten as follows:

$$\frac{\partial \hat{f}(x,Q)}{\partial Q} = \frac{\partial \hat{\sigma}(Q)}{\partial Q}\hat{\sigma}(Q)\frac{\partial^2 \hat{f}(x,Q)}{\partial^2 x} \qquad \text{(A-4)}$$

Applying this expression to Eq. (A-1), the first derivative of the expected profit can be written as:

$$\frac{\partial \hat{\pi}_C(Q)}{\partial Q} = (R-C)\left[1-\hat{F}(Q,Q)\right]-(C-V)\left[\hat{F}(Q,Q)-\hat{F}(0,Q)\right]+(R-C)\frac{\partial \hat{\sigma}(Q)}{\partial Q}\hat{\sigma}(Q)\int_{x=Q}^{+\infty}\left[(x-Q)\frac{\partial^2 \hat{f}(x,Q)}{\partial^2 x}\right]dx+(C-V)\frac{\partial \hat{\sigma}(Q)}{\partial Q}\hat{\sigma}(Q)\int_{x=0}^{Q}\left[(Q-x)\frac{\partial^2 \hat{f}(x,Q)}{\partial^2 x}\right]dx \qquad \text{(A-5)}$$

We now use the integration by part theorem and the fact that the first derivative of the *pdf* with respect to x is given as follows:

$$\frac{\partial \hat{f}(x,Q)}{\partial x} = -\left[\frac{x-\mu}{\hat{\sigma}(Q)^2}\right]\hat{f}(x,Q) \tag{A-6}$$

The first derivative of the expected profit function can be summarized as:

$$\frac{\partial \hat{\pi}_C(Q)}{\partial Q} = (R-C) - (R-V)\left[\hat{F}(Q,Q) + \frac{\partial \hat{\sigma}(Q)}{\partial Q}\hat{\sigma}(Q,p)\hat{f}(Q,Q)\right] + (C-V)\left[F(0,Q) + \frac{\partial \hat{\sigma}(Q)}{\partial Q}\hat{\sigma}(Q)\hat{f}(0,Q)\left\{1 + Q\frac{\mu}{\hat{\sigma}(Q)^2}\right\}\right] \tag{A-7}$$

By observing that $\lim_{Q\to 0}\frac{\partial \hat{\pi}_C(Q)}{\partial Q} = R - C$ and $\lim_{Q\to +\infty}\frac{\partial \hat{\pi}_C(Q)}{\partial Q} = -\frac{C-V}{2}$, the existence of at least one solution maximizing the expected profit is straightforward.

Assuming that the parameters (particularly $L^{earliest}$) exist in such a way that negative demands do not occur ($\hat{F}(0,Q) \approx 0$ for each Q), the last component of the first derivative of the expected profit becomes negligible. The remaining part can therefore be simplified as:

$$\frac{\partial \hat{\pi}_C(Q)}{\partial Q} = (R-C) - (R-V)\left[\hat{F}(Q,Q) + \frac{\partial \hat{\sigma}(Q)}{\partial Q}\hat{\sigma}(Q)\hat{f}(Q,Q)\right] \tag{A-8}$$

In order to verify the uniqueness of the solution, it is helpful to further analyze the second derivative of the expected profit function. The first derivative of $\hat{f}(Q,Q)$ with respect to Q is given as:

$$\frac{\partial \hat{f}(Q,Q)}{\partial Q} = -\left[\frac{\partial \hat{\sigma}(Q)}{\partial Q}\left\{1 - \left(\frac{x-\mu}{\hat{\sigma}(Q)}\right)^2\right\} + \frac{Q-\mu}{\hat{\sigma}(Q)}\right]\frac{\hat{f}(Q,Q)}{\hat{\sigma}(Q)} \tag{A-9}$$

Using the Leibniz rule, the first derivative of $\hat{F}(Q,Q)$ with respect to Q is given as:

$$\frac{\partial \hat{F}(Q,Q)}{\partial Q} = \left[1 - \frac{\partial \hat{\sigma}(Q)}{\partial Q}\frac{Q-\mu}{\hat{\sigma}(Q)}\right]\hat{f}(x,Q) \tag{A-10}$$

Applying Eqs. (A-9) and (A-10), the second derivative of the expected profit function becomes:

$$\frac{\partial^2 \hat{\pi}_C(Q)}{\partial^2 Q} = -(R-V)\left\{\left[1 - \frac{\partial \hat{\sigma}(Q)}{\partial Q}\frac{Q-\mu}{\hat{\sigma}(Q)}\right]^2 + \hat{\sigma}(Q)\frac{\partial^2 \hat{\sigma}(Q)}{\partial^2 Q}\right\}\hat{f}(Q,Q) \tag{A-11}$$

If $\hat{\sigma}(Q)$ is convex (which is not the case in our problem), the expected total profit function $\hat{\pi}_C$ would be concave, and the optimal order quantity would be obtained by applying the first derivative condition.

We now define $S(Q) = \left[1 - \frac{\partial \hat{\sigma}(Q)}{\partial Q}\frac{Q-\mu}{\hat{\sigma}(Q)}\right]^2 + \hat{\sigma}(Q)\frac{\partial^2 \hat{\sigma}(Q)}{\partial^2 Q}$. The mathematical analysis of the function $S(Q)$ permits deriving the cases where the expected profit function is concave and developing an optimization procedure for the opposite case.

If $k - 4\sigma^2 p^2 - 4kp(\mu + p\tau) < 0$, $S(Q)$ continuously decreases from $+\infty$ to $\frac{1}{4}$ when Q converges from $-\frac{\sigma^2 + k\tau}{k}$ to $+\infty$. In such a case, $S(Q)$ is always positive. Consequently, the expected profit function is concave and the first derivative condition allows deriving the optimal order quantity. However, if $k - 4\sigma^2 p^2 - 4kp(\mu + p\tau) \geq 0$, $S(Q)$ is negative on the interval (a, b) with $a = k^2 - 4\sigma^2 p^2 - k\left[2p(\mu + 2p\tau) + \sqrt{k - 4\sigma^2 p^2 - 4kp(\mu + p\tau)}\right]$ and $b = k^2 - 4\sigma^2 p^2 + k\left[2p(\mu + 2p\tau) + \sqrt{k - 4\sigma^2 p^2 - 4kp(\mu + p\tau)}\right]$ as shown in Figure A-1 before converging to $\frac{1}{4}$ for $Q \to +\infty$. In this case, the expected profit function is not concave, and the first derivative condition may have two extreme points at maximum. In the latter case, the choice of the extreme point maximizing the expected profit depends on the sign of the first derivative of the expected profit function at $Q = 0$, which is equal to $(R - V)\left[\hat{F}(0,0) + \hat{\sigma}(0, \mathrm{p})\frac{\partial\hat{\sigma}(Q,p)}{\partial Q}(0)\hat{f}(0,0,\mathrm{p})\right] - (R - C)$. If this expression is positive, the smaller solution of the first derivative condition (a in the example in Figure A-1), maximizes the expected profit, otherwise, the larger solution (b in the example in Figure A-1), maximizes it. ■

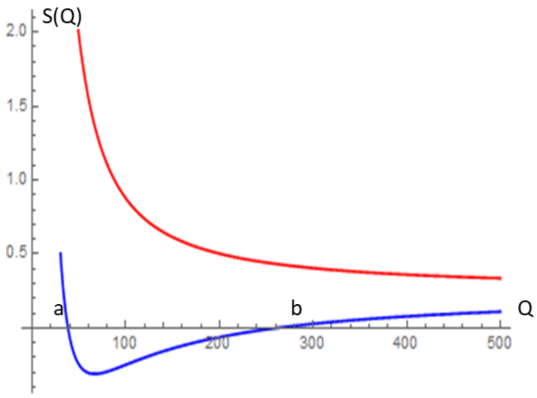

Figure A-1: Behavior of the function S(Q)

Appendix B: Proof of Proposition 2

Proof.

By applying some basic algebraic techniques, the first derivative of the manufacturer's expected profit (15) can be calculated as follows:

$$\frac{\partial\pi_{DU}^{M,PI}}{\partial Q_{DU}} = (R - C) - (R - V)\left[\hat{F}(Q_{DU}^{PI}, Q_{DU}^{PI}) + \sigma(Q_{DU}^{PI})\frac{\partial\sigma(Q)}{\partial Q}(Q_{DU}^{PI})\hat{f}(Q_{DU}^{PI}, Q_{DU}^{PI}) + \left[\left\{1 - \frac{\partial\sigma(Q)}{\partial Q}(Q_{DU}^{PI})\frac{Q_{DU}^{PI} - \mu}{\sigma(Q_{DU}^{PI})}\right\}^2 - \left\{\frac{\partial\sigma(Q)}{\partial Q}(Q_{DU}^{PI})\right\}^2\right] Q_{DU}^{PI}\hat{f}(Q_{DU}^{PI}, Q_{DU}^{PI})\right] \quad \text{(A-12)}$$

It is important to note that:

$$\lim_{Q_{DU}^{PI}\to 0} \frac{\partial \pi_{DU}^{M,PI}}{\partial Q_{DU}^{PI}} = (R-C) \quad \text{(A-13)}$$

$$\lim_{Q_{DU}^{PI}\to +\infty} \frac{\partial \pi_{DU}^{M,PI}}{\partial Q_{DU}^{PI}} = -(C-V) \quad \text{(A-14)}$$

Since $(R-C)$ and $(C-V)$ are both positive, we can deduce that the first derivative of the manufacturer's expected profit function is equal to zero for at least one optimal order quantity. To prove the uniqueness of such a solution, we consider the second derivative of the manufacturer's expected profit, which is given as follows:

$$\frac{\partial^2 \pi_{DU}^{M,PI}(Q_{DU}^{PI})}{\partial^2 Q_{DU}^{PI}} = -(R-V)\hat{f}(Q_{DU}^{PI}, Q_{DU}^{PI})Z(Q_{DU}^{PI}) \quad \text{(A-15)}$$

with

$$Z(Q_{DU}^{PI}) = \left[\sigma(Q_{DU}^{PI})\frac{\partial\sigma(Q_{DU}^{PI})}{\partial Q_{DU}^{PI}} + M(Q_{DU}^{PI})^2 Q_{DU}^{PI}\right]\left[\frac{\partial\sigma(Q_{DU}^{PI})}{\partial Q_{DU}^{PI}}\frac{1}{\sigma(Q_{DU}^{PI})}\left\{1-\left[\frac{Q_{DU}^{PI}-\mu}{\sigma(Q_{DU}^{PI})}\right]^2\right\} - \frac{Q_{DU}^{PI}-\mu}{\sigma(Q_{DU}^{PI})^2}\right] +$$

$$\left[\frac{\partial\sigma(Q_{DU}^{PI})}{\partial Q_{DU}^{PI}}\right]^2 - 2\frac{\partial\sigma(Q_{DU}^{PI})}{\partial Q_{DU}^{PI}}\frac{1}{\sigma(Q_{DU}^{PI})}M(Q_{DU}^{PI})^2 Q_{DU}^{PI} + M(Q_{DU}^{PI})^2 + M(Q_{DU}^{PI}) \quad \text{(A-16)}$$

and

$$M(Q_{DU}^{PI}) = 1 - \frac{\partial\sigma(Q_{DU}^{PI})}{\partial Q_{DU}^{PI}}\frac{Q_{DU}^{PI}-\mu}{\sigma(Q_{DU}^{PI})} \quad \text{(A-17)}$$

Observing that $\lim_{Q_{DU}^{PI}\to 0} Z(Q_{DU}^{PI}) = +\infty$ and $\lim_{Q_{DU}^{PI}\to +\infty} Z(Q_{DU}^{PI}) = 0^-$, it can be shown analytically and verified numerically that $Z(Q_{DU}^{PI})$ is not always positive. Consequently, proving concavity of the supplier's expected profit function is not possible. However, we know that at least one solution exists. If more than one solution exists, the decision maker could choose the one maximizing his/her expected profit. Note that during the numerical tests we performed with the below problem parameters, we obtained one unique solution to the problem for all instances. ■

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