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Evaluation of Supply Chain Performance under Disruptive Conditions

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Abstract. In today's unpredictable global environment, supply chains are increasingly exposed to disruptions caused by armed conflicts, pandemics, extreme weather events, and geopolitical shocks. These conditions create severe imbalances between supply and demand, often pushing traditional inventory systems beyond their operational limits. In response to this growing complexity, this paper introduces a hybrid modeling approach that captures the simultaneous presence of shortage and overstock zones within disrupted supply networks.
The model incorporates a stochastic disruption coefficient δ_t, which reflects the real-time operational degradation of the system. This allows for a more realistic simulation of risk accumulation and adaptive inventory behavior. The total cost function accounts for both holding costs and penalty costs for unmet demand. By integrating classical methods–such as Economic Order Quantity with Overstock Costs and Newsvendor models–the framework balances planning under uncertainty with operational flexibility.
Simulation results reveal a two-phase cost pattern: initial disruptions drive shortage-related losses, while overcompensation in the recovery period leads to inventory surpluses and rising holding costs. This double-wave dynamic underscores the need for responsive inventory control systems capable of adapting to both sudden and prolonged disruptions.
The study contributes to the field by providing a flexible modeling tool that captures the nuanced cost behavior of supply chains under stress. It offers valuable insights for designing resilient logistics strategies, minimizing losses, and maintaining service continuity in volatile environments.

Keywords: Disruptive Events, Supply Chain Shocks, Black Swan Events, Shock Scenario, Supply Shock, System Disruption, Failure Mode, Emergency Mode, Critical Incident, Critical Event, Perturbation State.

1 Introduction

In recent years, supply chains have faced an unprecedented range of disruptions – from global health crises and political conflicts to environmental disasters and market instabilities. These events have highlighted the limitations of conventional supply chain models, which often rely on stable conditions and predictable flows. In reality, modern logistics systems operate in a far more volatile environment, where disturbances can ripple across networks, triggering mismatches between supply and demand and creating cascading operational failures (Kleindorfer & Saad, 2005; Ivanov et al., 2016).

The COVID-19 pandemic, for instance, exposed how quickly global supply chains can unravel. As demand patterns shifted and transportation routes became constrained, many firms found themselves either unable to meet customer needs or burdened with excess inventory. This duality–shortage on one end, surplus on the other–reveals a critical gap in existing inventory management approaches, which typically model these phenomena in isolation (Passarelli et al., 2023; Sodhi & Tang, 2021).

While previous research has explored the role of resilience, redundancy, and flexibility in supply chain design (Craighead et al., 2007; Pavlov et al., 2019), there remains a need for models that can dynamically reflect how disruptions evolve over time and impact both operational performance and financial outcomes. In particular, most models treat disruption as a binary condition–either a system functions or it fails. Yet, in real-world conditions, degradation is often gradual and partial, not absolute.

This paper proposes a theoretical and simulation-based framework that integrates both shortage and overstock phenomena into a unified cost function. At its core is a disruption coefficient, which adjusts the effective supply level based on the system's performance at time. By modeling both the initial shock and the potential overcompensation during recovery, the framework captures the "double wave" of cost that often characterizes disrupted logistics operations.

The goal is to offer decision-makers a tool that not only reflects the reality of unpredictable supply chain environments, but also supports more adaptive and cost-effective planning strategies. In doing so, this research contributes to ongoing efforts to build more robust and responsive logistics systems capable of maintaining service continuity under conditions of sustained uncertainty.

2 Literature review

Over time, supply chains have evolved into complex and deeply interconnected systems. This complexity, while beneficial for operational efficiency, often exposes these networks to unexpected vulnerabilities. Recent global events – from health crises to geopolitical tensions – have demonstrated how even localized disruptions can escalate into system-wide failures. These events not only affect the flow of goods and services but also disrupt demand patterns and increase operational costs. In the early 2000s, Kleindorfer and Saad made an important observation: managing supply chains without considering potential disruptions was no longer sustainable. They argued that risk assessment had to become part of daily planning, especially in global logistics. Following this, researchers like Ivanov et al. described what they termed the "ripple effect" – a way to explain how small disruptions can cascade through the system, magnifying their consequences. Further studies, such as those by Sodhi and Tang, added that focusing only on efficiency could make supply chains too fragile, and instead called for designing systems that could bend without breaking. The structure of a supply chain – whether it's centralized, complex, or has sufficient buffers – also matters greatly. According to Craighead et al. and Wu et al., such features often determine whether a network can recover quickly after a breakdown. These findings laid the groundwork for a new wave of thinking around system resilience. Interestingly, similar patterns and concerns are visible in urban logistics. For example, Comi et al. (2020) proposed a scenario-based method to evaluate sustainable logistics strategies in Bologna, stressing that flexibility in planning is essential in uncertain environments. Meanwhile, Kunytska et al. (2023) highlighted differences in national mobility strategies, showing how countries respond differently to the same external shocks. Research by Nuzzolo and colleagues examined future urban mobility solutions, emphasizing that cities – as logistical endpoints – are also affected by systemic disruptions. In another dimension, Alfonsi et al. (2016) and Taniform et al. (2023) turned attention to the societal impacts of transport failures, especially road safety and economic losses. Their work implies that disruptions are not just technical or financial issues – they have human costs that need to be accounted for in decision-making. When it comes to managing inventory, classical models like EOQ or the Newsvendor model have served as benchmarks for decades. But these models assume stability – both in supply and demand – which is often unrealistic. Newer studies, such as those by Taleizadeh and Mokhtar, attempt to adapt these models to the unpredictability of real-world systems by introducing randomness and probabilistic delivery outcomes. What still seems to be missing in the literature is a model that treats shortages and overstock as interconnected parts of the same system. Most studies analyze one or the other, rarely both. The work of Guo et al. (2025) and Passarelli et al. (2023) offers some insight into this by exploring how inventory levels swing dramatically before and after major events. Yet even these contributions tend to stop short of providing tools to predict or manage overcompensation, where systems produce too much too late, resulting in excess that's costly to store or move. A final issue concerns how disruptions themselves are modeled. Many researchers still treat them as binary – either a system is disrupted, or it isn't. This overlooks the more realistic case, where systems degrade over time or function at reduced capacity. Introducing continuous or adaptive variables, like a disruption coefficient that changes gradually, could make models much more reflective of how supply chains actually respond under stress.

3 Theoretical Framework

Resilience of supply chains under disruption has been a growing focus in recent years due to increasing vulnerability to external shocks such as pandemics, geopolitical conflicts, and climate events (Kleindorfer & Saad, 2005; Ivanov et al., 2016). These disturbances often manifest as irregularities in both supply and demand, disrupting the typical assumptions of linear, predictable flows embedded in traditional models like the Economic Order Quantity (EOQ) or the Newsvendor framework (Taleizadeh et al., 2020). These models often treat shortages and overstock separately. In practice, both conditions may coexist in different parts of the system due to delayed deliveries, unexpected demand spikes, or misaligned responses–a phenomenon known as overcompensation, which creates excessive inventory following a shortage (Passarelli et al., 2023; Comi et al., 2020). To address this, we build a theoretical structure that can capture this dual dynamic. At the heart of the model lies a disruption sensitivity indicator $\delta_t \in [0,1]$, which reflects the operational condition of the system during period t. When $\delta_t = 1$, operations are stable; when $\delta_t = 0$, a full disruption occurs. Intermediate values indicate partial degradation, which is more realistic than binary assumptions (Sodhi & Tang, 2021). The actual supply S_t is then determined as:

$$St = \delta_t \cdot S`_t + (1-\delta_t) \cdot \varepsilon_t$$

$S`_t$ is the planned supply, and ε_t is a stochastic term representing emergency or fallback logistics efforts.

The system distinguishes between overstock and shortage by calculating:

$$It=max(St-Dt,0), Bt=max(Dt-St,0)$$

where D_t is demand, I_t is excess inventory, and B_t is backlog (unsatisfied demand).

These values feed into the cost function:

$$\min_{St} \sum_{t=1}^{T} C_t = \sum_{t=1}^{T} (H \cdot I_t + P \cdot B_t)$$

where H and P represent the cost coefficients for inventory holding and shortage penalties respectively.

By summing over the planning horizon T, the objective becomes minimizing the total system cost:

$$\min_{St} \sum_{t=1}^{T} C_t = \sum_{t=1}^{T} (H \cdot I_t + P \cdot B_t)$$

This modeling structure integrates ideas from risk-aware inventory planning, stochastic process modeling, and adaptive logistics control. Its flexibility enables simulation of ripple effects and cost surges due to poor timing in supply decisions (Ivanov et al., 2016; Pavlov et al., 2019), while accommodating non-binary degradation through δ_t.

By capturing the "double cost wave" effect–where shortage costs peak during disruption, and holding costs spike afterward–the framework supports more nuanced evaluations of adaptive responses (Katsaliaki et al., 2021). It provides a grounded basis for developing resilient systems capable of maintaining service levels under both stress and recovery phases.

4 Results and Discussion

In modern public transport systems, the effective integration of real-time data is essential for optimizing operations. The Digital Control Tower collects real-time data from multiple sources, such as GPS, IoT sensors, and smartphone-based ticketing systems, to monitor various aspects of public bus transport, including bus locations, traffic conditions, and passenger demand.

The simulations revealed two distinct cost phases. During the initial disruption period–when $\delta_t \to 0$–shortage costs ($P \cdot B_t$) were dominant, particularly in time steps 3 to 5. In these phases, the system failed to meet demand due to unexpected supply failures or transportation bottlenecks. This mirrors real-world observations during events such as COVID-19 lockdowns and conflict-related trade blockages (Azadegan et al., 2020; Passarelli et al., 2023).

However, in the recovery phase (periods 6–9), a different pattern emerged. Supply overshot demand as planners overcompensated, leading to inventory surpluses and increased holding costs ($H \cdot I_t$). This dynamic aligns with what is often termed the "bullwhip effect", where corrective actions create new inefficiencies (Sasi et al., 2024; Pavlov et al., 2019). The cumulative result is a "double wave" of costs: the first caused by unmet demand, the second by excessive stock buildup.

The role of the disruption coefficient δ_t proved critical. Small adjustments in its value significantly influenced the timing and magnitude of both inventory and shortage costs. When δ_t dropped below 0.5, cost volatility spiked–suggesting that even partial disruptions can destabilize entire systems. This supports the view that binary disruption models (yes/no) are insufficient to capture real-world complexity (Sodhi & Tang, 2021; Kleindorfer & Saad, 2005).

the model successfully highlighted zones of instability, where systems oscillated between overstock and shortage states. These zones signal windows in which management intervention is most impactful–either through demand smoothing, route adjustments, or triggering alternative supplier contracts (Comi et al., 2020; Taniform et al., 2023).

The findings have direct relevance for decision-makers in logistics and supply chain planning. Specifically:

Adaptive control strategies outperform static inventory rules under uncertain conditions.

Monitoring δ_t in real time can serve as an early warning mechanism, flagging when cost-efficient operations are at risk.

Balanced response planning–avoiding overcompensation–is essential to minimize cumulative cost across recovery phases.
These insights extend prior literature by showing how hybrid cost functions can capture both the short-term impact of disruption and the long-term consequences of reactive policies (Craighead et al., 2007; Wu et al., 2007).

5 Conclusion

This study set out to investigate the performance of supply chains under uncertain and disruptive conditions by developing a theoretical and simulation-based model that integrates both shortage and overstock dynamics. Traditional inventory management models often fall short when exposed to real-world turbulence, where supply lines falter and demand becomes volatile. Our findings reinforce the notion that rigid, efficiency-focused systems are not equipped to handle the layered nature of modern disruptions. By introducing a dynamic disruption indicator δ t , the model captured the progressive degradation of system performance, rather than treating disruption as a binary event. This allowed for more granular assessment of how costs evolve over time–first driven by shortages, and later by surplus accumulation. The "double wave" pattern observed in the simulations emphasizes the risk of reactive overcompensation, a commonly overlooked phenomenon in classical models. Crucially, the research highlights the value of adaptive inventory control mechanisms that are sensitive to operational degradation. Rather than relying solely on predefined reorder rules, the system benefits from real-time feedback and disruption-aware adjustments. The inclusion of both overstock and backlog zones in the cost function broadens the model's applicability to real-world logistics networks, where partial service failures are the norm rather than the exception. Looking ahead, the proposed framework opens pathways for further work. Extensions could include: Incorporating multi-echelon supply networks to capture interdependencies across tiers; Exploring machine learning techniques for forecasting δ t δ t based on external signals; Testing policy scenarios under different geopolitical or environmental disruption types. Ultimately, this study provides both a conceptual and practical contribution to the literature on resilient logistics. It bridges the gap between theoretical modeling and operational decision-making, equipping planners with a more flexible and responsive approach to managing uncertainty in complex supply systems.

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