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Article

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Operations Research Perspectives

Provided in Cooperation with:

Elsevier

Suggested Citation: Hamdan, Sadeque; Boulaksil, Youssef; Ghoudi, Kilani; Hamdouch, Younes (2025) : Simplicity or flexibility? Dual sourcing in multi-echelon systems under disruption, Operations Research Perspectives, ISSN 2214-7160, Elsevier, Amsterdam, Vol. 14, pp. 1-27, <https://doi.org/10.1016/j.orp.2025.100333>

This Version is available at:

<https://hdl.handle.net/10419/325810>

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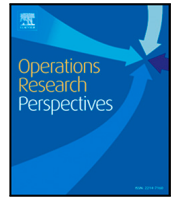
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Simplicity or flexibility? Dual sourcing in multi-echelon systems under disruption

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ARTICLE INFO

Keywords:

Inventory management
Dual-sourcing
Multi-echelon
Order expediting
Demand disruption

ABSTRACT

Disruptive events like the COVID-19 pandemic have exposed supply chain vulnerabilities. This study focuses on dual sourcing as a resilient strategy and examines a stochastic, single-item, multi-echelon, multi-period, dual sourcing inventory system under backorders. In each echelon, the decision-maker faces a dual-sourcing situation wherein the item can be replenished from a slow regular supplier or a more expensive and faster emergency supplier. We compare two inventory management policies: the Dual-Index Policy (DIP) and the Tailored Base-Surge (TBS) Policy, while also investigating how various factors influence policy effectiveness and the role of demand disruptions. Our findings indicate that the TBS policy generally relies more on upstream suppliers than the DIP. However, in scenarios of high demand uncertainty, upstream suppliers are seldom used. DIP is more effective for short networks facing sudden demand drops, whereas TBS excels when experiencing demand spikes.

1. Introduction

The growing need for resiliency in many industries has become especially clear after the COVID-19 pandemic, which revealed significant vulnerabilities in supply chains [1]. As a result, numerous companies now employ a dual sourcing strategy that combines a cost-effective offshore supplier with a local onshore supplier capable of providing shorter lead times [2]. This approach uses two suppliers (or different transportation modes) for the same product, which enhances resilience and customer responsiveness by combining the economic benefits of the regular supplier with the increased flexibility offered by the expedited onshore supplier [3–5]. This approach can reduce risks associated with supply chain disruptions, while maintaining high service levels, thereby ensuring business continuity and competitiveness in an unpredictable market environment. A recent study conducted by McKinsey, which surveyed 113 global supply chain leaders across various industries, found that 81% had adopted dual-sourcing strategies in 2021, which is a significant rise from 55% in 2020 [6]. Another study revealed that 92% of manufacturing companies in the UAE use dual- or multi-sourcing strategies to secure their supply of critical products [7].

Furthermore, several studies in the literature have shown that dual sourcing practices are widespread in industry. Rao et al. [8] reported on Caterpillar's dual sourcing strategy for compact work tools, Bayer

and Ward [9] on Hewlett-Packard's dual sourcing strategy for its manufacturing plants, and Allon and Van Mieghem [10] on a US-based \$10 billion manufacturer of wireless transmission components with two assembly plants: one in China and another in Mexico. This strategy ensures that production lines can continue operating even when disruptions affect the primary supply chain, ultimately maintaining customer satisfaction and enhancing operational resilience. Another practical example is in the automotive industry [11]. Many car manufacturers rely on a primary supplier located in regions known for cost-effective production (often in Asia) for critical components like semiconductors or auto parts. However, during disruptions such as natural disasters or the COVID-19 pandemic, these manufacturers may face significant delays. To mitigate this risk, they establish relationships with local suppliers who, although more expensive, can deliver components more quickly. These local suppliers must maintain high service levels and often source their inputs both locally and from international markets. This approach creates an extended supply chain characterised by multiple layers of dual sourcing. Hence, not only do car manufacturers engage in dual sourcing by using both offshore and local suppliers, but the suppliers themselves often adopt dual sourcing strategies to secure their raw materials or intermediate goods. As a result, the overall network evolves into a complex, multi-tiered supply chain,

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<https://doi.org/10.1016/j.orp.2025.100333>

Received 9 September 2024; Received in revised form 14 February 2025; Accepted 11 March 2025

Available online 21 March 2025

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where dual sourcing is practised at various levels. Understanding these interconnected dual sourcing arrangements is critical for optimising supply chain performance and enhancing resilience, which is the central focus of this study. More specifically, the goal is to gain insights into the use of different policies to guide procurement managers in decision-making.

Supply chain (SC) disruptions, like the COVID-19 pandemic, increase vulnerabilities, necessitating flexible and redundant supply strategies [1,12–14]. Multiple sourcing reduces dependency on a single supplier [15]. Considering multi-echelon SCs mitigates disruptions' negative impact, with different impacts on high-demand and low-demand products [1,16]. Thus, this paper presents a numerical study on stationary and disrupted demand cases.

The optimal policy for general dual sourcing systems remains unknown. Therefore, several heuristics have been proposed in the literature [17]. In this paper, we focus on two well-studied heuristic policies: the dual-index policy (DIP) and the tailored base-surge (TBS) policy. The TBS policy integrates both push and pull mechanisms by placing a fixed order with the regular supplier each period (push) while relying on the expedited supplier only in critical situations (pull). One key advantage of this approach is that the regular supplier benefits from consistent order quantities, making it particularly practical and easy to implement in real-world scenarios. In contrast, the DIP policy follows a purely pull-based approach, utilising two base-stock levels as control parameters—one for each supplier—allowing for greater flexibility in inventory management. While TBS prioritises simplicity through its simple ordering structure, DIP offers flexibility by dynamically adjusting inventory levels based on the state of the system. These two represent opposite ends of the spectrum: in a single-echelon setting, the DIP policy is optimal when the lead time difference is one period [18], while the TBS policy becomes optimal as the lead time difference grows to infinity [19]. These insights lead to a critical question: do these optimality results persist in a multi-echelon environment, which more accurately reflects real-life supply chains? In practice, supply chains involve multiple echelons, each with its own lead times, uncertainties, and operational challenges. Such layered systems might exhibit different dynamics, potentially affecting the performance and applicability of the DIP and TBS policies [20]. Therefore, in this study, we extend the analysis to multi-echelon dual sourcing systems to determine whether the insights drawn from single-echelon models can be generalised, especially when disruptions are taken into consideration. Our investigation aims to provide a deeper understanding of the conditions under which each heuristic policy might be preferable in a multi-echelon dual sourcing supply chain under disruptions. Under DIP, two base-stock levels are defined, one for the emergency supplier and the other for the regular supplier. Whenever the inventory position falls below its associated base-stock level, an order is placed at the corresponding supplier(s). For the buyer, such a policy is optimal when the lead time difference is one period [21,22]. Under the TBS policy, a constant quantity is placed at the slow supplier. The demand uncertainty is covered using the emergency supplier based on the inventory position and the defined base-stock level. This policy is optimal when the lead time difference between the two suppliers goes to infinity (or grows large) [19,23]. Klosterhalfen et al. [22] showed that the buyer may prefer the TBS policy over the DIP. However, all these studies consider a single-echelon setting. It remains unclear how these policies would perform in a multi-echelon setting with different decision makers at each echelon. Such a setting is closer to a real-life setting, which is the perspective we take in this study.

Boulaksil et al. [20] examined the buyer's decision impact on suppliers with one period lead time difference, suggesting that while the buyer prefers the DIP, TBS policy performs better for emergency suppliers. The regular supplier's preference, however, depends on both suppliers' wholesale prices. This suggests the preferred policy from a SC perspective may differ even with a one period lead time difference. Boulaksil et al. [20] emphasised the need to consider perspectives

beyond just the buyer and prompted research into how the number of echelons affects policy preference in dual-sourcing, the focus of this research. Notably, there is a scarcity of literature on dual-sourcing in multi-echelon systems, with no studies comparing both policies in a multi-echelon environment, despite real-life SCs being complex multi-echelon networks. In this research, we compare the DIP and TBS policy performance in a multi-echelon setting, assuming installation stock levels. We model demand backorder for insufficient inventory, with emergency suppliers committed to meet their demand. We give decision-makers the option to place costly “rush” orders, a tactic seen in industries like automotive [24]. These rush orders can be interpreted as emergency suppliers using faster transportation or as a penalty measure for “lost sales”. The latter is commonly used in inventory system simulations [25].

In this paper, we will consider a multi-echelon system where at each echelon orders can be placed at different suppliers with different levels of responsiveness. This type of system can be found in electronic companies that purchase high-quality electronic components and rely on dual sourcing for SC resilience. Ignoring the upstream dual sourcing settings will simplify our setting to the single-echelon system studied in Janakiraman et al. [23] and Xin and Goldberg [19] where they consider the regular supplier to have a long lead time. Hence, this paper aims to address the following main question: Which dual sourcing policy is preferred in a multi-echelon system under different parameter scenarios? Therefore, for the sake of comparison, we extend the one-echelon network of Boulaksil et al. [20] to multiple echelons. While Boulaksil et al. [20] provided analytical results for the one-echelon system, due to the model complexity caused by the complicated demand distributions at higher echelons, it is impossible to obtain analytical results for the multi-echelon setting. Therefore, we use simulation-based optimisation to address our research question. In this simulation-based optimisation approach, demand scenarios are simulated, and inventory parameters are optimised using the interior point algorithm such that the long-run expected total profit is maximised. The study's main contributions are threefold:

- First, we compare the DIP and TBS policy in a multi-echelon stochastic inventory system. In this regard, we present insights related to each policy's behaviour in a multi-echelon setting and the factors that determine the preferred policy as the number of echelons increases. Through our numerical experiments, we show that the TBS policy is dominant in the size of the SC network, that is, as the number of echelons increases, more profit is secured under the TBS policy and the largest profit portion is achieved at the first echelon. Subsequently, the marginal profit decreases according to the number of echelons. This holds when the wholesale price difference between the suppliers is limited because as this difference grows, the DIP may outperform the TBS policy. This is an important insight given that most SCs are fragmented and consist of several echelons.
- Second, we show how the preferred policy changes for a multi-echelon system under different parameter settings. For example, more orders are rushed when the level of demand uncertainty or the inventory holding cost increases because using the more expensive option of placing rush orders becomes a profitable alternative. However, at a certain level of demand uncertainty, this may no longer be profitable under the TBS policy, and the DIP becomes the better performing policy.
- Third, we compare the DIP and TBS policy under the demand disruption. We consider the demand disruption in products such as essential and healthcare items that showed a sudden demand spike during the COVID-19 crisis and products such as textile, oil, and automobile that showed a sudden demand drop during the COVID-19 crisis [26]. We study the impact of both disruption scenarios on the two policies' performance under different demand variability conditions and demand recovery duration lengths.

We observe that when demand suddenly drops in short supply networks, the DIP becomes dominant, and in extended supply networks, the dependency on emergency suppliers increases with the recovery duration increase. If a product is subject to sudden demand drop, DIP becomes preferred in small networks even when the wholesale price difference between the supplier is small. We also notice that the TBS policy is preferred when a product is subject to a demand spike in both short and extended networks; however, with the increased demand variability, the preferred policy might change faster in short networks.

The remainder of this paper is organised as follows. Section 2 reviews related works in the literature. Section 3 presents the studied problem. Section 4 presents the numerical results and shows the impact of increasing the number of echelons and varying parameters on the preferred policy. Section 5 shows the impact of demand disruption on the preferred policy. Section 6 highlights the impact of the wholesale price difference in the preferred policy. Section 7 summarises the extracted managerial insights. Finally, Section 8 concludes the paper and outlines future directions.

2. Literature review

This study examines two dual-sourcing policies in a multi-echelon environment where upstream suppliers commit to fulfilling their demand. The customer's demand may be subject to disruption due to for example epidemic outbreak. The suppliers have the option to expedite orders in the necessary cases, but this is an expensive option. Therefore, our work is related to four main streams in the literature: dual-sourcing inventory models, multi-echelon inventory systems, expediting orders, and SC disruption.

First, dual-sourcing or multi-sourcing inventory models have received attention since the 1960s from several scholars such as Barankin [27], Fukuda [21], Rosenshine and Obee [28], Sculli and Shum [29] and Mohebbi and Posner [30]. More recently, Veeraraghavan and Scheller-Wolf [18] studied a capacitated single-stage dual-sourcing inventory system under periodic review and stationary demand using the DIP and showed that the DIP is near optimal in most cases. Further, Sajadieh and Eshghi [31] considered a dual-sourcing model under the order-splitting policy; these authors showed that order-dependent unit prices can reduce the percentage savings from dual sourcing compared to single sourcing. Chung et al. [32] examined a decentralised SC with two suppliers, where one supplier offers a quantity flexibility contract, and the other offers a cheaper price. In addition, Allon and Van Mieghem [10] explored the TBS policy in a single-stage inventory system; these authors provided an analytic expression of the asymptotically optimal TBS policy and the overshoot process. Wang et al. [33] extended dual sourcing models by allowing buying firms to influence supplier reliability, relaxing the common assumption of fixed supplier performance. Their findings reveal that the preference for improvement, dual sourcing, or a combined strategy depends on supplier cost, capacity, and reliability heterogeneity, with a combined approach adding value when both capacity and reliability are low. Glock [34] studied the impact of different delivery structures on the SC and reported that using unequal delivery frequencies leads to the highest total cost improvement. Sting and Huchzermeier [35] investigated the correlated supply and demand uncertainty in the dual sourcing problem. Glock [36] compared single- and dual-sourcing strategies under learning conditions, where suppliers update their production costs and capacities. The author showed that it is not necessarily optimal to contract the supplier with the highest learning rate. Song et al. [37] focused on a multi-product dual-sourcing inventory management system under demand forecast update. These authors developed a sequential approximate algorithm, which was found to be efficient and effective in solving instances with thousands of product types. Serel [38] studied the optimal production and pricing policy in

a dual-sourcing problem. Huang and Xu [39] studied mitigating supply risks using dual sourcing and backup production in a single period model.

Biçer [40] studied the demand tail heaviness impact (i.e., niche items demand) on dual-sourcing optimality. Boute and Van Mieghem [41] considered order-smoothing policy in single- and dual-sourcing problems; their model accounted for capacity costs and overtime. Meanwhile, Janakiraman et al. [23] provided a numerical investigation on the optimality of TBS policy as the lead time difference increased, which was followed by the work of Xin and Goldberg [19], who proved it analytically. Ray and Jenamani [42] developed risk-neutral and risk-averse dual-sourcing newsvendor models for short lifecycle products under uncertain demand and supply. Chao et al. [43] investigated the impact of yield uncertainty in dual-sourcing and showed that high yield certainty can lower the selling price. Li and Li [44] studied the inventory management problem under disruption, where a loss-averse firm faced a stochastic demand and sources from two suppliers. These authors found that the reliable supplier was not used when its purchasing cost was too high. Tan et al. [45] characterised the optimal policy for dual sourcing problem with uncertain capacities. Janakiraman and Seshadri [46] analysed a backordering dual sourcing system where items can be returned to the slow supplier (negative orders) and showed that in the long run, no cost advantages are achieved. Lückert and Seifert [47] studied the relationship between dual-sourcing, risk mitigation inventory and agility capacity in pharmaceutical industry. They showed that during disruption, the optional dual-sourcing production rate decreases. Furthermore, to compare single and dual sourcing, Ivanov [48] considered capacity disruption, different demand patterns, and big data in a simulation-based study; a distribution centre was used to fulfil the supplier's demand in the single-sourcing problem, whereas a back-up distribution centre was considered in the dual-sourcing case. Li [49] studied a dual-sourcing problem with an unreliable supplier. Kouki et al. [50] considered a single-stage dual-sourcing perishable inventory system under fixed and exponential lifetimes. Huang et al. [51] investigated several auction formats accommodating wholesale price bids for dual sourcing with unreliable suppliers. In addition, Niu et al. [52] analysed an inventory system with non-competitive unreliable supplier and a competitive supplier. Dong et al. [53] showed that at a low fixed cost, the manufacturer prefers dual-sourcing in the absence of contract, while at a high yield rate, single-sourcing is preferred. Gheibi et al. [54] examined optimal capacity reservation policies for sourcing activities under exchange-rate and demand uncertainty, including two dual sourcing policies: a defensive approach and an opportunistic approach. It also shows how risk aversion increases the likelihood of dual sourcing and suggests financial hedging as a means to mitigate negative consequences of risk aversion in sourcing decisions. Xu et al. [55] considered a backordering dual sourcing system and showed that partial backordering in the case of one supplier might be as cost efficient as dual sourcing. Ai and Xu [56] reported that dual sourcing might benefit the reliable supplier when its cost is sufficiently low or the unreliable supplier when its yield variability is small. Boulaksil et al. [20] compared the performance of the DIP and TBS policy in a single-echelon system wherein the impact of the buyer's decisions on the SC was studied with a lead time difference of one period. They presented conditions for the preferred policy from a SC perspective. Hamdouch et al. [7] compared the DIP and the TBS policy under nonconsecutive lead times and reported that TBS becomes optimal with the increase in the lead time difference from the total SC profit perspective. The present research extends that of Boulaksil et al. [20] by investigating the preferred policy when the number of echelons increases. Xie et al. [57] proved that the robust optimal policy is a combination of the base-stock policy and a gap-of-base-stock policy with capping effect on supply sources except the fastest source for multi-sourcing under some conditions. Zhou et al. [58] considered multi-stage games in coordinating dual-sourcing problems. They showed that combining technology licensing contracts and dual-sourcing improves technology

capability in the short term, while jointed contract yields more efficient supplier development in the long term. Yang et al. [5] studied a multi-index base-stock policy for periodic-review inventory systems with multiple capacitated suppliers. This policy balances cost efficiency and responsiveness by tailoring inventory positions for each supplier and using a modified base-stock approach. They show that this policy performs comparably to dynamic programming solutions, with the added advantage of computational efficiency through a proposed heuristic. Mahmoudzadeh and Chaturvedi [59] examined how consumer reactions — either paying more for certified products (supporting) or boycotting firms with irresponsible sourcing — affect a firm's incentives towards responsible dual sourcing. Using a stylised and behavioural model, the study finds that boycotting reliably increases responsible sourcing, while consumer support induces a dual-sourcing bias. The results suggest that for products with few substitutes, encouraging consumer support improves responsible sourcing, whereas for products with many substitutes, promoting boycotting reactions is more effective in driving firms towards ethical sourcing practises. Lou et al. [60] compared three resilience strategies — investment in a fixed supplier, dual sourcing, and a hybrid approach — to assess their impact on supply chain resilience under disruptions. The findings indicate that dual sourcing is the most effective for increasing manufacturer profits, while the hybrid strategy ensures supply stability at the cost of potential profit reductions. Ghoudi et al. [61] studied the game-theoretic dynamics of a dual-sourcing supply chain where a buyer follows a TBS policy. They modelled two- and three-player game scenarios, analysing pricing strategies, equilibrium conditions, and coordination possibilities and found that while coordination between the buyer and regular supplier increases their combined profit, it negatively impacts the expedited supplier. Moreover, the expedited supplier adopts aggressive pricing strategies to either eliminate competition or maximise revenue, highlighting the strategic complexities of dual sourcing under competitive conditions. Tang et al. [62] investigated a periodic-review dual-sourcing inventory system where the firm does not have prior knowledge of the demand distribution and must learn from past demand realisations. They developed a non-parametric online learning algorithm that minimises regret relative to the optimal dual-index policy, achieving near-optimal performance. Chen and Shi [63] examined a periodic-review dual-sourcing inventory system where the demand distribution is unknown, and the firm must make adaptive ordering decisions based on past sales data. The authors develop a non-parametric learning algorithm that minimises regret relative to the best full-information TBS policy. By integrating bisection search and stochastic gradient descent, the approach provides a provably efficient method for learning near-optimal inventory policies in uncertain demand environments. Kim and Chung [64] proposed a data-driven distributionally robust optimisation model for dual-sourcing inventory management under uncertain demand. By leveraging partial distributional information, the model provides a tractable solution with closed-form optimal policies, addressing challenges like dimensionality and conservativeness in traditional stochastic and robust approaches. Fang et al. [65] examined dual sourcing under supplier quality heterogeneity, where a manufacturer sources from both an incumbent high-quality supplier and an entrant supplier with lower initial quality that may improve through R&D. They found that dual sourcing generally benefits the manufacturer unless the entrant supplier is highly uncompetitive, and that R&D success may unexpectedly disadvantage the entrant supplier. The results highlight the strategic trade-offs in dual sourcing when supplier quality and market structure influence sourcing decisions. For detailed reviews of multiple-source inventory models, see Minner [66] and Svoboda et al. [67].

The second stream is the multi-echelon or serial inventory systems. Notably, only a few works have considered the dual-sourcing problem in a multi-echelon context [68]. For instance, Bertsimas and Thiele [69] introduced a robust optimisation approach for supply chain control under stochastic demand without assuming a specific demand

distribution. Unlike dynamic programming, which faces dimensionality challenges, the method remains computationally tractable and allows for adjustable robustness levels to balance performance and uncertainty protection. The authors demonstrated that the resulting optimal policy retains a base-stock structure, similar to stochastic policies, making it applicable to various inventory systems, including dual sourcing and multi-echelon supply chains. Wang and Yang [70] extended the work of Bertsimas and Thiele [69] to a periodic-review multi-supplier series inventory system with demand uncertainty. The authors derive a closed-form robust optimal policy that integrates echelon base-stock policies and a gap-of-echelon-base-stock policy, ensuring computational efficiency and practical applicability. By reformulating the uppermost stage as a single-stage multiple-sourcing problem, the study demonstrates the robustness of the proposed policies, particularly in environments with high demand uncertainty and limited forecasting accuracy. Yu [71] studied a three-echelon dual-sourcing inventory problem for deteriorating items, where the replacement of corrupted items was forbidden. Their experiments revealed that when the deterioration cost increased, deliveries from the distributor increased; however, deliveries remained the same when the deterioration rate increased. In addition, Arts and Kiesmüller [72] extended the DIP into a three-index policy in a two-echelon environment. The first index represented the inventory position at the first stock point, which places orders to the upstream level that deals with two suppliers, resulting in another two inventory positions. The system was assumed to be centrally controlled, and all information concerning outstanding orders and inventory was available during decision-making. The authors showed that dual sourcing led to substantial cost savings in longer lead times, higher backlog costs, and increased demand variability. Sajadieh and Thorstenson [73] analysed four sourcing models based on cooperative versus non-cooperative planning and sole versus dual sourcing in a two-stage supply chain. Using an (r, Q) inventory policy with stochastic lead times, they found that while dual sourcing is often considered beneficial, its advantages depend on the total system cost structure. The results highlighted the importance of detailed cost analysis in determining the most effective sourcing strategy, challenging the common assumption that order splitting always improves performance. Shen et al. [74] examined a two-echelon inventory system with periodic review and a minimum order quantity constraint at the warehouse level and proposed a refined base-stock policy that ensures compliance with minimum order quantity while minimising long-run system costs. Wu et al. [68] studied a serial inventory system with a batch-ordering structure in which each echelon replenished from two suppliers: a regular and an emergency one. They studied the dual-index echelon (R, nQ) policy. In this policy, if the emergency (regular) inventory position falls below the emergency (regular) reorder point R , it places an integer multiple of quantity Q (i.e., batch size) from the supplier. Item shortage is allowed at the buyer and supplier levels. These authors showed that the dual-index echelon policy was optimal when the lead time difference was one period and that the order size satisfied an integer-ratio constraint. Further, using a scenario-based distribution requirement-planning approach, Firoozi et al. [75] developed a two-stage stochastic inventory model in a multi-echelon SC network. The network faced a nonstationary demand, and the model considered lateral transshipments and multi-sourcing strategies. A substantial increase in the service level was when considering lateral transshipments and multiple-sourcing strategies. Zhu et al. [76] evaluated a modified echelon (r, Q) policy for a two-echelon distribution system, demonstrating its asymptotic optimality as system parameters scale. They show that this heuristic balances cost efficiency and responsiveness, particularly as the number of retailers grows, offering a practical alternative to complex optimal policies in dual-sourcing settings. Recent research by Gijbrecchts et al. [77] explored the effectiveness of deep reinforcement learning in solving complex inventory problems, including dual-sourcing and multi-echelon systems. By modelling these problems as Markov Decision Processes, the study finds

that deep reinforcement learning can match state-of-the-art heuristics and approximate dynamic programming methods. While initial hyperparameter tuning is computationally demanding, this approach demonstrates strong adaptability across different inventory settings, making it a promising general-purpose approach for supply chain optimisation. Drent and Arts [78] studied dual sourcing in a spare parts distribution two-echelon network with a central warehouse and multiple local warehouses, incorporating both regular and expedited repair options. Using queueing theory and optimisation techniques, the study demonstrates that dynamic expediting policies can significantly reduce stock investments while maintaining asset availability. Khakbaz et al. [79] developed an EOQ-based cross-docking inventory model for a retail supply chain, considering a two-stage procurement process involving multiple suppliers and retailers. The proposed model minimises total inventory costs by optimising ordering and holding costs at both the central warehouse and retail stores. The findings demonstrate the model's efficiency in determining optimal inventory policies, providing valuable insights into cost drivers and decision-making in cross-docking systems. Li and Yang [80] examined a two-echelon distribution system with dual delivery modes, where expedited shipments offer shorter lead times at a higher cost. The authors proposed an echelon dual-index policy, extending established dual-sourcing and multi-echelon inventory policies to this setting. Through numerical experiments, they demonstrate the efficiency of their heuristic optimisation algorithm and evaluate the impact of different rationing policies and demand characteristics, highlighting the strategic value of dual delivery modes in managing inventory costs and service levels.

The third stream is the use of order expediting (rush orders) to satisfy the demand, which can take several forms. One form is through a lead time reduction. Ben-Daya and Raouf [81] optimised the order quantity and lead time in an (s, Q) inventory system, with the option of reducing the lead time at extra cost. Ouyang et al. [82] extended the aforementioned investigation by including shortage and stock-out cost. Moreover, Aggarwal and Moinsadeh [83] considered expedited orders when the number of outstanding regular orders exceeded a predetermined value in a multi-echelon production system. Lawson and Porteus [84] considered a multi-echelon serial SC network where orders flowing from one echelon to another can be expedited by reducing the lead time. Klosterhalfen [85] considered accelerating outstanding orders under the dual-sourcing order-splitting policy in a guaranteed service inventory model. For a comprehensive review of the guaranteed service inventory model, refer to Eruguz et al. [86]. Another form of order expediting is placing new orders after emergency ones. Smith [87] studied a model that expedited orders or considered them lost sales in the case of shortage under continuous review base-stock policy. The author provided an analytical expression for the base-stock calculation. Meanwhile, Huggins and Olsen [88] analysed the case wherein a supplier must fulfil the demand from an assembler using rush orders with an additional setup and variable costs. The third form of order expediting is the ability to skip some stages in the SC. Sapra [89] investigated the case where the regular supplier shipped orders to the most upstream stage and the expedited supplier rushed orders to the downstream stage in a serial inventory network with general lead times and finite horizon under periodic review. In addition, Song et al. [90] analysed a dual-sourcing system where orders from the regular supplier followed two processing stages, whereas orders from the emergency supplier could skip one stage. Moreover, Benbitour et al. [24] calculated the safety stock for multiple components and finished goods system under a periodic review base-stock, where rush orders were used in the case of stock-out. These authors tested the model on a real case and found a significant reduction in the average rush order probability compared to the company's model. Finally, inspired by Song et al. [90], Drent and Arts [91] studied a repair configuration where normal repair passed through two queues and the expedited repair skipped one queue.

The fourth stream is SC disruption. Disruption occurs due to natural disasters (e.g., earthquakes and tsunamis), human-made catastrophes (e.g., explosion), strikes, legal disputes, or epidemic outbreaks [11,92,93]. Disruption causes fluctuations in prices, supplies, and demands Chowdhury et al. [1], Fransoo and Udenio [94] and Gupta et al. [95]. In price disruption, de Paulo Farias and de Araújo [96] studied the impact of COVID-19 on prices in food supply chains and found that affected regions by COVID-19 showed great price variations and that the stockpiling period had the highest prices. Several works discussed supply disruption in inventory management problems before the COVID-19 pandemic. Ang et al. [97] studied sourcing in multi-tier supply networks under supply disruption and different configurations. The results showed that the manufacturer prefers less configuration overlap that is V-shaped network, and tier 1 suppliers may prefer overlapped network, that is diamond-shaped network. Gaur et al. [98] developed a mixed-integer nonlinear mathematical programming model for the closed-loop supply chain management problem under supply disruption. They showed that multi-sourcing generates higher supply chain profit than single sourcing. Gupta and Ivanov [99] coordinated a two-echelon supply chain network with one risk-neutral retailer and two risk-averse suppliers, who sell two substitute products. The demand for one product is stochastic and impacted by the price of the other product. They found that when a supplier increases the wholesale price for one product, the retailer reduces the price of the substitute product to achieve profit maximisation. Regarding demand disruption, Fransoo and Udenio [94] estimated the SC demand and inventory during the COVID-19 pandemic under different variation and lock-down scenarios. They revealed that inventory build-up will result in near-zero orders and that items with high lead time require placing orders ahead of the inventory decline. Singh et al. [100] simulated the food supply chain under demand disruption to help in developing resilient strategies. Zhao et al. [101] coordinated a make-to-order fashion supply chain under demand disruption using revenue sharing and linear quantity discount contracts. The analysis revealed that a revenue-sharing contract could not be used without demand disruption in the fashion supply chain, and a linear quantity discount contract cannot be used with demand disruption. Non-stationary demand was considered in some dual sourcing inventory management models. For instance, Yu et al. [102] compared single-sourcing and dual-sourcing under non-stationary and price sensitive demand setting. Zhou et al. [103] studied the platelets inventory management in hospitals with two replenishment modes and seasonal demand. In this system, regular orders are placed at the beginning of each cycle of two periods, and emergency orders can be placed in between two regular orders. They showed that placing one regular and three emergency orders can achieve significant cost savings, especially when demand variability is very high. Cheaitou and Van Delft [104] studied a network with two sourcing modes under three demand cases: stationary, decreasing and increasing. Su and Liu [105] discussed the impact of correlated operational and disruption risks on the optimal allocation strategy in dual sourcing and found that the unreliable regular supplier becomes less attractive during disruption. Hou et al. [106] studied the capacity reservation contracts during disruptions, where a backup supplier is used to help fulfil the demand. Their results revealed that a reliable supplier always induces the backup supplier to provide a low capacity reservation price to attract a larger quantity from the buyer. Schmitt et al. [107] studied the effect of disruption on orders during a disruption in a four-echelon system using simulation. They showed that the long-lasting impact of disruption occurs at echelons close to ultimate consumption. They also revealed that dynamic order-up-to levels rather than expediting orders lead to promising results. Jakšić and Fransoo [108] studied the relationship between lead time and uncertain capacity in a non-stationary dual-sourcing model. The first supplier offers immediate delivery but has a limited stochastic capacity, and the second supplier is uncapacitated but with a longer lead time. They found that ordering from the fast supplier and a state-dependent base-stock give the optimal

policy. By contrast, Sun and Van Mieghem [17] studied the case where the slow supplier has a capacity limitation, and the fast supplier's capacity is unlimited. They proved that a dual index, dual base-stock policy that limits the slow orders is optimal in the demand non-stationary case. To reduce market risks, Boute et al. [109] considered a fast onshore supplier called "SpeedFactory" and an offshore supplier. They highlighted the structural differences between stationary, correlated, and non-stationary demand environments. Yee et al. [110] examined dual sourcing under stochastic and non-stationary demand, where the underlying demand distribution changes over time and is only partially observable. The authors propose an adaptive dual base-stock policy that combines stable pre-committed orders from a slow source with flexible short-term orders from both sources. By leveraging partial information from demand observations, the policy dynamically adjusts replenishment decisions, reducing reliance on costly expedited orders. Numerical validation highlights the benefits of incorporating flexible slow sourcing to improve supply chain resilience under demand uncertainty. For a review on the SC disruption and resilience, refer to Katsaliaki et al. [111]

Several other works also discussed the impact of epidemic outbreaks on the SC. Iyengar et al. [112] discussed the challenges in managing healthcare SC networks during the COVID-19 pandemic and reported that low-cost and just-in-time strategies before the pandemic left companies with no buffer inventory and resulted in product shortages. Ivanov [11] used a simulation approach and reported that the timing of the opening and closing of the facilities at different echelons, lead time, the speed of epidemic propagation, and upstream disruption duration are key factors in determining the impact of epidemic outbreaks on the supply chain. Okafor et al. [113] conducted a systematic literature review and recommended increasing local production and resilience of healthcare supply chains to overcome the impact of the COVID-19 pandemic. Ivanov and Dolgui [114] provided a systematic review on SC disruption propagation and categorised contributions and managerial insights into network, process, and control groups. They suggested simulating and articulating operation policies during the disruption and exploring reallocation of supply and demand among several recommendations. For a comprehensive review on the COVID-19 impact on the SC, refer to Chowdhury et al. [1].

In the aforementioned streams in the literature and as shown in Table 1, the vast majority of the research on dual sourcing examined single-echelon systems rather than the total SC. Furthermore, works on placing new orders after regular ones to fulfil demand are substantially limited. In addition, most of the dual-sourcing inventory management models focused on stationary demand, and only a few models use non-stationary demand. By contrast, this paper considers a multi-echelon setting for which the performance of two policies (the TBS policy and DIP) is analysed from a SC perspective and the impact of increasing the number of echelons on the preferred policy is investigated. We consider order expediting using rush orders after normal orders to allow emergency suppliers to fulfil consumer demands. In addition, with the current demand disruption due to the COVID-19 pandemic, we analyse the performance of both policies in demand sudden increase and sudden decrease cases.

3. Problem description

Here, a multi-echelon, multi-period, and single-product inventory management problem under stochastic customer demand and installation stock is studied. In installation stock, decisions are decentralised, and orders are placed based on the inventory position of each supplier [116,117]. The starting echelon ($k = 0$) represents the buyer who must fulfil stochastic external demand (Fig. 1). This type of system can be found in electronic companies that purchase high-quality electronic components and rely on dual sourcing for SC resilience. The external demand during each period is a nonnegative random variable. For the stationary case, demand is assumed to be independent and identically

distributed. The SC network studied here consists of a series of suppliers in the same geographical region, called emergency suppliers. Each emergency supplier may place an order at an emergency upstream supplier or a regular supplier. In this setting, the buyer and the emergency suppliers are assumed to make decisions on their inventory. Similar to all upstream emergency suppliers, the buyer can replenish its inventory from two suppliers: a regular supplier with a low purchasing cost and an emergency supplier with a higher purchasing cost. The former has a longer lead time than the latter ($l_k^r > l_k^e$). The buyer's unfulfilled demand is backordered, except for the last period of the planning horizon, where demand is lost. Moreover, excess stock can be salvaged at the end of the planning horizon. Note that we deliberately did not model the scenario where the regular supplier can source from different suppliers, as this would be completely redundant when considering the TBS policy. Under the TBS policy, the regular supplier supplies a fixed constant quantity, which makes dual sourcing not needed for the regular supplier. Therefore, our network design choice, as presented in Section 4.1 enables a fair comparison between the two policies. By focusing on the dual sourcing problem of the buyer and local suppliers, we can more accurately evaluate the performance differences between DIP and TBS.

In echelon k , $k = 1, \dots, K - 1$, the emergency supplier replenishes its inventory from the regular and emergency suppliers in the next (upstream) echelon ($k + 1$). Regular suppliers do not manage inventories, and their decisions are straightforward. Further, the emergency supplier must fulfil the demand that comes from the buyer or emergency supplier $k - 1$. In the case of stock-out, rush orders are placed at a higher cost, which guarantees the reliability of the emergency supplier. In practice, the lead times of these rush orders are shorter than those of emergency orders. Here, rush orders are assumed to be delivered in the same (discrete) period. This reflects the practice of suppliers who use faster transportation modes to fulfil orders rapidly. Adopting this approach simplifies the analysis by allowing us to focus on the performance of the policies under disruption without explicitly modelling safety stocks and delayed deliveries. This modelling approach (of zero lead time for rush orders) is common in the stochastic multi-echelon inventory management literature (e.g. [24,89]). It provides a tractable and realistic representation of emergency delivery scenarios, which is essential for evaluating and comparing different inventory policies.

We conduct experiments by varying several model parameters, including the lead time difference experiments with a lead time difference between regular and emergency suppliers of one time period and also with larger lead time differences. The salvage value at the end of the planning horizon is assumed to be zero. The objective of this paper is to compare the DIP and TBS policy in a multi-echelon setting. Therefore, we will look at the individual profit of each party in the SC as well as the total SC profit under each policy. This allows us to compare the performance of the two policies in a multi-echelon setting. Subsequently, we present the notations used in describing the two policies studied — the DIP and TBS policy — and provide the sequence of events under each policy.

3.1. Notations

The parameters, stochastic variable, decision variables, state variables, and performance evaluation are as follows:

3.1.1. Parameters

- k = echelon index, $k = 0, \dots, K$, and $k = 0$ represents the buyer's echelon;
- μ_t = mean external demand faced by the buyer in period t ;
- σ_t = standard deviation of the external demand in period t ;
- p = unit selling price to the external customer;
- h^k = unit inventory holding cost in echelon k , $k = 0, \dots, K$;
- b = unit backorder cost at echelon 0 (buyer);

Table 1
Literature summary.

Paper	Sourcing			Model/Policy	Non-stationary demand	Rush order	Number of echelons		Notes
	Single	Dual	Multi				One/two	More than two	
Yu [71]		✓		Mathematical model				✓	Constant demand and deteriorating item
Veeraraghavan and Scheller-Wolf [18]		✓		DIP				✓	Stationary demand
Sajadieh and Eshghi [31]	✓	✓		Order splitting				✓	Constant demand and stochastic lead times
Chung et al. [32]		✓		Quantity flexibility contract				✓	
Allon and Van Mieghem [10]		✓		TBS				✓	
Sting and Huchzermeier [35]	✓	✓		–				✓	Uncertain supply and demand and unreliable offshore suppliers
Cheaitou and Van Delft [104]		✓		Near-optimal myopic policy	✓			✓	
Arts and Kiesmüller [72]		✓		Three base-stock policy				✓	
Song et al. [37]		✓		Newsvendor model				✓	Multiple products and demand forecast update
Serel [38]	✓			Newsvendor model		✓		✓	Local supplier is used after realisation of the demand
Biçer [40]		✓		–				✓	Heavy-tailed demand
Boute and Van Mieghem [41]	✓	✓		Lagrange inversion theorem				✓	Order smoothing
Janakiraman et al. [23]		✓		TBS				✓	
Ray and Jenamani [42]			✓	Newsvendor model				✓	Uncertain supply and demand
Tan et al. [45]		✓		–				✓	Uncertain supply and demand
Chao et al. [43]		✓		Periodic-review model				✓	Random-yield suppliers and uncertain demand
Ivanov [48]	✓	✓		Simulation model				✓	Deterministic demand and unreliable suppliers
Li [49]	✓	✓		Optimal policy				✓	Inventory system with return option
Janakiraman and Seshadri [46]		✓		Optimal policy				✓	Minimum order quantity, capacity reservation and uncertain supplier
Hou et al. [106]		✓		–	✓			✓	
Schmitt et al. [107]		✓		Simulation model	✓			✓	
Sapra [89]		✓		Modified echelon-basestock policy		✓		✓	Uncapacitated suppliers
Song et al. [90]		✓		Tandem queueing system and queue's optimal policy				✓	Expedited orders skip a stage
Jakšič and Fransoo [108]		✓		Near-optimal myopic policy	✓			✓	Stochastic capacity limitations and long lead times
Xin and Goldberg [19]		✓		TBS				✓	Analytically proof
Kouki et al. [50]		✓		Base-stock policy				✓	Perishable items with a fixed or exponential lifetime
Huang et al. [51]		✓		Newsvendor model				✓	Procurement auctions and supply risks
Li and Li [44]		✓		Stochastic dynamic programming				✓	Unreliable supplier
Niu et al. [52]		✓		–				✓	Unreliable supplier
Sun and Van Mieghem [17]		✓		Capped dual index policy	✓			✓	
Benbitour et al. [24]	✓			Periodic-review base-stock		✓		✓	
Wu et al. [68]		✓		Dual-index echelon-(R,nQ)				✓	Batch orders

(continued on next page)

Table 1 (continued).

Paper	Sourcing			Model/Policy	Non-stationary demand	Rush order	Number of echelons		Notes
	Single	Dual	Multi				One/two	More than two	
Boulaksil et al. [20]		✓		DIP and TBS			✓		Comparative study between two policies lateral transshipment strategy
Firoozi et al. [75]			✓	Mathematical model	✓			✓	
Drent and Arts [91]		✓		Queueing theory		✓	✓		
Boute et al. [109]		✓		Celebrated order-up-to policy	✓		✓		Order smoothing
Dong et al. [53]	✓	✓		–			✓		Yield uncertainty, reliability improvement and supplier encroachment
Gheibi et al. [54]		✓		Defensive action policy/opportunistic approach			✓		Exchange rate and uncertain demand
Xu et al. [55]		✓		Base-stock and reservation quantity			✓		
Zhou et al. [115]		✓		–			✓		Deterministic demand
Yee et al. [110]		✓		Adaptive dual base-stock policy	✓		✓		Demand distribution changes over time and is only partially observable
This work		✓		DIP and TBS	✓	✓		✓	Comparative study between policies under demand disruptions in a multi-echelon setting.

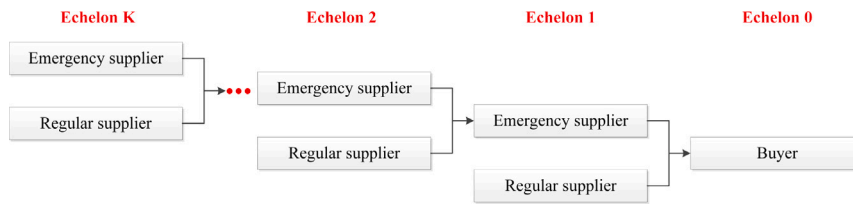


Fig. 1. The multi-echelon inventory system under investigation.

- w_k^r, w_k^e = unit wholesale cost from the k th regular and the k th emergency suppliers;
- Δw_k = wholesale cost difference between the k th emergency and the k th regular suppliers;
- c_k^r, c_k^e = unit manufacturing or purchasing cost of the k th regular and the k th emergency suppliers $k, 1 \leq k \leq K$, and the purchasing cost c_k^e is $\{w_{k+1}^e, w_{k+1}^r\}$ for an emergency supplier who purchases from upstream suppliers ($k \leq K$);
- c_k^{rush} = unit cost for placing a rush order by the k th emergency supplier ($k \geq 1$);
- l_k^e, l_k^r = lead time of the k th emergency and the k th regular suppliers.

3.1.2. Stochastic variable

- D_t = external stochastic demand faced by the buyer in period t . It has a mean (μ_t) and a standard deviation (σ_t).

3.1.3. Decision variables

- S_k^r, S_k^e = regular and emergency base-stock levels under the DIP;
- $Q_{k,t}^r, Q_{k,t}^e$ = quantities ordered from the k th regular and emergency suppliers in period t under the DIP;
- \tilde{S}_k^e = emergency base-stock level in echelon k under TBS policy;
- $\tilde{Q}_{k,t}^e$ = quantity ordered from the k th emergency supplier in period t under the TBS policy.
- \tilde{Q}_k^r = fixed order quantity purchased from the k th regular supplier under the TBS policy;

3.1.4. State variables

- $IP_{k,t}^e, IP_{k,t}^r$ = inventory positions at emergency and regular suppliers in period t and echelon k under the DIP;
- $\tilde{IP}_{k,t}^e$ = inventory position at an emergency supplier in period t and echelon k under the TBS policy;
- x_t^k = starting inventory level in period t and echelon k ;
- y_t^k = inventory level in period t and echelon k after receiving orders.

3.1.5. Performance evaluation

- $\pi_t^B, \tilde{\pi}_t^B$ = buyer's profit in period t under the DIP and TBS policy, respectively;
- $\pi_{k,t}^e, \tilde{\pi}_{k,t}^e$ = profit of the k th emergency supplier in period t under the DIP and TBS policy, respectively;
- $\pi_{k,t}^r, \tilde{\pi}_{k,t}^r$ = profit of the k th regular supplier in period t under the DIP and TBS policy, respectively;
- π_t^{DIP}, π_t^{TBS} = total SC profit in period t under the DIP and TBS policy, respectively.

3.2. DIP

DIP policy keeps track of two inventory positions: regular and expedited inventory positions and employs two basestock levels, one for each of the two suppliers. If the expedited inventory position (on-hand inventory level plus outstanding orders delivered within the emergency lead time minus the backorders) is less than the lower basestock level

at a certain period, then the difference is ordered from the expedited supplier. Next, the regular inventory position is raised to the higher basestock level by ordering from the regular supplier. More specifically, the following sequence of events occurs in each period.

1. We start in period t with the starting inventory level for the buyer ($k = 0$). The buyer reviews its inventory position at the emergency supplier, which is based on the starting inventory level and all outstanding orders from both emergency and regular suppliers.

$$IP_{0,t}^e = x_t^0 + \sum_{i=t-l_1^e}^{t-1} Q_{1,i}^e + \sum_{i=t-l_1^r}^{t-(l_1^r-l_1^e)} Q_{1,i}^r. \quad (1)$$

2. The buyer ($k = 0$) then decides on the emergency quantities to be ordered ($Q_{k+1,t}^e$) to reach the emergency base-stock level.

$$Q_{1,t}^e = (S_0^e - IP_{0,t}^e)^+. \quad (2)$$

3. After considering the emergency order, the buyer updates its inventory position at the regular supplier (Eq. (3)) and decides on the regular order quantities to raise its inventory to the regular base-stock level (Eq. (4)).

$$IP_{0,t}^r = IP_{0,t}^e + Q_{1,t}^e, \quad (3)$$

$$Q_{1,t}^r = (S_0^r - IP_{0,t}^r)^+. \quad (4)$$

4. The customer's external demand (D_t) is subsequently observed. The buyer updates its inventory considering the received quantities from the emergency supplier that were ordered at $t - l_{k+1}^e$ and from the regular supplier at $t - l_{k+1}^r$ and uses the inventory to fulfil the demand in as much as possible.

$$y_t^0 = x_t^0 + Q_{1,t-l_1^e}^e + Q_{1,t-l_1^r}^r. \quad (5)$$

5. The starting inventory level at the next period is the remaining stock or shortage after fulfilling the demand ($x_{t+1}^0 = y_t^0 - D_t$).
6. Finally, the expected profit is calculated as the difference between the total revenue and the total cost. The total cost includes the purchasing costs from the emergency and regular suppliers, the inventory holding, and backordering costs.

$$\pi_t^B = \mathbb{E}(pD_t - w_1^e Q_{1,t}^e - w_1^r Q_{1,t}^r - h^0(y_t^0 - D_t)^+ - b(D_t - y_t^0)^+). \quad (6)$$

7. The emergency supplier in the k th echelon has the same sequence of event (Steps 1–6), but the demand to be fulfilled becomes $Q_{k,t}^e$ instead of the customer's demand (D_t). The emergency suppliers must fulfil their demands; therefore, in the case of stock-out (after realising the demand in Step 4), a rush order is placed ($Q_{k,t}^e - y_t^k$), and the starting inventory level at the next period is calculated as $(y_t^k - Q_{k,t}^e)^+$. The total profit function becomes

$$\pi_{k,t}^e = \mathbb{E}(w_k^e Q_{k,t}^e - w_{k+1}^e Q_{k+1,t}^e - w_{k+1}^r Q_{k+1,t}^r - h^k(y_t^k - Q_{k,t}^e)^+ - c_k^{rush}(Q_{k,t}^e - y_t^k)^+). \quad (7)$$

8. The total profit of the k th regular supplier is calculated as $\pi_{k,t}^r = \mathbb{E}((w_k^r - c_k^r) Q_{k,t}^r)$; the total profit of the K th emergency supplier is calculated similarly as $\pi_{K,t}^e = \mathbb{E}((w_K^e - c_K^e) Q_{K,t}^e)$.
9. The total SC profit under the DIP is:

$$\pi_t^{DIP} = \pi_t^B + \sum_{k=1}^K (\pi_{k,t}^e + \pi_{k,t}^r). \quad (8)$$

3.3. TBS policy

Under the TBS policy, the buyer places every period a fixed order quantity at the regular supplier and fulfils excess demand by ordering

a variable quantity via the expedited supplier. An order is placed at the expedited supplier whenever the inventory position (net inventory plus all outstanding orders from both suppliers minus the backorder quantities) is below the basestock level which depends on the regular supplier order. The sequence of events under the TBS policy is considerably similar to that under the DIP. However, the following differences are present.

1. The inventory position at the regular supplier is not used (in Step 3); instead, a constant regular quantity (\bar{Q}_k^r) is placed. Consequently, the buyer's profit and the k th emergency supplier's profit become

$$\bar{\pi}_t^B = \mathbb{E}(pD_t - w_1^e \bar{Q}_{1,t}^e - w_1^r \bar{Q}_1^r - h^0(y_t^0 - D_t)^+ - b(D_t - y_t^0)^+). \quad (9)$$

$$\bar{\pi}_{k,t}^e = \mathbb{E}(w_k^e \bar{Q}_{k,t}^e - w_{k+1}^e \bar{Q}_{k+1,t}^e - w_{k+1}^r \bar{Q}_{k+1}^r - h^k(y_t^k - \bar{Q}_{k,t}^e)^+ - c_k^{rush}(\bar{Q}_{k,t}^e - y_t^k)^+). \quad (10)$$

2. The total profit of the k th regular supplier ($\bar{\pi}_{k,t}^r$) is no longer a function of the uncertain demand as \bar{Q}_k^r is constant ($\bar{\pi}_{k,t}^r = ((w_k^r - c_k^r) \bar{Q}_k^r)$).
3. The total SC profit under the TBS policy is

$$\pi_t^{TBS} = \bar{\pi}_t^B + \sum_{k=1}^K (\bar{\pi}_{k,t}^e + \bar{\pi}_{k,t}^r). \quad (11)$$

4. Numerical study

Here, we evaluate the performance of the DIP and TBS policy over several instances. In this system, the buyer and emergency suppliers manage inventories and consequently make decisions by optimising their own objective functions. For the regular suppliers, we observe the impact of optimal decisions on their profits. Therefore, the buyer's policy parameters are determined first, followed by the policy parameters of emergency supplier 1, and so on. The policy parameters were determined using the simulation-based optimisation approach. The approach utilises a static simulation to generate demand values from a known distribution and a non-linear solver to optimise the inventory parameters. It was implemented in MATLAB and solved by using the interior-point algorithm, which is a technique used to solve non-linear optimisation problem [118]. In the interior point algorithm, the feasibility region is constrained by $S_k^r \geq S_k^e$ for the DIP and $\bar{Q}_k^r \leq \mu_t$ for the TBS policy and inequality constraints are converted to equality by adding nonnegative slack variables. Then, these nonnegativity constraints are converted to a natural log barrier function ($-\psi \ln(x)$). As ψ decreases in each iteration, it pushes the solution closer to the optimal one by searching the feasible interior region. The objective function with the barrier function is approximated using the Karush-Kuhn-Tucker (KKT) conditions, and the approximated objective function is solved in an iterative process. The Newton-Raphson or the conjugate gradient method is used in each iteration until the KKT tolerance is met [119–121].

We develop a base case in which the wholesale price difference is set to 5. The parameter Δw_1 will be varied in most experiments to illustrate the behaviour of the multi-echelon SC, where Δw_1 plays a critical role in determining the preferred policy [20]. We vary all Δw_k in one of the experiments, where we change the number of echelons, the choice of varying only Δw_1 in the remaining experiments is due to the following two reasons. First, upstream suppliers contribute in insignificant quantities compared to the suppliers in echelon 1; thus, changing Δw_1 will have the highest impact. Second, we would like to limit the number of parameters that changed simultaneously and thus reduce the factors affecting the behaviour of the system. We assume that the external demand follows a Gamma distribution with $\mu_t = 10$. Unless otherwise mentioned, the standard deviation (σ_t) is set to 5. Initially, all regular suppliers and emergency suppliers have a lead time of two periods and one period, respectively. Cost parameters are

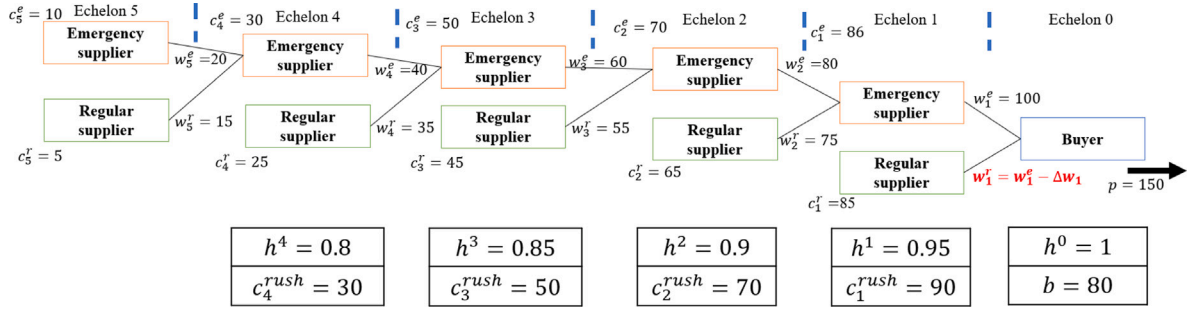


Fig. 2. System structure and cost parameters for the base case.

presented in Fig. 2, which we define as the base case, and the network design choice is explained in Section 4.1. In Section 4.2, we vary the number of echelons to study its impact on the preferred policy. We provide the analysis on different parameters in Appendix A. In Appendix A, we analyse the behaviour of the two policies while varying the level of demand uncertainty; the inventory holding, backorder, and rush costs; and the lead time, respectively. The experiments in Appendix A are conducted using $K = 5$ where the total number of echelons in the SC is $K + 1$.

4.1. Network design choice

The multi-echelon network design used in this paper is inspired by the interview outcomes and extends the single-echelon network design used in [20]. This similarity helps to analyse and understand the impact of the number of echelons. Emergency suppliers are responsive, and to ensure their order fulfilment, they are given the option to place a second instant order (rush order) after the demand is realised. Since regular suppliers are located in less expensive geographical locations; their inventory costs are considered negligible compared to the emergency suppliers. The configuration in this study is an extension to the network of Boulaksil et al. [20]. The cost parameters used in this work follow the same trend in [20] for comparison purposes. Other configurations and further generalisation on the network design can be considered in future research work.

Remark 1. In our multi-echelon configuration, the buyer and emergency suppliers adopt the same policy. This configuration represents the extreme case. We conducted numerical experiments with $K = 5$ while varying the policy among different entities. We verified that adapting TBS only or DIP only represents an extreme case. Although each entity is independent and can choose any policy other than DIP and TBS policy, we limited the choice to be between TBS policy and DIP for the sake of comparison, (see Appendix C.1).

Remark 2. In our configuration and during demand disruption, the adapted policy remains unchanged. This setting represents an extreme case (all DIP or All TBS policy). We conducted experiments while changing the policy during disruption. The total profit boundaries are defined by the cases when DIP and TBS remain unchanged, (see Appendix C.1).

Remark 3. While Schmitt et al. [107] states that dynamic policy parameters during disruption can be beneficial, our analysis showed that it is applicable only for the buyer in the positive disruption case and for the regular upstream suppliers. However, the total SC profit in the positive and negative disruption scenario remains bounded by the cases where policy parameters are not updated, (see Appendix C.2).

Remark 4. Note that varying the selling price p affects the profit magnitude of the buyer only and has no impact on suppliers since the demand is independent of the selling price (see Appendix A.1).

4.2. Effect of the number of echelons

We examined the impact of increasing the number of echelons on the performance of the two policies by considering the base case (Fig. 3(a)). In addition, the cases of varying Δw of all echelons (Fig. 3(b)), high demand variability ($\sigma_i = 20$) (Fig. 3(c)), and low backorder cost ($b = 2$) (Fig. 3(d)) were tested.

Boulaksil et al. [20] showed that for the case of two suppliers and a buyer with $c_1^r < c_1^e$, the DIP outperforms the TBS policy for the entire Δw_1 domain. This result aligns with our finding for $K = 1$. However, our results show that as K increases, the TBS policy starts to outperform the DIP for a wider range of Δw_1 . The difference decreases for large Δw_1 . In particular, at $K = 5$ in the base case, the TBS policy outperforms the DIP for the entire Δw_1 domain (Fig. 3(a)). To better understand the factors that contribute to the preferred policy as the number of echelons increases, we show the profit difference between the TBS policy and DIP in Fig. 4 for the extreme cases $K = 1$ and $K = 5$. The buyer prefers the DIP regardless of the value of Δw_1 , whereas emergency supplier 1 benefits more under the TBS policy. The regular supplier under the TBS policy receives constant orders that are practical and convenient, but the quantities ordered are less than those under the DIP. This reduction in the purchased quantities results in regular supplier 1 preferring the DIP. As the number of echelons increases, the profit difference in emergency supplier 1 increases. Moreover, the upstream and regular suppliers under the TBS policy contribute to the profit gain, thereby leading to a more profitable total SC under said policy. Note that the increase in the profit difference in emergency supplier 1 is justified by the sourcing options from the emergency and regular suppliers or order rushes that become available as the SC extends from $K = 1$ to $K > 1$.

A similar general behaviour (i.e., the increase in the total profit of the TBS policy compared to the DIP as K increases) can be observed in the other cases, especially with a small wholesale price difference between the emergency and regular suppliers. Varying all wholesale prices increases the unit profit of upstream emergency suppliers (Fig. 3(b)). Thus, a policy that depends on an emergency supplier will boost its total profit. However, as more quantities are placed from the regular suppliers with the increase in Δw_k , the total profit decreases rapidly. Under the TBS policy, upstream suppliers are more utilised; under the DIP, only downstream suppliers are used, mainly owing to the high usage of the flexible regular supplier 1.

In the case of a higher level of demand uncertainty, the TBS policy and DIP become insensitive to the increase in the number of echelons when $\Delta w_1 \geq 9$ (Fig. 3(c)). This insensitivity happens because emergency supplier 1 places more rush orders and relies more on regular quantities when under a high variability. Consequently, the SC relies on the downstream echelons, and adding extra echelon has hardly any impact on the total profit. Therefore, the DIP's flexibility outperforms the TBS policy's rigidity at high demand variability and large Δw_1 . The reduction in the total profit under high demand variability (\$360 – \$450) compared to the base case (\$550 – \$750) is due to the increased inventory holding and rush order costs, because the SC tends to build more stock and deliver orders instantaneously to account for variability.

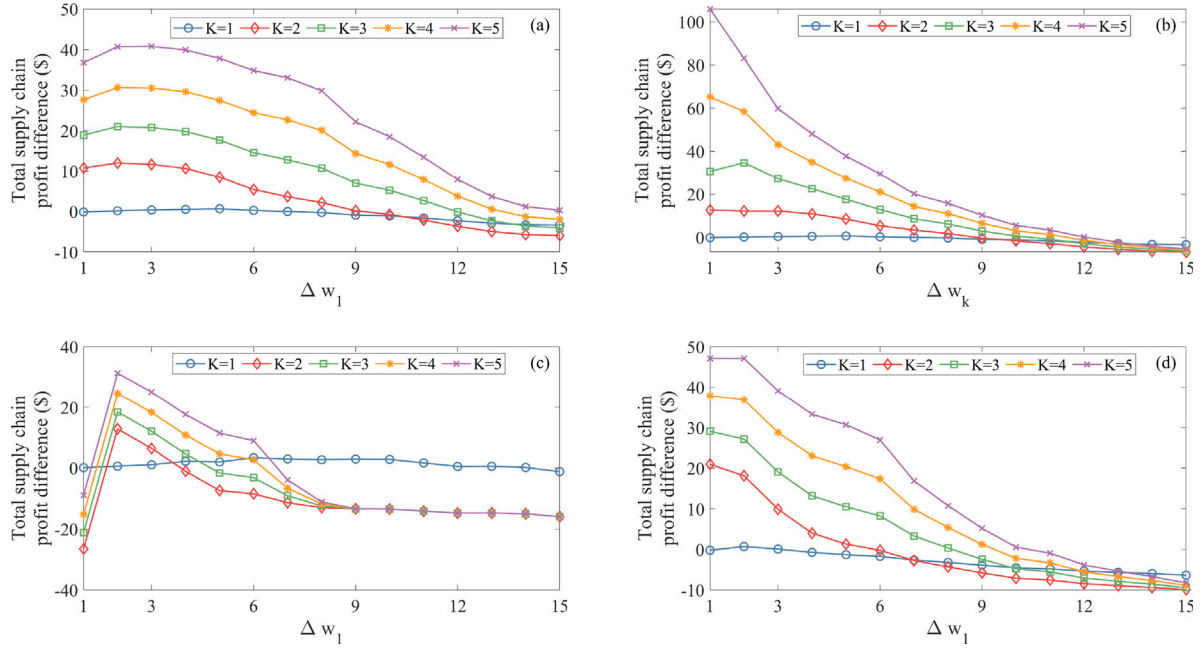


Fig. 3. Total SC profit difference between TBS and DIP (TBS - DIP) as a function of Δw_1 for (a) the base case, (b) the case of varying all Δw_k , (c) high demand variability $\sigma_r = 20$, and (d) low backorder cost $b = 2$.

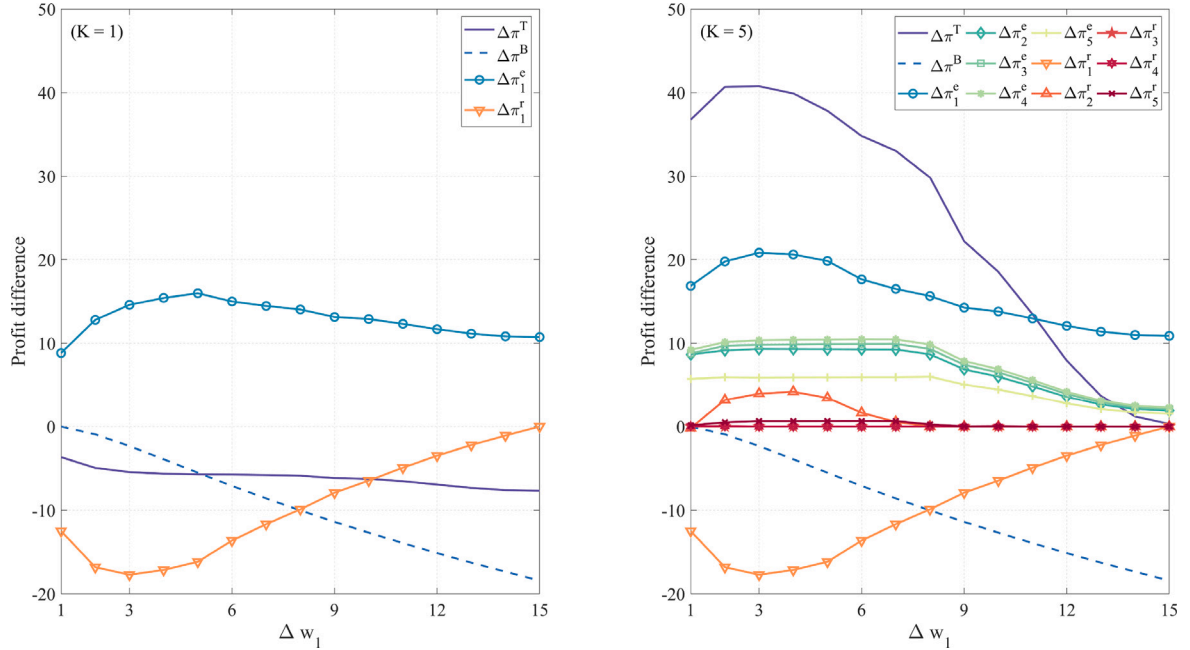


Fig. 4. Difference in profit functions ($\Delta\pi^T = \pi^{TBS} - \pi^{DIP}$, $\Delta\pi^B = \tilde{\pi}^B - \pi^B$, $\Delta\pi^e = \tilde{\pi}_k^e - \pi_k^e$, and $\Delta\pi^r = \tilde{\pi}_k^r - \pi_k^r$) for each party as function of Δw_1 .

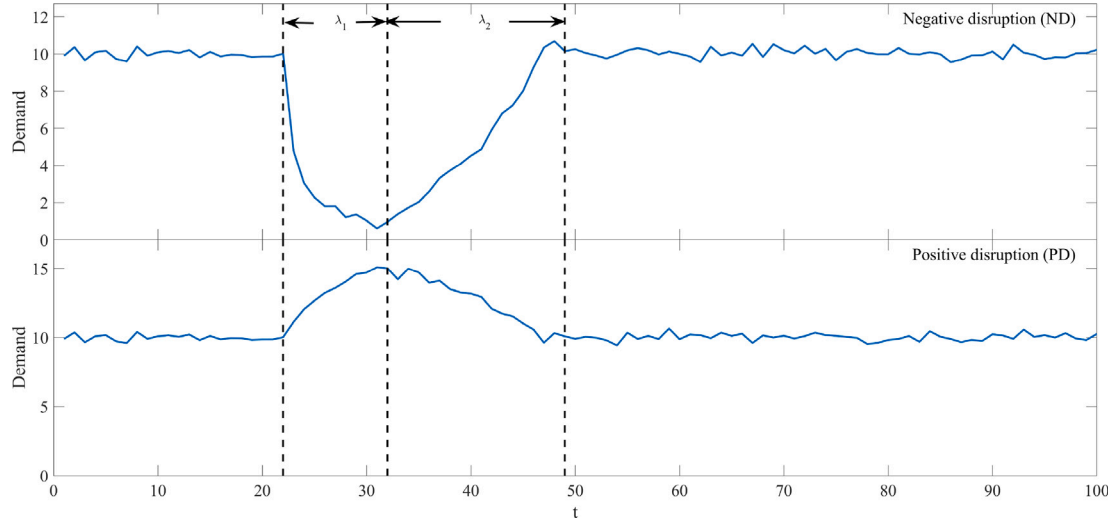
In the case of low backorder cost as in Fig. 3(d), the SC moves to the less expensive option by relying more on the regular supplier as Δw_1 increases. The regular suppliers' flexibility under the DIP allows for a better management of the demand variability than the regular suppliers' rigidity under the TBS, resulting in a better demand matching, fewer backorder quantities, and reduced inventory levels.

When extending the SC from $K = 1$ to $K = 2$, the profit gain under the TBS policy and that under the DIP differ within cases (Table 2). This difference is mainly due to the change in the unit of profit emergency supplier 1. When $K = 1$, the unit profit of emergency supplier 1 is $(w_1^e - c_1^e)$; when $K = 2$, the unit profit depends on the source of purchasing (emergency, regular, or rush). When K increases

from 2 to 5, the profit per added echelon under the TBS policy is around 1.5% higher than that under the DIP. This gain per echelon is not sensitive to the parameter setting (Table 2). The maximum gain per echelon increases in the case of varying all Δw_k compared to the other cases. Moreover, the change in all Δw_k increases the total SC profit under the TBS policy substantially compared to the DIP at small wholesale price differences. This increase is because of the rise in the unit profit of the emergency suppliers when placing orders from the regular suppliers. However, it drops fast owing to the reduction in quantities placed by the buyer at emergency supplier 1, consequently lowering the utilisation of upstream suppliers. For the high level of

Table 2Percentage gain per echelon from the TBS policy over the DIP (max/at $\Delta w_1 = 5$) as the SC grows from $K = 1$ to $K = 5$.

Case	From $K = 1$ to $K = 2$ (%)	From $K = 2$ to $K = 3$ (%)	From $K = 3$ to $K = 4$ (%)	From $K = 4$ to $K = 5$ (%)
Base case	1.95/1.33	1.54/1.51	1.60/1.57	1.63/1.60
Varying all Δw_k	1.98/1.33	3.50/1.51	3.99/1.57	4.25/1.60
$\sigma_t = 20$	3.08/-2.45	1.53/1.53	1.63/1.63	1.70/1.70
$b = 2$	2.75/0.42	1.45/1.45	1.50/1.50	1.53/1.53

**Fig. 5.** Demand behaviour under disruption.

demand uncertainty, the total profit drops as the number of echelons increases from 2 to 3 (Fig. 3(c)).

This profit drop is mainly due to the order rushing option that becomes available for emergency supplier 1, which is used to cope with the high uncertainty level. The profit drop under the TBS policy is greater than that under the DIP at $\Delta w_1 = 5$. Thus, adding one echelon to expand the SC from $K = 1$ to $K = 2$ decreases the profit gain by 2.45% as emergency supplier 1 starts to manage inventory at $K = 2$ (Table 2). Subsequently, the profit gain starts to increase with each added echelon from $K = 2$ to $K = 5$.

5. Impact of demand disruption

Here, the demand becomes subject to disruption, which is a sudden decrease or a sudden increase. The sudden decrease is referred to as “Negative disruption (ND)” and the sudden increase is referred to as “Positive disruption (PD)”. The ND simulates the demand behaviour during the COVID-19 of general products and automobiles. The PD simulates the demand behaviour during the COVID-19 of most edible products and some non-edible products such as paper products and over-the-counter healthcare products. The planning horizon is assumed to be 100 periods (Fig. 5). The first 22 periods represent the pre-COVID-19 situation of stationary demand. With the spread of the COVID-19 virus, customers’ behaviours changed, and stockpiling of several products has begun. The stockpiling behaviour (λ_1) that caused disruption is set to 10 periods. At the end of the stockpiling, customers’ panic ended, and the purchasing behaviour started slowly to return to its normal level (pre-COVID-19 levels). The demand recovery state (λ_2) is set to 17 periods. The remaining periods in the planning horizon represent stationary demand as the behaviour is back to its normal levels.

We study the impact of demand disruption on the base $K = 1$ network reported in Boulaksil et al. [20], and the base $K = 5$ network reported in Section 4 in this paper. In Appendix B, we study the impact of demand uncertainty and the recovery duration.

5.1. Effect of demand disruption

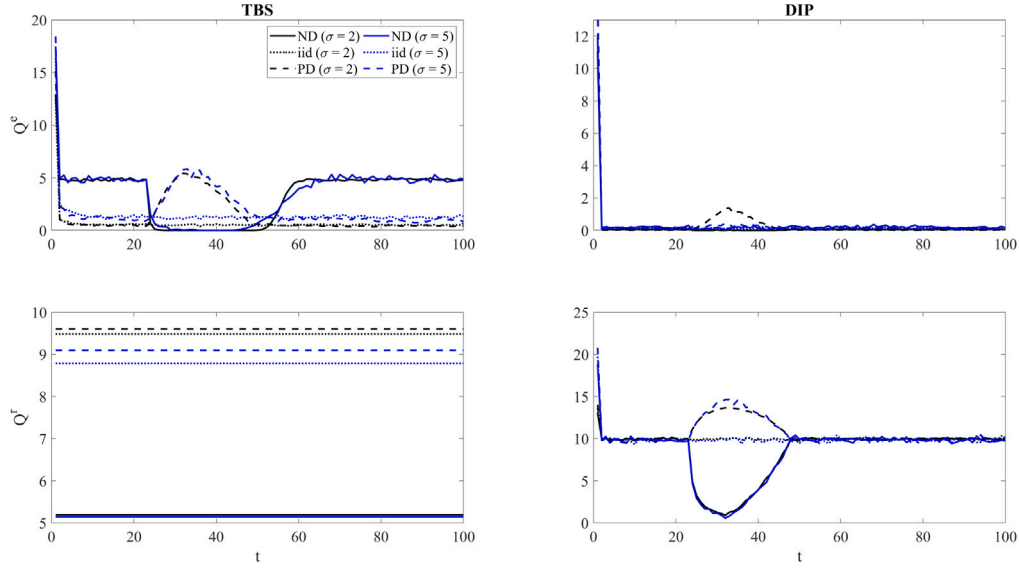
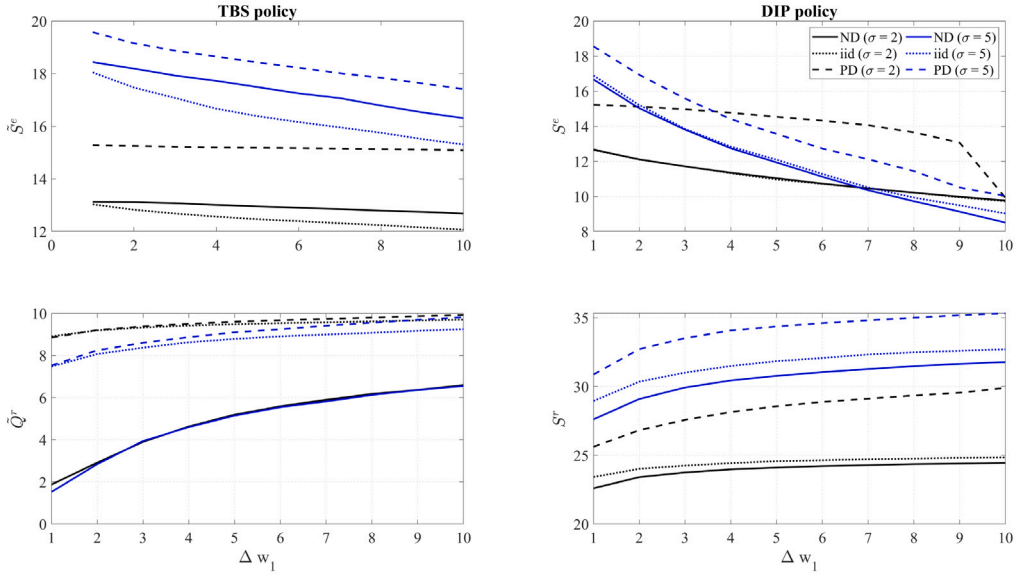
We compare the two policies under disrupted and stationary demand cases for the $K = 1$ and $K = 5$ networks.

5.1.1. $K = 1$

In the ND case, more emergency orders and less regular orders under the TBS policy are placed in the pre-COVID-19 and post COVID-19 periods compared to the stationary demand case (Fig. 6(a)). By contrast, in the PD case, order levels before and after the disruption remain unchanged. The same happens in both cases under DIP.

During the pandemic and in the ND case, orders from the emergency supplier under the TBS policy are significantly reduced as demand drops, and quantities accumulate significantly due to the constant orders from the regular supplier (Fig. 6(a)). Consequently, during the recovery period, the inventory is used first to fulfil demand. The orders from the emergency supplier are resumed when the inventory level goes back to its normal levels pre-COVID-19. In the PD case, orders from the emergency supplier and the inventory are used to respond to the demand changes; emergency orders go back to normal as soon as the demand level goes back to its normal level. The flexible regular supplier under the DIP allows for a better response to demand changes without stocking up large inventories in the ND and PD cases; order quantities from both suppliers are adjusted. In the case of ND, the emergency base-stock level is higher than that in the stationary demand case, and under TBS policy (Fig. 6(b)). The emergency base-stock level under DIP is insensitive to the demand sudden decrease except for large Δw_1 values ($\sigma_t = 5$ and $\Delta w_1 > 7$). Regular base-stock levels under the DIP and TBS policy are lower than that of the stationary demand case. In the PD case, the emergency base-stock level increases significantly compared to the ND case under the TBS policy. The regular base-stock level under the TBS policy, the emergency and regular base-stock levels under the DIP are higher than that of stationary demand case (Fig. 6(b)).

In the ND case, the total SC profit under DIP becomes much higher than that under the TBS policy for a wider Δw_1 range (Fig. 7(a)). Although the emergency supplier secures a higher profit under the TBS

(a) Quantity ordered under the TBS policy and DIP at $\Delta w_1 = 5$.

(b) Policy parameters under the TBS policy and DIP in the ND and PD cases.

Fig. 6. Quantity and policy parameters under the TBS policy and DIP.

policy than under DIP, the additional profit secured by the buyer and regular supplier under DIP is more dominant. It leads to a significant increase in the total SC profit under the DIP. In the PD case, TBS policy outperforms for a wider Δw_1 range. The profit of the buyer and the regular supplier under DIP increased slightly while the profit of the emergency supplier under TBS policy increased significantly; thus, the SC under the TBS policy outperforms that under the DIP for a wider Δw_1 range.

5.1.2. $K = 5$

In both disruption cases, ordering behaviour by the upstream suppliers follows the same behaviour as in the buyer's behaviour described in $K = 1$ network as the demand propagate through the network. The total SC profit increases under the TBS policy in the ND case compared to the stationary demand case, although the total demand

is less in the former case (Fig. 7(b)). The total SC profit quickly drops as Δw_1 increases. The explanation for the profit increase is that more utilisation of the emergency orders increases the upstream suppliers' contribution. The total supply profit chain under the DIP and the ND case is less than stationary demand but behaves the same as Δw_1 changes. The difference in the profit between the two policies increased significantly under disruption compared to the stationary case. The PD case contributes to increasing the profit difference between the two policies due to the significant use of emergency suppliers.

6. Impact of wholesale price

Here, we summarise the impact of varying the wholesale price on the policy preference for the experiments conducted in Sections 4 and 5. Table 3 provides the maximum relative profit difference between

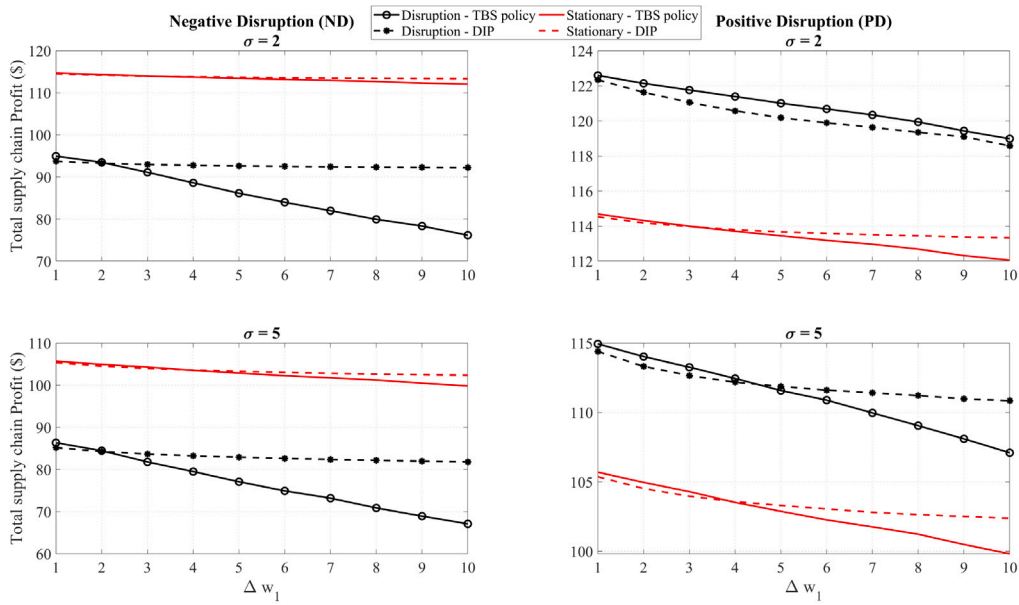
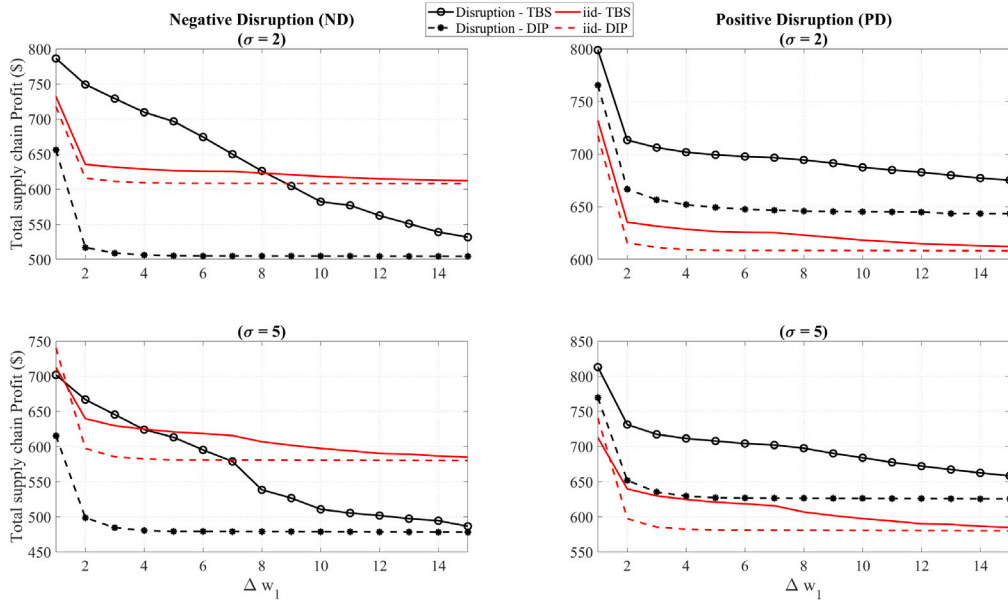
(a) In $K = 1$ SC network.(b) In $K = 5$ SC network.

Fig. 7. Profit under the TBS policy and DIP for the different standard deviation cases.

the two policies ((DIP–TBS) and (TBS–DIP)) and Δw^* , indicating the wholesale price range where the preferred policy changes for the different number of echelons.

In all cases except for that of high demand variability and immense lead times of all suppliers, the difference between the two policies (DIP–TBS) is less than 2% when the DIP is the preferred policy. However, when the TBS policy is preferred, relative differences can reach 12% for $K = 5$. In addition, as the number of echelons increases, the DIP is preferred only at a larger wholesale price difference between the emergency and regular suppliers.

Table 4 shows the relative profit difference between the two policies and the wholesale price difference at which the preferred policy changes (Δw^*) under different conditions. Table 4 also clarifies the relationship between various conditions and the range of Δw_1 where the preferred policy changes. For instance, increasing all holding costs

results in slight differences between the two policies (around 1%). Varying all holding costs from 10 to 25 results in almost the same relative profit difference, which indicates that both policies behave similarly for this range. Notably, the wholesale price at which the preferred policy changes decreases as the unit inventory holding cost increases. Increasing the holding cost of the buyer makes the TBS policy preferable with a difference of up to 11.6%. Varying rush cost, low demand uncertainty, or high backorder cost does not change the preferred policy, whereas a high demand variability changes the preferred policy from the TBS policy to the DIP. Moreover, as demand variability or the lead time of all suppliers increases, the switch in the preferred policy occurs at a smaller wholesale price difference.

In the case of demand disruption, as the demand variability increases from $\sigma_i = 2$ to 5 the maximum difference between both policies slightly increases in short networks with ND (Table 4). In the case of

Table 3

Maximum relative total SC profit difference between the two policies while varying the number of echelons.

K	DIP–TBS (%)	TBS–DIP (%)	Δw^*	DIP–TBS (%)	TBS–DIP (%)	Δw^*
Base case ($b = 80$ and $\sigma_i = 5$)			Base case while varying all Δw_k			
1	0.58	0.12	6–7	0.58	0.12	6–7
2	1.04	1.98	9–10	1.18	2.05	8–9
3	0.70	3.42	11–12	1.09	5.51	10–11
4	0.34	4.95	13–14	1.00	8.94	11–12
5	N/A	6.50	N/A	0.93	12.24	12–13
Base case but with $\sigma_i = 20$			Base case but with $b = 2$			
1	0.30	0.86	14–15	1.02	0.11	3–4
2	6.28	3.24	1–2&3–4	1.62	2.82	5–6
3	4.95	4.58	1–2&4–5	1.53	4.18	8–9
4	4.35	6.01	1–2&6–7	1.44	5.58	9–10
5	4.35	7.51	1–2&6–7	1.34	7.02	10–11

PD, short networks move from preferring TBS policy independently from the Δw_1 to preferring TBS when $\Delta w_1 < 5$, where the maximum relative difference slightly changed. Changing the recovery duration has more impact in the ND case compared to the PD case. By contrast, in extended networks, the preferred policy (the TBS policy) remains unchanged. The maximum relative difference between the two policies only decreases as the demand variability increases in the ND case (Table 4).

7. Summary of results and managerial insights

The following points summarise the main observations from the conducted experiments on extending the number of echelons and studying the multi-echelon SC behaviour under different parameter settings and stationary demand.

- As the number of echelons increases, the TBS policy becomes the preferred policy primarily because of the contribution of the emergency suppliers in the higher echelons to the total profit. The flexibility in the DIP allows the inventory system to rely on a few echelons (up to $K = 2$), whereas upstream emergency suppliers are more often used under the TBS policy.
- Adding one more echelon increases the difference between the TBS policy and DIP by 1.5% when Δw_1 is small and 0.5% when Δw_1 is large. However, when the variability increases, adding an extra echelon increases the relative difference by almost 0.5% when Δw_1 is small but has no impact when Δw_1 is large because the system relies only on downstream echelons (up to $K = 2$).
- The flexibility of the DIP is preferred under the following conditions: high inventory holding costs in all echelons, an extremely low backorder cost, a high level of demand uncertainty, or long suppliers' lead times.
- The responsiveness of the TBS policy is preferred under the following conditions: a considerably low holding cost in all echelons, a high inventory holding cost at the buyer level, a high backorder cost, a low demand variability, and considerably slow regular suppliers. This policy is also preferable when rush costs decrease, which promotes more quantities from emergency supplier 1, and increase, which encourages the involvement of upstream emergency suppliers.
- The SC becomes more profitable under the TBS policy as the lead time difference increases; in the case where all suppliers become slow, the SC secures more profit under the DIP. Moreover, upstream stages are hardly used under conditions such as a high demand variability or long suppliers' lead times, where even the TBS policy avoids relying on upstream suppliers and the system is used up to $K = 2$. This result leads the DIP to outperform the TBS policy.

- In the case of higher echelons (e.g., $K = 5$), the relative profit difference between the DIP and TBS policy is insignificant if the DIP outperforms the TBS policy (a maximum relative difference of less than 2% is observed). However, if the TBS policy outperforms the DIP, the relative difference may reach 12%. This indicates that the preferred policy should be set carefully to maximise the SC profits. The policy choice criticality depends highly on the cost settings. For example, the policy choice in the case of high inventory holding cost (e.g., $h^k = 25$ with a relative difference of 0.68% and 0.71% towards the DIP and TBS policy, respectively) is less critical than the case of low backorder cost (e.g., $b = 20$ with a relative difference of 0.08% and 6.63% towards the DIP and TBS policy, respectively).
- In most of the experiments and in a multi-echelon environment, the TBS policy is preferred when the wholesale price difference between the emergency supplier 1 and regular supplier 1 is small despite other parameter changes. The preferred policy might switch with the increase in the wholesale price difference.

The following points summarise the main findings from the conducted experiments under demand disruption.

- In short SCs (i.e., $K = 1$), the SC under DIP outperforms the SC under the TBS policy for a wider range of Δw_1 in the ND case, and the SC under the TBS policy becomes the preferred one in industries that might face PD.
- When $K = 1$, the SC under the TBS policy becomes the preferred policy as the demand recovery duration increases in the ND case for a wider Δw_1 range. By contrast, in the PD case, the DIP outperforms the TBS policy for a wider Δw_1 .
- In a multi-echelon network, the SC under the TBS policy can secure higher total profit in the case of ND than the stationary demand because of the increased contribution of the upstream suppliers. In addition, disruption does not lead to a change in the preferred policy.
- In a multi-echelon network, the dependency on emergency suppliers increases with the recovery duration and consequently the responsiveness of the TBS policy becomes significantly important compared to the flexibility of the DIP.

Managers are recommended to strategically choose between these policies based on several parameters, such as the inventory holding costs, backorder costs, level of demand uncertainty, and supplier lead times. For instance, if a company has high inventory holding costs and faces high demand uncertainty, it would be advantageous to opt for the DIP policy, as it offers more flexibility. On the other hand, if the backorder costs are high, or the regular suppliers are slow, choosing the TBS policy would be beneficial. In addition, managers need to consider the size of their SCs (number of echelons) and the extent of reliance on emergency suppliers when designing and operating their SCs. For instance, if demand variability is high or supplier lead times are long, relying heavily on higher echelons or upstream suppliers may not be the best strategy, even under the TBS policy. On the contrary, when dealing with slow regular suppliers or a low holding cost, involving upstream emergency suppliers can prove beneficial.

One key takeaway for SC managers is the need to assess cost settings closely when choosing their operational strategy, deciding between DIP and TBS policies in particular. Such decisions, when made correctly, can lead to substantial improvements in the SC performance. Hence, SC managers need to conduct thorough cost analyses prior to making policy decisions. This is a crucial step towards making informed choices that align with the organisation's financial objectives. When inventory holding costs are high, the decision between DIP and TBS policies does not greatly impact the profit margins. In these circumstances, SC managers have a bit more flexibility in policy selection. Thus, other strategic factors might be prioritised in the decision-making process,

Table 4

Maximum relative total SC profit difference between the two policies under different conditions.

Condition	DIP–TBS (%)	TBS–DIP (%)	Δw^*	Condition	DIP–TBS (%)	TBS–DIP (%)	Δw^*
$h^k = 5$	1.00	2.01	7–8	$h^0 = 5$	N/A	7.51	N/A
$h^k = 10$	0.83	1.01	4–5	$h^0 = 10$	N/A	8.89	N/A
$h^k = 15$	0.74	0.75	4–5	$h^0 = 15$	N/A	10.07	N/A
$h^k = 20$	0.68	0.71	4–5	$h^0 = 20$	N/A	11.06	N/A
$h^k = 25$	0.69	1.05	4–5	$h^0 = 25$	N/A	11.57	N/A
$C_k^{rush} - 30$	N/A	6.58	N/A	$C_k^{rush} + 30$	N/A	8.57	N/A
$C_k^{rush} - 20$	N/A	4.24	N/A	$C_k^{rush} = 75$	N/A	3	N/A
$C_k^{rush} - 10$	N/A	2.08	N/A	$C_k^{rush} = 85$	0.4	1.7	10–11
$C_k^{rush} + 10$	N/A	8.93	N/A	$C_k^{rush} = 95$	N/A	7.17	N/A
$C_k^{rush} + 20$	N/A	8.98	N/A	$C_k^{rush} = 100$	N/A	7.09	N/A
$\sigma_i = 1$	N/A	1.59	N/A	$\sigma_i = 20$	4.66	7.89	7–8
$\sigma_i = 2.5$	N/A	3.99	N/A	$\sigma_i = 25$	6.47	4.83	1–2&4–5
$\sigma_i = 7.5$	2.43	8.74	1–2&14–15	$\sigma_i = 30$	9.16	N/A	N/A
$\sigma_i = 10$	2.23	9.18	11–12	$\sigma_i = 35$	15.51	2.41	1–2
$\sigma_i = 15$	3.49	10.34	8–9				
$b = 2$	1.34	7.02	10–11	$b = 60$	N/A	6.65	N/A
$b = 20$	0.08	6.63	14–15	$b = 100$	N/A	6.59	N/A
$b = 40$	N/A	6.55	N/A	$b = 120$	N/A	6.64	N/A
$l_k^e = 3, l_k^e = 1$	N/A	7.97	N/A	$l_k^e = 3, l_k^e = 1$	N/A	6.96	N/A
$l_k^e = 4, l_k^e = 1$	N/A	9.41	N/A	$l_k^e = 4, l_k^e = 1$	N/A	6.99	N/A
$l_k^e = 5, l_k^e = 1$	N/A	13.37	N/A	$l_k^e = 5, l_k^e = 1$	N/A	10.82	N/A
$l_k^e = 3, l_k^e = 2$	1.49	3.65	10–11	$l_k^e = 3, l_k^e = 2$	0.15	7.14	14–15
$l_k^e = 4, l_k^e = 3$	1.68	2.04	5–6	$l_k^e = 4, l_k^e = 3$	0.61	7.72	13–14
$l_k^e = 5, l_k^e = 4$	1.81	1.90	4–5	$l_k^e = 5, l_k^e = 4$	0.52	8.32	13–14
$l_k^e = 6, l_k^e = 5$	2.12	1.73	4–5	$l_k^e = 6, l_k^e = 5$	0.89	9.27	13–14
$l_k^e = 7, l_k^e = 6$	2.45	1.59	3–4	$l_k^e = 7, l_k^e = 6$	0.87	10.45	14–15
$l_k^e = 8, l_k^e = 7$	3.11	4.25	3–4	$l_k^e = 8, l_k^e = 7$	1.29	13.02	14–15
$l_k^e = 9, l_k^e = 8$	4.49	4.37	3–4	$l_k^e = 9, l_k^e = 8$	2.11	17.23	13–14
$l_k^e = 10, l_k^e = 9$	8.05	9.35	2–3	$l_k^e = 10, l_k^e = 9$	4.33	25.91	13–14
ND, $K = 1, \sigma_i = 2$	21.1	1.29	2–3	PD, $K = 1, \sigma_i = 2$	N/A	0.68	N/A
ND, $K = 1, \sigma_i = 5$	21.9	1.34	2–3	PD, $K = 1, \sigma_i = 5$	3.50	0.62	4–5
ND, $K = 5, \sigma_i = 2$	N/A	31.0	N/A	PD, $K = 5, \sigma_i = 2$	N/A	7.18	N/A
ND, $K = 5, \sigma_i = 5$	N/A	25.2	N/A	PD, $K = 5, \sigma_i = 5$	N/A	11.5	N/A
ND, $K = 1, \lambda = 32$	22.9	2.47	3–4	PD, $K = 1, \lambda = 32$	4.52	0.71	4–5
ND, $K = 1, \lambda = 42$	16.5	3.54	5–6	PD, $K = 1, \lambda = 42$	5.56	0.71	4–5
ND, $K = 5, \lambda = 32$	N/A	36.5	N/A	PD, $K = 5, \lambda = 32$	N/A	14.9	N/A
ND, $K = 5, \lambda = 42$	N/A	40.0	N/A	PD, $K = 5, \lambda = 42$	N/A	16.3	N/A

such as operational efficiency or customer service considerations. In contrast, when backorder costs are low, the chosen policy can significantly influence profit margins. The impact of policy choice is more profound in such scenarios, indicating that careful consideration should be given to policy selection. Managers should be aware that a strategic decision at this juncture could yield considerable financial benefits. The occurrence of demand disruptions and the duration of recovery significantly affect the performance of the SC under both TBS and DIP policies. Therefore, businesses need to be prepared for such disruptions and plan their policies accordingly. For shorter SCs ($K = 1$), DIP seems to perform better in decreasing demand cases, while TBS is preferable when demand spikes are expected. This trend changes with increasing demand recovery duration. For multi-echelon networks, increased dependency on emergency suppliers with recovery duration makes the TBS policy more important compared to the flexibility of DIP.

Finally, managers are recommended to closely monitor and evaluate the wholesale price differences between regular and emergency suppliers. Changes in these price differences can influence the preferred policy between DIP and TBS. Managers should dynamically evaluate and select their sourcing policies based on their specific cost structures, SC structure (number of echelons), and market conditions (such as demand variability and supplier lead times). They should also be prepared to adapt their strategies in response to disruptions and changes in recovery duration.

8. Conclusions and future work

In this paper, a multi-echelon dual-sourcing setting was studied in which the performance of two policies, namely, the DIP and TBS policy, was compared. Through numerous experiments, the TBS policy was found to outperform the DIP when the SC was extended, namely, when

the number of echelons increased under normal setting. This is mainly due to the dependency of the TBS policy on upstream suppliers; such a dependency does not hold under the DIP. In addition, the following cases in which the DIP is preferred over the TBS policy in a multi-echelon system were presented: a high level of demand uncertainty, long lead times of both emergency and regular suppliers, high inventory holding cost in all echelons, and extremely low backorder cost. In addition, several parameters were varied, such as the inventory holding cost, backorder cost, rush cost, level of demand uncertainty, and the lead times. Increasing the inventory holding cost in all echelons yielded conservative ordering behaviour to avoid building up inventories. The flexibility of regular suppliers under the DIP outperformed emergency suppliers' responsiveness under the TBS policy because emergency suppliers tended to rush more orders. Further, high backorder cost increased the need for responsiveness and, consequently, dependency on upstream emergency suppliers. Reducing rush costs made responsiveness less expensive and, because the TBS policy is more responsive than the DIP, secured more profit. Conversely, increasing rush costs reduced rush orders but increased the profit contribution of upstream suppliers under the TBS policy compared to the DIP. In the case of a high level of demand uncertainty, the SC used its flexible regular suppliers under the DIP, whereas it placed more expensive rush orders under the TBS policy. Therefore, more profit was generated by SC systems under the DIP. As both suppliers became slow in delivering orders, upstream suppliers became unnecessary under both policies. Because there were fewer rush orders under the DIP than the TBS policy owing to the flexibility of regular suppliers, the DIP achieved a slightly higher total profit. In the case of demand disruption, the TBS policy becomes dominant when demand suddenly drops in short supply networks with the recovery duration increase. In addition, it is preferred when a product is subject to demand spike in short networks when demand variability is low, or demand recovery duration is short.

The findings from this research provide managers with clear guidance for strategically choosing between the two policies – DIP and TBS – in a multi-echelon dual-sourcing setting. Decisions regarding policy selection can be influenced by a variety of factors, such as inventory holding costs, backorder costs, level of demand uncertainty, and supplier lead times. For example, if a company experiences high inventory holding costs coupled with a high level of demand uncertainty, it may benefit from opting for the DIP policy, due to its inherent flexibility. Conversely, in cases of high backorder costs or slow regular suppliers, the TBS policy could be a better choice. In addition to these parameters, managers need to take into account the size and structure of their SCs, especially the number of echelons and the extent of reliance on emergency suppliers. This is particularly important when dealing with high demand variability or long supplier lead times. Even under the TBS policy, overreliance on higher echelons or upstream suppliers might not be the most advantageous strategy. On the other hand, in situations where regular suppliers are slow or holding costs are low, engaging upstream emergency suppliers (i.e. the TBS policy) could provide substantial benefits. The ability to adapt to these varying conditions underlines the importance of cost analysis in policy decision-making. With a thorough cost analysis, managers can make informed choices that align with their financial objectives, potentially leading to significant improvements in SC performance. Another critical point for managers to consider is the occurrence of demand disruptions and their recovery durations. Both TBS and DIP policies are significantly affected by these disruptions, thus necessitating proactive planning and adaptation. For shorter SCs, the DIP policy might be preferable in decreasing demand cases, while TBS could be better suited for handling demand spikes. However, this tendency changes with longer recovery durations. In multi-echelon networks, increased dependency on emergency suppliers during recovery makes the TBS policy more advantageous, compared to the flexibility offered by DIP. Managers must be prepared to adapt their strategies in response to disruptions, changes in recovery durations, and shifts in the marketplace. By doing so, they can maintain the resilience and effectiveness of their SCs, ensuring optimal performance under a variety of conditions.

This research offers guidance for managers on choosing between the DIP and TBS policies in multi-echelon dual-sourcing contexts. Policy choice can be shaped by factors such as inventory costs, backorder costs, demand uncertainty, and supplier lead times. High inventory costs and demand uncertainty may favour DIP for its flexibility. However, if backorder costs are high or regular suppliers are slow, TBS may be a better fit. Along with these parameters, SC size and structure, number of echelons, and reliance on emergency suppliers should be considered, especially with high demand variability or long lead times. Overreliance on higher echelons or upstream suppliers under TBS might not always be advantageous. But, when regular suppliers are slow or holding costs are low, upstream emergency suppliers under TBS can offer substantial benefits. Thus, cost analysis is crucial for informed policy decisions that enhance SC performance. Additionally, managers must account for demand disruptions and recovery durations. Both TBS and DIP are significantly impacted by disruptions, demanding proactive planning. In shorter SCs, DIP may be more suitable for decreasing demand, while TBS can handle demand spikes. This dynamic shifts with longer recovery durations. In multi-echelon networks, increased reliance on emergency suppliers during recovery makes TBS more beneficial, as compared to DIP's flexibility. Thus, managers need to adapt to disruptions, recovery duration changes, and marketplace shifts, maintaining SC resilience and optimal performance under various conditions.

This research can be extended in various ways. In this study, we considered a serial multi-echelon SC configuration where each emergency supplier can place orders from two suppliers. Future studies might consider different SC configurations, such as the possibility of having a distribution centre, a supplier who fulfils the demands of multiple customers, or skipping some echelons. Such analyses could

underscore the impact of the SC configuration on the preferred policy. One potential direction is to focus on the food and pharmaceutical industries, where products may be perishable, and industries have strict regulations. Alternatively, the fashion industry's seasonality and trend sensitivity could present unique challenges worth exploring. Future research might also investigate the impact of sustainability in the SC on the choice and effectiveness of these policies. This could include exploring how the demand for sustainable sourcing or fair trade might impact SC structures and sourcing strategies. Another promising avenue for future research is to investigate the theoretical properties of the optimal policy in multi-echelon settings. While deriving formal results is challenging due to the complex nature of the demand function, future studies could formulate conjectures based on numerical experiments obtained in this work and attempt to prove them rigorously. Additionally, developing new heuristic strategies grounded in the characteristics of multi-echelon systems could enhance both the theoretical and practical understanding of such policies.

CRediT authorship contribution statement

Sadeque Hamdan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Formal analysis, Conceptualization. **Youssef Boulaksil:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Kilani Ghoudi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization, Formal analysis. **Younes Hamdouch:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Funding

This work was supported by the UPAR grant from the UAEU Research Office under Grant [number 12B033].

Declaration of competing interest

No potential conflict

Appendix A. Effect of varying parameters under stationary demand

In this [Appendix A](#), we analyse the behaviour of the two policies while varying the selling price, the level of demand uncertainty; the inventory holding, backorder, and rush costs; and the lead time, respectively. The experiments in [Appendix A](#) are conducted using $K = 5$ where the total number of echelons in the SC is $K + 1$.

A.1. Varying selling price (p)

We investigate the impact of the unit selling price to the external customer p on the quantities ordered by the buyer and the total supply chain profit. We examine four scenarios with selling prices $p = \{110, 150, 200, 250\}$. The results are presented in [Figs. 8 and 9](#).

[Fig. 8](#) illustrates that the quantities ordered from the emergency and regular suppliers under both the DIP and TBS policies remain unaffected by variations in the selling price p . This result is consistent with the nature of the demand, which is independent of the selling price. The consistent ordering quantities confirm that the selling price influences only the buyer's profit and not the supplier decisions or the inventory dynamics within the supply chain.

[Fig. 9](#) demonstrates how the total supply chain profit difference between the TBS and DIP policies (TBS - DIP) changes as a function

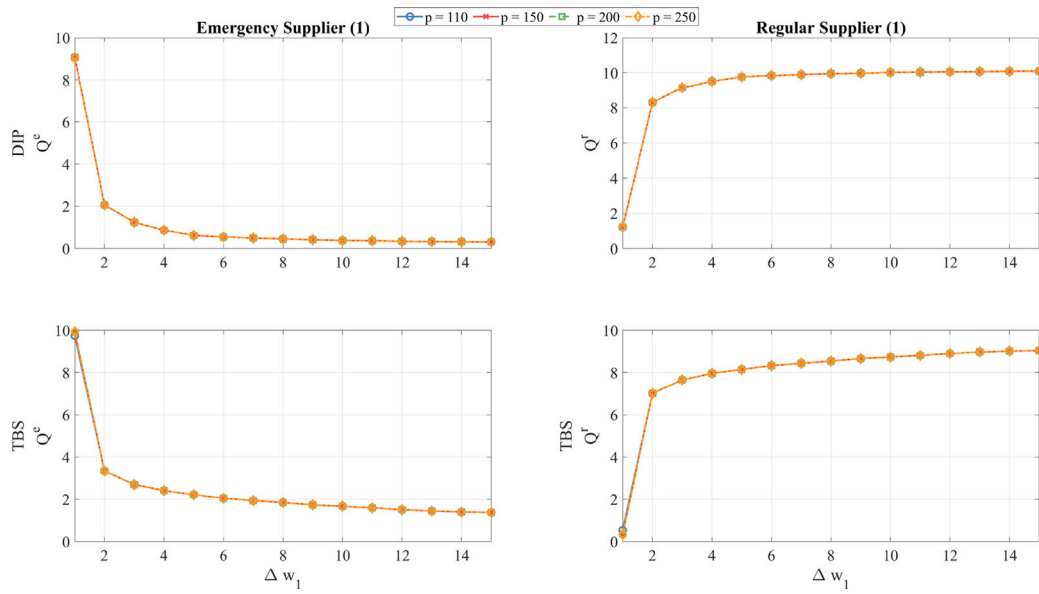


Fig. 8. Quantities ordered under the DIP and TBS policy while varying p .

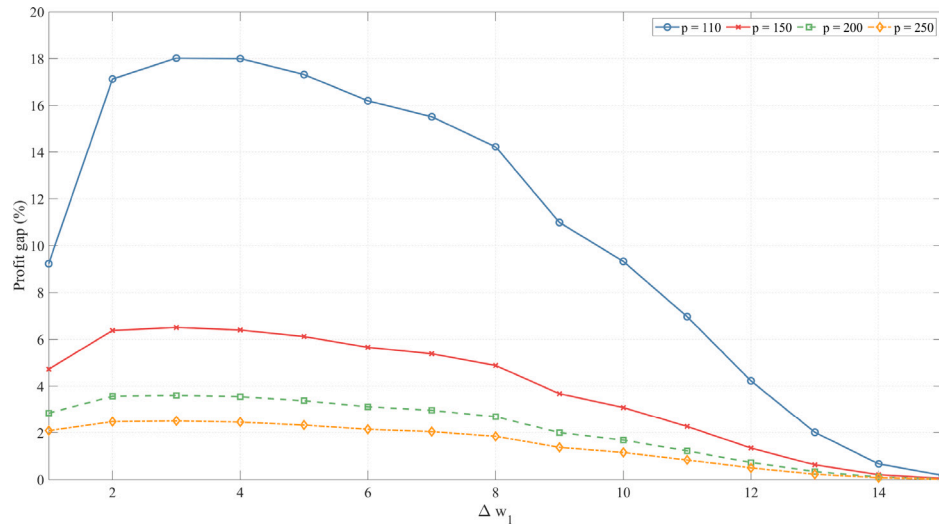


Fig. 9. Total SC profit difference between TBS and DIP (TBS - DIP) as a function of Δw_1 for different selling prices.

of Δw_1 , under different selling prices. As the selling price p increases, the profit gap between the TBS and DIP policies narrows. This trend indicates that higher profit margins for the buyer, who prefers DIP, diminish the relative performance advantage of the TBS policy over the DIP policy. The profit difference peaks at Δw_1 values around 3 to 4, particularly for lower selling prices. For larger values of Δw_1 , the profit difference diminishes across all selling prices, reflecting a convergence in the performance of the TBS policy and DIP.

A.2. Varying holding costs (h^k)

We also conduct experiments by varying the unit inventory holding cost (h^k) to study its impact. In Case 1, we increase all holding costs simultaneously, which are multiplied by a factor $\delta = \{1, 5, 10, 15, 20, 25\}$; in Case 2, we only increase the buyer's holding cost using the same δ . Fig. 10(a) and (b) show the relative difference between the TBS policy and DIP (calculated as $100 \times \frac{\pi^{TBS} - \pi^{DIP}}{\pi^{TBS}}$) in Cases 1 and 2, respectively, $\Delta w_1 = 5$.

In Case 1, as the unit inventory holding cost increases, the relative profit difference between the TBS policy and DIP decreases. At a high

unit holding cost, the DIP starts outperforming the TBS policy because the suppliers become more conservative in ordering when the inventory holding cost increases in all echelons. They prefer rushing orders, that is, placing orders after the demand is revealed to avoid building up expensive inventories. The result shows that the base-stock level from emergency supplier 1 under the TBS policy remains relatively high. Moreover, orders from emergency supplier 1 are fulfilled mostly as rush, and upstream emergency suppliers are hardly used. Consequently, the responsiveness of the emergency suppliers becomes costly, and with the rigidity of the regular suppliers, the DIP starts to outperform the TBS policy.

By contrast, the relative profit difference increases as the buyer's inventory holding cost increases, and the SC continues to perform better under the TBS policy (Case 2). This result is due to the emergency suppliers' high responsiveness in all echelons under the TBS policy. Meanwhile, the DIP relies more on its regular supplier's flexibility. Only the buyer avoids building up inventories and the unaffected inventory holding cost at the emergency supplier level; hence, the involvement of upstream emergency suppliers remains profitable under the TBS policy and contributes to the increased total profit.

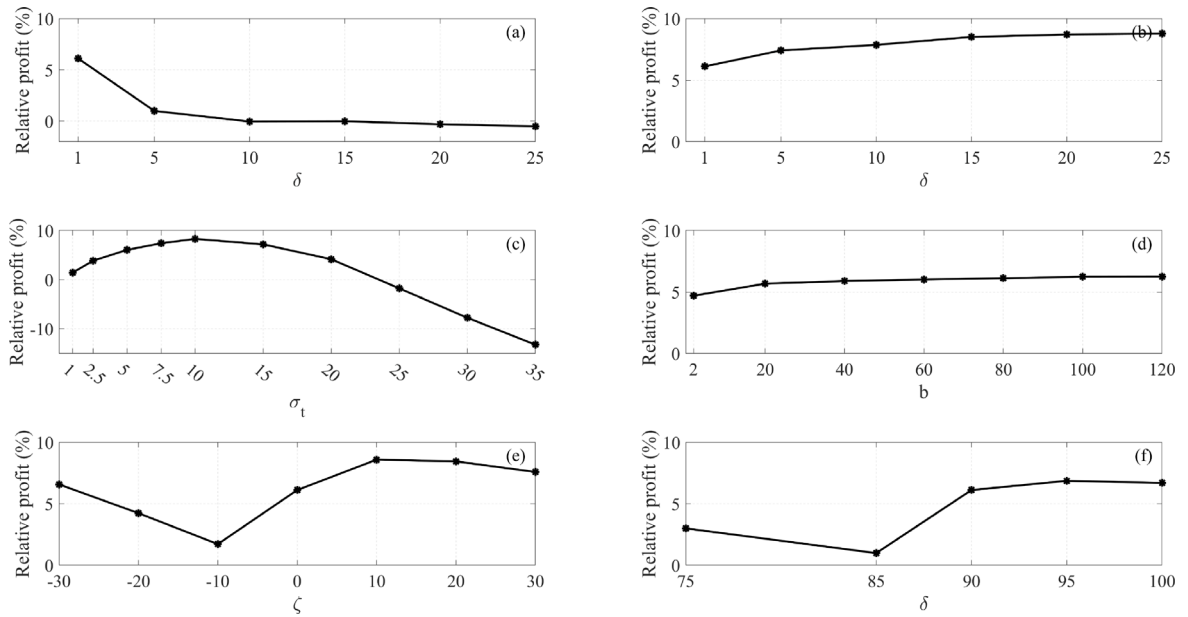


Fig. 10. Relative profit difference between the TBS policy and DIP at $\Delta w_1 = 5$ for varying (a) all holding costs h^k ("Case 1"); (b) the buyer's holding cost h^0 ("Case 2"); (c) demand uncertainty σ_t ; (d) backorder cost b , (e) all rush costs c_k^{rush} , and (f) rush cost of emergency supplier 1 c_1^{rush} .

A.3. Varying demand uncertainty (σ_t)

We conduct additional experiments with the two policies' behaviour by varying demand uncertainty value $\sigma_t = \{1, 2.5, 5, 7.5, 10, 15, 20, 25, 30, 35\}$; see Fig. 10(c) for the relative profit difference at $\Delta w_1 = 5$. At $\sigma_t = 1$, the two policies behave similarly as the demand is almost deterministic. Placing constant orders at the less expensive supplier (regular supplier 1) is the most cost-efficient policy because the demand is almost constant.

As the variability (σ_t) increases from 1 to 10, more profit is secured under the TBS policy than the DIP because of the emergency suppliers' involvement in compensating for the regular suppliers' rigidity. In this situation, building inventories is more beneficial than rushing orders. Consequently, order levels from upstream emergency suppliers remain high, leading to more profit under the TBS policy.

As demand variability (σ_t) increases beyond 10, the relative difference between the TBS policy and DIP starts decreasing. Under the TBS policy, the emergency suppliers in higher echelons ($K = 2, \dots, 5$) are replaced by rush orders, which increases the flexibility and responsiveness cost. This increase leads the DIP to become the preferred policy. Because the emergency and regular suppliers deliver after the lead time, the SC absorbs uncertainty either by building inventories or rushing orders, which guarantees immediate availability. As the demand variability increases, more inventories become needed, thereby resulting in higher holding costs. Consequently, the SC switches from building inventories to rushing orders when the cost incurred from rushing orders becomes less than the cost from building inventories.

In general, the analysis for the different Δw_1 values reveals that the high variability drives the increase in base-stock level from emergency supplier 1 under the DIP. However, the base-stock level decreases significantly as Δw_1 increases, and most of the demand is fulfilled through regular supplier 1 because of its flexibility. Orders from emergency supplier 1 are fulfilled mainly as rush orders. Under the TBS policy, the base-stock level of emergency supplier 1 is less sensitive to the change in Δw_1 . Orders from emergency supplier 1 are primarily fulfilled as rush orders and as orders from upstream emergency suppliers.

Remark 5. The experiment was repeated, assuming that the demand follows a normal distribution. The standard deviation was varied from 1 to 3. The same behaviour was observed in the SC system under both

policies, indicating that the observed impact was driven by demand variability and not by distribution shape.

A.4. Varying the backorder cost (b)

We compare the DIP and TBS policy while varying backorder cost ($b = \{2, 20, 40, 60, 80, 100, 120\}$). Fig. 10(d) shows the relative profit difference between the two policies under the different backorder cost values at $\Delta w_1 = 5$; it is slightly affected by varying the backorder cost. Under the TBS policy, a high backorder cost drives an increased dependency on upstream emergency suppliers, which generates more profit to the SC compared to the DIP. However, the difference between the TBS policy and DIP remains considerably limited. The increase in the backorder cost leads to more rush orders and higher inventory levels, which slightly reduce the total SC profit under both policies at an almost similar rate.

The analysis on the wholesale price difference shows that as the backorder cost (b) increases, the TBS policy tends to depend more on upstream emergency suppliers for a larger Δw_1 domain, which is not presented herein owing to space limitations. Therefore, emergency suppliers prefer to keep large stocks when the backorder cost is high. Moreover, the dependency on upstream emergency suppliers decreases with the increase in Δw_1 . Consequently, the profit difference becomes less and allows the DIP to outperform the TBS policy in certain cases such as $b = 2$ and $\Delta w_1 > 10$. In addition, emergency supplier 1 increases the quantities rushed as the backorder cost increases. The regular suppliers remain insensitive to the backorder cost changes for the entire domain of Δw_1 . By contrast, under the DIP, regular quantities increase with the increase in backorder cost and Δw_1 . The base-stock levels from emergency supplier 1 increase significantly as the backorder cost increases but start to decline as Δw_1 increases.

The SC aims to minimise backordering as its cost increases by building inventories and rushing orders. Under the TBS policy, the SC keeps relying on the emergency suppliers with the increase in wholesale price difference because of the regular suppliers' inflexibility. Under the DIP, as the wholesale price difference increases, the system relies less on emergency supplier 1 and more on regular supplier 1. Thus, the quantities ordered from emergency supplier 1 tend to go to zero, and rush orders decrease.

A.5. Varying rush costs (c_k^{rush})

The impact of varying rush is analysed using two cases. In the first case, we vary all rush costs using $c_k^{rush} = c_k^{rush} + \zeta$, where $\zeta = \{-30, -20, -10, 0, 10, 20, 30\}$. Fig. 10(e) shows the relative profit difference between the TBS policy and DIP under Case 1 at $\Delta w_1 = 5$. Two behaviours can be observed. The first corresponds to the case of reducing all rush costs. In this situation, emergency suppliers tend to rush more orders. Since the TBS policy relies more on emergency suppliers, it secures more profit than the DIP owing to the inexpensive cost of responsiveness. Consequently, the relative difference between the two policies increases as rush costs are reduced (i.e., as ζ gets smaller). The second behaviour is observed when all rush costs are increased. In this situation and under the TBS policy, the rush orders placed by emergency supplier 1 start decreasing, and more quantities are ordered from upstream emergency suppliers. This move increases the total SC profit that comes from the upstream emergency suppliers' contributions (see $\zeta = 0$ vs. $\zeta = 10$). However, as the dependency on upstream suppliers increases, the rush orders placed by upstream emergency suppliers increase. Consequently, the total profit starts to decrease slightly (see $\zeta = 10$ vs. $\zeta = 30$). Similarly, under the DIP, rush orders by emergency supplier 1 are replaced by orders from emergency supplier 2, which increases the rush orders placed by emergency supplier 2. However, the DIP relies on its downstream suppliers and mainly on its regular supplier, the impact of varying rush costs is less than that under the TBS policy. Namely, more quantities are ordered from the flexible regular supplier under the DIP, which makes it less sensitive to rush cost changes than the TBS policy.

In the second case (Fig. 10(f)), we vary the rush cost of the first emergency supplier as follows: $c_1^{rush} = \{75, 85, 90, 95, 100\}$. Note that $c_1^{rush} = 75$ is the same as the unit wholesale price from regular supplier 2 (w_2^r). Thus, at $c_1^{rush} = 75$, no regular quantities are purchased from regular supplier 2; rather, emergency supplier 1 places rush orders. Since the TBS policy relies heavily on emergency suppliers, more profit is secured under TBS policy than under the DIP. At $c_1^{rush} = 85$, emergency supplier 1 moves from rushing orders to purchasing them from its regular supplier, resulting in a profit reduction under the TBS policy. A further increase in c_1^{rush} (from 85 to 100) reduces the rush orders by emergency supplier 1 but increases orders from upstream emergency suppliers and consequently the rush orders by upstream suppliers. The increased contribution of upstream emergency suppliers increases the total SC profit under the TBS policy and leads to a large profit gap.

In general, the impact of varying rush costs under the DIP is minimal. This impact can be observed when the wholesale price difference Δw_1 is small because the quantity purchased from emergency supplier 1 goes to zero with the increase in Δw_1 . Under the TBS policy, even at large Δw_1 , emergency suppliers are still used. In the case of inexpensive rush costs, the emergency suppliers benefit from the reduced cost of responsiveness and place more rush orders. In the case of expensive rush costs, upstream emergency suppliers are used more and consequently contribute to a higher profit.

A.6. Lead time analysis

We vary lead times in four ways. Cases 1 and 2 involve increasing the regular supplier's lead time while keeping the lead time of the emergency supplier unchanged. Thus, the lead time difference is increased. In Cases 3 and 4, we increase both lead times such that the difference is kept unchanged ($l_k^r = l_k^e + 1$).

In Case 1, we vary the lead times of all the regular suppliers such that the difference ranges from 1 to 4; in Case 2, we limit the change to only the first regular supplier. Increasing the lead time difference increases the profit difference between the TBS policy and DIP in both cases, especially at large Δw_1 (Fig. 11(a)).

As all the regular suppliers' lead times increase (Case 1), these suppliers become less attractive and less preferable under both policies, particularly at a small wholesale price difference, and the emergency suppliers become more viable. The increase in lead time differences reduces the buyer and regular supplier 1's profit and increases the emergency suppliers' profit, resulting in a rise in the total SC profit (see the vertical rise in Fig. 11(a)). Moreover, the emergency suppliers' base-stock levels start decreasing at larger Δw_1 . The dependency on upstream emergency suppliers under the TBS policy decreases with an increase of Δw_1 , and more orders are fulfilled as a rush. This behaviour results in a slight reduction in the profit under both policies as Δw_1 increases (see the horizontal reduction in Fig. 11(a)).

As the DIP relies more on its flexible regular suppliers, at a large Δw_1 , the reduction in regular quantities with the increase in the lead time difference reduces the total SC profit. By contrast, under the TBS policy, the SC becomes more dependent on upstream suppliers as the regular suppliers become slower, thereby resulting in an increased total profit. This behaviour increases the profit differences between the two policies as the lead time difference increases. Notably, although the buyer prefers the DIP over the TBS policy, the difference between them decreases as the regular suppliers become slower. Klosterhalfen et al. [22] report similar behaviours for the buyer problem. The findings for Case 1 also apply to Case 2 since regular upstream suppliers are either used slightly or not used.

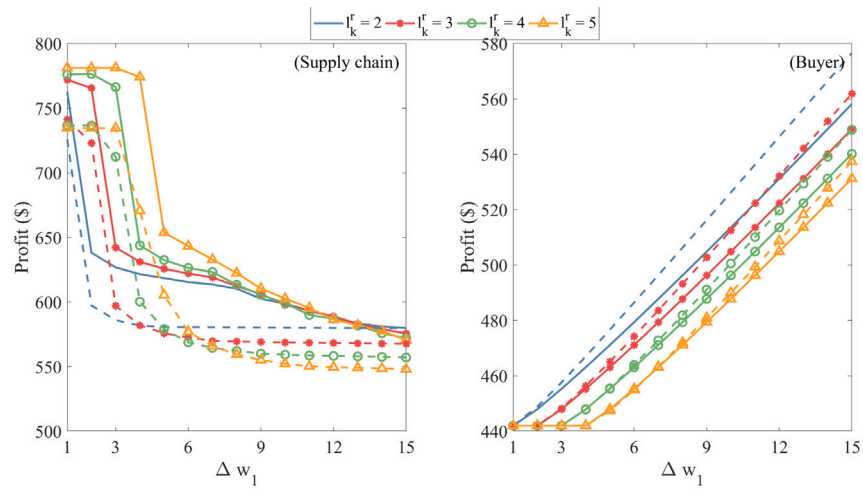
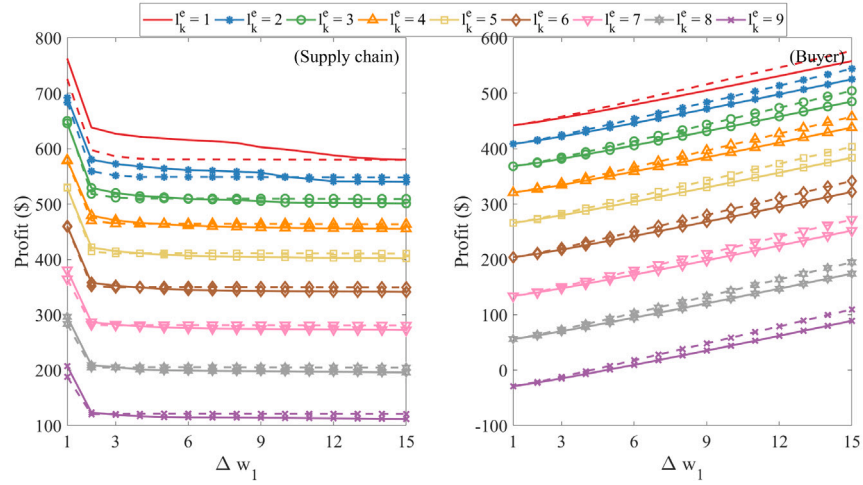
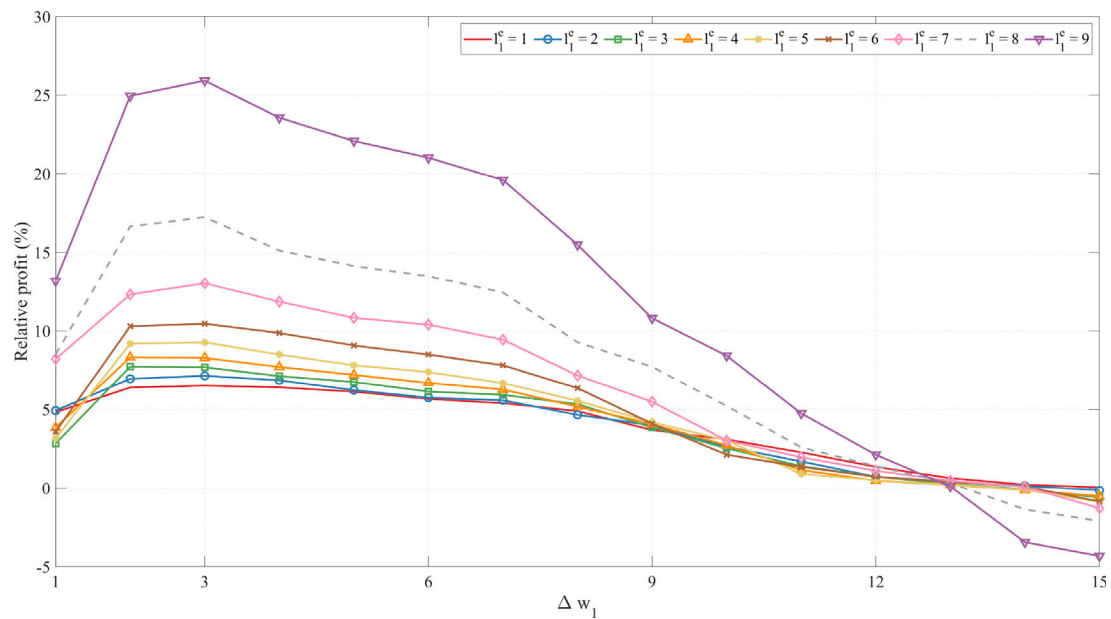
The responsiveness of the TBS policy becomes more viable than the flexibility of the DIP as the lead time difference increases. More quantities are purchased from regular supplier 1 under the DIP, and more emergency quantities are purchased under the TBS policy. Consequently, when regular suppliers become slower in fulfilling orders, the greater responsiveness of the TBS policy outperforms the flexibility of the DIP.

Remark 6. The same behaviour can be observed while varying lead times as in Case 1 during disruption but with a greater difference between TBS policy and DIP. Results are available from the authors upon request.

In Case 3, as suppliers become slow in delivering orders, upstream emergency and regular suppliers become unnecessary under both policies, and emergency supplier 1 places more rush orders. Moreover, backorders and inventory holding levels increase significantly. Consequently, the DIP outperforms TBS policy because of regular suppliers' flexibility under the DIP (Fig. 11(b)). As all suppliers become slow, the SC relies on rush orders that are more expensive but instantaneous (responsive). Few echelons (up to $K = 2$) are used under both policies. With more flexibility under the DIP, that is, more regular quantities, the SC secures more profit under the DIP than the TBS policy.

Remark 7. The same behaviour can be observed while varying lead times as in Case 3 during disruption. Results are available from the authors upon request.

In Case 4, as the emergency and regular suppliers in the first echelon become slower, slightly more orders are placed from emergency supplier 1 under both policies. Meanwhile, upstream emergency suppliers remain unaffected at early values of Δw_1 ; therefore, the TBS policy continues to outperform the DIP. However, at large values of Δw_1 , quantities purchased from upstream emergency suppliers decrease as l_1^e and l_1^r increase. In addition, the use of rush orders increases under both policies, where it is less sensitive to the change in Δw_1 under the TBS policy than under the DIP; namely, rush orders decrease as Δw_1 increases under the DIP. This behaviour decreases the total SC profit under the TBS policy; consequently, the DIP starts to outperform the TBS policy (Fig. 12).

(a) Case 1: Varying l_k^r .(b) Case 3: Varying l_k^r and l_k^e .Fig. 11. Profit under the TBS policy (solid lines) and DIP (dashed lines) as a function of Δw_1 for the lead time analysis.Fig. 12. Relative profit difference between the TBS policy and DIP as a function of Δw_1 for Case 4 of the lead time analysis.

Appendix B. Effect of varying parameters under demand disruption

B.1. Varying the standard deviation

We conduct experiments to understand the two policies' behaviour under disruption by varying the standard deviation $\sigma_i = \{2, 5\}$ for the $K = 1$ and $K = 5$ networks.

B.1.1. $K = 1$

In the ND case, regular and emergency orders are almost insensitive to the change in the standard deviation. By contrast, in the PD case, emergency and regular orders under TBS policy change with the standard deviation change (Fig. 6(a)). Emergency responsive orders increase with the increases in the standard deviation while regular rigid orders decrease. emergency and regular orders under the DIP react to the standard deviation changes in the disruption period (sudden increase and recovery periods), where emergency responsive orders decrease, and regular flexible orders increase with the standard deviation.

In the case of ND, the emergency base-stock level increases with the increase in the standard deviation and the regular base-stock level remains insensitive under the TBS policy (Fig. 6(b)). The emergency base-stock level under DIP decreases with Δw_1 at a faster rate as the standard deviation increases. Consequently, although the emergency base-stock level increases with the standard deviation, for some Δw_1 values the opposite occurs (for instance, $\Delta w_1 > 7$). The regular base-stock level increases with the increase in the standard deviation.

In the PD case, the emergency base-stock level increases significantly compared to the ND case under the TBS policy and increases with the standard deviation. The regular base-stock level decreases with the demand variability (Fig. 6(b)). The emergency and regular base-stock levels under the DIP increases with the increase in the standard deviation. However the emergency base-stock level starts to decrease with the increase in the demand variability after a certain Δw_1 value ($\Delta w_1 > 4$).

In the ND case, the preferred policy is insensitive to the demand variability, where the SC network under DIP outperforms that under the TBS policy for a wider Δw_1 range (Fig. 7(a)). This insensitivity in the preferred policy is due to the order levels insensitivity under the TBS policy with the change in the standard deviation.

Although the TBS policy outperforms in the PD case for a wider Δw_1 range due to its responsiveness, the preferred policy changes with the increase in the demand variability, especially when Δw_1 is large where purchasing from the regular supplier becomes more viable.

B.1.2. $K = 5$

Emergency and regular orders under the TBS policy placed by upstream suppliers decrease with the increase in the standard deviation, except for regular orders placed by emergency supplier 1, where orders increase with the increase in standard deviation. No emergency orders are placed by emergency supplier 1 under the DIP, while regular orders represent a small fraction and insensitive to the standard deviation changes. By contrast, in the PD case, regular orders placed by the buyer under the TBS policy and placed by emergency supplier 1 under the DIP decrease with the increase in the standard deviation. All other orders — emergency orders placed by the buyer and all emergency and regular orders placed by all emergency suppliers under the TBS policy, and regular orders placed by the buyer under the DIP — increase with the increase in the standard deviation.

In the ND case and under the TBS policy, the emergency base-stock at the buyer level increases while it decreases at the emergency suppliers' levels with the increase in the standard deviation. The emergency and regular base-stock levels at the buyer under the DIP increase with the increase in the standard deviation. In the PD case, emergency and

regular base-stock levels increase with the increase in the standard deviation at all levels under both policies, except for the regular base-stock level at the buyer level under the TBS policy. The increase in standard deviation from 2 to 5, does not change the preferred policy in both disruption cases. The difference between the total profit slightly decreases as the demand variability increases (Fig. 7(b)).

B.2. Varying recovery duration (λ_2)

We conduct experiments to understand the two policies' behaviour under disruption by varying the recovery duration $\lambda_2 = \{17, 32, 42\}$ for the $K = 1$ and $K = 5$ networks.

B.2.1. $K = 1$

In the ND case, emergency orders increase, and regular orders decrease with the recovery duration increase under the TBS policy. The reduction in the regular orders reduces the inventory level since emergency supplier becomes more involved in fulfilling the demand. The opposite occurs in the PD case. The flexible regular orders under the DIP match the demand behaviour in the ND and PD cases. The increased contribution of the emergency supplier with the increase in the recovery duration results in less inventory cost and higher total SC profit. Thus, the SC under the TBS policy outperforms that under DIP for a wider Δw_1 range (Fig. 13).

In the ND case, TBS becomes the preferred policy as the recovery duration increases. In the PD case and as the recovery duration increases, although the SC under the TBS policy remains dominant at small Δw_1 values, this Δw_1 range reduces slowly (Fig. 13).

B.2.2. $K = 5$

In the ND case at $\Delta w_1 = 5$, emergency orders placed by all entities increase, and regular orders placed by the buyer decrease under the TBS policy with the rise in the recovery duration, while in the PD case, the changes are insensitive to the recovery duration change. The emergency base-stock level at the buyer in the ND case is less than that in the stationary demand case and less sensitive to the change in the recovery duration than the PD case, where the base-stock level is higher and more sensitive to the recovery duration. Emergency base-stock levels at emergency suppliers in the ND case under the TBS policy are higher than that in the PD case but decrease faster with the increase in Δw_1 .

Regular orders placed by the buyer under the DIP act to absorb the disruption effect. In the ND case, emergency and regular base-stock levels at the buyer are less than that in the stationary demand case and decrease with the recovery duration increase. The opposite occurs in the PD case.

Fig. 14 shows the relative profit between the two policies calculated as $100 \times \frac{\pi^{TBS} - \pi^{DIP}}{\pi^{TBS}}$. Although the recovery duration has not changed the preferred policy, the total SC profit difference between the TBS policy and the DIP increases with the recovery duration (Fig. 14). For instance at $\Delta w_1 = 10$, the relative profit increased from 6% to 20% and 28%. In the PD case, the rate of increase in the relative profit is slower (8.5% to 11.5% to 12.8% at $\Delta w_1 = 10$). This profit increase under TBS policy is because of the increased contribution of emergency suppliers as mentioned previously.

Appendix C. Effect of varying the inventory policy

C.1. Varying the policy between SC players

In the paper, we assumed that all supply chain players adopt the same policy, either the DIP or the TBS policy. Here, we relax this assumption and conduct numerical experiments to explore scenarios where different entities adopt distinct policies. For the analysis, we focus on the buyer (B) and emergency supplier 1 (e1), as these entities are the primary contributors to supply chain quantities. We run the experiments for the cases of stationary and non-stationary demands.

We develop the following four scenarios for this investigation:

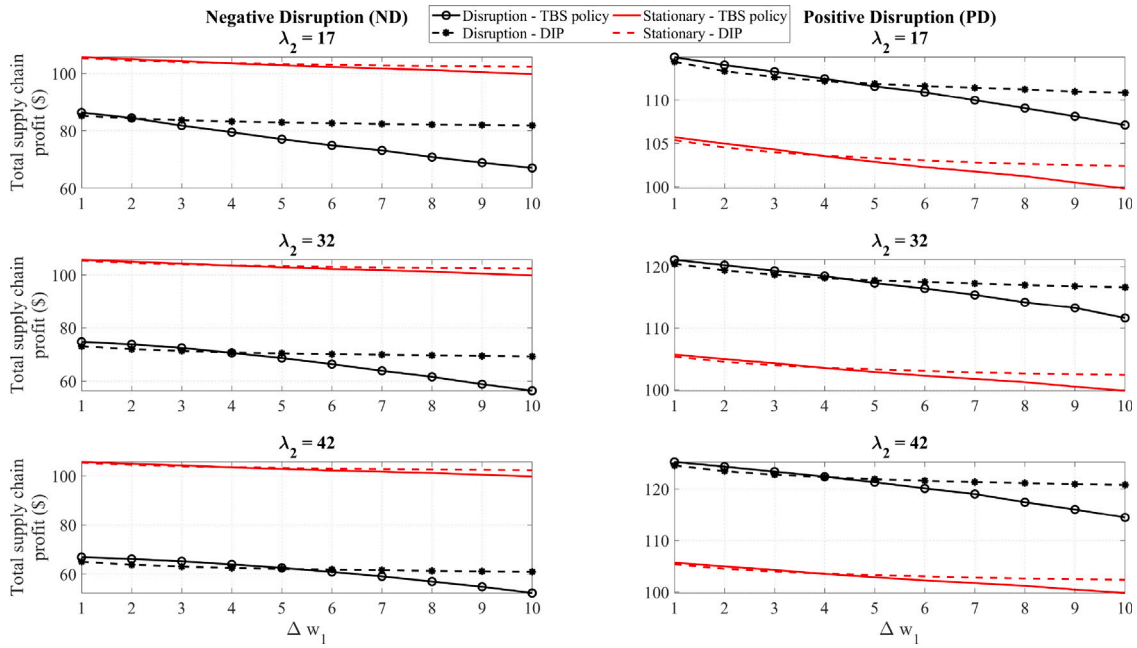


Fig. 13. The total SC profit when varying the recovery duration for the $K = 1$ network.

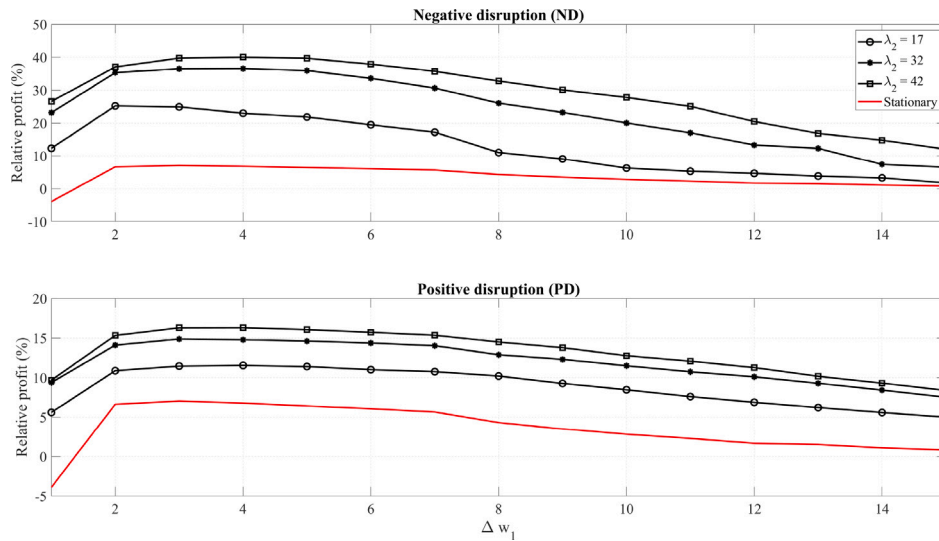


Fig. 14. Relative profit when varying the recovery duration for the $K = 5$ network.

- Scenario 1: The buyer adopts the DIP, while emergency supplier 1 and the other suppliers use the TBS policy.
- Scenario 2: The buyer adopts the TBS policy, while emergency supplier 1 and the other suppliers use the DIP.
- Scenario 3: Emergency supplier 1 adopts the DIP, while the buyer and other suppliers use the TBS policy.
- Scenario 4: Emergency supplier 1 adopts the TBS policy, while the buyer and other suppliers use the DIP.

Fig. 15 presents the total supply chain profit for each scenario under the stationary demand case, along with the two extreme cases where all supply chain entities uniformly adopt either the DIP or TBS policy. The results indicate that the scenarios where all supply chain players use the same policy serve as boundary cases. Specifically, the scenario where all entities adopt the DIP policy represents the lower bound for total profit, while the scenario where all entities adopt the TBS policy represents the upper bound.

Fig. 16 presents the total supply chain profit for each scenario under non-stationary demand conditions (ND and PD), along with the two extreme cases where all supply chain entities uniformly adopt either the DIP or TBS policy. The results show that the extreme cases of “all DIP” and “all TBS” policies define the profit boundaries during demand disruptions. Specifically, the “all DIP” case represents the lower bound of total profit, while the “all TBS” case represents the upper bound, consistent with the findings under stationary demand conditions. However, the observed profit trends are influenced by the nature of demand disruptions (ND vs. PD), underscoring the importance of adapting policies in response to demand variability.

C.2. Varying the policy during disruption

Schmitt et al. [107] suggested that dynamic policy parameter adjustments during disruptions can yield beneficial outcomes for supply chain performance. To test this in multi-echelon setting, we conduct

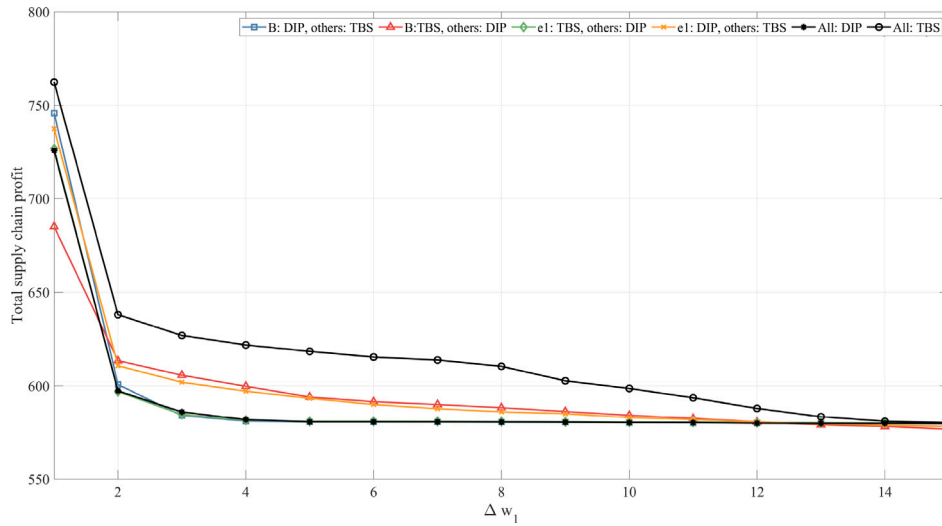


Fig. 15. Total supply chain profit under stationary demand while varying inventory policies for the buyer and emergency supplier 1.

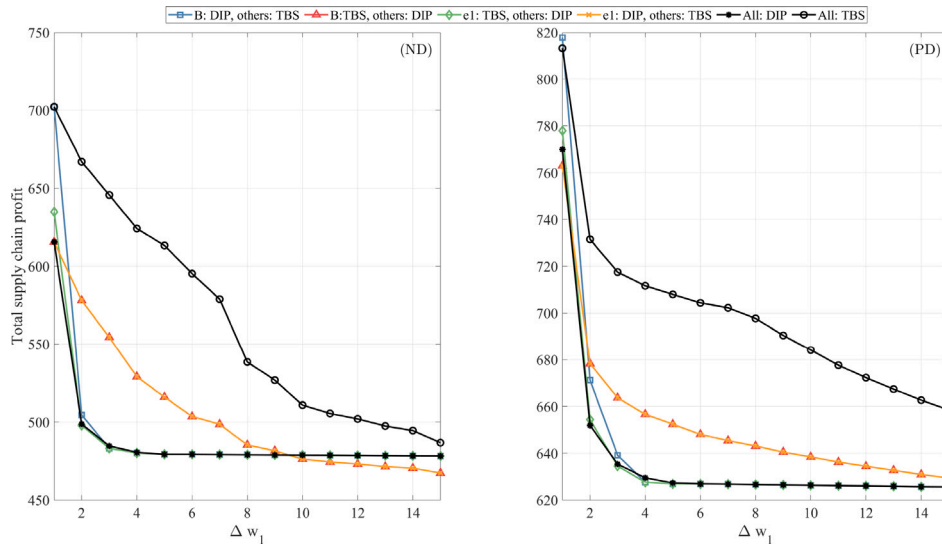


Fig. 16. Total supply chain profit under non-stationary demand (ND and PD) while varying inventory policies for the buyer and emergency supplier 1.

experiments where policy were changed during disruption periods and compared the results to scenarios where policy parameters remained unchanged. Specially, we run experiments the following scenarios:

- Scenario 1: DIP is used all the time with a new DIP is introduced during disruption.
- Scenario 2: DIP is used all the time and all SC parties switch to TBS during disruption.
- Scenario 3: TBS policy is used all the time and all SC parties switch to DIP during disruption.
- Scenario 4: TBS policy is used all the time with a new TBS policy is introduced during disruption.

Our analysis considers both positive demand (PD) and negative demand (ND) disruptions, focusing on their impact on individual supply chain entities (buyer, emergency supplier 1, and regular supplier 1) and on the total supply chain profit. The results are summarised in Figs. 17 and 18.

The results are compared to scenarios where policy parameters remained consistent throughout the disruption. In the PD case, we show that dynamic policy adjustments yield high profit for the buyer and regular supplier under DIP (Fig. 17). However, the total supply chain

profit remained bounded by the consistent-policy scenarios, as shown in Fig. 18. While in the ND case, dynamic policy adjustments offer limited or no benefit, with profits for all entities remaining within the boundaries defined by the consistent-policy scenarios (Fig. 17). This is also reflected in the total supply chain profit results (Fig. 18). In addition, the scenarios where policy parameters remained unchanged (e.g., all DIP or all TBS) define the upper and lower bounds for total supply chain profit. Dynamic adjustments could not surpass these boundaries for the entire supply chain, indicating that their benefit is constrained by the underlying policy framework.

These findings suggest that while dynamic policy adjustments may provide localised benefits (e.g., for the buyer or regular upstream supplier during PD disruptions), their overall impact on total supply chain profit is limited. This highlights the importance of policy consistency, especially under ND disruptions, where dynamic adjustments do not lead to significant performance gains.

Data availability

Numerical data used in this paper is available upon reasonable request from the authors.

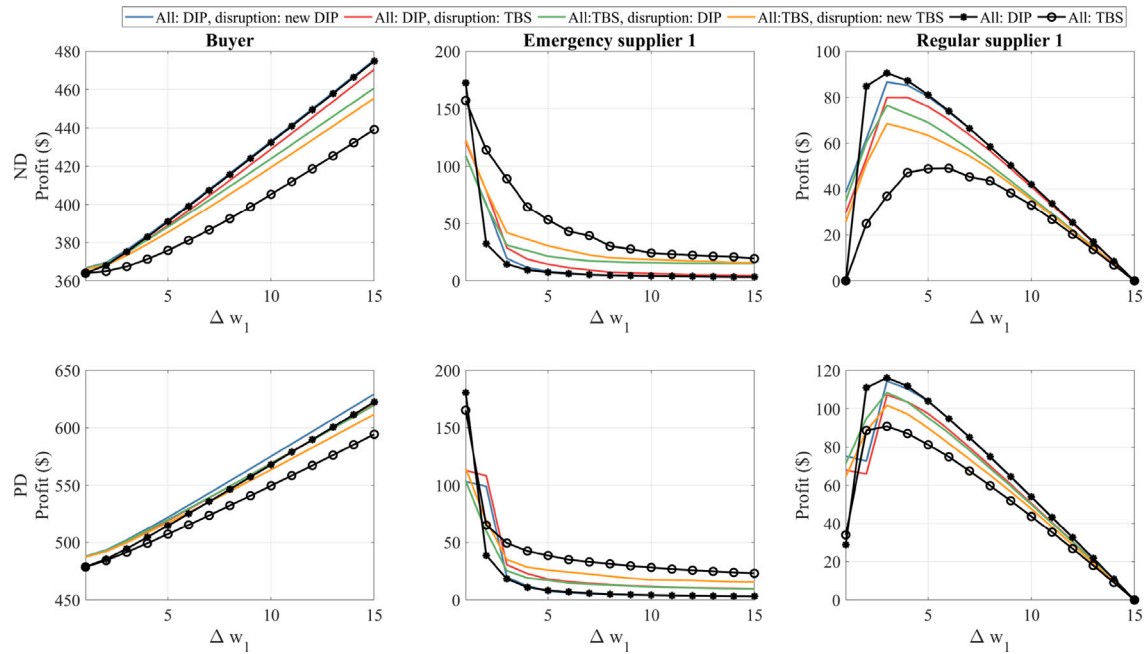


Fig. 17. Individual profit comparison for the buyer, emergency supplier, and regular supplier under dynamic and consistent policy settings during disruptions (ND and PD).

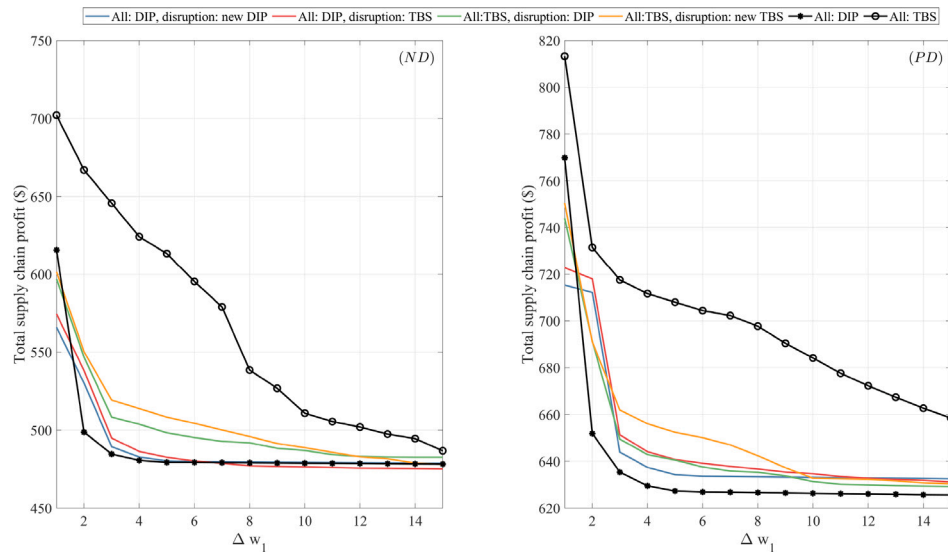


Fig. 18. Total supply chain profit comparison under dynamic and consistent policy settings during disruptions (ND and PD).

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