Information and Incentives in Inventory Management

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Abstract Over the past two decades, the foundational theory of inventory management has evolved to capture several complexities inherent in global supply chain operations. The impact of technology, firm-level collaborative practices, and more recently the explosion of data has added several dimensions to explore inventory management problems. Alongside, advances in management science has provided scholars with enhanced tool kits to study and analyze complexities inherent in these problems. In this chapter, we will discuss problems that arise at the confluence of (demand- or supply-side) information and incentives of firms. Our emphasis will be on highlighting models that capture the dynamic nature of information and incentives, and in particular, how they interact in the context of inventory management.

1 Introduction

The theory and practice of inventory management have gone hand-in-hand for past several decades. What started with the study of centralized multi-echelon inventory

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management has evolved to capture the reality of today's global supply chains which involve interactions among multiple firms, with their own institutional objectives and information, adhering to terms of complex supply chain agreements, and catering to a host of different and innovative business models. In these rapidly evolving business environments, oftentimes, the firm-level incentives do not align with that of the supply chain and hence, the supply chain as a whole may not provide the best value to its end-customer. We shall explore in this chapter, how inventory may be used as a lever to mediate conflicting incentives in supply chains and avoid, as observed in some cases, a market failure.

The issue of misaligned incentives and misreported private information has been widely observed in practice. For example, long-term collaborative practices such as *vendor-managed inventory* (VMI) have proven difficult to maintain over multiple planning horizons, resulting in companies terminating such agreements (e.g., Kouvelis et al. 2006; Brinkhoff et al. 2015). One frequently cited reason for such failed relationships has been the declining of trust (both in terms of credibility and capability) among firms implementing such partnerships. In case of VMI, point-of-sale (POS) data is usually transferred to the supplier by the retailer on a regular basis to enable the supplier to perform the inventory management task. However, POS data suffers from two limitations: they are censored demand realizations (which complicate statistical inference) and do not convey private demand information (e.g., in-store promotions) that the retailer may possess. In the classical case, Hammond (2006) describes the stern opposition to VMI practice from Barilla's distributors. The article points out the difficulty Barilla had in incorporating promotional data, that is seperate from the usual electronic data interchange (EDI) information, into their forecasting process. Giorgio Maggiali, then Director of Logistics at Barilla, noted,

> *"We're grappling with how to treat these promotions in our operations planning processes, including forecasting, manufacturing, and logistics."*

Ineffectively managing inventory lead to disappointment of some distributors over VMI implementation, and eventually falling out of the relationship.[1]

The above issues (in a slightly different form) are also applicable to contemporary online marketplace platforms such as Amazon, Tabao, and eBay. These platforms which serve as an intermediary connect manufacturers/sellers with potential consumers. The e-commerce ecosystem on these platforms allows them to access and analyze sales data of the individual sellers and in turn provide valuable market insights to the sellers. However, individual sellers may not always be willing to share their proprietary information related to their pricing strategy (e.g., upcoming sales promotions) potentially lowering the value created in the marketplace platform. For

[1] Other examples of failed VMI partnerships include Spartan Stores, Inc., a grocery chain, halted its VMI programs after 12 months of operations, blaming part of the failure on the fact that the VMI vendors had not taken promotions data into account (Mathews, 1995). Furthermore, K-Mart cut VMI contracts from more than 300 to about 50, blaming poor performance (partially) on the fact that the suppliers did not have adequate forecasting skills (Fisher, 1997).

example, Amazon regularly replenishes inventory in their distribution centers in anticipation of consumer demand. Without accurate pricing and promotion information, Amazon may fail to accurately anticipate consumer demand, leading to either excess overage or underage costs (which can otherwise be avoided through credible communication).

Establishing a dolphin choiris a long-term commitment which requires firms to put in place processes that govern information and material flow. Long-term partnerships introduce a host of new (theoretical and implementation) challenges and opportunities that one may not encounter in a single-shot interaction. The focus of this chapter is to highlight precisely some of these challenges and how to address them in a dynamic inventory management setting. One popular solution approach considered in the literature (and to be discussed in this chapter) to tackle the problem of incentives and information in a dynamic setting is through the use of *dynamic contracts*. The developments in economic theory in the area of dynamic mechanism design have been particularly valuable in providing suitable frameworks to analyze the dynamic settings. The landmark result of the *revelation principle* (Myerson, 1979), which forms the bedrock of the analysis in the static setting can be extended to the dynamic setting (Myerson, 1986). While there is no general methodology to solve the dynamic contracting problem, recent advances provide some guidance (e.g., Eső and Szentes 2007; Oh and Özer 2013; Pavan et al. 2014).

We anchor our discussions in the chapter to the role of (*demand-side* and *supply-side*) information in dynamic inventory management problems. In § 2, we discuss inventory models with focus on different information settings (pertaining to customer demand and on-hand inventory levels) with the underlying assumption that the supply chain functions in a centralized fashion without incentive-related concerns. One may think of the results and insights in this section as the basis to quantify the *value of information* due to technological developments (EDI, radio frequency identification, or superior forecasting technologies). In § 3, we consider supply chain settings in which one of the firms is better informed (about demand-related or inventory-related information) than the other firm. Furthermore, the objectives of firms in the supply chain are such that without proper monetary incentives in place credible information sharing cannot take place, often leading to a lose-lose outcome. This stream of literature while still in its infancy is rich enough to provide a flavor for the modeling challenges encountered in studying the dynamic settings. We note that § 3 is the main focus of this chapter. Therefore, to keep our discussions streamlined, we only briefly discuss emerging developments in the related topics and we refer the reader to prior review studies where necessary.

2 Information in Inventory Models

Demand and on-hand inventory information are perhaps the two most essential inputs to effectively implement and monitor an inventory management policy. The classical inventory models, as in Clark and Scarf (1960), impose strong assumptions about the inventory manager's access to demand and on-hand inventory information to compute the optimal policy. A number of studies have since relaxed these assumptions to characterize optimal inventory policies under various settings. In this section we review the issues that surface when the assumptions about demand-related information (§ 2.1) and inventory-related information (§ 2.2) are relaxed, and how they can be addressed, with emphasis on modeling approaches and the insights derived.

2.1 Demand Information

Demand information is perhaps one of the most fundamental inputs to inventory management problems. Here, we briefly discuss literature that relaxes the demand informational requirements in the classical inventory management problems (Clark and Scarf, 1960; Veinott, 1966). In most supply chain contexts, demand in each period are not independent and identically distributed (i.i.d.) according to a *known* probability distribution. To the contrary, demand (forecast) models are periodically updated based on new information that becomes available in each period. There are several statistical approaches proposed in the literature to model demand (forecast). Broadly, these statistical approaches can be classified as Bayesian, time-series, and martingale model of forecast evolution. We refer the reader to several excellent reviews of other demand models in dynamic inventory management: Gallego and Özer (2002), Özer (2011), Chen and Mersereau (2015), Chen and Lee (2017) and Kurtuluş (2017), to list a few. Research in this field is growing to accommodate other demand learning models, which are based on data-driven methods, see for example, Ban and Rudin (2019) and Ban (2020).

Building on the earlier works of joint demand (forecast) modeling and inventory management literature (with a single firm), researchers have since explored the *value* of demand information in supply chains involving multiple firms. In particular, as the supply chain networks have become globalized, collaborative practices for inventory management have grown in prominence. For example, *vendor-managed inventory* (VMI) was popularized by the Walmart and P&G partnership in the 1980s; *collaborative planning, forecasting, and replenishment* (CPFR) in 1990s (Aviv, 2001). One of the important drivers for this supply chain revolution in partnerships may be attributed to the rapid evolution of (information) technology around the same time (e.g, EDI, *retail link* by Walmart, and more recently, B2C e-commerce).

At same time, the growing complexity of the supply chain networks also brought forward several challenges. Among these is the *Bullwhip Effect*, i.e., the variability of the order process is higher than the variability of the demand process at each level of the supply chain. Essentially, the Bullwhip effect is an inefficiency that results from distortion of information flows in supply chain. In one of the most celebrated papers in management science, Lee et al. (1997) identify demand signal processing, i.e., updating order quantities based on past demand observations, as one of the drivers of the bullwhip phenomenon. Nevertheless, they also suggest a natural remedy to overcome the bullwhip—demand *information sharing* between supply chain members.

Following Lee et al. (1997), the value of information sharing to increase supply chain efficiency was extensively investigated by several scholars. Broadly speaking, the goals in the follow-up studies was to (i) quantity the value of information sharing (to better negotiate agreements within a partnership program) and (ii) explore different sources (demand model, demand forecast, order-policy) of information sharing leading to varying benefits in lowering supply chain costs; see for example, Lee et al. (2000). Gavirneni et al. (1999) investigate different degrees of information sharing ranging from *no-sharing* benchmark to *partial* to *complete* information sharing. In the partial information sharing model, the supplier know the retailer's end-consumer demand distribution and the retailer also shares the details of its ordering policy (value of the parameters s, S of a (s, S) policy). Based on a simulation study, Gavirneni et al. (1999) investigate how: production capacity at upstream supplier, cost structure (ratio of penalty to holding costs), and market conditions (demand variability) impact the value of (*partial* or *complete*) information sharing.

Aviv (2001, 2002, 2007) investigates these questions under different demand models. Gallego and Özer (2001) show that demand information sharing is valuable when the upstream supplier *cannot* infer current demand from the retailer's order history. Chen and Lee (2009) consider a most general demand model based on Martingale Model of Forecast Evolutions (MMFE) (Heath and Jackson, 1994) to quantify the value of information sharing and the bullwhip effect. They relax the assumption that the supplier knows the retailer's demand model and order policy (within the scope of information sharing). The authors find that having information about retailer's *projected* future orders (which are *suitably* revised), the supplier achieves identical cost savings (compared to the case with complete information about demand model and order policy).

A relevant and important question in the above context is whether a decentralized supply chain can be coordinated using only *local* (e.g., site inventory as opposed to echelon inventory) information. In a decentralized supply chain setting with the possibility of some oversight within the supply chain (e.g., but not limited to, the headquarters overseeing different departments within an organization), Lee and Whang (1999) propose a performance measurement scheme that has the desirable properties of being incentive compatible, conserves cost (e.,g., the scheme is self-supporting without payments from the headquarters) and requires only local (and *not* echelon inventory) information to manage inventory in the supply chain. Kapuściński and Parker (2021) consider a similar setting under capacity limits and illustrate how the performance scheme proposed in Lee and Whang (1999) can be suitably updated to achieve coordination.

Much of the follow up literature on this topic has been devoted to empirically testing whether and under conditions the bullwhip effect is actually observed (see, e.g., Cachon et al. 2007; Bray and Mendelson 2012). Significant progress has been made in this dimension and it is outside the scope of this chapter to discuss this literature. We refer to Chen and Lee (2017) for an extensive discussion of the empirical challenges and observations in measuring the bullwhip effect using field data.

2.2 Inventory Information

On-hand inventory (also like demand) information is inherently dynamic and is impacted by various processes that may or may not be under the control of an inventory manager. Not surprisingly, the accuracy of inventory information has been a topic of much interest in operations management. Industry estimates for the inaccuracy are staggering. In one of the earlier studies, Raman et al. (2001) estimate that nearly 65% of inventory records were inaccurate at store-SKU level. Following that a number of studies have empirically investigated the extent of inventory record inaccuracy in the retail industry (Ton and Raman, 2010). We also refer to the extensive review of this topic by Chen and Mersereau (2015).

An important step to countering inaccurate inventory information is to enrich inventory management models to account for inventory inaccuracy. In particular, Atali et al. (2009) identify and explicitly model three possible drivers of inventory inaccuracy: misplacement, shrinkage, and transaction errors. In addition, to adjusting optimal ordering policy based on the sources of inaccuracy (Atali et al., 2009), firms may also optimally decide when to audit or inspect their inventory, see Kök and Shang (2007); DeHoratius et al. (2008); Bassamboo et al. (2020); Chen (2021). These analytical models also help practitioners quantify the value of inventory tracking technologies, such as Radio Frequency Identification (RFID). In theory, RFID technology allows retailers to digitize and simplify access to inventory information (with little human intervention). By comparing models with and without accurate inventory information, the above papers quantify the value of RFID technology. For a detailed overview of inventory models with RFID, we refer to Lee and Özer (2007). Based on a field experiments at several stores of a retail chain, Hardgrave et al. (2013) empirically find that RFID helps with reducing inventory inaccuracy by about 26%.

In terms of future research and opportunities, a growing stream of literature explores the strategic role of inventory information on the demand side of operations. How should the retailer communicate its on-hand inventory information with its consumers? This question has been answered in a few different retail contexts which we discuss next. One of the issues faced by retail platforms is that, the quantity of product they receive from their suppliers cannot be contracted upon precisely. In these cases, inventory is pushed to retail platforms depending on what is available with the supplier and therefore, the on-hand inventory information is random from the platform's point-of-view. In a setting with two vertically-differentiated products, Cui and Shin (2018) consider a model where the starting inventory of each product and the total inventory are random variables. Its realization is available only to the retail platform who *ex-post* (i.e., after observing the inventory realization) decides whether to provide disaggregate, aggregate or no-information about its inventory to its consumers. Assuming truthful disclosure, they show that ex-post, the retailer benefits from always providing aggregate inventory information to consumers (i.e., total inventory of the two variants of the product) rather than disaggregate inventory information. The equilibrium results are driven by the retailer's desire to lower supply-demand mismatch.

The above assumption of truthful inventory communication can be relaxed by noting that perhaps the retailer may have an interest in manipulating consumer beliefs about its on-hand inventory. For example, all major online retailers/intermediaries display some form of inventory information to its consumers: some examples include: "in stock" on Amazon.com; detailed SKU-level inventory information by IKEA, Target; "almost gone!" by Sierra Trading Post. What can consumers learn from such communication (when the retailer need not be truthful)? In one of the earlier studies, Allon and Bassamboo (2011) model the communication game between the retailer and the consumer as a cheap-talk game, i.e., the inventory-related messages do not directly affect consumer payoff, are unverifiable (by the consumer) and non-binding. They show that the messages (e.g., "buy now") shared by the retailer cannot credibly communicate any inventory-related information with the consumers.

In contrast to the above disclosure schemes, a recent emerging body of literature considers the question of how should a retailer communicate inventory information by *committing* to a signaling mechanism *ex-ante*. In particular the retailer reveals the conditional probability distribution (based on the inventory realization) that will be used to generate the communication message, *prior* to the realization of randomness (in inventory level). Drakopoulos et al. (2021) consider such a setting in the context of personalized inventory information, i.e., there is a possibility to communicate real-time inventory information on a one-on-one basis with consumers. In particular, the paper explores the joint problem of pricing and designing a signaling mechanism, prior to observing their on-hand inventory using a *Bayesian persuasion* framework (Kamenica and Gentzkow, 2011). The signal (about on-hand inventory) that is communicated to consumers after the realization of on-hand inventory, impacts the consumer's belief about product availability and their decision to buy the product in one of two periods (if at all). They find that personalizing the communication, i.e., sending different messages—"buy now" vs. "wait"— depending on consumer valuation, can significantly increase the retailer's profit. Küçükgül et al. (2021) consider an online retail platform's information provision problem in the context of "time-locked sales" using a *dynamic* Bayesian persuasion framework (Kremer et al., 2014). In particular, an online retail platform dynamically decides what information to provide each arriving customer to maximize its revenues. The information provided by the platform—which can potentially be any function of past sales data—fuels social learning among consumers about the valuation of the product. In such a setting, they show it is sufficient for the platform to consider providing only one of three messages: "neutral", "positive", or "negative" to impact a consumer's purchase decision.

3 Information and Incentives in Inventory Models

In this section we append the discussions in § 2 by investigating how information and incentives (of sharing information) evolve in a dynamic decentralized inventory management problem. In particular, we consider the arguably more realistic scenario where one of the supply chain firms has superior information than other firms in the supply chain, i.e., there is *information asymmetry* in the supply chain. Furthermore, we relax the assumption that firms do not strategically act on their private information. If the incentives of all firms are aligned with that of the entire supply chain then the assumption is non-binding, and hence, it can be ignored. Anecdotal evidence suggests otherwise (see § 1 for examples).

Our discussion in this section focuses on two aspects of the problems that arise due to information asymmetry in dynamic inventory management problems. *First*, as in the previous section, we focus on the different *sources* of information asymmetry, pertaining to: demand information (§ 3.1), on-hand inventory information (§ 3.2), and cost information (§ 3.3). Furthermore, in § 3.4 we consider demand information asymmetry in capacity planning models. *Second*, through our discussion of the various information asymmetry settings we wish to illustrate the breadth and depth of the *modeling approaches* employed to tackle information asymmetry in dynamic inventory management problems.

Related to the *first* point above, our goal is to highlight how inventory dynamics and information asymmetry interact in various supply chain settings. In § 3.1, we consider inventory management problems where one of the firms, typically, the downstream retailer, has superior demand information than the upstream supplier in a multi-period setting. In § 3.2 we consider a setting where downstream retailer has superior information about on-hand inventory and may use that information strategically in its interaction with an upstream supplier. In § 3.3, we discuss inventory management problems with information asymmetry due to cost information (shortage cost and production cost).

Related to the *second* point above, our goal is to illustrate the different solution approaches in the literature used to tackle problems of information asymmetry in dynamic inventory models. Generally speaking, the most common solution approach is to design contracts (i.e., *order quantity–payment* plan), that facilitate information sharing, improve supply chain performance, and create a win-win outcome.[2] The complexity in determining terms of a contract in dynamic settings, however, arises due to the fact that one needs to account for and prescribe action (and payment) for all possible contingencies that may arise in future interactions. That is, the contract dictates the terms of trade in the period the contract is signed (as in single-period setting), and also for all future periods in a dynamic setting.

Contracts in dynamic multi-period settings can be broadly classified based on how the terms of trade in the contract are determined (*static* vs. *dynamic*) and on the duration of the contract (*short*- vs. *long-term*). If contract terms depend

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[2] Given the focus of the chapter is on dynamic inventory models, we refer the reader to Cachon (2003) and Chen (2003) for an extensive treatment of static incomplete information settings.

on the realization of some randomness in the setting, then such a contract is a dynamic contract, i.e., terms are contingent on the realization of the randomness in the environment. In contrast, the terms of a static contract can be pinned down completely at the start of the planning horizon. If the contract binds the firms for a single time period (in a multi-period relationship), then such a contract is a short-term contract. In contrast, if the contract binds the firms for the entire duration of their relationship, then such a contract is referred to as a long-term contract. For example, in a short-term dynamic contract, a firm chooses whether to offer a contract on a period-to-period basis. Whereas once a long-term dynamic contract is set in motion, it lasts until the end of the planning horizon. Note that in both cases the contract terms can be dynamically determined. In a single-shot interaction without the possibility of evolution of information or incentives, it makes sense to consider only static contracts. Of course, there is no possibility to offer long-term contracts in these settings. In a multi-period setting where information and incentives may evolve, however, all four possibilities emerge: $\{\text{static, dynamic}\} \times \{\text{short-term, long-term}\}$. Given our interest in studying settings with information evolution, in this section, we devote our discussions to dynamic contracts, which can be short- or long-term.

3.1 Demand Information Asymmetry

In this section, we consider inventory management problems where a downstream retailer has superior demand information than an upstream supplier. In § 3.1.1, we discuss Kadiyala et al. (2020) in which the upstream supplier (statistically) learns about demand information through sales data, which in turn affects the timing (i.e., the period in which to offer the contracts) and the design of contracts. In § 3.1.2, we discuss Lobel and Xiao (2017), who design contracts to be offered at the start of planning horizon, which facilitate information sharing in an environment where the retailer's private information is non-stationary. These two papers also illustrate complementary approaches to modeling demand information asymmetry—*persistent* vs. *non-persistent*. In both approaches, a relevant parameter of the demand distribution is privately known to the retailer. In Kadiyala et al. (2020), the parameter of demand distribution remains constant over the planning horizon whereas in the non-persistent setting as in Lobel and Xiao (2017), the parameter also evolves over time, i.e., the parameter is non-stationary.

3.1.1 Sharing Stationary Demand Information

Kadiyala et al. (2020) consider an inventory management problem faced by an upstream supplier that is in a collaborative agreement, such as vendor-managed inventory (VMI), with a retailer. A VMI partnership provides the supplier an opportunity to manage inventory for the supply chain in exchange for point-of-sales (POS) and inventory-level information from the retailer. However, retailers typically possess superior local market information beyond POS data. Although this information is useful to the supplier for inventory planning purposes, it is often difficult to communicate even in long term agreements such as VMI, resulting is firms terminating such agreements (see § 1 for examples). This paper investigates how a supplier should manage inventory and update an ongoing VMI agreement to maximize profit by facilitating credible demand information sharing.

As is typical in a VMI agreement, at the start of each review period, the supplier decides the amount of product to produce (at unit cost c) and delivers it to the retailer. The retailer satisfies the demand to the extent possible (unmet demand is lost) and shares the point-of-sales (POS) data with the supplier. The supplier is liable for any leftover inventory, incurring unit holding cost of h per period. If the retailer stocks out, then neither the supplier nor the retailer observe the true demand realization. The retailer earns a per unit revenue r and pays the supplier a unit wholesale price w, which are all stipulated in the *on-going* VMI agreement. The demand in each period is i.i.d. with cdf $G(\cdot)$ and probability density function (pdf) $g(\cdot)$. The downstream retailer has superior information about local demand conditions, which is modeled in a parametric fashion. There is a parameter of the demand distribution denoted by ξ which is known to the retailer but not the supplier.[3] The supplier, however, has a probabilistic information about the parameter ξ, i.e., prior distribution π on the set of values taken by ξ.

In the above supply chain setting, the supplier has two channels to acquire information about the unknown parameter of the demand distribution. First, based on the periodic POS data, the supplier can dynamically update his[4] belief π_t in each period to make better inventory decisions over time (*learn* approach). Alternately, as in a static contracting problem, the supplier may seek to credibly elicit this information from the retailer at the start of the planning horizon by offering an appropriately designed menu of screening contracts (*screen* approach) within the purview of the ongoing VMI agreement. This paper explores a *learn-and-screen* approach which dynamically considers the tradeoff between choosing either information acquisition channels in each time period. Below we focus on the interplay between the learn and screen approaches in a dynamic inventory problem.

Suppose that supplier offers a menu of contracts $\{S(\cdot), P(\cdot)\}$ in the first period. If the retailer with private demand information ξ chooses a contract $S(\tilde{\xi}), P(\tilde{\xi})$ from the menu, then the supplier maintain a base-stock level $S(\tilde{\xi})$ in each of the following periods in exchange for a one-time payment[5] $P(\tilde{\xi})$ from the retailer in period one.[6] The retailer's and the supplier's profit, denoted by Π^r, Π^s, for the remaining time-horizon is given by

[3] Further, larger ξ represents larger average demand, i.e., $G(\cdot|\xi_1) \geq G(\cdot|\xi_2)$ if $\xi_1 \leq \xi_2$.

[4] Throughout the chapter, we will refer to the downstream firm, who is typically the retailer, as "she" and the upstream supplier/manufacturer as "he".

[5] Equivalently, a payment can be charged on a per-period basis.

[6] For the symmetric information setting, the suboptimalinventory policy is a base-stock policy.

$$\Pi^r(S(\tilde{\xi}), P(\tilde{\xi}), \xi) = \mathbb{E}\Big[\sum_{t=1}^{\infty} \alpha^{t-1}\big((r-w)\min\{S(\tilde{\xi}), D_t\} - P(\tilde{\xi})\big)\Big]$$

$$\Pi^s\big(x_1, S(\tilde{\xi}), P(\tilde{\xi})\big) = \mathbb{E}\Big[\sum_{t=1}^{\infty} \alpha^{t-1}\big(w\min\{S(\tilde{\xi}), D_t\} - c(S(\tilde{\xi}) - x_t) - h(S(\tilde{\xi}) - D_t)^+ + P(\tilde{\xi})\big)\Big],$$

where α is the discounting factor and x_t is the starting inventory level in period t. Due to the *revelation principle*, it is sufficient for the supplier to restrict attention to contracts that facilitate truth-telling (Myerson, 1979). That is,

$$\Pi^r(S(\xi), P(\xi), \xi) \geq \Pi^r(S(\tilde{\xi}), P(\tilde{\xi}), \xi), \quad \forall \tilde{\xi} \neq \xi. \tag{1}$$

Further, the menu of contracts should improve the retailer's profit over her reservation profit, which in this case is the profit obtained from the on-going VMI agreement. However, the profit under on-going VMI agreement is quite complex since the supplier's inventory policy does not have a closed-form solution; see also Chen (2010); Bisi et al. (2011). Thus to ensure participation we also need to have:

$$\Pi^r\big(S(\xi), P(\xi), \xi\big) \geq \overbrace{(r-w)\sum_{t=1}^{\infty} \alpha^{t-1}\mathbb{E}\big[\min\{y_t^o, D_t(\xi)\}\big]}^{\Pi^r_{\min}(x_1, \mathbf{y}^o, \xi)}, \quad \forall \xi, \tag{2}$$

where $\Pi^r_{\min}(x, \mathbf{y}^o, \xi)$ is the type-ξ retailer's reservation profit when the on-hand inventory level is x and the supplier maintains post-order inventory levels $\mathbf{y}^o = (y_1^o, y_2^o, \dots)$ if the retailer rejects the menu of contracts offered. The supplier's incentive problem can be summarized as follows:

$$\tilde{\Pi}^{sr}(x_1, \pi_1) := \max_{S(\cdot), P(\cdot)} \mathbb{E}_{\xi}[\Pi^s(x_1, S(\xi), P(\xi)]; \text{ subject to } S(\cdot) \geq x_1, (1), \text{and } (2). \tag{3}$$

Kadiyala et al. (2020) solve the above contract design by first determining a closed-form upper bound $\overline{\Pi}^r_{\min}(x_1, \mathbf{y}^o, \xi)$ on the retailer's reservation $\Pi^r_{\min}(x_1, \mathbf{y}^o, \xi)$. Replacing the original reservation profit with an upper bound provides a feasible solution to the contract design problem.

In the learn-and-screen approach, the supplier also optimally decides *when* to offer the screening contracts. Prior to that period, the supplier makes inventory decisions to meet demand *and* also learn about the underlying demand (in a Bayesian fashion). Thus, the learn-and-screen approach gives rise to a unique Bayesian inventory-optimal stopping problem. The corresponding value function is given by

$$\tilde{V}(x_1, \pi_1) := \sup_{(\mathbf{y}, \tau)} \mathbb{E}\Big[\sum_{n=1}^{\tau-1} \alpha^{n-1}\big(cx_n + (w-c)y_n - (w+h)\int_0^{y_n} Q_n(z)\,\mathrm{d}z\big) + \alpha^{\tau-1}\tilde{\Pi}^{sr}(x_\tau, \pi_\tau)\Big], \tag{4}$$

where $\mathbf{y} := (y_1, y_2, \dots, y_{\tau-1})$ are the post-order inventory levels prior to offering the screening contracts; $\tau \in \{1, 2, \dots\} \cup \{+\infty\}$ is a contract offering time, and Q_t is the posterior predictive distribution given by $\int_0^z \int_\xi g(z|\xi)\pi_t(\xi)\,\mathrm{d}\xi$. The optimal policy under the learn-and-screen strategy can be obtained using a dynamic programming approach. Note that the screening contracts in the learn-and-screen approach are dynamic in that, the exact terms of the contract depend on the time period in which they are offered, which in turn depends on the entire history of (random) sales and inventory decisions. Furthermore, the contracts are long-term since it is binding for the remaining time horizon.

The value function associated with the learn-and-screen approach (4) brings to fore the interplay between the two sources of information acquisition. The supplier's production/inventory decisions prior to offering screening contracts determine the evolution of the supplier's belief process. The supplier updated belief in the screening period π_τ in turn determines the retailer's information rent (and also the retailer's reservation profit).

Underlying the optimal contract, there are two (sometimes, opposing) forces based on the learning dynamic and the incentive necessary for credible communication of demand information, which together determine the optimal menu of base-stock levels. To illustrate how these forces interact, consider two arbitrary but consecutive time periods. In the first period, the POS can reveal either a censored or an uncensored demand realization. A censored demand observation in the first period suggests to the supplier that the average market size must be larger than what was expected previously. Counter-intuitively, however, the optimal menu of base stock levels offered in the following period are smaller. The increased confidence in a larger market size implies that the retailer makes greater expected profit than the previous period. As a result, the supplier lowers the menu of base stock levels (and hence, the incentive) offered to the retailer, while still facilitating credible communication.

Likewise, an uncensored demand observation in the first period suggests to the supplier that the average market size may be smaller *or* larger than what was previously expected. The direction of this ordering depends on the magnitude of the sales observation. Following a small demand realization, the optimal menu of base stock levels become larger to increase the incentive for the retailer to share the demand information in the following period. However, as the magnitude of the demand observation increases the supplier becomes more confident that the underlying average market size is large. In the event of a *large* uncensored demand observation, the supplier mimics his actions following a censored demand observation in the first period, i.e., resorts to lowering the menu of base stock levels.

In summary, Kadiyala et al. (2020) propose and characterize a dynamic learn-and-screen approach, which suitably augments an *ongoing* VMI agreement to facilitate credible communication of demand information. Notably, the proposed learn-and-screen approach can be easily incorporated into an ongoing VMI agreement for the following reasons. First, the learn-and-screen approach does not disturb the terms of the ongoing VMI agreement (ownership and control of inventory, wholesale price) between the firms. Second, the form of the contract (base-stock policy) is optimal because the supplier faces the classical periodic review inventory control problem with lost sales after demand information is (and can be) credibly shared. Third, monitoring the contract terms, after they are accepted, requires minimal effort. The supplier collects a one-time payment from the retailer, and the retailer periodically monitors the base-stock inventory level maintained by the supplier. In fact, current VMI frameworks, such as PeopleSoft Enterprise Inventory and Fulfillment Management by Oracle, already implements this feature.

3.1.2 Sharing Non-Stationary Demand Information

Lobel and Xiao (2017) consider a two-level supply chain consisting of an upstream supplier and a downstream retailer. The retailer owing to her proximity to consumer demand is equipped with better demand forecast information compared to the supplier. The supply chain setting considered is decentralized in that the periodic demand and inventory at the downstream retailer is not shared with the supplier.

The paper considers an infinite horizon periodic review inventory control problem. In each period t, the retailer first obtains a (private) demand forecast $\mu_t \in [\underline{\mu}, \overline{\mu}]$ with a cumulative distribution function (cdf) $F(\cdot)$. The retailer then places an order with the supplier for q_t units of product raising the on-hand inventory level from x_t to $x_t + q_t$. The supplier operates in a make-to-order setting with zero lead-time to produce and deliver the quantity ordered by the retailer. Further, the marginal production cost is c, the retail price is r, and unit holding and backlogging costs are h, b per period, respectively. All these parameters are public information. The actual demand realized in period t is given by $\mu_t + \epsilon_t$, where $\epsilon_t \in [\underline{\epsilon}, \overline{\epsilon}]$ with cdf $G(\cdot)$, is a zero-mean random variable, capturing the error in demand forecast. Importantly, ϵ_t is realized after the retailer places the order for period t with the manufacturer. Both μ_t, ϵ_t in each period are the retailer's private information but distribution functions F, G are public information.

Given this model setup, Lobel and Xiao (2017) use a principal-agent framework to formulate and solve the supplier's (supply) contract design problem that maximizes his profit under backlogging and lost-sales settings. We highlight some of the unique aspects of the modeling framework. First, the private information in this setting is non-persistent. That is, the retailer's private demand forecast information is different in each period, drawn i.i.d. from $F(\cdot)$. Second, the focus of the paper is on long-term (dynamic) contracts. The contracts are long-term in that the contract specifies the terms of the trade for the entire time horizon. In addition, these contracts are dynamic in that, the terms of the contract in period t are dependent on all the information available until period t, i.e., they are *history-dependent*. The contract needs to be signed by the retailer in period one, although the precise realization of the future terms of trade are not realized by then. This feature of *long-term* contracts also highlights the difficulty in incentivizing the retailer to sign such a contract. Further, the supplier needs to have sufficient commitment power to convince the retailer that he would not deviate from the contract terms in the future.

To put the key results in perspective, we first note that the retailer's optimal inventory policy *without* information asymmetry is a simple base-stock policy (under both backlogging and lost-sales settings) where in the average order size is equal to μ_t and the safety-stock is used to counter the uncertainty due to the forecasting error

ϵ_t. With information asymmetry, the contract design problem is significantly more complex due to the space of the possible contract forms: it consists of a combination of order-quantity and payment. Under both backlogging and lost-sales settings, the authors show that the optimal contract prescribes the use of a base-stock policy. Note that the base-stock level in the case without information asymmetry may be different than in the case with information asymmetry. The optimal long-term contract is designed carefully to put in place the incentive necessary for the retailer to choose the appropriate base-stock levels. The optimal payment (to the supplier) structure is a combination of fixed-fee and a wholesale price agreement.

To highlight the key modeling features, we first introduce the notion of a long-term contract more formally. We also refer the reader to Zhang and Zenios (2008) for a related long-term contracting model. To that end, we define the history of realized and forecasted demand by $h_t = \{\mu_1, \epsilon_1, \mu_2, \epsilon_2, \ldots, \mu_t\}$. In other words, h_t is all the information available to the retailer prior to making the order decision in period t. The long-term contract offered by the supplier would elicit the retailer's private information in each period. We denote the history of reported information by the retailer as $\hat{h}_t = \{\hat{\mu}_1, \hat{\epsilon}_1, \hat{\mu}_2, \hat{\epsilon}_2, \ldots, \hat{\mu}_t\}$. As such, $h_t \neq \hat{h}_t$.

As is the case in the static contracting problems, the difficulty in solving the contract design problem essentially arises from the generality of the retailer's response $\hat{h}_t$, which makes the set of possible contracts to consider extremely large and intractable. The *revelation principle* in static contract design problems states that any feasible contract can be equivalently implemented by a contract that enables truth-telling (Myerson, 1979). This result significantly reduces the set of feasible contracts to consider, making the problem more tractable. The revelation principle can be extended to case of dynamic contracting under commitment (Myerson, 1986). In this case, it sufficient to consider dynamic contracts that ensure truth-telling $h_t = \hat{h}_t$, in each period t. Even with this simplification, the dynamic contracting problem is still challenging due to the fact that truth-telling has to hold in every period.

Consider any arbitrary long-term contract $\{q_t(\hat{h}_t), T_t(\hat{h}_t)\}_{t\geq 1}$ which induces the retailer to report $\hat{h}_t$ to the supplier. In particular, the retailer chooses quantity $q_t(\hat{h}_t)$ and makes a payment $T_t(\hat{h}_t)$ to the supplier in period t. The retailer's profit from period t onward denoted by $\Pi_t(h_t, \hat{h}_t)$, for any reported history $\hat{h}_t$ and realized history h_t, is given by:

$$\begin{aligned}\Pi_t(h_t, \hat{h}_t) = p\mu_t - \mathbb{E}[h(y_t - \epsilon_t)^+ + b(\epsilon_t - y_t)^+] - T_t(\hat{h}_t) \\ + \delta\mathbb{E}[\max_{\hat{h}_{t+1}} \Pi_{t+1}(h_{t+1}, \hat{h}_{t+1})]. \qquad (5)\end{aligned}$$

The above profit function consists of the retailer's revenue minus holding and backlogging costs, and the payment to the supplier in period t. Further, $y_t = q_t - \mu_t$ is the safety stock over the mean demand (μ_t) ordered to satisfy demand.

The supplier's contract design problem can be formulated as

$$\max_{\{q_t, T_t\}} \mathbb{E}\left[\sum_{t=1}^{\infty} \delta^{t-1}(T_t(h_t) - cq_t(h_t))\right], \tag{6}$$

$$\text{s.t. } \Pi_t(h_t, h_t) \geq \Pi_t(h_t, \hat{h}_t), \forall t \text{ and} \tag{7}$$

$$\Pi_1(h_1, h_1) \geq 0. \tag{8}$$

Under the incentive compatibility constraint (7), the equilibrium response of the retailer is to truthfully share $h_t = \{\epsilon_{t-1}, \mu_t\}$ in each period. The supplier's objective function (6) as a result depends on h_t. The supplier has to ensure that the retailer signs the contract in period one, when it goes into effect for the remaining time horizon. To that end, (8) ensures that the retailer obtains at least her reservation profit, which is normalized to zero above.[7] The manufacturer's contract design problem under the backlogging and lost-sales models is similar with the exception of the inventory dynamics. In the case of backlogging, the dynamics are linear whereas in the case of lost-sales they are non-linear.

Lobel and Xiao (2017) characterize the optimal solution to the contract design problem in (6)–(8) based on a relaxation (of the space of feasible contracts) approach (Eső and Szentes, 2007). Under the backlogging model, the optimal contract is a combination of wholesale price $w(\mu_1)$ and a fixed fee $T(\mu_1)$ (only for the first period), which together induce the retailer to order according to a base-stock policy. The induced base-stock level in each period is determined by the average demand in the period μ_t and a safety-stock level y_t which remains constant throughout the time horizon and is equal to $y_1(\mu_1)$. In other words, it is sufficient to incentivize the retailer to credibly reveal private information $h_1 = \mu_1$ in the first period.

The optimal long-term contract in the case of lost-sales model exhibits a similar structure, i.e., wholesale price $w(\mu_1)$ and a fixed fee $T(\mu_1)$ (albeit different values), to ensure truthful communication of the retailer's private information h_t. However, due to the lost-sales inventory dynamics, the first period demand forecast μ_1 no longer impacts the ensuing inventory problem after the first stock-out (as long as stock-out event is credibly communicated with the supplier). In fact, the inventory problem after stock-out event is the same regardless of the initial demand forecast μ_1. Therefore, under the optimal long-term contract, after the first stock-out event, the supplier lowers the wholesale price to equal the production cost c. As a result, the optimal ordering policy after the stock-out event is a base-stock policy, with the base-stock level that maximizes the total supply chain profit. Nevertheless, to facilitate credible communication of stock-out event requires another payment from the retailer, which is exercised when the first stock-out happens.

In summary, this paper justifies the use of simple wholesale price and two-part tariff contracts in dynamic inventory problems when the supplier has the commitment power to execute a long-term dynamic contract. Further, contrasting the optimal contract under backlogging and lost-sales settings reveals that the supply chain can be coordinated under the lost-sales setting after the first stock-out event.

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[7] We refer the reader to Kadiyala et al. (2021) for an extensive discussion of the impact of the retailer's outside option (due to an alternative sourcing option) on the contract design problem in a single-period setting.

3.2 Inventory Information Asymmetry

In this section we discuss Zhang et al. (2010) who consider information asymmetry pertaining to on-hand inventory level in dynamic inventory management problem. Note that by definition, on-hand inventory information evolves over time and the solution approach prescribed in the paper is based on dynamic short-term contracts (in contrast to the dynamic long-term contracts discussed in § 3.1).

Zhang et al. (2010) considers a dynamic inventory problem in a two-level supply chain setting where the downstream firm (the retailer) has more information about local inventory compared to the upstream firm (the supplier). There are two noteworthy aspects of the supply chain setting considered in the paper. First, periodic demand/sales observed by the retailer is not shared with the supplier. This assumption captures the plight of missing credible communication channel in real world supply chains. Second, the authors consider a short-term contracting framework to analyze and solve the dynamic inventory problem. That is, the supplier can only commit to procurement contracts that are time-bound. There are a few reasons that motivate the short-term contracts. For one, it simplifies execution and monitoring contracts in that the terms of a short-term contract are valid only for a single period. Furthermore, the supplier may just not have the history/reputation to credibly offer and execute long-term contracts. In this sense, the supply chain considered in the paper is not fully matured, yet, wherein long-term partnership programs such as vendor-managed inventory or consignment-type arrangement may apply.

This paper considers a two-level supply chain with a periodic-review inventory model with lost-sales. The retailer's inventory level at start of the time horizon x_1 is her *private* information. At the start of each period $t \geq 1$, the retailer places an order for q_t units of product with the supplier, raising her on-hand inventory level to $y_t := x_t + q_t$. The supplier has zero lead time to produce and ship the retailer's order quantity in each period. The demand in period t denoted by the random variable D_t, is i.i.d. with cdf $F(\cdot)$ (and pdf $f(\cdot)$)—which is *public* information. The retailer's single period revenue function is denoted by $v(y_t) := r\mathbb{E}[\min\{y_t, D_t\}]$, where r denotes the retail price. The retailer carries any leftover inventory in period t after satisfying the period's demand, i.e., $x_{t+1} := \min\{y_t, D_t\} - D_t$ at a unit holding cost h. Parameters r, h are assumed to be public information.

The supplier operates in a make-to-order setting and incurs a marginal production cost c to satisfy retailer's order. The supplier's knowledge of the retailer's initial inventory is modeled in a probabilistic fashion with cdf G_1 (and pdf g_1) with support over $[0, y_0]$. Note that G_t may have a jump at $x_t = 0$, which happens when the retailer stocks out of inventory and this discontinuity of the distribution has important consequences for the optimal solution. Only the retailer observes demand realization in each period, and as a result, the retailer's inventory level in all subsequent periods are also her private information.

We briefly discuss the single-period problem (aka *newsvendor* problem) since the solution in the static setting reveals an important property of the optimal solution which also later applies to the dynamic problem. According to the *revelation principle*, it is sufficient for the supplier to restrict attention to contracts that induce *truth-telling*, i.e., the supplier offers a menu of contracts $\{s(x_1), q(x_1)\}$, such that the retailer with on-hand inventory x_1 chooses the order quantity $q(x_1)$ in exchange of the payment $s(x_1)$ to the supplier. In choosing so, the retailer credibly reveals her on-hand inventory level to be x_1. Truth-telling is achieved by imposing the *incentive compatibility* (IC) constraint(s):

$$v_1(x_1 + q_1(x_1)) - s_1(x_1) \geq v_1(x_1 + q_1(\hat{x}_1)) - s_1(\hat{x}_1), \qquad x_1, \hat{x}_1 \in [0, y_0] \tag{9}$$

where $\hat{x}_1$ is any arbitrary inventory level reported by the retailer when her true inventory level is x_1. In addition, the optimal menu of contracts $\{s(x_1), q(x_1)\}$ should provide the retailer at least as much *reservation profit* as the retailer would obtain from her outside option, specified in the following *individual rationality* (IR) constraint.

$$v_1(x_1 + q_1(x_1)) - s_1(x_1) \geq v_1(x_1), \qquad x_1 \in [0, y_0] \tag{10}$$

Unlike (IR) constraint in standard static contracting problems, the above constraint features a type-dependent reservation profit $v_1(x_1)$. If the retailer rejects the supplier's menu of contracts, then she makes profit by satisfying demand (to the extent possible) with existing inventory (which is her private information). The supplier's contract design problem is given by

$$\max_{\{s_1(x_1), q_1(x_1)\}} \int_0^{y_0} (s_1(x_1) - cq_1(x_1)) g(x_1)\, \mathrm{d}x_1; \qquad \text{subject to (9), (10).} \tag{11}$$

We focus our attention on the structure of the optimal contract in the static setting, when the demand distribution $F(\cdot)$ is exponential with mean $\frac{1}{\lambda}$. Further, we also assume that the initial inventory $x_1 = [y_0 - D_0]^+$, where y_0 is a known constant and D_0 is i.i.d. according to distribution F.[8] The optimal solution in this setting exhibits a special structure:

$$q_1(x_1) = \begin{cases} \frac{1}{\lambda} \log(\frac{r}{c}), & x_1 = 0; \\ 0, & x_1 \in (0, y_0], \end{cases} \tag{12}$$

$$s_1(x_1) = \begin{cases} \frac{r-c}{\lambda}, & x_1 = 0; \\ 0, & x_1 \in (0, y_0]. \end{cases} \tag{13}$$

There are a couple of points worth highlighting here: First, the supplier transacts *only* with the retailer who has zero on-hand inventory, i.e., $x_1 = 0$. Second, the retailer with zero on-hand inventory makes *zero* profit (by accepting the supplier's contract) which is also her reservation profit since she has no inventory of her own to satisfy demand. Fundamentally, the retailer's value for additional inventory from the

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[8] This assumption implies that the supplier knows the retailer's inventory level prior to designing the current menu of contracts. Technically, this assumption ensures that the $\frac{G_1(x)}{g_1(x)} = \lambda$, which ensures that the first derivative of the objective function is always negative for $x > 0$. Lacking this assumption, the structure of the contract has an additional segment wherein the retailer truthfully reveals her private information and the optimal quantity is based on their type.

supplier reduces as her on-hand inventory increases. The above contract form, called the *batch-order contract* (BOC), is a consequence of this economic force taken to the extreme. What is even more remarkable is that BOC with appropriately designed terms, is optimal even in the dynamic setting under some conditions!

From a modeling perspective, the focus in the paper is on designing *short-term* contracts: A short-term contract lasts one time period and it specifies terms of the trade, i.e., the quantity-payment schedule for *that* period. Therefore, in any period, the retailer may choose to participate in the mechanism by choosing a contract, or alternately, choose not to participate in the mechanism in that period. In the latter case, the retailer may satisfy demand in that period using inventory carried over from previous periods (if at all). In contrast to the static problem, the sequence of contract offer and response repeats in each period. To summarize, the supplier designs and offers a menu of contract $\{s_t(x_t), q_t(x_t)\}$ in each period t to credibly elicit the retailer's private on-hand inventory information x_t.

With repeated interactions between the supplier and the retailer truthfully revealing on-hand inventory level in the first period may work against the retailer in the long-term. The supplier can learn the information in the first period and may then exploit the retailer in the future. Realizing this issue, the retailer may not reveal her private information credibly in the first period. As a result, the optimal contracting may result in *pooling* and *separating* equilibrium. In fact, the optimal BOC (12)–(13) in the static setting only screens the retailer with zero on-hand inventory while the other retailers with positive on-hand inventory pool, albeit in an extreme fashion.

The challenge in solving a dynamic short-term contracting problem (in general) arises from the fact that the supplier's contract offer in a period should to take into account the retailer's objective in that period *and* the retailer's expectation of the supplier's contract offering in the next period. The contract offered in the next period, however, depends on the supplier's belief at the start of the next period (which in turn depends on the retailer's order quantity decision in the current period). This dynamic gives rise to the possibility that the retailer may manipulate her ordering decisions in the current period not only for immediate gains[9] but also to impact the supplier's future (belief and hence,) contract offer. A suitable equilibrium concept for this dynamic game of incomplete information is the *perfect Bayesian equilibrium* (Fudenberg and Tirole, 1991). This equilibrium concept puts reasonable restrictions on not just actions (quantity/payment decisions) but also on the evolution of the supplier belief about the retailer's on-hand inventory.

Now consider the dynamic version of the problem. Consider the supplier's problem in period t. The (IC) constraint[10] is given by:

$$\begin{aligned} &v(x_t + q_t(x_t)) - s_t(x_t) + \delta U_{t+1}(x_t + q_t(x_t)|x + q_t(x_t)) \\ &\qquad \geq v(x_t + q_t(\hat{x})) - s_t(\hat{x}) + \delta U_{t+1}(x_t + q_t(\hat{x}_t)|\hat{x}_t + q_t(\hat{x}_t)), \end{aligned} \tag{14}$$

[9] Anand et al. (2008) show how the retailer may distort her actions (order quantity) in a period to obtain better wholesale price in the future periods.

[10] With a slight abuse of notation we use $v(\cdot)$ to the single-period profit function which includes the holding cost.

where $U_{t+1}(\cdot)$ represents the retailer's expected value-to-go from period $t+1$ onwards. Consider the left-hand side (lhs) of the above inequality and a retailer with on-hand inventory level x_t in period t. The first part $v(x_t + q_t(x_t)) - s_t(x_t)$ is similar to lhs of (9). The new term $\delta U_{t+1}(x_t + q_t(x_t)|x_t + q_t(x_t))$ is the retailer's expected value-to-go (discounted by a factor δ) when she truthfully reports her inventory level to be x_t by choosing a contract $q_t(x_t)$. This function encapsulates the retailer's (rational) expectation of the contract offering in the next period. Consider now the right-hand side (rhs): the term $\delta U_{t+1}(x_t + q_t(\hat{x}_t)|\hat{x}_t + q_t(\hat{x}_t))$, which represents the expected value-to-go if the retailer with on-hand inventory level x_t chooses to report, instead, $\hat{x}_t$, by choosing order quantity $q_t(\hat{x}_t)$. In this case, the supplier believes the retailer's inventory level after replenishment is $\hat{x}_t + q_t(\hat{x}_t)$ and updates his belief process accordingly. The individual rationality constraints are also updated based on the multi-period setting as follows:

$$v(x_t + q_t(x_t)) - s_t(x_t) + \delta U_{t+1}(x_t + q_t(x_t)|x_t + q_t(x_t)) \geq v(x_t) + \delta \underline{U}_{t+1}(x_t), \quad (15)$$

where $\underline{U}_{t+1}$ is the retailer's reservation profit obtained by not ordering from the supplier from period $t+1$ onward.

The supplier designs the menu in period t, $\{s_t(x_t), q_t(x_t)\}$ to maximize his total profit from transaction in period t and his value-to-go:

$$\max_{\{s_t(x_t), q_t(x_t)\}} \int \underbrace{\left\{s_t(x_t) - cq_t(x_t) + \delta \Pi_{t+1}(x_t + q_t(x_t))\right\}}_{J_t(x_t + q_t(x_t)|x_t)} g_t(x_t)\,\mathrm{d}x \quad (16)$$

where Π_{t+1} is the supplier's value-to-go from period $t+1$ onward. The standard procedure[11] of solving for the optimal contract to offer in period t is to maximize $J_t(x_t + q_t(x_t)|x_t)$ point-wise, which in turn depends on the structure of the first derivative of J_t.

The optimal contract in period t (other than the terminal period when it is BOC) can be quite complicated to derive in general. Considering an infinite horizon, simplifies the problem to some extent due to stationarity of the value-to-go functions and the optimal contract. In fact, an optimal short-term contract in the infinite horizon problem turns out to be astonishingly simple—a BOC with fixed (b^*, s^*) under some conditions on the cost parameters. That is, in any period, the supplier offers to supply b^* units of the product in exchange for a payment of s^* from the retailer. Like in the static case, only the retailer with zero on-hand inventory in that period would choose to participate in the mechanism. We note that the inventory dynamics under BOC (b^*, s^*) is similar to that under a (s, S) policy with $s = 0$ and $S = b^*$. This resemblance is particularly counter-intuitive since there are no fixed costs in the model.

The complexity in this problem (and more generally in dynamic contracting problems) arises from keeping track of the supplier's belief process $\{G_t\}_{t\geq 1}$. However, under exponential demand distribution (as in the static case) significant simplifi-

[11] (IC) constraints are rewritten in terms of local conditions using the *envelope theorem* and substituted back in to the objective function to obtain J_t.

cation can be achieved. Suppose that the starting inventory in period t is given by $x_t + q_t(x_t)$ and demand is exponentially distributed. Then the starting inventory in period $t+1$, $[x_t + q_t(x_t) - D_t]^+$, with distribution G_{t+1}, is *weakly reverse exponential* (WRE), i.e.,

$$\frac{G_{t+1}(x_{t+1})}{g_{t+1}(x_{t+1})} \geq \frac{1}{\lambda}, \qquad \text{for any belief distribution } G_t. \tag{17}$$

What is interesting about WRE property is that under exponential demand distribution, the supplier's belief in any period $t \geq 2$ satisfies WRE.[12] More remarkably, WRE property of the G_t along with high holding cost and production cost relative to retail price ensures that $\frac{\delta J_t(x_t+q_t(x_t))}{\delta q_t} < 0$ for any $q_t > 0$ when $x_t > 0$ when a BOC is being used from period $t+1$ onward. Referring back to (16), this implies that the optimal order in period t: $q_t = 0$ when $x_t > 0$, i.e., the optimal contract in period t is also BOC type.

The optimal batch-order contract can be simply characterized using first-order conditions. In addition to the analytical tractability, batch-order contracts are simpler to execute and monitor. Nevertheless, the batch-order contract and the inventory dynamics under batch-order contract is unlike that under the base-stock policy, which is optimal for the supply chain with symmetric information (and zero fixed costs). However, with asymmetric information, the batch-order contract allows the supplier to nullify the retailer's informational advantage by only contracting with the retailer with zero on-hand inventory. As a result, the supplier is able to extract most of the channel profit leaving only the reservation profit for the retailer.

We conclude this section by noting that the general theme of the literature on dynamic contracting in inventory management is to identify *simple* contracts (and the underlying optimal inventory control) that are optimal or in some cases, near-optimal. This is especially important in the dynamic context since the optimal contract mechanism need not be unique and in general can be quite complex. Further, doing also helps us reconcile theory with practice: some of the dynamic contracts forms typically observed in practice are in fact linear-price, quantity-discount along with base-stock and (s, S)-type inventory policies.

3.3 Cost Information Asymmetry

In this section we consider inventory management problems with incomplete information pertaining to supply chain cost structures. In § 3.3.1, we discuss Lutze and Özer (2008) who consider a supply chain setting in which the downstream retailer has superior information about a stationary shortage (penalty) cost. In particular the authors propose and characterize long-term contracts to be offered by the supplier at the start of the planning horizon that facilitate information sharing and

[12] The distribution G_1 also has WRE property if, for example, the starting inventory x_1 is carried over from an earlier period $[y_0 - D_0]^+$, with D_0 also exponentially distributed.

optimizes the supplier's inventory/production costs. § 3.3.2 we discuss Gao (2015) where the upstream supplier has private information about non-stationary production cost structure. The focus in this paper is on long-term dynamic contracts which are designed and offered by the retailer to the supplier.

3.3.1 Inventory Shortage Cost Information Asymmetry

Lutze and Özer (2008) is one of the first papers to study dynamic inventory management under information asymmetry. They consider a two-level supply chain where the downstream retailer has private information about *shortage cost*, i.e., the unit cost of not satisfying customer demand. Both the retailer and the upstream supplier manage inventory to minimize operational cost at their respective locations. Motivated by practice, the paper considers a *promised lead-time* contract as a vehicle for sharing risk associated demand uncertainty between the two supply chain firms.

The promised lead time contract, designed by the supplier, specifies two parameters: the lead time τ promised by the supplier and a payment K made by the retailer to the supplier. This contract stipulates that the supplier would ship the retailer's order in its entirety, τ periods after it is placed by the retailer. Once the order is shipped by the supplier, there is also a lead time ℓ for delivery. If the supplier does not have enough inventory on hand by the promised lead time, then he procures inventory from an alternative source to meet the retailer's order quantity. For a given promised lead time τ, the optimal base-stock levels for the retailer and the supplier, which balances the shortage and overage costs, are given as follows:

$$Y_s^*(\tau) := F_{L+1-\tau}^{-1}\left(\frac{p_s-(1-\alpha)c_s}{h_s+p_s}\right) \tag{18}$$

$$Y_r^*(p_r,\tau) := F_{\ell+1+\tau}^{-1}\left(\frac{p_r-(1-\alpha)c_r}{h_r+p_r}\right) \tag{19}$$

where p_j, c_j, h_j represent the unit penalty (shortage) cost, marginal procurement cost, and unit holding cost per period, respectively, for the supplier ($j = s$) and the retailer ($j = r$). Furthermore, L represents the supplier's procurement lead time and F is the cdf associated with end-customer demand. In (18), the supplier's optimal base-stock level takes into account uncertainty in demand over the effective planning horizon $L+1-\tau$. Likewise, in (19), the retailer's optimal base-stock level takes into account uncertainty in demand over the effective planning horizon $\ell+1+\tau$. As expected, it follows from (19) that the retailer's optimal base-stock level Y_r^* increases in p_r.

The promised lead time contract accomplishes two things: first, the retailer is guaranteed shipment of her entire order, thus eliminating the uncertainty on her supply-side. Second, the supplier has a longer planning horizon (thereby, greater flexibility) to better plan and meet the retailer's order quantity. While both the firms have potential benefits from the arrangement, tension arises since the retailer prefers a smaller promised lead time τ, whereas the supplier would prefer to offer a larger τ. In an environment where the supplier knows the retailer's shortage cost p_r, the supplier can optimally design the promised lead time so that the retailer finds it in her best interest to accept the contract.

In the asymmetric information setting, which is the primary focus of Lutze and Özer (2008), the supplier does not know p_r. In this case, the above mentioned tension renders any communication between the retailer and the supplier as uninformative cheap talk; see Proposition 3 of Lutze and Özer (2008). In particular, the supplier knows that the retailer's shortage cost is one of N values: $p_1, \ldots, p_N$ with a prior distribution given by $\lambda_1, \ldots, \lambda_N$, where $\lambda_i \geq 0$ for all i and $\sum_i \lambda_i = 1$. The supplier's problem is to design a menu of promised lead time contracts which are offered at the start of the planning horizon. Due to the *revelation principle*, the supplier can restrict search for the optimal menu contracts to the menu of contracts that facilitates truth-telling (Myerson, 1979). That is, the search for the optimal menu of contracts can be restricted to a menu of N promised lead time contracts, such that the retailer chooses a contract from the menu that communicates her private truthfully and also maximizes her profit. The supplier's optimal contract design problem can be formulated as:

$$\min_{(\tau_i, K_i)_{i=1,\ldots,N}} \sum_{i=1}^{N} \lambda_i (G_s^*(\tau_i) - K_i) \tag{20}$$

$$\text{s.t. } G_r^*(p_i, \tau_i) + K_i \leq U_r^{\max}, \ \forall i = 1, \ldots, N \tag{21}$$

$$G_r^*(p_i, \tau_i) + K_i \leq G_r^*(p_i, \tau_j) + K_j, \ \forall j \neq i, \tag{22}$$

where $\tau_i \in \{0, \ldots, L+1\}$ for all $i \in \{1, \ldots, N\}$. The supplier's objective function in (20) consists of the supplier's optimal inventory cost, $(G_s^*(\tau_i) - K_i)$, associated with promised lead time contract $(\tau_i,\ K_i)$ offered to retailer with shortage cost p_i. The expectation is taken over the supplier's prior information about the retailer's type. Equations (21) and (22) feature the retailer's participation and incentive-compatibility constraints under truth-telling contract mechanism, respectively. In particular, $G_r^*(p_i, \tau_i) + K_i$ is the optimal inventory cost incurred by the retailer with shortage cost p_i if she accepts a promised lead time contract (τ_i, K_i) from the menu offered by the supplier. We also highlight here that the analysis of mechanism design problem with finitely many retailer types is markedly different compared to the problem with continuum of types; we refer the reader to Lovejoy (2006) for details.

Next, we discuss some of the important insights that can be gleaned from the optimal menu of contracts characterized in the paper. As noted above, a retailer with higher shortage cost is offered a shorter promised lead time in return for a higher payment to the supplier. In fact, all the retailers (except the one with the *smallest* shortage cost) is offered a promised lead time that is *shorter* than their first-best promised lead time (i.e., the optimal promised lead time when the supplier knows the retailer's shortage cost). As a result, the supplier bears more of risk associated with demand uncertainty when dealing with a retailer with high shortage cost.

In addition to contract design problem, the paper also considers the question of when should the supplier forgo working with a retailer? The supplier may want to keep inventory cost below a threshold, which may be due to limited operational budget or an outside option of working with a different retailer (who presents a lower risk). From our above discussions note that, as the retailer's shortage cost increases, the supplier ends up bearing more of the inventory risk. By extending this intuition, Lutze and Özer (2008) characterize a *cutoff-type* policy, wherein the supplier only transacts with retailers whose shortage cost do not exceed a certain cutoff level.

3.3.2 Production Cost Information Asymmetry

Gao (2015) considers a supply chain setting with product cost information asymmetry, by abstracting away from the specific supply side factors contributing to the information asymmetry. The upstream supplier has dynamic private information about the *supply state* which directly impacts his production cost structure. The downstream buyer (a traditional retailer) makes periodic inventory decisions and carries leftover inventory to meet demand. The supply chain setting considered in the paper assumes that the retailer has greater bargaining power compared to the supplier, and is therefore, modeled as the *principal* who designs and offers long-term dynamic contracts to the supplier (the *agent*). As is standard in related literature, these contracts are offered on a *take-it-or-leave-it* basis.

The supplier's supply state in period $t \geq 1$ denoted by z_t are drawn i.i.d. from a publicly known cdf $G(\cdot)$ and pdf $g(\cdot)$. The supply state information z_t is the supplier's private information. Thus, the supplier's private information is non-persistent in this setting. The supplier's marginal production cost $c(z_t)$ is convex decreasing in the supply state. The buyer places an order with the supplier and carries inventory in each period to satisfy end consumer demand. Any unmet demand is lost. The retailer incurs a unit holding cost h per period and the unit revenue is given by r.[13]

At the start of time horizon, the retailer designs and offers a long-term contract $\{T_t(\hat{h}_t), q_t(\hat{h}_t)\}_{t\geq 1}$ to the supplier, where $\hat{h}_t$ denotes the supplier's report of the supply state until period t, i.e., $\hat{h}_t = (\hat{z}_1, \ldots, \hat{z}_t)$. The terms of the contract evolve based on all the information available from prior periods. In each period t, the retailer orders $q_t(x_t, \hat{h}_t)$ raising the on-hand inventory level to $y_t = q_t + x_t$, where x_t is the starting inventory in period t and makes a payment $T_t(x_t, \hat{h}_t)$ to the supplier.[14] As noted in our discussion in § 3.1.2, the search for the optimal *dynamic* contracts can be restricted to contracts that induce truth-telling (Myerson, 1986). The caveat, however, is that truth-telling needs to be induced in each period t.

The supplier's cost function from period t onward $u_t(x_t, h_t, \hat{h}_t)$ depends on her report process $\hat{h}_t$ and her expected cost from period $t+1$ onward based on the report in period t. This cost function satisfies a dynamic programming recursion:

$$u_t(x_t, h_t, \hat{h}_t) = c(z_t)q_t(x_t, \hat{h}_t) - T_t(x_t, \hat{h}_t) + \gamma\mathbb{E}[u_{t+1}(x_{t+1}, h_{t+1})], \tag{23}$$

[13] The paper also discusses the case in which the retailer incurs a fixed cost in each period for placing an order with the supplier.

[14] It is to be noted that the buyer's inventory level x_t is also observable to the supplier.

where $x_{t+1} = (y_t - D_t)^+$, demand D_t, $t \geq 1$ is i.i.d. drawn from pdf f and γ is discounting factor. The dynamic incentive compatibility (IC) constraints can be represented as

$$u_t(x_t, h_t, h_t) \leq u_t(x_t, h_t, \hat{h}_t), \quad \forall t. \tag{24}$$

Further the supplier's total production cost under the optimal dynamic contract should lower than what it would be without signing the contract. Thus, the individual rationality (IR) constraints can be formulated as

$$u_t(x_t, h_t, h_t) \leq 0, \quad \forall t. \tag{25}$$

The (IR) constraints need to be satisfied in each period in a dynamic contract, else, the supplier may not persist with the dynamic contract for the entire time horizon. Given the above, the retailer's dynamic contracting problem can be formulated as follows:

$$\min_{\{T_t, q_t\}} \quad \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \left(h[y_t - D_t]^+ - r\min\{y_t, D_t\}\right)\right], \quad \text{subject to } (24), (25).$$

The solution approach is based on first finding the optimal solution to a relaxed problem in which the (IC) and (IR) constraint need to be satisfied only in the first period, i.e., a static contract design problem. In this relaxation the supply state in all remaining periods is assumed to be publicly known. Gao (2015) show that the optimal solution for the relaxed problem can be suitably modified to satisfy the above dynamic (IC) and (IR) constraints. In particular, the payment structure T_t can displaced over time while still ensuring the (IC) and (IR) are satisfied in each period. The buyer's cost under this modified dynamic contract is equal to that under the dynamic contract for the relaxed problem, thereby establishing optimality of the modified dynamic contract for the problem with dynamic (IC) and (IR) constraints.

The optimal dynamic contract has some of the features of the optimal (dynamic) long-term contract proposed in Lobel and Xiao (2017) for the lost-sales setting. The optimal policy is a state-dependent base-stock policy and the base-stock level that minimizes total supply chain cost can be implemented after a finite number of periods. In Gao (2015), it can be implemented from the second period onward whereas it was the *first* stockout event that triggered the switch to channel efficient base-stock levels. It is, therefore, reassuring to know the robustness of base-stock policy in asymmetric information settings.

In this section, we have discussed supply chain models based on information asymmetry of cost structure or parameters in a dynamic inventory management setting. There is also related research that considers cost information asymmetry in a single-shot setting; see, for example, Ha (2001) and Corbett and Tang (1999) for an extensive review.

3.4 Demand Information Asymmetry in Capacity Management

In this section we consider capacity management problems with asymmetric demand forecast information, which evolves in a dynamic fashion. The problem of capacity management share some similar features to inventory management, with the important difference that unused capacity cannot be carried over to future periods.

Ren et al. (2010) investigate if truthful demand forecast information sharing can emerge in a long-term relationship between an upstream supplier and a downstream retailer without using pricing levers. They investigate this question in the context of the supplier's multi-period capacity planning problem (similar to a multi-period newsvendor model). Demand in each period is modeled using a multiplicative form $D_t = \theta_t \cdot X$, where X is non-negative normal random variable with a given mean and standard deviation, which are publicly known. The scaling factor $\theta_t \in \{\theta^l, \theta^h\}$ determines if demand for that period is forecasted to be low or high, with probability α and $1 - \alpha$, respectively.

The retailer *privately* observes forecast θ_t and decides what messages $m_t \in \{l, h\}$, indicating low or high demand forecast, to communicate to the supplier. Based on this message, the supplier decides to build capacity for the period K_t at a unit cost of c. Following that, the retailer *privately* observes demand realization D_t and places an order q_t with the supplier. The supplier produces and ships $\min\{q_t, K_t\}$ to the retailer. The retailer pays the supplier unit price r and sells in the market for unit price p. The supplier incurs a unit cost h for any leftover capacity in the period and the retailer incurs a unit cost g for any unmet demand. The single period profit functions for the supplier and the retailer are given as:

$$
\begin{aligned}
u_t &= r \min\{K_t, q_t\} - h(K - q_t)^+ - cK_t \\
v_t &= (p - r) \min\{K_t, q_t\} - g(D_t - q_t)^+.
\end{aligned}
$$

The total profit expected profit of the supplier is $\mathbb{E}[\sum_{t \geq 1} \delta^{t-1} u_t]$ and that of the retailer is $\mathbb{E}[\sum_{t \geq 1} \delta^{t-1} v_t]$.

In each review cycle (a fixed number of periods R), the supplier maintains a *score* for the retailer which is updated at end of each period based on the information provided (forecasts and order sizes) by the retailer. During the review period, the supplier trusts the retailer's messages $\{L, H\}$ to be true. The review strategy consists of statistical hypothesis tests (depending on whether the reported forecast is low or high) to check whether the information shared by the retailer matches the long-run averages given by the primitives (μ, σ, α which are publicly known). That is, demand forecast should be high on an average $1 - \alpha$ fraction of the periods and the average demand corresponding to high demand forecast periods should be $\theta_h \mu$. If the retailer passes the statistical tests during the review period (i.e., their score exceeds a credibility assessment threshold), then another review cycle commences. If the retailer fails statistical tests during the review period, the supplier punishes the retailer by discarding the her messages for a certain number of period, i.e., resorts to the single-period equilibrium of the game. Ren et al. (2010) show that for sufficiently large: discount rate, review period length, and credibility assessment threshold; truth-telling can be sustained in equilibrium under the review strategy. As a result, the supplier trusts the retailer's message and maintains the supply chain optimal capacity level in each period.

Once again, simple linear price contracts are shown to have the capability to coordinate a dynamic inventory problem with asymmetric information. This capability arises due to threat of the uninformed firm "punishing" the informed firm in future for inaccurate reports. As such, the findings in this paper illustrate how a "scorecard" based system may also be used to elicit private information which may improve capacity/production planning in the supply chain (in addition to, for example, evaluating supplier effectiveness).

We conclude this section by highlighting related research that has considered incentive problems in multi-period interactions resulting in a one-time capacity/production decision. Oh and Özer (2013) propose a general framework to model multiple evolutions of forecasts generated by multiple firms. Using this framework, they introduce Martingale Model of Asymmetric Forecast Evolutions (MMAFE) and propose a mechanism for an upstream supplier to elicit a downstream retailer's information credibly before making a single-shot capacity decision. There are two unique aspects to the mechanism design problem considered in this paper. First, due to dynamically evolving forecasts, they investigate *when* is the right time for the supplier to offer the mechanism (screening contracts) to the retailer. Second, in contrast to the other static/dynamic mechanism design problems considered above, the supplier builds capacity *even* if the retailer rejects the menu of contracts.[15] Thus, the retailer's decision to accept/reject the mechanism is explicitly handled in the paper. The resulting mechanism design problem not does admit standard solution methodology and we refer to Oh and Özer (2013) for further details. Feng et al. (2015) study a model of dynamic interactions, in particular, a dynamic bargaining game between a buyer (with private demand information) and a seller that ensues prior to a one-time demand realization. In each round of negotiation one of the firm moves to offer a contract, i.e., the informed firm offers a contract to signal type or the uninformed firm may offer contracts to screen the other firm. The negotiation continues until an agreement on quantity and payment for the trade of a product is reached. In the process, the contract offers are updated by each party, based on outcomes of the previous negotiation stages.

Liu et al. (2019) consider an innovative multi-period agreement for sharing capacity (built by a single supplier firm) among multiple downstream manufacturing firms. The supplier makes a one-time capacity decision at the start of the time horizon, and in each period, the capacity has to be allocated among all the firms. They consider the case in which all firms (the supplier and manufacturers) have private information about their demand. The supplier too has access to a spot-market with private demand information where it can choose to sell its capacity. One of the uniqueness of this multi-firm, multi-period agreement is that it is *budget-balanced*, i.e., the total payment received is equal to the total payment made in *each* period as a part of the agreement. In other words, the partnership is financially self-supporting.

[15] There is no possibility of credible information sharing in the event the retailer rejects the menu of contracts. Nevertheless, the supplier can still make (coarse) inference about the retailer's type.

The proposed agreement not only ensures truthful sharing of private demand information but also that the supplier builds (ex-ante) efficient capacity and the capacity is allocated efficiently (ex-post) among all the firms.

4 Conclusion and Future Directions

In this chapter we have reviewed inventory management literature with special focus on information and incentives in dynamic settings. This literature, while still in its infancy, already illustrates a variety of problems that can be handled equipped with the machinery of *dynamic* mechanism design. There are several promising research directions at the confluence of information and incentives both in a traditional inventory management and emerging contexts. Below we highlight a few:

- *Information design approach.* In contrast to monetary transfer as a part of the contract mechanisms discussed in the chapter, non-price levers such as information may also be used by the informed firm to communicate its private information. This approach has been explored in the context of demand-side of operations but a similar approach may also be used in managing inventory within a supply chain.
- *Social and environmental considerations.* Recent research has shown the value and impact of incentives to motivate socially- and environmentally-responsible operations from upstream firms; see, for example, Porteous et al. (2015); Kraft et al. (2020). Supply chain settings such as these are fraught with incomplete information (e.g., about sourcing methods) and unobservable upstream actions (e.g., labor practices). In these supply chain contexts, besides knowing the quantity of inventory, firms also need to know where the inventory is being sourced from. For example, the US government recently had announced a ban on imports of cotton and tomatoes from the Xinjiang area of China, including products made with those materials, due to human rights violations (Swanson, 2021). In that sense, it is not just information about inventory but also about the sourcing of materials that go into the product that matters. An important question in this context is what role does/can inventory management (under incomplete information or moral hazard) play in improving the social and environmental performance of the supply chain?
- *Empirical research.* The theoretical contract forms discussed in this chapter need to be reconciled with what is observed in practice. In particular, examining performance of long-term contracts based on field data may validate the theoretical insights as well as provide opportunities for future research.

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