

Dynamic lead time coordination in supply chains under bilateral operational information asymmetry

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ABSTRACT

Coordinating modern supply chains (SCs) is hindered by market volatility and, critically, by bilateral operational information asymmetry, where partners hold private, unverifiable information about their real-time capabilities. This study addresses this challenge by developing and testing a novel coordination framework for a dyadic SC, centered on a dynamic lead time negotiation coupled with an adaptive revenue-sharing mechanism. A comparative simulation analysis reveals that while lead time negotiation alone enhances responsiveness by significantly reducing delivery times, it can paradoxically destroy total SC profit in decentralized settings due to uncompensated operational costs. However, the proposed integrated framework – combining negotiation with adaptive revenue sharing – proves highly effective. It not only fosters cooperation but also recovers nearly all profit losses from decentralization, while ensuring an equitable profit distribution. Furthermore, the study uncovers a critical insight into pricing power: a leader's ability to charge for faster service is fundamentally limited by the partner's economic viability, with a clear threshold beyond which an aggressive pricing strategy becomes value-destructive for the entire SC. This research contributes a novel operational contract that effectively mitigates the impacts of information asymmetry and enhances system-wide efficiency by explicitly linking dynamic operational decisions (lead time) to their shared financial consequences, offering a practical path toward resilient and profitable SC collaboration.

1. Introduction and motivation

In contemporary volatile markets, effective supply chain (SC) coordination is not only beneficial but imperative to achieve the responsiveness and resilience essential to competitive advantage (Flynn et al., 2016; Richey et al., 2022). Yet the prevalent decentralized structure of SCs, composed of independent, self-interested firms, inherently breeds coordination challenges stemming from conflicting objectives and, critically, informational friction (Shen et al., 2019). These tensions are most acute in time-sensitive, capacity-constrained dyads, where a manufacturer and a downstream intermediary must repeatedly align prices, promotions, and service levels under tight delivery commitments.

The practical relevance of this problem is heightened by structural trends in contemporary markets: greater product differentiation and shorter life cycles amplify demand volatility, while downstream customers increasingly require competitive prices together with high service levels, rapid replenishment, and reliable delivery, particularly during promotions, seasonal peaks, and product launches, when demand may shift abruptly in response to marketing actions, regulatory changes, or technological innovation. Meeting these expectations

is challenging because upstream plants must allocate finite capacity across products and customers while managing changeovers, schedules, maintenance, and pre-existing commitments. These tensions are documented empirically across several industries. In the automotive sector, model ramp-ups, configuration changes, and recall campaigns generate bursts of deadline-sensitive demand that propagate upstream through tiered supplier networks, where empirical evidence on first-tier suppliers shows that meeting tight delivery windows under capacity constraints is a decisive yet fragile source of competitive advantage (Holweg, 2005; Jayaram et al., 1999). In grocery and fast-moving consumer goods, manufacturers and large retailers must synchronize replenishment around promotional calendars and seasonal events, where even short delays translate into lost sales or costly markdowns; empirical studies of manufacturer–retailer collaboration in this sector document significant operational and financial gains from jointly managed forecasting and replenishment (Hill et al., 2018), yet also reveal persistent perceptions of inequity on the supplier side, underscoring the need for balanced value sharing (Corsten and Kumar, 2005). In consumer electronics, frequent product launches and refreshes concentrate demand into narrow time windows that must be absorbed

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by plants operating close to capacity, while in fashion and apparel short product life cycles and high volatility make quick replenishment decisive (Christopher et al., 2004; Cachon and Swinney, 2011). Analogous pressures arise in time-critical spare parts, where service-level commitments hinge on the rapid availability of constrained capacity.

Across these settings, the friction that governs coordination is operational and bilateral. Downstream firms are typically closer to the market and better informed about demand responsiveness to price, promotion, and service, whereas upstream firms retain private knowledge of internal cost, effective capacity, and contemporaneous workload, including competing orders and urgent local needs that are difficult for the counterpart to verify in real time. This downstream/upstream information structure is widely adopted in the coordination literature (Yan et al., 2023; Huang et al., 2025); however, the few studies addressing genuinely bilateral asymmetry (Schoenmeyer and Graves, 2022; Zissis et al., 2020) focus on largely static economic parameters rather than on the dynamic, unverifiable operational states that determine the feasibility and cost of meeting a given lead time. Moreover, in these dyads bargaining power is often sufficiently balanced that neither party can simply impose unilateral terms, so that lead time becomes an endogenous coordination lever to be negotiated rather than dictated.

This operational, bilateral friction differs sharply from the asymmetries most often studied in the literature. While unilateral information asymmetry about aggregate economic parameters (e.g., demand forecasts or production costs) is well studied (Chen et al., 2016; Zhang et al., 2014; Ha, 2001), such models typically rely on a principal–agent structure with a single privately informed party, for which a rich set of coordinating contracts (wholesale-price, buy-back, revenue-sharing) mitigates frictions by inducing revelation or self-selection over largely static private parameters (Albrecht, 2010). Operational information, by contrast, is dynamic, local, and hard to verify in real time, and it directly shapes feasible lead time commitments. This makes the direct transposition of contract forms developed for unilateral asymmetry problematic: with interdependent operational private information and balanced bargaining power, the principal–agent hierarchy blurs into mutual opacity and an endogenous allocation of decision rights. Consequently, unilateral contracts may still support aggregate coordination and risk sharing, but without substantial redesign they offer limited scope to adjust lead time to period-by-period fluctuations in capacity and workload (Vosooghizadeh et al., 2020; S.-H. Kim and S. Netessine, 2013).

In this environment, lead time transcends its traditional role as a fixed parameter or a simple performance outcome. It emerges as a critical, endogenous coordinating variable that reflects the dynamic operational state of SC partners and profoundly influences inventory levels, service performance, and overall profitability (Hua et al., 2010; Palaka et al., 1998). Coordination therefore requires mechanisms for dynamic lead time negotiation; yet standard contracts often treat lead time as exogenous and offer limited support for state-contingent operational adjustment (Chen and Lee, 2017; Shen et al., 2019), coordinating aggregate prices and quantities while implicitly assuming that operational execution is transparent, an assumption that fails under dynamic operational asymmetry.

This bilateral environment, in which private and interdependent values must be reconciled, is precisely where foundational mechanism-design results expose the limits of efficient coordination (Myerson and Satterthwaite, 1983). We take such impossibility results as a theoretical upper bound on what fully efficient and incentive-compatible mechanisms can achieve, and instead adopt a more operational perspective, asking whether a practically implementable negotiation scheme can still deliver substantial performance improvements. Canonical lenses are individually limited here: Mechanism Design (MD) faces well-known obstacles with interdependent values and non-verifiable, time-varying operational states (Myerson and Satterthwaite, 1983; Maskin and Tirole, 1999), whereas Game-Theoretic (GT) SC models often rely on static or stylized operational representations, making repeated

bargaining over evolving feasibility conditions hard to capture tractably (Cachon, 2003a; Yang and Babich, 2015). These considerations motivate moving beyond revelation-centric approaches toward mechanisms that explicitly embed the operational layer, actively involving both parties in adjusting orders, prices, and lead times to align decentralized decisions with system-wide performance.

Complementarily, analytical frameworks for modeling operational performance and lead time variability (Hopp and Spearman, 2011) clarify the physical dynamics of capacity and congestion, but they rest on a critical behavioral assumption: that operational parameters such as capacity, workload, or congestion are truthfully reported. This assumption is untenable precisely in the bilateral setting we consider, where each party's operational state is private, unverifiable, and directly tied to the price and feasibility of a lead time commitment, giving self-interested agents both the ability and the incentive to strategically misrepresent it during negotiation (in contrast with strategic customer behavior within a single queue, e.g., Hassin and Haviv, 2003). Standard operational models therefore lack the framework to analyze such strategic misrepresentation, and even studies that couple operational and economic models (Plambeck and Ward, 2006) rarely embed inter-firm negotiation over privately held, and potentially distorted, operational congestion. Capturing this interplay between operational feasibility and the strategic reporting of hidden operational states is one of the central challenges this paper addresses.

Consequently, a significant research gap persists: coordination mechanisms for dynamic, iterative lead time negotiation under bilateral operational information asymmetry remain underdeveloped, particularly when no party is dominant. Although experiments confirm that dynamic bargaining can improve SC efficiency (Davis and Hyndman, 2021), the field still lacks a structured operational process that translates this insight into implementable lead time coordination, integrating strategic interaction with capacity and workload dynamics for this specific information structure and organizational context.

This paper addresses this void by proposing and analyzing a dynamic coordination mechanism tailored to this environment. Our approach centers on dynamic lead time negotiation as the primary coordination lever, where lead time emerges endogenously from a structured, sequential negotiation process. Agents apply an internal, capacity-aware logic to evaluate the feasibility and cost of lead time requests; this evaluation incorporates each party's private and evolving assessment of its operational state (e.g., estimated utilization, buffer status), which informs its strategy but is neither observable nor verifiable by the counterpart and may therefore be strategically misrepresented during negotiation. Rather than assuming truthful disclosure, the mechanism is deliberately designed to operate under such opacity: coordination is achieved through observable operational requests and responses (orders, requested and proposed lead times, wholesale prices, and revenue-sharing terms) rather than through the direct revelation of private states. Recognizing the risk of impasses or one-sided outcomes when no leader is present, the mechanism further incorporates an adaptive, negotiation-responsive revenue-sharing rule that adjusts the profit split according to the negotiated lead time outcome. This design shares coordination gains more equitably and counterbalances temporary bargaining advantages (e.g., negotiation skill or short-lived leverage), making it well-suited to relationships with balanced or complex power: by grounding negotiation in operational feasibility and aligning incentives through dynamic revenue sharing, it promotes cooperative behavior and system-wide efficiency even when neither party can dictate terms.

The primary contributions of this research are therefore threefold: (i) the development of a novel, dynamic coordination mechanism for lead time negotiation under bilateral operational asymmetry, integrating an internal, capacity-aware logic for private, strategic operational assessment; (ii) the development and analysis of an integrated, adaptive revenue-sharing scheme designed to function within this mechanism, demonstrating how financial incentives can respond to and support

operational negotiation outcomes to foster cooperation in settings with balanced power; and (iii) a rigorous simulation-based performance analysis evaluating the framework's impact on SC profitability, operational metrics (e.g., lead time, capacity), and strategic behavior under various information scenarios (symmetric vs. asymmetric) and organizational structures (decentralized vs. centralized). Overall, the work offers a more operationally and strategically grounded approach to managing SC coordination in complex, dynamic, and information-constrained environments with balanced bargaining power.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature and highlights the research gap; Section 3 presents the proposed coordination mechanism and analytical model; Section 4 details the experimental methodology and simulation design; Section 5 discusses the results and managerial implications; and Section 6 concludes and outlines future research directions.

2. Literature review

This study is positioned at the intersection of several important research streams in operations and SC management, including coordination mechanisms, information asymmetry, dynamic interaction, and operational modeling. This section reviews key contributions in these areas to highlight the unique challenges addressed by our work and define its specific contribution to the literature.

2.1. SC coordination and information asymmetry

Decentralized SCs, characterized by independent firms pursuing self-interest, face inherent coordination challenges leading to inefficiencies (Shen et al., 2019). A vast body of literature proposes various contractual mechanisms, such as wholesale price, buy-back, revenue-sharing, and quantity flexibility contracts, to align incentives and improve system-wide performance (Cachon, 2003b; Chen et al., 2016). While effective under conditions of perfect information, the efficacy of these contracts is significantly diminished by the ubiquitous presence of information asymmetry between partners (Esmaeili et al., 2009; Zissis et al., 2015; Özer and Raz, 2011).

Prior research on information asymmetry in SCs has largely focused on unilateral settings, where private information (e.g., retailer demand forecasts, supplier cost structures, risk attitudes) resides with only one party (Chu et al., 2017). In such principal-agent scenarios, mechanisms like contract menus or signaling games are employed to elicit or infer private information (Vosooghizadeh et al., 2020). These approaches, however, often rely on specific assumptions regarding the type of information (e.g., static, verifiable) and the structure of the relationship (e.g., clear leader-follower), which are not applicable to scenarios involving complex, bilateral, and dynamic information friction (Shen et al., 2019).

2.2. Bilateral asymmetry, bargaining, and the limits of MD

Coordination becomes substantially more complex under bilateral information asymmetry, where both buyer and supplier possess private, decision-relevant information (S.-H. Kim and S. Netessine, 2013). The foundational impossibility theorem in Mechanism Design (MD) by Myerson and Satterthwaite (Myerson and Satterthwaite, 1983) demonstrates the theoretical difficulty of achieving ex-post efficiency in bilateral trading environments with interdependent private values. While originally applied to economic valuations (e.g., buyer's valuation, seller's cost), this principle extends critically to the operational context of our study. Here, a supplier's true production capacity or a buyer's genuine urgency represent interdependent private values that impact the feasibility and desirability of a specific lead time commitment for both parties.

This theoretical hurdle highlights the need for practical mechanisms that, while perhaps not perfectly efficient, can significantly improve

outcomes. Recent experimental evidence from Davis and Hyndman (Davis and Hyndman, 2021) supports this direction, demonstrating that multi-round dynamic bargaining over economic terms can substantially increase SC efficiency compared to static, one-shot mechanisms, by facilitating partial information revelation. However, their study focuses on bargaining over costs and does not propose a specific, structured process for negotiating operational variables.

Existing work addressing bilateral asymmetry in SCs has often explored complex multi-dimensional contracts leveraging various levers (e.g., price, quantity, risk-sharing) to handle multi-faceted private information like production costs and market efforts (S.-H. Kim and S. Netessine, 2013; Wang et al., 2017). These often involve sophisticated communication protocols and carefully designed incentive compatibility conditions (Mobini et al., 2019). Some studies also explore sophisticated pricing schemes, like contracts combining fixed and indexed price components, to manage sourcing under volatile input costs when the supplier's underlying cost structure is private (Zhang et al., 2014). However, these mechanisms typically struggle to handle the dynamic, high-frequency, and non-verifiable nature of real-time operational information (e.g., current capacity/congestion vs. static costs), which is the core focus of our paper. Applying these frameworks to continually evolving, opaque operational states introduces significant theoretical and practical hurdles. Within this perspective, these challenging results formally bound what can be achieved in such bilateral settings: any budget-balanced and individually rational process can, at most, deliver a second-best outcome, so that some loss of efficiency relative to the full-information centralized benchmark is unavoidable.

2.3. Dynamic interaction and bargaining

Dynamic bargaining theory provides a framework for analyzing sequential interactions where private information can be revealed over time (Ritzberger, 2002). Applied to SCs, bargaining models have been used to study the negotiation of economic terms. For instance, Feng et al. (2015) model a dynamic game where a supplier bargains over price with a retailer who holds private demand information. Other works, like (S.-H. Kim and S. Netessine, 2013), analyze how contracts can mitigate unilateral information asymmetry regarding a supplier's strategic cost-reduction efforts. Experimental evidence largely supports the notion that multi-round bargaining can improve efficiency compared to static mechanisms (Katok and Wu, 2009; Davis and Hyndman, 2021).

While these studies offer crucial insights, they often focus on economic parameters (price) or unilateral, strategic decisions (investment). They have not adequately addressed the dynamic negotiation of operational variables, most critically lead time, where feasibility and strategic value depend on complex, continuously changing, and bilaterally held private operational states (e.g., current capacity utilization, queue lengths, urgent local priorities). Modeling bargaining over such dynamic and non-verifiable operational realities, especially in a context of balanced power without a clear principal-agent structure, introduces challenges beyond those typically considered in the SC bargaining literature. Our work aims to fill this specific gap.

2.4. Operational modeling and lead time dynamics

Operational efficiency and responsiveness are tightly tied to lead time management (Richey et al., 2022; Talay et al., 2022). Queueing-theoretic and related operational models capture how capacity utilization and workload variability shape lead times (Hopp and Spearman, 2011), and these insights have been incorporated into economic models for pricing, capacity planning, and lead time-based decision making (Palaka et al., 1998; Lee and Kim, 1993; Biçer et al., 2017; Hua et al., 2010; Modak and Kelle, 2019; Lei et al., 2012). However, a key limitation is that standard QT models typically assume operational states (e.g., service rates, queues, capacity) are observable or truthfully

reported (Hopp and Spearman, 2011; Hassin and Haviv, 2003). As a result, they are not designed to analyze strategic misrepresentation and inter-firm negotiation over privately known, unverifiable operational conditions that determine feasible lead times. Although prior work studies strategic behavior within queues (e.g., jockeying or delays) (Hassin and Haviv, 2003; Srai and Ané, 2016; Dimitrakopoulos et al., 2021) and highlights the value of transparency for supply risk (Qin and Shao, 2019), only limited research explicitly models bilateral strategic negotiation when lead time depends on opaque operational states (S.H. Kim and S. Netessine, 2013). This leaves a gap between operational performance modeling and strategic interaction under deep operational asymmetry.

2.5. Adaptive mechanisms and coordination under operational uncertainty

Recognizing the dynamic nature of SCs, researchers have explored adaptive contracts and relational governance to facilitate cooperation and manage non-verifiable actions or evolving conditions (Rojo et al., 2018; Özer and Raz, 2011). Relational contracts can support cooperation in settings with non-verifiable information (Zhang and Luo, 2009; Zhang et al., 2014). However, building and sustaining the necessary trust can be challenging, particularly when rapid, dynamic adjustments are needed based on highly fluctuating and tempting-to-misrepresent operational states like real-time capacity. Existing adaptive contractual mechanisms often adjust economic parameters (e.g., pricing, profit shares) based on realized outcomes (e.g., sales volume) or verifiable signals (Cachon, 2003b), offering greater clarity and robustness in certain contexts (Tunca and Zenios, 2006). What remains significantly underdeveloped are mechanisms that dynamically link financial incentives (such as revenue sharing parameters) to the outcomes of negotiations over unverifiable operational parameters like committed lead times. Designing incentives that respond to and influence the strategic negotiation process itself, particularly concerning opaque operational feasibility, is a critical missing element for effective coordination in dynamic and asymmetric SC environments.

2.6. Synthesis and research gap

This review reveals a clear research gap at the intersection of SC coordination, information asymmetry, and operational modeling: robust mechanisms for dynamic lead time negotiation in decentralized dyadic SCs with bilateral, time-varying, and unverifiable operational information remain underdeveloped, especially when no party has dominant power. Existing approaches address only parts of the problem. Contract menus are ill-suited to dynamic, non-verifiable operational information (Chen et al., 2016; Esmaeili et al., 2009; Wang et al., 2017); bilateral mechanism design clarifies theoretical limits under private values but does not provide implementable negotiation process under operational opacity (Myerson and Satterthwaite, 1983); and dynamic bargaining has not been extended to negotiations over operational feasibility based on private states (Davis and Hyndman, 2021; Feng et al., 2015). Operational performance models add realism but typically assume truthful reporting and omit strategic inter-firm negotiation (Hassin and Haviv, 2003), while adaptive/relational contracts, though valuable, rarely tie incentives directly to the outcomes of negotiations over unverifiable feasibility (Rojo et al., 2018; Özer and Raz, 2011; Tunca and Zenios, 2006).

Our study addresses these limits by developing a novel dynamic coordination mechanism for lead time negotiation that integrates a structured and sequential negotiation process with an adaptive revenue-sharing scheme dynamically linked to negotiation outcomes. This integrated approach effectively bridges the gap between modeling operational “physics” and inter-firm “strategy”, offering a structured means to manage operational friction and intended to enhance flexibility, mitigate informational inefficiencies, and promote cooperative behavior in complex SCs characterized by deep bilateral operational asymmetry and strategic interaction.

3. Problem definition and coordination model development

Building upon the identified gaps in the literature, this section details the proposed dynamic coordination mechanism designed to manage bilateral operational information asymmetry in a dyadic SC through lead time negotiation. Our framework integrates three core components: (i) a structured sequential negotiation mechanism where lead time is the primary negotiation variable, reflecting parties’ private operational assessments; (ii) the incorporation of operational logic, informed by core principles of capacity utilization, to guide feasibility assessments under capacity constraints; and (iii) an adaptive revenue-sharing mechanism dynamically linked to the negotiated lead time outcome to foster participation and balanced distribution of gains.

3.1. Input parameters and decision variables

The model considers a dyadic SC consisting of a single manufacturer (M) and a single retailer (R), operating over a discrete-time horizon indexed by week t . We define the input parameters, distinguishing between those assumed to be common knowledge (Common System Parameters, Table 1) and those subject to information asymmetry (Dynamic Private Parameters, Table 2).

The decision variables for each actor in week t are outlined in Table 3. For notational convenience, while the Dynamic Private Parameters (Table 2) are inherently subject to weekly estimation by the uninformed party (e.g., M forms $\hat{\beta}_t$ and $\hat{\alpha}_t$), the subscript t and the notation $\hat{\cdot}$ may be omitted in the general model formulation to simplify notation and enhance readability. The precise mechanisms for their weekly sampling, the formation of estimates under asymmetry, and their use by each actor will be fully elaborated in Section 4.

3.2. Problem statement and assumptions

Within the context of this single-product dyadic SC, negotiations and decisions related to operational parameters occur on a week-to-week basis (t). Consistent with common manufacturer–retailer relationships, we model a bilateral information asymmetry in which the retailer, being closer to the final market and promotional activities, has privileged knowledge of demand responsiveness, while the manufacturer has privileged knowledge of its internal cost structure and the workload induced by other customers (as summarized in Table 2). This allocation captures the key demand- and supply-side levers that drive lead time negotiation in a broad class of vendor–buyer dyads, where downstream firms directly observe market reactions whereas upstream firms observe internal cost and congestion conditions that are typically difficult for the counterpart to verify in real time.

The retailer faces end-customer market demand, D_t , which is influenced by the retail price P_t and marketing expenditure E_{m_t} , according to Lee and Kim (1993) and Esmaeili and Zeepongsekul (2010):

$$D_t(P_t, E_{m_t}) = k_d P_t^{-\alpha} E_{m_t}^{\beta} \quad (1)$$

The model formulation relies on the following key assumptions:

1. **External Demand at Manufacturer:** The manufacturer serves the retailer’s demand D_t but also faces an additional weekly demand Q_{ext_t} from external customers or channels. It is exogenous to the M–R dyad and modeled as a stochastic variable to reflect its variable and unpredictable nature. Being sampled weekly, it contributes dynamically to the manufacturer’s total workload and operational constraints.
2. **Manufacturer’s Operational Model:** The manufacturer’s production facility operates with a finite daily production capacity (service rate) μ (units/day) over N working days per week. We model the manufacturer’s operational decision process using an average-rate capacity constrained framework. This approach, which reflects the fundamental principle that higher utilization

Table 1
Common system parameters.

Parameter	Unit	Description
i	%/unit/week	Weekly inventory holding cost rate per unit
E_o	€/order	Retailer's ordering cost
k_d	/	Scaling constant for the demand function ($k_d > 0$)
L	/	Ratio of marketing elasticity to price elasticity ($L = \beta/\alpha$)
μ	unit/day	Manufacturer's maximum daily production rate (service rate)
ρ_{MAX}	/	Maximum target daily utilization coefficient ($0 < \rho_{MAX} < 1$)
N	day/week	Number of working days per week
C_{pa}	€/unit	Unit production cost at the auxiliary facility
f	€· days/unit	lead time price sensitivity parameter for W_{LT_i}
k_w	/	Markup factor for manufacturer's break-even price component W_0

The ratio L is assumed to be a constant market characteristic known to both parties, even though individual elasticities may vary or be subject to estimation while respecting this relationship.

Table 2
Dynamic private parameters.

Actor	Parameter	Unit	Description
M	C_p	€/unit	Manufacturer's internal unit production cost
M	E_s	€/setup	Manufacturer's internal production setup cost
M	Q_{ext_i}	unit	Demand from manufacturer's other customers in week i
R	α	/	Price elasticity of demand ($\alpha > 1$)
R	β	/	Marketing elasticity of demand ($0 < \beta < 1, \beta + 1 < \alpha$)

This table reflects the asymmetric information structure outlined in Section 3.2. Manufacturer holds private information on internal costs (C_p , E_s) and external operational load (Q_{ext_i}). Retailer holds private information on market demand parameters (α , β).

Table 3
Decision variables per Week i .

Actor	Variable	Unit	Description
M	Q_i	unit/batch	Manufacturer production batch size
M	W_i	€/unit	Wholesale price charged to the retailer
R	P_i	€/unit	Selling price charged to the final customer
R	E_{m_i}	€/unit	Marketing expenditure per unit demanded

increases operational strain and potential for congestion, allows for tractability within the strategic negotiation context. Key operational metrics are the average daily arrival rate of demand at the manufacturer, λ_{M_i} (units/day), and the resulting daily capacity utilization, $\rho_{M_i} = \lambda_{M_i}/\mu$ (where $\mu > \lambda_{M_i}$ must hold for stability). The average daily arrival rate, λ_{M_i} , is obtained from the inter-week stochastic drivers (the retailer's order D_i and the external demand Q_{ext_i}), which jointly define the realized weekly workload in period i . This workload is then converted into an intra-week average rate by spreading it uniformly over the N working days:

$$\lambda_{M_i} = \frac{D_i + Q_{ext_i}}{N} \quad (2)$$

Accordingly, λ_{M_i} and ρ_{M_i} are average-rate quantities conditional on the weekly state; they vary stochastically from week to week as the underlying state evolves. While this average-rate representation abstracts from intra-week stochastic queueing dynamics, it captures the planning level trade-off between congestion and speed that governs feasible lead time commitments within recurrent weekly decision cycles. Operations are managed to keep this average utilization below a predefined maximum target level ρ_{MAX} ($0 < \rho_{MAX} < 1$) to ensure a practical level of service reliability and avoid deterministic overload, representing the point where stochastic congestion would become excessive in a real system (Corrado and Matthey, 1997).

3. Outsourcing Option: If meeting a requested lead time would require operating above the target utilization ρ_{MAX} , the manufacturer has the option to outsource a portion X_i of the production volume to an auxiliary facility. This facility is assumed to have flexible production capability, able to produce any required

quantity, but incurs a higher unit production cost $C_{pa} > C_p$. Following standard practice in backup-sourcing and spot-market models (Inderfurth et al., 2013; Echefaj et al., 2024), we treat this auxiliary capacity as non-binding over the demand range considered, so that overload situations are managed through an explicit cost penalty rather than an additional hard capacity constraint. This modeling choice, while simplifying the treatment of overload situations, allows us to focus on the interaction between internal capacity limits, lead time negotiation, and information asymmetry.

4. Lead Time Determination: The final delivery lead time LT_i (days) for the retailer's order D_i is not fixed but determined endogenously through the negotiation described in Section 3.3. Conditional on the weekly utilization state ρ_{M_i} , the model returns an agreed committed lead time, which is treated as fixed for intra-week feasibility assessment. Accordingly, stochastic variability in LT_i arises through the week-to-week evolution of the state variables driving ρ_{M_i} , rather than through an explicitly modeled intra-week queueing process.
5. Lead Time Pricing Component: The wholesale price W_i set by the manufacturer includes a component W_{LT_i} that depends on the agreed-upon lead time LT_i . We assume an inverse relationship, reflecting that shorter lead times typically require more effort, prioritization, or cost, justifying a price premium. We adopt the tractable hyperbolic form:

$$W_{LT_i}(LT_i) = \frac{f}{LT_i + 1} \quad (3)$$

where $f \geq 0$ is the lead time price sensitivity parameter (Table 1). This functional form captures diminishing price sensitivity to lead time changes and ensures a finite price even for near-zero lead times (similar inverse relationships explored in Hua et al., 2010; Kelle et al., 2003).

3.3. Negotiation mechanism

We propose a structured sequential negotiation mechanism that takes place each week i to determine the agreed lead time LT_i and the associated operational actions. The mechanism is specified as a finite, rule-based interaction process embedded in the weekly planning cycle and explicitly constrained by operational feasibility. Rather

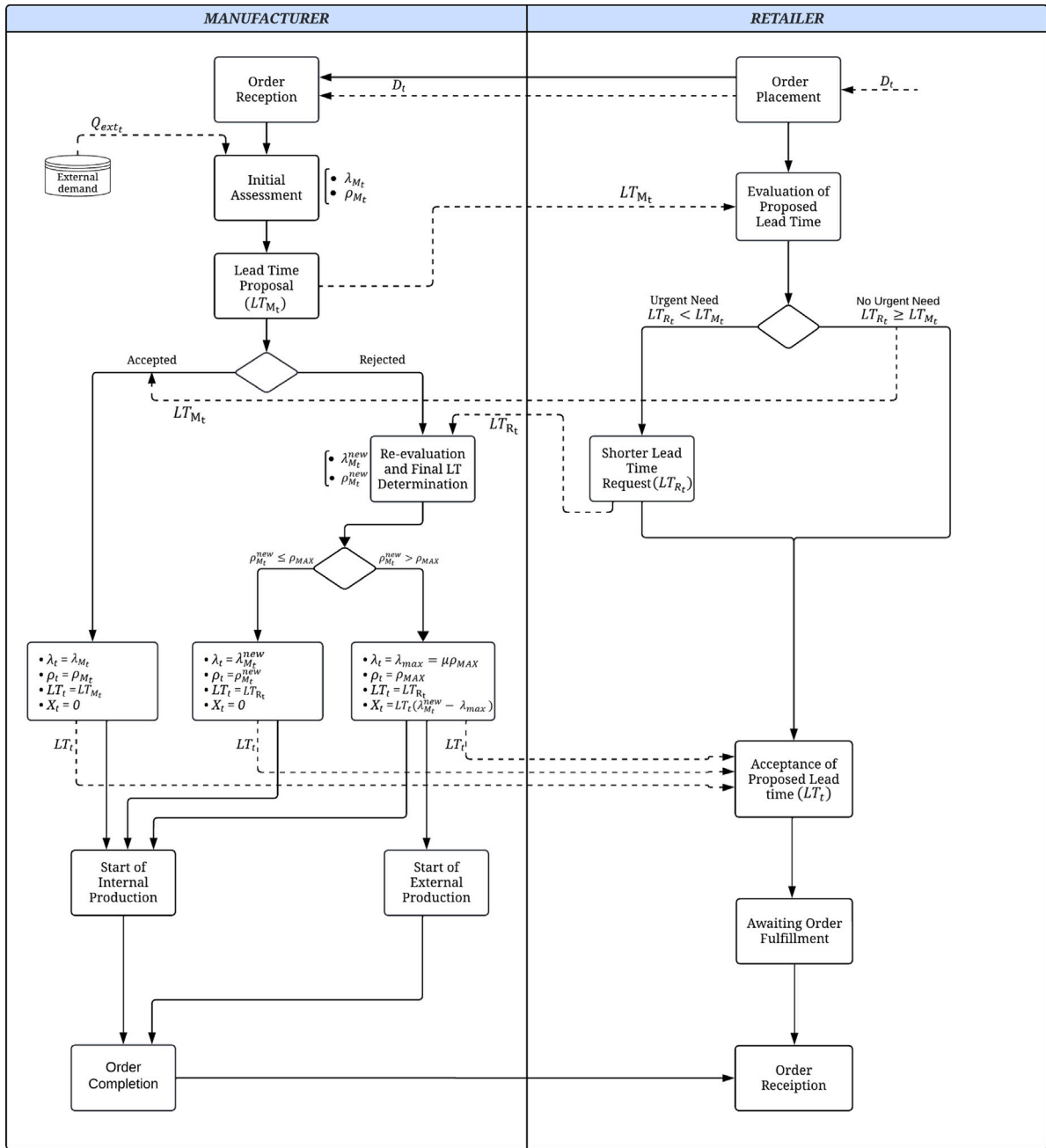


Fig. 1. Flowchart of the proposed negotiation mechanism.

than modeling an open-ended bargaining equilibrium, we formalize a capacity-feasible negotiation process that maps the within-period operational state and the contractual rules into a unique lead time commitment LT_t and the corresponding operational decisions. The flow of the process is depicted in Fig. 1.

1. **Order Placement:** At the start of week t , the retailer observes demand drivers and places an order of size D_t (determined by optimizing its expected profit based on its private information α, β and expectations about manufacturer's private parameters, as formalized in Eq. (13) in the next section).
2. **Manufacturer's Initial Assessment:** Upon receiving the order D_t , the manufacturer, using its private information on Q_{ext_t} , calculates the required average daily production rate to meet the total demand within the standard weekly cycle (N days), according

to Eq. (2). It then assesses its initial capacity utilization: $\rho_{M_t} = \lambda_{M_t} / \mu$.

3. **Manufacturer's Lead Time Proposal (LT_{M_t}):** The manufacturer proposes a potential lead time LT_{M_t} (in days), reflecting the delivery speed achievable considering internal operational constraints and other workload. When the current workload allows processing D_t within the target utilization ($\rho_{M_t} \leq \rho_{MAX}$), LT_{M_t} is calculated according to the planned rate λ_{M_t} . Conversely, if utilization exceeds the target, LT_{M_t} is extended to the minimum time needed to process the total demand ($D_t + Q_{ext_t}$) at the maximum sustainable rate ρ_{MAX} . Eq. (4) formally defines LT_{M_t} under these conditions.

$$LT_{M_t} = \begin{cases} \frac{D_t}{\lambda_{M_t}}, & \text{if } \rho_{M_t} \leq \rho_{MAX} \\ \frac{D_t + Q_{ext_t}}{\mu \rho_{MAX}}, & \text{if } \rho_{M_t} > \rho_{MAX} \end{cases} \quad (4)$$

4. **Retailer's Evaluation:** The retailer receives the proposed LT_{M_i} and evaluates its acceptability against its own required lead time LT_{R_i} . We posit that LT_{R_i} is an exogenous input for the retailer, reflecting downstream customer requirements or market-driven urgency (e.g., a key end-customer demanding early delivery, potentially at a premium, or a need to rapidly replenish stock to avoid a stockout). In this initial modeling approach, we assume the retailer aims to satisfy this required LT_{R_i} whenever it is shorter than the manufacturer's proposed LT_{M_i} . To capture the dynamic and unpredictable nature of such urgencies within a weekly planning cycle, LT_{R_i} is modeled as a stochastic variable drawn each week from a discrete uniform distribution over $[LT_{R_{min}}, LT_{R_{max}}]$. This choice reflects the practical constraint that required lead times must fall within a plausible operational window (e.g., cannot be instantaneously zero or exceed a certain maximum within a weekly planning horizon). This sampling mechanism introduces variability representing fluctuating urgency levels, allowing for an assessment of how SC coordination can mitigate their impact on costs and operational performance.
5. **Scenario Branching Based on Retailer's Evaluation:** Following the retailer's evaluation in Step 4, two potential scenarios arise based on the comparison between the manufacturer's proposed lead time (LT_{M_i}) and the retailer's required lead time (LT_{R_i}):
 - Case 1 - Urgent Need ($LT_{R_i} < LT_{M_i}$): The retailer finds the manufacturer's proposal too long and requests its expedited lead time LT_{R_i} . This scenario proceeds to Step 6 below, detailing the manufacturer's re-evaluation and final lead time determination under this constraint.
 - Case 2 - No Urgent Need ($LT_{R_i} \geq LT_{M_i}$): The retailer finds the manufacturer's proposal acceptable or shorter than required. This scenario proceeds to Step 7 below, detailing the final lead time determination in this simpler case.
6. **Manufacturer's Re-evaluation and Final LT Determination:** At this point, the required lead time, LT_{R_i} , becomes a temporal constraint for the manufacturer to fulfill the order D_i . As a result, the manufacturer re-evaluates its operational parameters accordingly:
 - (a) Calculate the new required daily production rate for the retailer's order:

$$\lambda'_{R_i} = \frac{D_i}{LT_{R_i}} \quad (5)$$
 - (b) Calculate the total effective daily rate needed $\lambda_{M_i}^{new}$, considering external demand Q_{ext_i} spread over the week:

$$\lambda_{M_i}^{new} = \lambda'_{R_i} + \frac{Q_{ext_i}}{N} \quad (6)$$
 - (c) Assess the resulting utilization: $\rho_{M_i}^{new} = \lambda_{M_i}^{new} / \mu$.

$$LT_{R_i} < LT_{M_i} \Rightarrow \lambda_{M_i}^{new} > \lambda_{M_i} \Rightarrow \rho_{M_i}^{new} > \rho_{M_i} \quad (7)$$
 - (d) At this stage, two distinct alternatives may arise:
 - i. $\rho_{M_i}^{new} \leq \rho_{MAX}$: The manufacturer can accommodate the request internally, although at higher utilization. The final agreed lead time is $LT_i = LT_{R_i}$ and no outsourcing is needed ($X_i = 0$). The higher utilization ($\lambda_i = \lambda_{M_i}^{new}$ and $\rho_i = \rho_{M_i}^{new}$) implies increased operational strain, justifying a higher W_{LT_i} component in the price.
 - ii. $\rho_{M_i}^{new} > \rho_{MAX}$: Accommodating the request internally would violate the operational constraint. The

manufacturer operates internally at $\lambda_i = \lambda_{max} = \mu \rho_{MAX}$, and outsources the excess volume:

$$X_i = LT_{R_i}(\lambda_{M_i}^{new} - \lambda_{max}) \quad (8)$$

The final agreed lead time is $LT_i = LT_{R_i}$. The manufacturer incurs additional outsourcing costs $C_{pa}X_i$, which will be reflected in the wholesale price W_i . In this way, when internal feasibility would be violated, the model does not translate the mismatch into an uncontrolled stochastic delay; it converts it into an explicit sourcing decision with a priced trade-off between service and cost, while keeping the weekly committed LT_i feasible.

7. **No Counter-Proposal:** If $LT_{R_i} \geq LT_{M_i}$, the retailer accepts the manufacturer's initial proposal. Consequently, the final lead time is $LT_i = LT_{M_i}$, the manufacturer operates with its initially planned rate $\lambda_i = \lambda_{M_i}$ and utilization $\rho_i = \rho_{M_i}$ and no outsourcing is needed ($X_i = 0$).

Once the final values for LT_i , λ_i (either λ_{M_i} , $\lambda_{M_i}^{new}$ or λ_{max}), ρ_i , and X_i are determined, production (internal and outsourced, if necessary) begins.

3.4. Model formulation - analytical model

This section presents the profit functions and optimization problems for the manufacturer, the retailer, and the overall SC. Building upon the model of [Esmaeili and Zeephongsekul \(2010\)](#), this work develops a framework that incorporates a dynamic lead time negotiation mechanism, explicit capacity constraints, and bilateral operational information asymmetry to achieve a closer representation of real-world operational complexities.

3.4.1. Manufacturer's model

The manufacturer aims to maximize its weekly profit Π_{M_i} by choosing the optimal value of their decision variables, the wholesale price W_i and the production lot size Q_i . The manufacturer's profit is expressed by the following equation:

$$\Pi_{M_i}(Q_i, W_i) = W_i D_i - C_p(D_i - X_i) - C_{pa}X_i - E_s \frac{D_i}{Q_i} - \frac{1}{2}iC_p Q_i \rho_i \quad (9)$$

where the terms represent:

- $W_i D_i$: manufacturer's revenue;
- $C_p(D_i - X_i)$: internal production cost;
- $C_{pa}X_i$: outsourcing production cost;
- $E_s(D_i/Q_i)$: setup cost, assuming setup occurs for each batch Q_i needed to fulfill D_i ;
- $(1/2)iC_p \rho_i$: inventory holding cost, expressed as a fraction of the production cost C_p , based on average inventory $Q_i/2$ and utilization ρ_i for EPQ-like settings.

Assuming D_i is treated as given in the manufacturer's optimization stage, Π_{M_i} is concave in Q_i . Applying the first-order condition ($\partial \Pi_{M_i} / \partial Q_i = 0$) yields the optimal batch size:

$$Q_i^* = \sqrt{\frac{2E_s D_i}{iC_p \rho_i}} \quad (10)$$

The wholesale price W_i is composed of a break-even component W_{0_i} (potentially with a markup $k_w \geq 1$) and the lead time dependent component W_{LT_i} :

$$W_i^* = k_w W_{0_i} + W_{LT_i}(LT_i) \quad (11)$$

where W_{LT_i} is given by Eq. (3), and W_{0i} covers average costs per unit, representing the operational break-even price component:

$$W_{0i} = \frac{C_p(D_i - X_i) + C_{pa}X_i + E_s(D_i/Q_i^*) + (1/2)C_p\rho_i Q_i^*}{D_i} \quad (12)$$

The markup factor k_w on the break-even component W_{0i} reflects the manufacturer's baseline profitability target or pricing power, distinct from the lead time specific surcharge W_{LT_i} .

3.4.2. Retailer's model

The retailer maximizes its weekly profit Π_{R_i} by choosing the selling price P_i and the marketing expenditure E_{m_i} . D_i is endogenous here, as defined in Eq. (1).

$$\Pi_{R_i}(P_i, M_i) = P_i D_i - W_i D_i - M_i D_i - E_o \frac{D_i}{Q_i} - \frac{1}{2} i W_i Q_i \quad (13)$$

The retailer incurs an ordering cost E_o per batch received from Manufacturer (with D_i/Q_i number of batches in week i) and inventory cost for average inventory $Q_i/2$ valued at a fraction of the wholesale price W_i .

Given the demand function in Eq. (1), Π_{R_i} is optimized with respect to P_i and E_{m_i} . The first-order conditions ($\partial \Pi_{R_i} / \partial P_i = 0$ and $\partial \Pi_{R_i} / \partial M_i = 0$) yield the following expressions, which represent the retailer's optimal decisions:

$$E_{m_i}^* = \frac{\beta \left(W_i + \frac{E_o}{Q_i} \right)}{\alpha - \beta - 1} \quad (14)$$

$$P_i^* = \frac{\alpha \left(W_i + \frac{E_o}{Q_i} \right)}{\alpha - \beta - 1} \quad (15)$$

3.4.3. Decentralized model under unbalanced power

To analyze strategic interactions within decentralized SCs characterized by bilateral private information and asymmetric bargaining power, we employ a Stackelberg leader–follower framework. This setting captures sequential decision-making under power imbalances and remains tractable when operational states are privately observed. In each period, both parties maximize their expected individual profit: the leader optimizes based on estimates of the follower's private parameters and best-response behavior, whereas the follower optimizes after observing the leader's decision using its own private information. Our analysis examines two distinct leader–follower configurations to provide a comprehensive understanding of how power distribution impacts outcomes. In both Stackelberg scenarios, the leader's optimization problem embeds the follower's reaction function, derived from the follower's own profit maximization (as detailed in Sections 3.4.1 and 3.4.2 respectively).

- **Manufacturer-Stackelberg Game (M-SG):** In this scenario, the Manufacturer (M) acts as the leader, determining its optimal wholesale pricing strategy W_i (influencing the negotiated LT_i via the sequential negotiation process in Section 3.3) and its production lot size Q_i (derived from Eq. (11) and (10) respectively). This decision is made to maximize its expected profit Π_{M_i} (Eq. (9)), conditional upon its estimates of the retailer's private demand parameters ($\hat{\alpha}_i, \hat{\beta}_i$) and anticipated optimal response functions for price P_i and marketing E_{m_i} (Eqs. (15) and (14)). The M-SG optimization problem is thus:

$$\begin{aligned} \text{Max} \quad & \Pi_{M_i}(W_i, Q_i) = \\ & W_i \hat{D}_i - C_p(\hat{D}_i - X_i) - C_{pa}X_i - E_s \frac{\hat{D}_i}{Q_i} - \frac{1}{2} i C_p \rho_i Q_i \\ \text{subject to} \quad & \hat{P}_i^* = \frac{\hat{\alpha}_i(W_i + \frac{E_o}{Q_i})}{\hat{\alpha}_i - \hat{\beta}_i - 1} \\ & \hat{E}_{m_i}^* = \frac{\hat{\beta}_i(W_i + \frac{E_o}{Q_i})}{\hat{\alpha}_i - \hat{\beta}_i - 1} \end{aligned} \quad (16)$$

After M commits to its strategy, R observes W_i and Q_i , then determines its actual P_i, M_i using its true α_i, β_i .

- **Retailer-Stackelberg Game (R-SG):** Conversely, in this configuration, the retailer assumes the leadership role, determining its optimal selling price P_i and marketing expenditure E_{m_i} to maximize its expected profit Π_{R_i} (Eq. (13)). This decision is contingent upon the estimates of manufacturer's private parameters ($\hat{C}_{pi}, \hat{E}_{si}, \hat{Q}_{ext_i}$) and its behavior in the lead time negotiation process. The R-SG optimization problem is:

$$\begin{aligned} \text{Max} \quad & \Pi_{R_i}(P_i, E_{m_i}) = \\ & P_i D_i - \hat{W}_i D_i - E_{m_i} D_i - E_o \frac{D_i}{\hat{Q}_i} - \frac{1}{2} i \hat{W}_i \hat{Q}_i \\ \text{subject to} \quad & \hat{Q}_i^* = \sqrt{\frac{2 \hat{E}_{si} D_i}{i \hat{C}_{pi} \hat{\rho}_i}} \\ & \hat{W}_i^* = k_w \left[\hat{C}_{pi} + \frac{(C_{pa} - \hat{C}_{pi}) \hat{X}_i + \frac{1}{2} i \hat{C}_{pi} Q_i \hat{\rho}_i}{D_i} + \frac{\hat{E}_{si}}{Q_i} \right] + \frac{f}{\hat{L}_i + 1} \end{aligned} \quad (17)$$

After R commits to P_i, E_{m_i} , M observes D_i , negotiates LT_i based on its true parameters, and subsequently sets W_i, Q_i .

In both Stackelberg game formulations, the leader's optimization problem is non-linear, requiring numerical solution. The leader chooses two continuous strategic variables over bounded, economically motivated intervals (for M-SG, (W_i, Q_i) ; for R-SG, (P_i, E_{m_i})), while the follower's best response is available in closed form and is directly embedded in the leader's objective. Consistent with (Esmaeili et al., 2009) and related Stackelberg SC studies (Naimi Sadigh et al., 2012; Saberi et al., 2019), we solve the resulting two-dimensional problem through a uniform exhaustive grid search.

As the leader's problem must be solved repeatedly at each negotiation iteration and across all simulation scenarios, we rely on a transparent and reproducible procedure that ensures numerical robustness and computational tractability, thereby supporting consistent cross-scenario comparisons.

To ensure methodological rigor, the decision variable bounds and grid design, in terms of step size and density, were adapted from the validated approach in Esmaeili and Zeephongsekul (2010) and refined for the specific setting. Grid refinement checks on representative instances by halving the step in both dimensions produced no material changes in equilibrium decisions or aggregated profit levels, indicating that the adopted resolution is sufficiently fine to yield numerically stable outcomes and that the grid search provides a convergent approximation over the economically relevant decision space.

3.4.4. Centralized model with balanced power

Effective SC coordination aims to align individual actor incentives with overall system efficiency. To explore this, we formulate a centralized SC model where all operations are coordinated to maximize total system profit, Π_{SC_i} . This centralized perspective serves a dual purpose. Primarily, when considered under conditions of perfect information and complete cooperation, it establishes the theoretical first-best performance benchmark. This benchmark quantifies the maximum achievable system profit when all information are perfectly shared and all actions perfectly coordinated, and serves as a reference to measure the “price of anarchy” – the loss in efficiency due to decentralized, self-interested behavior. Secondly, the centralized framework provides a structure to analyze whether specific mechanisms can induce cooperative behavior and improve outcomes despite the presence of bilateral information asymmetry.

We hypothesize that the proposed dynamic lead time negotiation mechanism, when coupled with an adaptive revenue-sharing mechanism (detailed in Section 3.4.5), can foster such collaboration. By analyzing a “cooperative” scenario built upon centralized optimization

logic but operating under information asymmetry, we can assess if these mechanisms enable the dyad to reduce the negative impacts of decentralization and information friction, thereby moving system performance closer to the first-best benchmark.

The total SC profit function Π_{SCt} , representing the net value created by the dyad, is defined as the total revenue from end customers less all real system-wide costs (production, outsourcing, setup, ordering, and inventory holding valued at true production cost):

$$\Pi_{SCt}(P_t, E_{m_t}, Q_t, W_t) = (P_t - E_{m_t} - C_p)D_t - (C_{pa} - C_p)X_t + (E_s + E_o)\frac{D_t}{Q_t} - \frac{1}{2}iQ_t(W_{0t} + W_{LTt} + \rho C_p) \quad (18)$$

Here, $D_t(P_t, E_{m_t})$ is given by Eq. (1), and X_t is endogenously determined by the chosen D_t and the operational constraints that would necessitate outsourcing if an optimal (centrally determined) lead time cannot be met internally at $\rho \leq \rho_{MAX}$. In this system-level formulation, the wholesale price W_t , as an internal transfer payment, does not contribute directly to the net system profit. However, its structural components (W_{0t} and W_{LTt}) remain intrinsically relevant for valuing retailer inventory. Specifically, retailer inventory is accounted for at the manufacturer's average break-even cost plus the lead time service cost component, reflecting a true system cost without internal profit margins:

$$W_t^* = W_{0t} + W_{LTt} = \frac{C_p(D_t - X_t) + C_{pa}X_t}{D_t} + \frac{(E_s + E_o)}{Q_t} + \frac{f}{LT_t + 1} \quad (19)$$

The centralized decision problem is to find $(P_t^*, E_{m_t}^*, Q_t^*)$ that maximize Π_{SCt} subject to operational feasibility. Assuming appropriate concavity conditions, the first-order conditions with respect to P_t , E_{m_t} , and Q_t yield the system-optimal decision variables:

$$Q_t^* = \sqrt{\frac{2(E_o + E_s)D_t}{i(W_t + \rho C_p)}} \quad (20)$$

$$P_t^* = \frac{\alpha(C_p + ((E_o + E_s)/Q_t))}{\alpha - \beta - 1} \quad (21)$$

$$E_{m_t}^* = \frac{\beta(C_p + ((E_o + E_s)/Q_t))}{\alpha - \beta - 1} \quad (22)$$

These equations, representing the first-best operational and marketing decisions, highlight how a centralized planner balances marginal revenues with true marginal system costs. This benchmark serves to quantify the 'price of anarchy' and the 'value of information' when compared against the decentralized scenarios.

3.4.5. Adaptive revenue-sharing mechanism for profit allocation

In the context of the centralized SC benchmark, the maximum total profit Π_{SCt} (Eq. (18)) must be allocated between the manufacturer and the retailer. To ensure that such allocation reflects the dynamics of operational decisions regarding lead time (which, even in a cooperative setting, involve evaluating trade-offs of effort and cost for different lead times), we propose an adaptive revenue-sharing mechanism. Let ϕ_t denote the retailer's share of the total SC profit, the allocated profits for the retailer and the manufacturer at time t are defined as:

$$\Pi_{Rt}^{\text{shared}} = \phi_t \Pi_{SCt} \quad ; \quad \Pi_{Mt}^{\text{shared}} = (1 - \phi_t) \Pi_{SCt} \quad (23)$$

The core of our adaptive mechanism lies in making ϕ_t responsive to the negotiated lead time price component, $W_{LTt}(LT_t)$, relative to its expected value. We define the retailer's share as:

$$\phi_t = \frac{\frac{1}{W_{LTt-1}^{\text{mean}}} W_{LTt}}{1 + \frac{1}{W_{LTt-1}^{\text{mean}}} W_{LTt}} \quad (24)$$

where W_{LTt-1}^{mean} is the historical mean of the lead time price component observed up to the previous period $t - 1$. This mean is updated dynamically, using an exponentially weighted moving average (EWMA):

$$W_{LTt}^{\text{mean}} = \gamma W_{LTt} + (1 - \gamma) W_{LTt-1}^{\text{mean}}, \quad \text{with } W_{LT0}^{\text{mean}} \text{ initialized.} \quad (25)$$

Here, $0 < \gamma \leq 1$ serves as the smoothing factor, determining the weight given to the most recent negotiation outcome (W_{LTt}) compared to the historical average from previous periods. The historical mean W_{LTt}^{mean} is initialized by setting W_{LT0}^{mean} to an initial estimate (i.e. $W_{LT0} = 0$). The EWMA formula (Eq. (25)) is then applied iteratively for all $t \geq 1$. The logic underpinning Eq. (24) is to create a balancing effect. If the current negotiated W_{LTt} is significantly higher than its historical average (i.e., $W_{LTt}/W_{LTt-1}^{\text{mean}} > 1$), indicating that the manufacturer has secured a substantial premium for a (presumably) shorter or more difficult lead time, the retailer's share ϕ_t of the total SC profit increases (becomes more than 0.5). This mechanism is designed with the intent to:

- Promote Perceived Fairness:** By adjusting profit shares such that a lead time price component significantly above its historical average leads to an increased share of the total SC profit for the retailer (and vice-versa), the mechanism aims to prevent one party from feeling unduly penalized by the outcome alone. This discourages the perception that one party consistently captures disproportionate gains from the lead time pricing, as the overall profit allocation provides a balancing compensation.
- Stabilize Long-Term Profit Distribution:** It tends to drive the profit split toward a 50-50 baseline when lead time price premiums are consistent with historical observations, potentially fostering a more stable and predictable cooperative environment.
- Discourage Extreme Opportunism:** Over time, if consistently high (or low) W_{LTt} values lead to unbalanced profit shares, parties might be incentivized to moderate their negotiation stances on the lead time price component to achieve a more balanced overall outcome.

The effectiveness of this adaptive revenue-sharing scheme in achieving these behavioral objectives and influencing overall SC performance, particularly in mitigating information asymmetry effects, is a key aspect evaluated through our simulation experiments.

4. Experimental methodology

To rigorously evaluate the impact of the proposed dynamic coordination mechanism on SC performance under varying structural and informational conditions, computational experiments were conducted using simulation implemented in Python.

A set of experimental scenarios was designed to systematically isolate and evaluate the effects of three key dimensions: (i) decision-making structure, (ii) information sharing levels, and (iii) the employed coordination mechanisms. Combining these dimensions constructs four distinct scenarios, summarized in Table 4.

The first dimension, denoted as SC configuration, captures the decision-making structure and the associated bargaining-power allocation, distinguishing between Decentralized and Centralized configurations. In Decentralized settings (Scenario 1 and 2), the manufacturer and retailer operate as independent profit-maximizing entities under unbalanced bargaining power. Their interaction is modeled through the Stackelberg formulation in Section 3.4.3, considering both leadership configurations (Manufacturer-leader: Scenarios 1.M and 2.M; Retailer-leader: Scenarios 1.R and 2.R). Conversely, Centralized settings (Scenarios 3 and 4) represent a cooperative configuration with balanced bargaining power, where decisions are coordinated through the negotiation process and the centralized model in Section 3.4.4 to maximize total SC profit, which is subsequently allocated through the adaptive revenue-sharing scheme.

The second dimension addresses the level of Information Sharing between parties, which critically influences strategic behavior and outcomes. Under information asymmetry, each SC actor possesses private data crucial to its operations or market assessment (Scenarios 1, 2 and

Table 4
Summary of the simulation scenarios.

Scenario	SC configuration		Information sharing		Coordination mechanism	
	Decentralized	Centralized	Asymmetry	Symmetry	LT Negotiation Mech.	RS Allocation
Scenario 1 ^a	✓		✓			
Scenario 2 ^a	✓		✓		✓	
Scenario 3		✓	✓		✓	✓
Scenario 4		✓		✓	✓	✓

^a Note: Decentralized scenarios are each examined under two Stackelberg leadership configurations: Manufacturer-leader (denoted as 1.M and 2.M) and Retailer-leader (denoted as 1.R and 2.R), to comprehensively assess the impact of power distribution.

3). In such cases, the uninformed party must make decisions based on its probabilistic assessment of the other's private parameters, derived from their known underlying distributions. In contrast, symmetric information describes an idealized state of perfect transparency where all relevant operational and market parameters are common knowledge to both SC members (Scenario 4).

The last dimension, regarding the employed coordination mechanisms, specifies the interaction process governing operational decisions and profit distribution. This involves evaluating scenarios with and without the activation of the proposed Lead Time Negotiation Mechanism to assess its impact on operational dynamics and actor interactions. Additionally, the adaptive rule for Revenue Sharing is applied in centralized settings to distribute the maximized total SC profit.

Specifically, in scenarios where the Lead Time Negotiation Mechanism is absent (Scenario 1 - Decentralized without mechanism), we model the interaction as a dictatorial process where the leader imposes its desired lead time. Following the steps outlined in Section 3.3, when the Manufacturer is the leader (Scenario 1.M), the lead time is always determined according to the Manufacturer's operational needs, aligning with Case 2 described in Step 5 of the sequential negotiation process. Conversely, when the Retailer is the leader (Scenario 1.R), the negotiation process invariably follows Case 1 of Step 5, as the Retailer effectively dictates its required lead time (LT_{R_i}). In contrast, in Scenarios 2–4, the full negotiation process (Section 3.3) is activated, so that LT_i is endogenously determined through potential counter-proposals and state-contingent adjustments driven by both parties' decision logic.

The proposed experimental scenarios incorporate stochastic elements, particularly in the sampling of private parameters under information asymmetry and the retailer's urgency requirements (LT_{R_i}). Consequently, simulation outputs, such as profits and operational metrics, are realizations of stochastic processes. To ensure that our conclusions reflect the long-run behavior of the system rather than transient effects or random noise, we first validated the statistical stability of the simulation.

For this purpose, we employed the method of cumulative mean analysis, a standard and robust technique for verifying convergence to a steady-state in long-run simulations. The cumulative average of a sequence of observations from a process will converge to the process's true expected value as the number of observations increases. In our study, we tracked the cumulative average of the primary performance indicators, namely, the Manufacturer's, Retailer's, and SC's profits, over the entire simulation horizon.

The resulting plots illustrating this convergence process are presented in Fig. 2. For each scenario, the curves exhibit high initial volatility, which is characteristic of a system in its transient phase. As the simulation progresses and more weekly data points are accumulated, this variance progressively dampens, and each curve converges to a stable, horizontal asymptote. This visual evidence of convergence confirms that the chosen simulation horizon of 520 weeks is sufficiently long to allow the system to reach a statistical equilibrium. The stable asymptote represents a reliable estimate of the long-run expected value for that performance metric under the specific conditions of that scenario. In addition, it provides the statistical foundation for a valid comparison between scenarios. While the parameters are sampled

from distributions, the convergence of the mean indicates that we have effectively accounted for this variability over the long run.

Therefore, the persistent differences observed in the converged values between, for instance, Scenario 1.M and Scenario 2.R, are not artifacts of stochastic noise. Instead, they represent significant structural differences in performance driven by the underlying variations in information structure, decision-making hierarchy, and coordination mechanisms. In summary, the cumulative mean analysis validates our experimental methodology, ensuring that the reported results are robust and that the ensuing discussion is based on a reliable characterization of the system's steady-state behavior.

The weekly decision period adopted in the simulation should therefore be interpreted as a generic planning cycle (e.g., weekly replenishment, order review, or campaign window), so that the long-run patterns we report are representative of multi-year behavior across settings with different calendar frequencies but comparable decision rhythms.

The simulation experiments utilize a set of fixed and dynamically changing parameters. Common System Parameters, assumed to be constant and common knowledge across all scenarios and listed in Table 5, have their specific values primarily adapted from Esmaeili and Zeephongsekul (2010) for relevant parameters (k_d, i, E_o, L, k_{it}), ensuring grounding and comparability. These are complemented by the selection of other operational parameters ($\mu, N, f, C_{pa}, \rho_{MAX}, \gamma$) designed to realistically characterize a stylized manufacturing environment with moderate capacity constraints, plausible cost structures, and variable demand conditions, thereby creating a suitable testbed for exploring lead time negotiation dynamics. The robustness of the simulation results to the specific values of these operational parameters was rigorously tested through sensitivity analysis.

In particular, the manufacturer is assumed to impose a utilization threshold at $\rho_{MAX} = 0.85$. This specific choice reflects common industry practice, where recommended saturation levels typically range between 70%–90% (Corrado and Mattey, 1997), ensuring an effective balance between maximizing efficiency and maintaining a suitable safety buffer to mitigate risks such as operational overloads and performance deterioration. The outsourcing production cost, C_{pa} , is set to be approximately 30% higher than the manufacturer's internal production cost, C_p . Finally, the retailer's requested lead time LT_{R_i} is sampled each week to reflect varying urgency, and once realized it becomes a known input for both parties for that week's decisions, reflecting fluctuations in market demands and required delivery speeds.

For scenarios with asymmetric information (Scenarios 1–3), in each week t each actor makes decisions using the true values of its own private parameters and sampled estimates of the counterpart's private parameters (Table 6). Accordingly, each actor perfectly observes only its own private information, while the counterpart's internal conditions remain unobserved. The uninformed party therefore maintains a subjective probabilistic belief over the other's parameters and draws a noisy point estimate at the start of each period for use in that week's optimization. In behavioral terms, the model does not assume fully shared information but embeds distorted perceptions, so that observable operational and pricing choices (e.g., prices, marketing effort, requested/agreed lead times, surcharges, and quantities) are shaped by these beliefs rather than by exact knowledge of the other party's parameters.

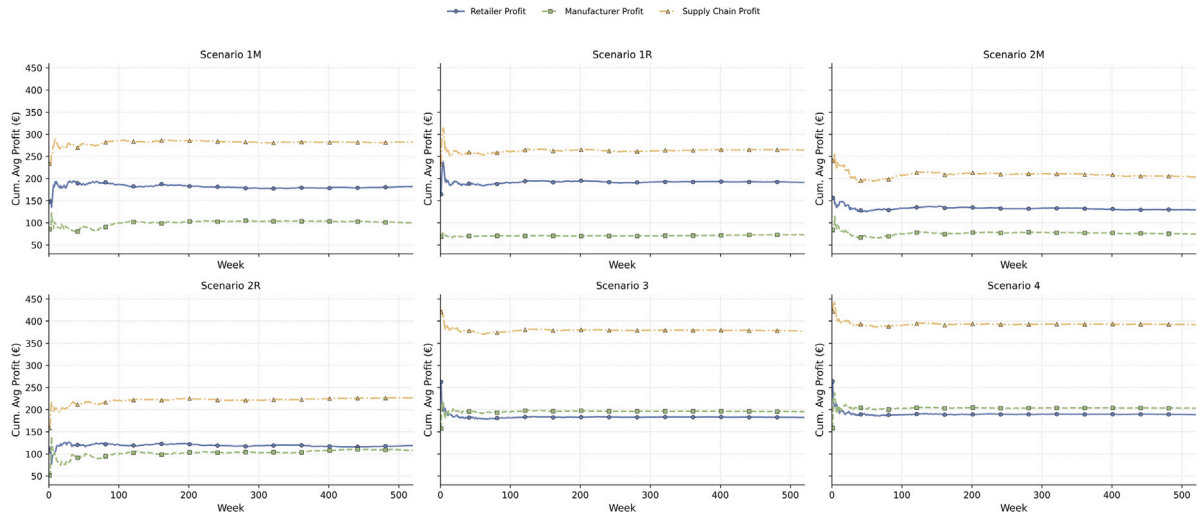


Fig. 2. Evolution of the cumulative average weekly profit obtained by the Retailer (blue, circle markers), the Manufacturer (green, square markers) and the overall SC (yellow, triangle markers) in the simulation scenarios.

Table 5

Simulation parameter values: Common system parameters.

Common system parameters		
Parameter	Value	Unit
k_d	3500	/
E_o	40	€/order
i	0.10	%/unit/week
L	0.09	/
N	5	days/week
f	10	€/unit (for W_{LTi})
μ	80	units/day
ρ_{MAX}	0.85	/
k_w	1.1	/
C_{pa}	2	€/unit
γ	0.5	/
$LT_{R,i}^a$	$U_d\{1, \dots, 7\}$	days

^a $LT_{R,i}$ is a stochastic input, sampled each week t from the specified discrete uniform distribution. Once sampled for a given week, its value becomes common knowledge to both actors for that week's operational decisions.

Specifically, beliefs are represented by uniform distributions over finite intervals with mean equal to the true parameter value and standard deviations reported in Table 6, following Esmacili and Zeepongsekul (2010). A new estimate is sampled each week t from the corresponding distribution and used in the actor's decision problem, capturing the impact of noisy perceptions of the opponent's operational and economic conditions.

In this way, the model preserves the realistic separation between internal, firm-specific data and the limited, noisy perceptions that trading partners typically hold about each other's operational and market conditions, avoiding any assumption of full transparency or bilateral sharing of sensitive information.

5. Results and discussion

This section presents a detailed analysis of the simulation results, evaluating the performance of the proposed dynamic lead time coordination mechanism under different scenarios. All reported metrics represent average values calculated over the steady-state horizon, based on data collected from the Python simulation runs as described in Section 4. This approach ensures that the results reflect the long-term equilibrium behavior of the system.

Figs. 3–7 visually summarize the key performance indicators and interaction dynamics across the simulated scenarios and provide the

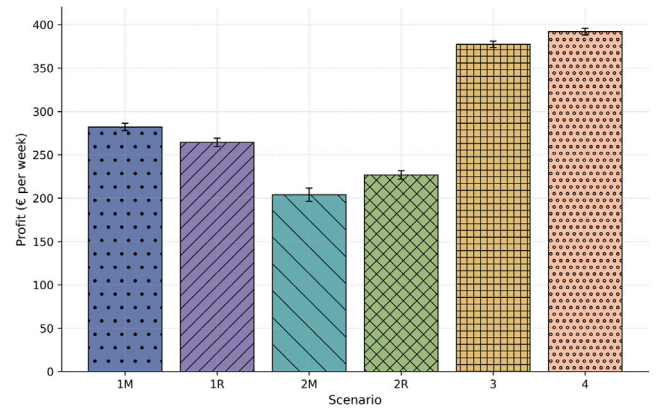


Fig. 3. Average total SC profit per week across different scenarios, calculated over the steady-state horizon. Bars are distinguished by scenario-specific colors and hatch patterns. Error bars indicate 95% confidence intervals, reflecting the statistical variability across simulation replications. Higher bars indicate better system-wide economic performance.

basis for the analysis presented below. Across the result figures, the scenarios are shown with the same colors, hatch patterns, markers, and line styles to facilitate cross-scenario comparison and interpretation. In Figs. 3–5, 95% confidence intervals are shown for aggregate mean values, indicating the statistical reliability of these estimates.

5.1. Decentralized negotiation: Operational speed at an economic cost (scenario 2 vs. Scenario 1)

We first examine the impact of introducing the dynamic lead time negotiation mechanism (Scenario 2) within a decentralized dyadic SC, comparing it to the baseline decentralized scenarios where operational lead time is primarily a function of initial capacity assessment without explicit bargaining (Scenario 1).

Fig. 4 clearly demonstrates the primary operational effect of the negotiation mechanism in a decentralized setting: a substantial reduction in the average delivery lead time. Compared to the baseline scenarios (1.M and 1.R, both averaging around 3.45 days), the average negotiated lead time drops significantly to 2.00 days in 2.M and 2.15 days in 2.R. This represents a reduction of approximately 38%–42% in average lead time.

Table 6
Simulation parameter values: dynamic private parameters.

Dynamic private parameters			
Parameter	Owner	True Value	Uninformed Party's Estimation at week t
β	R	0.15	M samples $\hat{\beta}_t \sim U[L_\beta, U_\beta]$, determined by mean value $\mu_\beta = \beta$ (true value) and standard deviation $\sigma_\beta = 0.001$
α	R	$\beta/L \approx 1.667$	M calculates $\hat{\alpha}_t = \hat{\beta}_t/L$, with M's sampled $\hat{\beta}_t$ and known L .
C_p	M	1.5 [€/unit]	R samples $\hat{C}_{p,t} \sim U[L_{C_p}, U_{C_p}]$, determined by mean value $\mu_{C_p} = C_p$ (true value) and standard deviation $\sigma_{C_p} = 0.001$
E_s	M	140 [€/setup]	R samples $\hat{E}_{s,t} \sim U[L_{E_s}, U_{E_s}]$, determined by mean value $\mu_{E_s} = E_s$ (true value) and standard deviation $\sigma_{E_s} = 0.5$
D_{ext}	M	$\sim U_d[100, 500]$	R samples $\hat{D}_{ext,t} \sim U_d[100, 500]$.

Note: For each parameter, the uninformed party samples an estimate $\hat{y}_t$ each week t from the specified uniform distribution $U[L_y, U_y]$, where $L_y = \mu_y - \sigma_y\sqrt{3}$ and $U_y = \mu_y + \sigma_y\sqrt{3}$.

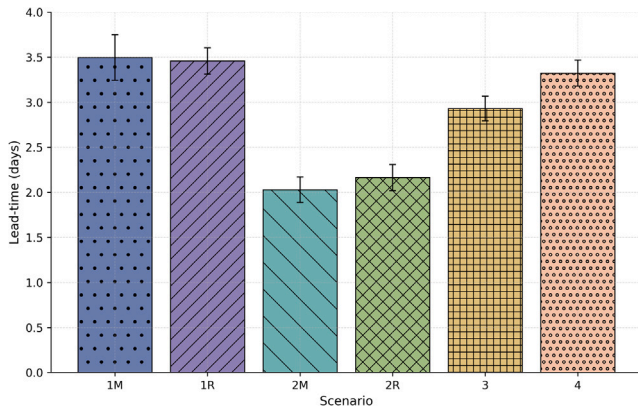


Fig. 4. Average agreed delivery lead time in days across different scenarios, calculated over the steady-state horizon. Bars are distinguished by scenario-specific colors and hatch patterns. Error bars indicate 95% confidence intervals. Lower bars indicate faster average delivery speed negotiated or determined in each scenario.

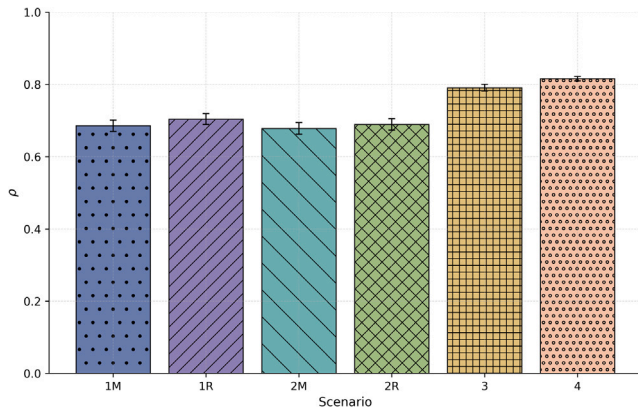


Fig. 5. Average Manufacturer's capacity utilization (ρ) across different scenarios, calculated over the steady-state horizon. Bars are distinguished by scenario-specific colors and hatch patterns. Error bars indicate 95% confidence intervals. Values approaching the ρ_{MAX} threshold (0.85) indicate higher operational strain.

Fig. 7 provides further insight, showing that the negotiation mechanism compresses the lead time distribution, effectively eliminating the long tail of excessive promised lead times observed in the baseline decentralized settings. This highlights the mechanism's effectiveness in enabling faster and more predictable delivery outcomes by allowing parties to react dynamically to urgent needs and operational status.

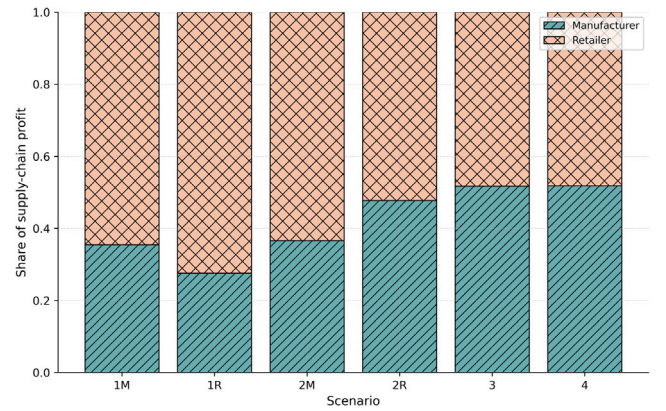


Fig. 6. Distribution of the total steady-state SC profit between the Manufacturer and the Retailer across different scenarios. The height of each stacked bar represents the total average profit for that scenario (corresponding to Fig. 3), while the stacked segments, distinguished by colors and hatch patterns, represent the proportion allocated to each party.

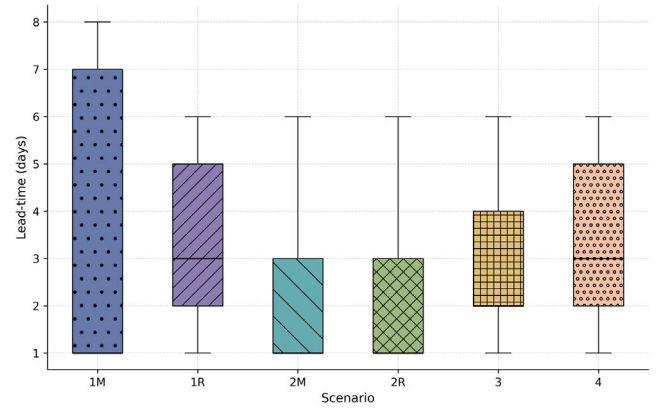


Fig. 7. Box plot showing the distribution of weekly negotiated/determined lead times in days across different scenarios over the steady-state horizon (weeks 101–520). Boxes are distinguished by the same scenario-specific colors and hatch patterns used in the bar charts. The box represents the interquartile range (25th to 75th percentile), the line within the box is the median, and the whiskers extend to show the range (excluding outliers, if any).

However, achieving this speed improvement comes at a significant economic cost in a purely decentralized setting without explicit incentive alignment, as evidenced by Fig. 3. The total SC profit decreases in both decentralized negotiation scenarios compared to their respective baselines without explicit negotiation. Specifically, total SC profit in Scenario 2.M represents a significant 27.7% decrease compared to

Scenario 1.M. In the Retailer-leader setting (Scenario 2.R), total SC profit shows a 14.0% reduction compared to its baseline (Scenario 1.R). This decrease is primarily due to the increased operational costs incurred to meet tighter lead times, such as higher utilization strain or the need for more frequent and costly outsourcing to the auxiliary facility (as permitted by the model logic when meeting tighter lead times below the ρ_{MAX} threshold, visible in Fig. 5 remaining below 0.85).

Moreover, analyzing the profit distribution (Fig. 6) reveals a critical insight: in these purely decentralized negotiation scenarios, the outcome for the dominant actor is mixed, and can involve a decrease in their own absolute profit compared to their baseline scenarios without explicit negotiation. In the Manufacturer-leader setting (comparing 1.M vs 2.M), the Manufacturer's profit is only slightly higher despite the negotiation. More notably, in the Retailer-leader setting (comparing 1.R vs 2.R), the Retailer's profit is significantly lower, representing a decrease of approximately 34.5% compared to their baseline. This outcome underscores a key challenge: simple decentralized negotiation for operational speed under asymmetry can lead to a "race to the bottom" in terms of profitability.

While the demanding party (Retailer in 2.R) successfully negotiates for faster delivery, the operational costs incurred by the supplier (Manufacturer) are not fully compensated through the lead time price component (W_{LT_i}), resulting in a smaller total profit pie (Fig. 3). Although the Manufacturer's share of this smaller pie increases significantly in 2.R (from 28% in 1.R to 45%), the total value is reduced. This highlights the risk that in the absence of coordinated incentive alignment, achieving operational flexibility through negotiation alone can be detrimental to overall value and can even harm the dominant party's profitability when they are forced to absorb additional costs without adequate compensation.

5.2. Enhanced coordination with adaptive revenue sharing: Unlocking value and equity (Scenario 3)

Building upon the insights from the purely decentralized negotiation, we now analyze the performance when the dynamic lead time negotiation is combined with the proposed adaptive revenue-sharing under bilateral information asymmetry (Scenario 3). This configuration represents a cooperative structure facilitated by the negotiation mechanism and supported by a profit allocation scheme explicitly designed to incentivize system-wide efficiency.

Scenario 3 demonstrates a significant improvement in total SC profitability and value creation (Fig. 3). The average total profit is substantially higher than in both decentralized negotiation scenarios (2.M, 2.R) and, importantly, significantly exceeds the profits achieved in the baseline decentralized scenarios without negotiation (1.M, 1.R). This represents an increase of 86.0% compared to Scenario 2.M and a notable 34.5% increase even compared to the best-performing decentralized baseline, Scenario 1.M. This result highlights the effectiveness of the combined mechanism in fostering cooperation, driving value creation, and recovering a large portion of the efficiency losses typically observed in decentralized settings with informational friction.

The adaptive revenue-sharing rule plays a crucial role not just in increasing the total pie, but also in distributing this increased value equitably (Fig. 6). Fig. 6 shows that in Scenario 3, the profit split converges to a near-equal distribution, with the Manufacturer receiving approximately 52% and the Retailer 48% of the total SC profit. This outcome is consistent with the design of the adaptive revenue sharing mechanism (Section 3.4.5), which dynamically adjusts the allocation based on the negotiated lead time premium (W_{LT_i}) relative to its historical average, aiming to provide compensatory allocation to the party bearing the cost/strain of speed and thus encouraging a more balanced distribution of gains over time. This fair distribution is crucial for fostering sustained cooperation under conditions of bilateral asymmetry and balanced power.

Analyzing individual profits in Scenario 3 reinforces this: the Manufacturer's profit is approximately double (+99.9%) its profit in the 1.M baseline. The Retailer's profit is slightly below its profit in the 1.R baseline (a 5.0% decrease), but significantly higher than in the decentralized negotiation-only scenarios (e.g., Retailer profit in 2.R was significantly lower than in 1.R, as shown in the previous section).

This demonstrates that the combined mechanism prioritizes system-wide efficiency and equitable distribution rather than strictly guaranteeing that both parties exceed their absolute best decentralized historical performance. Nevertheless, it achieves a state where the significantly larger total pie is allocated in a way that provides substantial gains for the Manufacturer and a profit level for the Retailer that is competitive with their baseline and far superior to outcomes under negotiation without incentive alignment. Operationally, Scenario 3 successfully maintains the benefits of faster lead times (average 2.00 days, Fig. 4) while effectively managing capacity (average utilization 0.79, Fig. 5, still below ρ_{MAX}).

5.3. Quantifying the residual value of perfect information (Scenario 4 vs. Scenario 3)

To quantify the performance gap solely attributable to the remaining effects of information asymmetry when our mechanism is in place, we compare Scenario 3 (asymmetric information with negotiation+RS) to the idealized centralized scenario with perfect and symmetric information (Scenario 4). Scenario 4 represents the theoretical first-best benchmark for system-wide optimality.

Comparing Scenario 3 and 4 (Fig. 3), the total SC profit in the centralized, symmetric information setting is only marginally higher than that achieved in Scenario 3. The difference is a mere 4.0%. This finding is highly significant, as it indicates that the proposed dynamic negotiation and adaptive revenue-sharing mechanisms are remarkably effective in mitigating the negative performance impact of bilateral operational information asymmetry. They enable the decentralized dyad to capture approximately 96% of the potential value achievable under perfect information and full centralization, demonstrating that information asymmetry is largely de-bottlenecked by this framework.

Interestingly, the centralized scenario (Scenario 4) results in a slightly longer average lead time (2.40 days) compared to Scenario 3 (2.00 days, Fig. 4). This reflects the optimal trade-off made by a fully informed central planner who balances the marginal cost of achieving very fast delivery against the marginal revenue, choosing a slightly less aggressive speed target compared to the outcomes driven partly by the Retailer's negotiation strategy in Scenario 3. The profit allocation in Scenario 4 (Fig. 6) remains strikingly similar to Scenario 3 (52% M, 48% R), further suggesting that the adaptive RS mechanism in Scenario 3 successfully emulates a fair system-optimal allocation even in the presence of significant information friction.

These results strongly support the conclusion that the combination of dynamic lead time negotiation, grounded in operational feasibility, and an adaptive financial mechanism effectively mitigates the performance losses typically associated with bilateral operational information asymmetry. The dyad achieves outcomes very close to the first-best benchmark, both in terms of total value creation and in terms of how this value is shared.

5.4. Sensitivity analysis

To further assess the robustness of the proposed coordination mechanism and its responsiveness to changes in key operational assumptions, we conducted a comprehensive sensitivity analysis. Specifically, we individually varied four core system parameters, the lead time price sensitivity f , the daily production rate μ , the maximum utilization rate ρ_{MAX} and the smoothing factor γ , by $\pm 25\%$ and $\pm 50\%$ around their baseline values, while keeping all other conditions fixed. For each

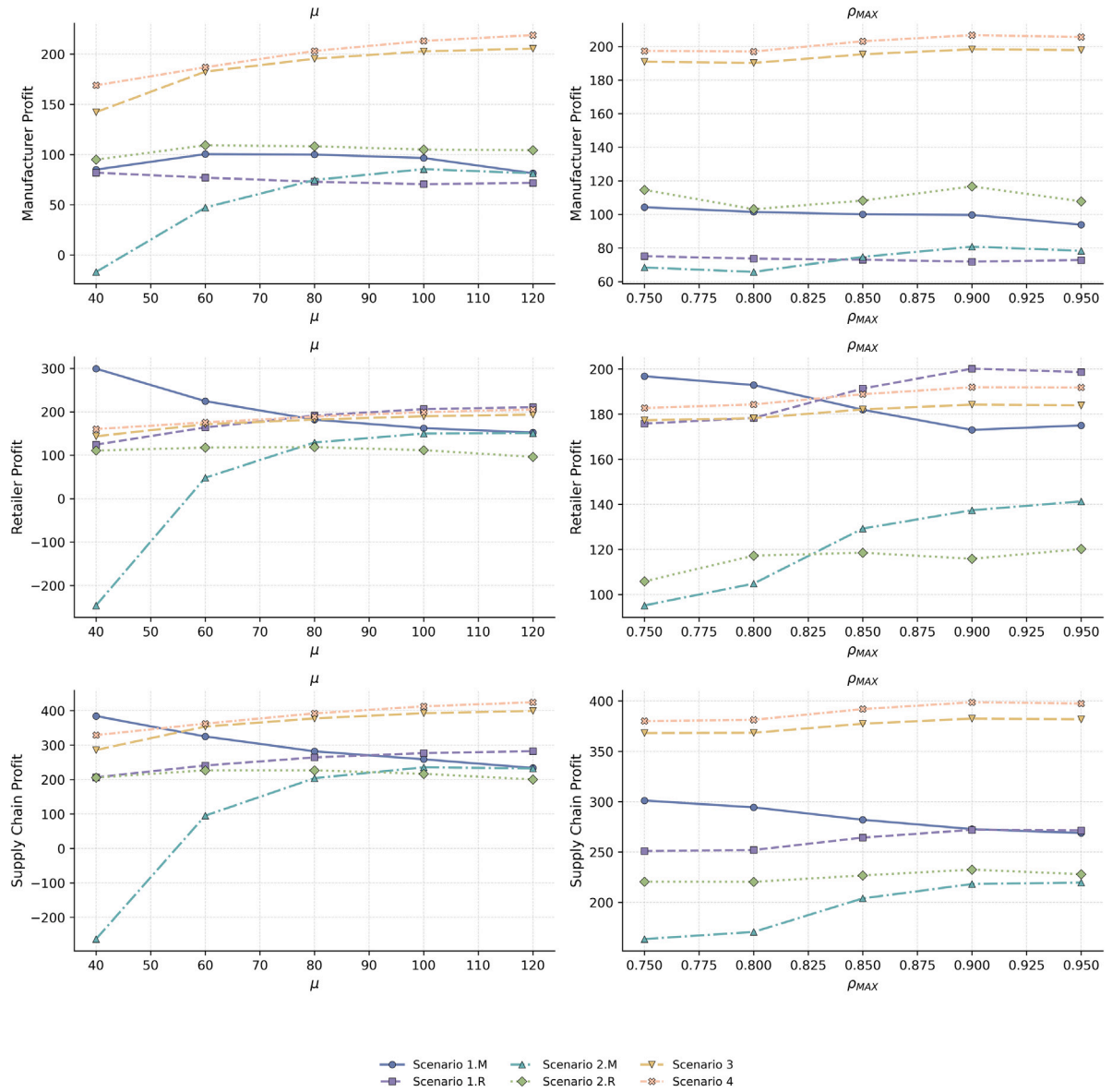


Fig. 8. Sensitivity analysis of Manufacturer, Retailer and SC profits as functions of μ and ρ_{MAX} in all simulation scenarios. Scenarios are distinguished by consistent colors, line styles and markers across all panels.

parameter configuration, the system was simulated over the full 520-week horizon across all scenarios described in Table 4, and we recorded the resulting average profits for the Manufacturer, the Retailer and the overall SC.

The production rate μ and the maximum utilization threshold ρ_{MAX} , in Fig. 8, both play a critical role in determining the manufacturer's operational flexibility and, consequently, the overall SC profitability, yet their benefits depend strongly on the governance structure. An increase in μ significantly enhances system performance, particularly in decentralized negotiation settings (Scenarios 2.M and 2.R), where limited internal capacity often forces reliance on the auxiliary production facility, incurring outsourcing penalties. Similarly, relaxing the constraint on ρ_{MAX} by allowing higher utilization rates, improves profitability by enabling more efficient use of existing capacity and reducing the frequency of external production.

Conversely, cooperative scenarios (3 and 4) exhibit more stable profits across the same variations in μ and ρ_{MAX} with diminishing returns. This suggests a saturation point beyond which other limiting factors, such as demand variability or marketing effectiveness, limit further gains. These findings underline the critical importance

of capacity-related decisions in uncoordinated SCs. Stricter internal capacity policies and low utilization thresholds can severely undermine performance unless offset by effective coordination mechanisms. In contrast, well-designed collaborative strategies enable SCs to operate near their optimal capacity levels, even under more conservative assumptions, ultimately supporting more stable and efficient operations.

The parameter γ , which sets the responsiveness of the revenue-sharing mechanism to recent negotiation outcomes, plays a crucial role in stabilizing cooperation. As shown in Table 7, in Scenario 3, an increase in γ leads to a rise of less than 6% in total SC profit, which tends to stabilize for values of γ greater than 0.5. Scenario 4, instead, is largely insensitive to variations in γ . These results underscore the specific purpose of the adaptive mechanism: to govern collaboration under uncertainty, not to create value in an ideal setting.

A higher γ value makes the profit split more sensitive to immediate negotiation dynamics, enabling a faster and more effective alignment of incentives. This timely financial feedback appears to discourage opportunistic behavior and promote decisions that maximize joint value, effectively managing the challenges of information asymmetry. The

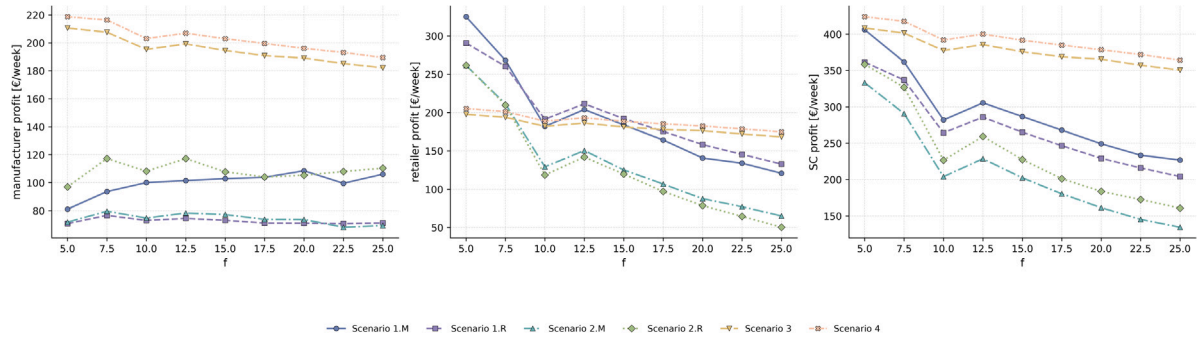


Fig. 9. Sensitivity analysis of Manufacturer, Retailer and SC profits as functions of f in all simulation scenarios. Scenarios are distinguished by consistent colors, line styles and markers across all panels.

Table 7

Profit sensitivity to γ under cooperative scenarios.

γ	Scenario 3			Scenario 4		
	M	R	SC	M	R	SC
0.10	189.73	176.94	366.67	196.31	195.74	392.04
0.30	191.26	176.25	377.51	196.87	196.31	393.18
0.50	193.10	176.02	379.12	195.35	195.30	390.65
0.70	195.72	176.39	387.03	195.31	195.84	391.15
0.90	195.20	175.08	387.10	194.90	195.46	390.36

stability of the results for $\gamma \geq 0.5$ suggests that a moderately high value (0.5–0.7) can be adopted as a robust default, ensuring a balance between responsiveness and stability without requiring complex calibration studies.

5.4.1. Sensitivity analysis of f

The sensitivity analysis for the lead time price parameter, f , provides critical insights into the SC's stability and profitability across the different scenarios. This parameter functions as the key tool for translating enhanced service speed into a price premium, and altering its value exposes a critical difference in the strategic responses observed within each scenario.

In decentralized settings (Scenarios 1.M, 1.R, 2.M, 2.R), a rising f consistently erodes overall SC profitability. This system-level value destruction, however, masks more complex and non-monotonic trends at the actor level. As shown in Fig. 9, the manufacturer's profit (when leader) initially benefits from a higher f , but peaks and then declines sharply past a critical threshold. Conversely, the retailer's profit is severely impacted, though it exhibits a brief, counter-intuitive increase near the same inflection point.

In contrast, cooperative Scenarios 3 and 4 demonstrate remarkable resilience. Their centralized optimization logic, combined with the adaptive revenue-sharing mechanism, effectively absorb the pricing pressure from a higher f , maintaining high system-wide profitability and preventing the destructive dynamics observed in the decentralized settings. This highlights that while negotiation alone is insufficient, coordinated frameworks can successfully manage pricing tensions.

5.4.2. Analysis of the strategic inflection point at $f \approx 12.5$

A critical finding from the sensitivity analysis is the non-monotonic profit behavior observed in decentralized scenarios, which empirically hinges on $f \approx 12.5$. This phenomenon is not a system optimum but a strategic threshold driven by the tension between the manufacturer's pricing and the retailer's discrete cost structure.

The retailer's decision-making is fundamentally shaped by the fixed ordering cost, E_o , included in its profit function (Eq. (13)). This structure means the retailer's core choice is not a marginal quantity adjustment, but selecting the optimal number of batches, n , to order. We define $\Delta\Pi_R^*(f)$ as the maximum incremental profit, excluding fixed

ordering costs, that the retailer can achieve by moving from an $(n-1)$ -batch strategy to an n -batch strategy. The retailer will order the n th batch only if the incremental profit gained from the sales generated by that batch exceeds the fixed cost for ordering it:

$$\Delta\Pi_R^*(f) > E_o \quad (26)$$

Since the wholesale price W_t is an increasing function of f , $\Delta\Pi_R^*(f)$ is a decreasing function of f : as f rises, the profitability of the final, marginal batch diminishes. This creates a tipping point: a threshold value, f^* , exists where the retailer is exactly indifferent between n and $n-1$ batches:

$$\Delta\Pi_R^*(f^*) = E_o \quad (27)$$

For any $f > f^*$, the retailer's optimal strategy shifts from a marginal adjustment to a discrete and substantial order cut, forgoing the entire final batch. This strategic shift explains the complex profit dynamics observed in the decentralized scenarios.

The manufacturer's behavior, particularly as the Stackelberg leader (Scenarios 1.M, 2.M), is a direct consequence of this threshold. Its profit rises with f only as long as $f < f^*$, because the retailer continues to absorb the price increase. The empirically observed peak at $f \approx 12.5$, a threshold specific to the chosen simulation parameters, thus represents the maximum pressure the manufacturer can exert before triggering the retailer's defensive order reduction. Once this threshold is crossed, the resulting sharp contraction in demand leads to a steep decline in the manufacturer's profit. The peak, therefore, represents the precipice of the partner's economic tolerance, starkly illustrating the risk of a myopic pricing strategy that fails to account for the follower's operational and financial constraints.

5.4.3. The role of outsourcing and sensitivity to the external capacity cost

In the proposed framework, outsourcing represents a flexible but typically more expensive backup capacity, activated whenever meeting the requested lead time would require operating above the utilization threshold ρ_{MAX} . Its role is evaluated along two dimensions: (i) a cross-scenario comparison of the average outsourced quantity at the baseline cost level, and (ii) a sensitivity analysis with respect to the outsourcing unit cost C_{pa} .

Fig. 10 reports the outsourced quantity percentage of total average weekly workload at $C_{pa} = 2.0$ €/unit. Scenario 1.M almost never activates the outsourcing option ($\bar{X} \approx 0$), consistent with the manufacturer's stronger bargaining position, which allows it to preserve standard lead time without resorting to the auxiliary capacity. The remaining decentralized configurations (1.R, 2.M and 2.R) exhibit limited and occasional outsourcing (about 7%–9%), reflecting sporadic congestion episodes of moderate intensity.

By contrast, cooperative scenarios 3 and 4 rely more on external capacity, with outsourcing accounting for about 19% and 16% of total workload, respectively. Nevertheless, outsourcing remains intermittent, confirming its role as an emergency buffer rather than as a permanent

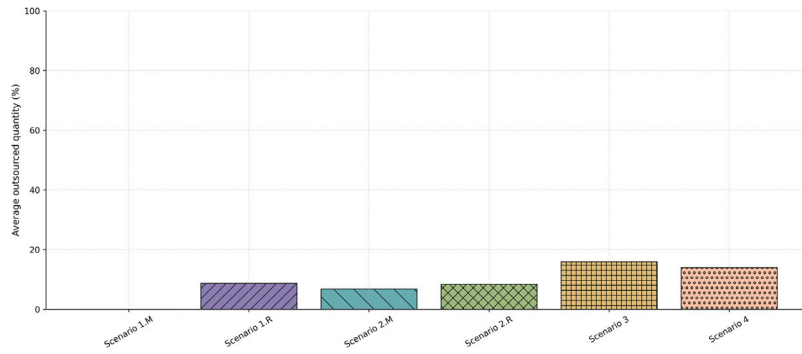


Fig. 10. Average outsourced quantity ($\bar{X}$) as a percentage of the manufacturer's total average weekly workload at the baseline outsourcing cost $C_{pa} = 2.0$ €/unit. Bars are distinguished by scenario-specific colors and hatch patterns.

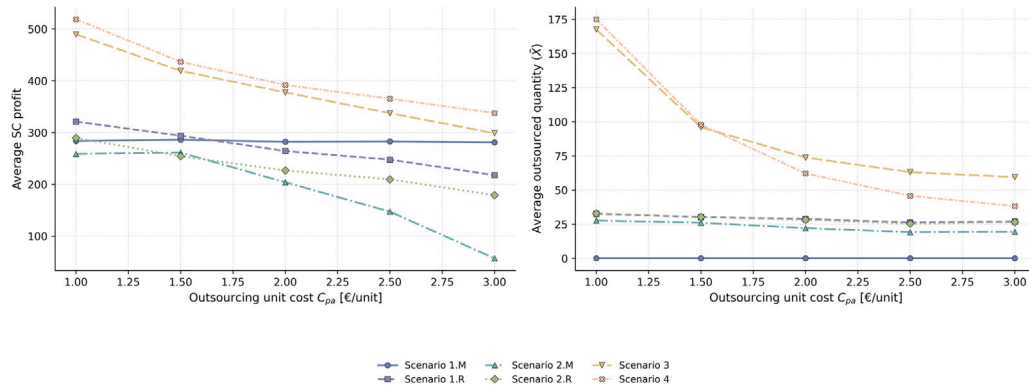


Fig. 11. Sensitivity of average SC profit (a) and average outsourced quantity $\bar{X}$ (b) to the outsourcing unit cost C_{pa} across all simulation scenarios. Scenarios are distinguished by consistent colors, line styles and markers across both panels.

second production line, and supporting the assumption of an auxiliary source with infinite capacity.

Building on this baseline comparison, a sensitivity analysis of C_{pa} is conducted by considering approximately $\pm 25\%$ and $\pm 50\%$ deviations. Fig. 11 reports the impact on total SC profit (panel a) and on the mean outsourced quantity $\bar{X}$ (panel b).

Fig. 11(a) shows that lower outsourcing costs increase profitability across scenarios, with stronger gains where outsourcing is used more intensively. Values of C_{pa} close to or below the internal production cost C_p should be interpreted as stress tests rather than as the primary operating regime; consistent with the literature, the economically relevant case remains $C_{pa} > C_p$, where outsourcing functions as a buffering layer rather than a cost-effective substitute for internal production.

Conversely, as C_{pa} increases, SC profit gradually erodes and the system becomes more reluctant to activate backup capacity. This effect is particularly pronounced in decentralized settings, where outsourcing is either structurally excluded (Scenario 1.M) or activated in a less systematic way (Scenarios 1.R, 2.M and 2.R), limiting its ability to offset misaligned incentives and information asymmetry.

Consistently, Fig. 11(b) shows that increasing C_{pa} reduces $\bar{X}$ in all configurations with positive outsourcing. Cooperative Scenarios 3 and 4 exhibit the steepest response: when C_{pa} decreases from 2.0 to 1.0 €/unit, their average outsourced volumes more than double, reflecting an aggressive exploitation of external flexibility to sustain fast lead times. Decentralized Scenarios 2.M and 2.R display a more moderate contraction of $\bar{X}$ (about 25%–30%), suggesting that, absent coordinated incentive alignment, firms partially substitute external capacity with longer lead times and/or higher internal utilization rather than absorbing very expensive outsourcing. Scenario 1.M remains at $X_t \equiv 0$ for all tested values of C_{pa} , confirming that outsourcing is never optimal under its contractual/decision structure.

Overall, the results clarify the dual role of outsourcing in the proposed framework. While C_{pa} governs the intensity of recourse to backup capacity, the coordination regime determines how effectively this flexibility is translated into improved service and higher SC profitability. Outsourcing thus emerges as an endogenous, contract-driven buffer that supports short and reliable lead times; however, its ability to translate flexibility into higher SC profitability depends critically on the coordination regime, and is strongest under cooperative settings that internalize the outsourcing cost-service trade-off.

5.4.4. Sensitivity to demand elasticities: The role of α and β

The last set of experiments investigates the robustness of the proposed coordination mechanism with respect to the demand elasticities α and β (Eq. (1)). By varying β (and the corresponding sampling mean μ_p) while preserving $\alpha = \beta/L$, we generate a family of (α, β) pairs that spans markets with different overall responsiveness while preserving the relative weight of price and marketing. Specifically, we consider $\beta \in \{0.12, 0.15, 0.17, 0.19, 0.22\}$; with $L = 0.09$, this implies $\alpha \approx \{1.33, 1.67, 1.89, 2.11, 2.44\}$.

Fig. 12 reports average Manufacturer, Retailer and SC profit as a function of β across scenarios. When demand is weakly sensitive ($\beta = 0.12$), profitability increases markedly relative to the baseline ($\beta = 0.15$), and cooperative settings remain dominant at the SC level. In this region, the coordination mechanism enhances efficiency without distorting the distribution of gains, as the additional surplus is allocated in a balanced way.

Beyond the baseline, profits become increasingly sensitive to β in all scenarios, with decentralized configurations exhibiting a markedly higher downside slope. In the upper part of the tested range, some decentralized configuration become structurally unprofitable at the SC level, indicating that uncoordinated pricing/ordering decisions combined with high responsiveness and capacity constraints may become value destructive.

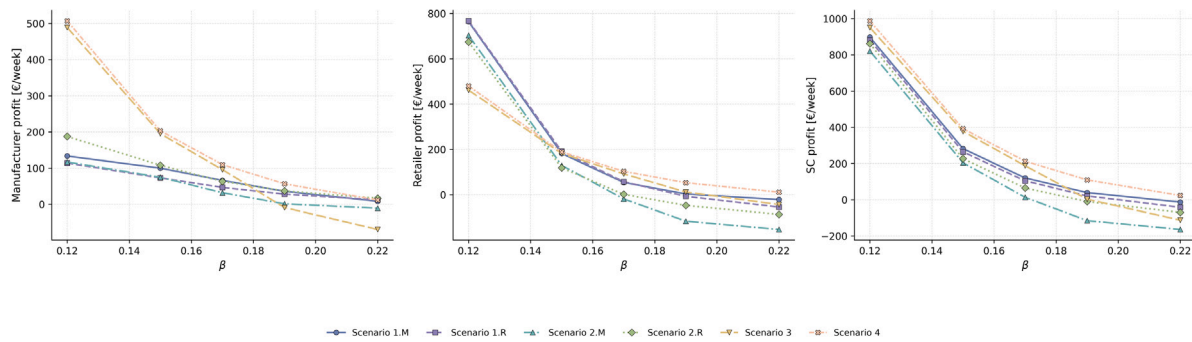


Fig. 12. Sensitivity of average Manufacturer, Retailer and SC profits to β (and consequently μ_β), with α adjusted to keep $L = \beta/\alpha$ constant across all scenarios. Scenarios are distinguished by consistent colors, line styles and markers across all panels.

Actor-level results confirm that this fragility concentrates upstream: under high sensitivity, the manufacturer absorbs most volatility and capacity-related risk, whereas the retailer can still preserve a sizable margin. In contrast, cooperative configurations keep both actors jointly profitable over a wider range of β , and the adaptive revenue sharing scheme sustain small but positive profits for each partners. Overall, the coordinated mechanism does not merely reallocate gains and risks: it increases the economic viability and stability of the dyad as demand becomes more responsive.

These results suggest that the economic relevance of the proposed mechanism increases with demand responsiveness. In weakly responsive markets, all governance structures remain profitable and the incremental gains from coordination are comparatively moderate. As responsiveness increases, dynamic lead-time negotiation coupled with adaptive revenue sharing becomes critical to prevent coordination failures on lead time and utilization from rapidly eroding profitability. In these environments, such as branded fast-moving consumer goods, consumer electronics components, and fashion assortments with short product life cycles, traditional decentralized contracts may become economically fragile, particularly under information asymmetry, whereas dynamic coordination helps preserve non-negative profitability for both parties.

5.5. Managerial insights

Drawing from the comparative analysis of the simulated scenarios and the sensitivity analysis, several actionable managerial insights emerge for managers navigating SC coordination under bilateral operational asymmetry:

- **Economic Cost of Operational Speed Through Decentralized Negotiation:** While dynamic lead time negotiation effectively enhances service responsiveness and reduces lead times (Figs. 4, 7), relying solely on negotiation in decentralized, self-interested structures can lead to significant decreases in total SC profitability (Fig. 3). Crucially, the analysis shows that the dominant actor in such settings may even see their own profit decline (Fig. 6). Managers should understand that without explicit incentive alignment, the operational costs of speed may not be adequately compensated or shared, ultimately destroying overall value.
- **Incentive Alignment as the Engine for Value Creation:** The most impactful finding is that integrating the negotiation process with an adaptive revenue-sharing mechanism is critical for unlocking substantial value (Fig. 3). This combined approach aligns incentives, encouraging cooperative behavior despite information asymmetry and enabling the capture of over 80% of potential decentralized losses. For managers, this highlights the necessity of contractual elements that go beyond simple price/quantity negotiations to address the financial implications of operational decisions like lead time.

- **Balanced Power and Aligned Incentives Bridge the Information Gap:** The success of Scenario 3, achieving performance near the perfect information optimum (4.0% gap: Fig. 3) while maintaining equitable profit distribution (Fig. 6), demonstrates that bilateral operational information asymmetry is not an insurmountable barrier to efficient coordination. A framework that facilitates dynamic operational negotiation grounded in feasibility and distributes the resulting value fairly, as enabled by adaptive revenue sharing, effectively mitigates the negative impacts of private information, even without a dominant party dictating terms.
- **Operational Feasibility Anchors Strategic Decisions:** The embedded checks against maximum utilization (ρ_{MAX}) within the negotiation process are vital (Fig. 5). They ensure that strategically negotiated lead times remain operationally achievable, preventing infeasible demands and maintaining system stability. Managers implementing such coordination mechanisms must ensure they are tied to realistic operational constraints.
- **Strategic Capacity Management Based on Coordination Strength:** The sensitivity analysis on production rate (μ) and maximum utilization (ρ_{MAX}) (Fig. 8) underscores that the criticality of tangible capacity investment and aggressive utilization policies is inversely related to the strength of coordination. When formal coordination is weak or absent, firms should prioritize tangible capacity investments and adopt more flexible utilization policies to avoid outsourcing penalties. Conversely, SCs that have robust coordination mechanisms can sustain high performance even with conservative utilization thresholds, leveraging information sharing and joint decision-making to operate closer to their feasible optimum without overinvesting in excess capacity.
- **Danger of Myopic Pricing Policies:** An aggressive pricing policy for value-added services like expedited delivery can be counterproductive. In non-cooperative contexts, attempting to maximize revenue from these services can trigger a chain reaction that depresses final demand, eroding the profitability of the entire SC and, ultimately, even their own profit. A moderate policy, instead, could incentivize greater collaboration and more stable orders, leading to higher and more sustainable overall profits in the long run. This underscores that the pricing lever must be calibrated with a system-wide perspective, as the leader's maximum achievable profit is found at the very edge of the follower's economic tolerance, a threshold beyond which an aggressive strategy becomes value-destructive even for its instigator.

The simulation findings provide compelling evidence for the efficacy of the proposed dynamic lead time coordination mechanism. By integrating a structured negotiation process grounded in operational feasibility with an adaptive revenue-sharing mechanism, the framework achieves significant improvements across key dimensions: speed (approximately 40% reduction in lead times), efficiency (closing the gap to perfect information to just 4.0%), and fairness (near-equal profit split).

Overall, these benefits are realized while maintaining operational feasibility and system stability (Figs. 5), and, crucially, without necessitating full disclosure of private operational or market information.

The proposed approach, therefore, contributes a novel class of operational contracts that directly address the complex challenges of bilateral, dynamic, and unverifiable asymmetry, offering a practical and theoretically grounded solution for managers seeking to enhance coordination, flexibility, and value creation in modern SCs. Because the mechanism operates on such standard, aggregate inputs – orders, requested lead times, and basic capacity and cost indicators – its implementation can build directly on existing data infrastructures, while the more sensitive parameters remain internal to each firm and are only reflected indirectly through the observed negotiation outcomes.

From an implementation standpoint, the proposed framework can be operationalized as a recurring routine within existing planning and order-management processes, without demanding data-integration efforts or mandated disclosure of sensitive information. On the data side, it relies only on indicators that each firm already tracks internally, and which are typically recorded in standard ERP/APS and order-management systems rather than requiring bespoke data collection or inter-firm system integration: on the manufacturer side, aggregate capacity, a target utilization threshold, the current external workload, and internal versus backup production costs, all of which are routinely maintained for master production scheduling and capacity planning; on the retailer side, order quantities per planning cycle, requested lead times (or service classes), and an approximate view of demand responsiveness derived from existing pricing and promotion analytics. The only information that must be explicitly exchanged between the parties, in addition to the order quantity, is the requested lead time – an item already embedded in conventional order and service-level negotiations. The negotiation mechanism is then embedded in the periodic order cycle: for each planning period, the retailer submits an order and a required lead time, the manufacturer computes an operationally feasible proposal based on its internal state and the utilization threshold, and, when the request is more aggressive, evaluates internal acceleration or backup capacity before committing to a final lead time and the associated lead-time price component. The adaptive revenue-sharing rule can in turn be formalized as a profit-allocation clause, applied at an agreed settlement horizon to the joint margin of the product line: the parties fix *ex ante* a small set of parameters (utilization threshold, lead-time price sensitivity, smoothing factor, and settlement frequency), and the sharing factor is then updated automatically from realized lead-time surcharges and joint profits. In practice, the settlement could be aligned with the periodic commercial reconciliation cycles that already exist in many of these relationships, so that the allocation clause does not require a separate administrative process. Because the rule reacts to observed outcomes rather than to declared private parameters, it remains implementable even when partners are reluctant to share detailed cost or demand information, and it progressively discourages persistently opportunistic behavior by shifting the allocation against a party that systematically extracts large speed premiums. This makes the mechanism particularly suited to time-sensitive, capacity-constrained dyads—such as fast-moving consumer goods, consumer electronics, and short-life-cycle fashion—where demand is highly responsive to price, promotion, and delivery speed, and where coordination must be sustained under persistent operational information asymmetry.

6. Conclusions

SC coordination is particularly challenging in dynamic environments with bilateral, dynamic, and unverifiable operational information asymmetry. Given the central role of lead time as a coordinating variable, this study proposes and evaluates a dynamic coordination mechanism that combines a feasibility-informed lead time negotiation process with an adaptive revenue-sharing scheme to align incentives and support cooperation.

Simulation results show that decentralized lead time negotiation alone can reduce delivery times but may also destroy value and generate unequal profit allocations. In contrast, coupling negotiation with the proposed adaptive revenue-sharing mechanism substantially increases total SC profitability, improves equity in value sharing, and delivers performance close to the perfect-information benchmark, mitigating the adverse effects of bilateral operational asymmetry.

From a managerial perspective, the findings stress that operational negotiation must be paired with explicit incentive-alignment mechanisms: effective coordination under asymmetry and balanced power requires contractual elements beyond price/quantity decisions to ensure both value creation and fair distribution. The analysis also highlights that a leader's pricing power is bounded by the follower's economic viability, as excessive premiums on value-added services can collapse demand and destroy value for the entire SC.

This study proposes a novel approach to operational contracts by explicitly connecting dynamic operational decisions (lead time) with strategic negotiation and adaptive financial incentives under asymmetry. It bridges insights from operations management, game theory, and contract design, offering a practical approach to enhance flexibility, resilience, and cooperation in opaque, time-critical SCs.

These conclusions should be interpreted in light of limitations that open avenues for future research. Key extensions include relaxing simplifying assumptions to incorporate tighter capacity constraints; exploring alternative negotiation process structures and strategic misrepresentation of operational states or urgency; and extending the analysis beyond a dyadic, single-product setting to multi-echelon networks and multi-product portfolios. Finally, a promising avenue for future research is the empirical implementation of the proposed negotiation and revenue-sharing mechanism on proprietary data from an industrial buyer–supplier dyad, leveraging detailed operational information to bring the simulation-based insights closer to industrial practice. Addressing these directions can broaden the applicability of dynamic operational coordination mechanisms in complex SC environments.

CRedit authorship contribution statement

Emma Salatiello: Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Francesca Papa:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Silvestro Vespola:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Andrea Grassi:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Generative AI tool in order to proofread the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data availability

Data will be made available on request.

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