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Modeling On-Demand Warehousing Strategies: A Comparative Static Framework for Supply Chain Decision- Making

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Declaration

Declaration of AI Assistance During the preparation of this master's thesis, I, Muath E. Basheer, utilized ChatGPT for the following purposes:

- R Code Debugging: ChatGPT provided guidance and support in identifying and resolving issues within the R code used for data analysis.
- LaTeX Assistance: ChatGPT offered support in using LaTeX for document preparation, ensuring proper formatting and professional presentation of the thesis.
- Writing Refinement: ChatGPT contributed to refining the text of the thesis, offering suggestions to improve clarity and coherence.

After using ChatGPT, I, Muath E. Basheer, diligently reviewed and edited all content produced by the tool to ensure its accuracy, and alignment with academic standards. Full responsibility for the final content presented in this thesis lies with the author.

By signing this declaration, I affirm that the content of this master's thesis reflects my original work, augmented by the responsible and ethical use of AI tools.

Muath E. Basheer

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Abstract

On-demand warehousing (ODW) offers a flexible, cost-effective solution for managing fluctuating demand and capacity constraints in supply chains. Despite its potential, the strategic integration of ODW into decision-making frameworks remains underexplored, particularly in balancing cost, capacity, and service levels under uncertain conditions. This research addresses this gap by developing a comprehensive framework to optimize capacity allocation, profitability, and service levels in ODW environments.

A systematic literature review and a quantitative modeling approach expose critical gaps in understanding ODW's operational dynamics. To bridge these gaps, a rigorous *Comparative Static Model* is formulated, capturing four distinct demand scenarios—low, high, extreme, and mixed. The model systematically evaluates how private warehousing capacity, ODW usage, and service levels interplay under varying cost structures and demand variability.

Key findings underscore the diminishing returns of private capacity investments beyond a certain threshold, emphasizing the need for cost-efficient resource allocation. In highly volatile scenarios, ODW emerges as an effective contingency mechanism that stabilizes service levels and mitigates unmet demand penalties. Complementing this, universal metric-based activation rules—such as service-level thresholds and profitability deltas—offer near-real-time operational triggers. This *dual* approach—combining scenario classification with metric-based activation—underlies a robust, adaptable decision framework for balancing resilience, profitability, and equity.

By offering a robust framework for optimizing ODW and clear guidelines for deploying ODW alongside private capacity, the study contributes to both academic discourse and industry practice. Future research directions include extending the model to multi-period settings, incorporating risk preferences, and validating these findings through industry collaborations. Overall, this research lays a data-driven foundation for scenario-specific capacity planning to navigate the complexities of ODW and advance supply chain resilience and efficiency.

Keywords: On-Demand Warehousing, Supply Chain Management, Warehousing Strategies, Decision-Making Framework.

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Chapter 1

Introduction

In the era of globalization and rapid technological advancements, businesses are navigating increasingly complex and competitive market landscapes (Christopher, 2016). Evolving consumer expectations, driven by e-commerce and the demand for faster, personalized services, have heightened the need for agility and responsiveness in supply chains (Hagberg et al., 2016). As a result, effective supply chain management has thus become a cornerstone of success, requiring optimization across all operational components, particularly warehousing (Dubey et al., 2019).

At the heart of supply chain management lies warehousing, a fundamental element ensuring that products are stored efficiently and delivered promptly to meet customer demand (Jum’a and Basheer, 2023). Traditional warehousing models—encompassing private ownership and long-term contracts with third-party logistics providers (3PLs)—have historically underpinned supply chain operations by offering control and economies of scale (Richards, 2017). However, these models come with inherent limitations, defined by fixed long-term leases, high capital investments, and limited flexibility, thereby stifling innovation and adaptability (Unnu and Pazour, 2019). Small and medium-sized enterprises (SMEs), in particular, struggle to adapt to fluctuating demand, seasonality, and unforeseen disruptions, as witnessed during the COVID-19 pandemic (Ivanov, 2020). Such challenges often result in underutilized space during periods of low demand or insufficient capacity during peaks, leading to inefficiencies, increased costs, and lost sales.

In response to these challenges, *On-Demand Warehousing (ODW)* has emerged as an innovative solution that offers scalability and flexibility. By leveraging digital platforms, ODW dynamically connects businesses requiring storage space with providers who have surplus capacity, optimizing underutilized resources and aligning with the principles of the sharing economy (Elia et al., 2024). This model enables businesses to realign their warehousing capacity in near real-time, addressing demand volatility without significant capital expenditures or long-term commitments (Tornese et al., 2020). As a result, ODW introduces operational agility, which is increasingly critical in modern, fast-paced markets.

Despite its potential, research on ODW remains scarce. While prior studies recognize its ability to improve scalability and cost efficiency, the strategic integration of ODW into decision-making frameworks is underexplored (Lee et al., 2024). As a result, decision-makers face uncertainties about capacity planning, cost management, and maintaining service levels under varying demand conditions. Without established frameworks, businesses may underutilize ODW’s benefits or struggle to mitigate associated risks (Correia and Melo, 2022).

This study seeks to address this gap by exploring the following research question:

What constitutes a suitable decision-making framework to optimize capacity allocation, profitability, and service levels in on-demand warehousing while addressing its strategic applications, operational limitations, and suitability under varying demand conditions?

To investigate this question, this thesis uses a systematic literature review and a quantitative modeling approach. The *Comparative Static Model* forms the core analytical engine for long-term strategic planning, emphasizing how different demand scenarios (e.g., *low, high, extreme, mixed*) and cost structures (such as ODW usage fees, penalty costs, and private capacity investments) interact to determine optimal capacity configurations. By simulating fixed capacity combinations for both private and on-demand warehousing, the model yields insights into profit-maximizing allocations and robust service levels.

Nevertheless, the research is subject to certain limitations. First, the parameters (e.g., cost structures, prioritization rules, and demand distributions) are predefined and may not universally reflect all industrial contexts. Second, external disruptions (e.g., geopolitical events or policy shifts) lie outside the model scope, potentially affecting the generalizability of the findings. Consequently, while the outcomes offer valuable benchmarks, decision-makers should adapt the model's recommendations to the specific structures and risk profiles of their supply chains.

The thesis is organized as follows: *Chapter 2* reviews the evolution of ODW and its role in digital logistics transformations. *Chapter 3* presents a state-of-the-art analysis of ODW frameworks and challenges. *Chapter 4* details the research approach and quantitative modeling process. *Chapter 5* outlines the development of the Comparative Static and the Multi-Period Capacity Adjustment models. *Chapter 6* validates these models through optimization analysis. *Chapter 7* applies the models to simulated scenarios. *Chapter 8* presents key findings related to profitability, service levels, and cost trade-offs. *Chapter 9* provides strategic recommendations for ODW adoption, and *Chapter 10* concludes with insights, limitations, and directions for future research.

By developing a robust decision-making framework, this research equips businesses with the conceptual and practical tools to optimize ODW utilization, enhance resilience, and advance the understanding of ODW as a pivotal enabler of modern supply chain excellence resilience.

Chapter 2

Literature Review

Logistics and supply chain management have long been the backbone of global trade, ensuring the efficient movement and storage of goods. In recent decades, however, the field has entered a transformative phase driven by technological advancements, shifting consumer expectations, and environmental challenges (Ivanov and Dolgui, 2021). Digital platforms, data-driven decision-making, and agile models now define modern logistics, with flexibility, scalability, and operational efficiency emerging as critical requirements for success in increasingly volatile markets (Parodos et al., 2022).

Traditional supply chain frameworks, designed for large-scale and predictable flows, are increasingly misaligned with the demands of e-commerce. E-commerce prioritizes frequent, tailored shipments that emphasize speed, responsiveness, and customization (Carbone et al., 2017). This shift places significant strain on conventional warehousing systems, which often struggle to adapt to fluctuating demand, seasonal peaks, and diverse product ranges (Pazour and Unnu, 2018). Compounding these pressures, critics argue that traditional logistics service providers (LSPs) often adhere to outdated models, relying on inflexible contracts that impede innovation and agility, effectively cementing their role as the last "immovable" component of the supply chain (Gnoni and Tornese, 2023).

To address these challenges, the logistics sector has embraced innovative models rooted in the principles of the sharing economy. By enabling collaborative asset utilization, the sharing economy promotes shared transportation fleets, co-warehousing spaces, and on-demand logistics solutions (Xenou et al., 2021). A prominent example is on-demand warehousing (ODW), which applies these principles to storage solutions, enabling businesses to flexibly access storage space based on immediate needs, thereby enhancing scalability and adaptability to market dynamics (Correia and Melo, 2022). Unlike traditional models, ODW enables businesses to adjust their storage capacities in near real-time, aligning operations with fluctuating demand while enhancing cost efficiency and agility (Ceschia et al., 2022).

Despite its potential, existing research on ODW remains largely descriptive, focusing on its benefits without fully exploring its strategic and operational integration into decision-making frameworks (Gnoni and Tornese, 2023; Elia et al., 2024). Key questions remain unanswered: How can businesses leverage ODW to optimize costs, capacity, and service levels under uncertain demand? What challenges arise in its practical implementation, and how can they be mitigated? These gaps highlight the need for a more structured and analytical exploration of ODW that bridges the theoretical underpinnings of the sharing economy with quantitative and practical frameworks for supply chain optimization.

This chapter addresses these gaps by providing a comprehensive review of the literature on ODW. Section 2.1 examines broader trends driving digital transformation in logistics, including the rise of e-commerce and the influence of the sharing economy. Section 2.2 explores the evolution of warehousing models, outlining the limitations of traditional approaches and the opportunities ODW presents in addressing emerging supply chain challenges.

2.1 Digital Transformations in Logistics

Looking toward the future, the logistics industry stands on the threshold of a significant transformative era, driven by the growing demand for on-demand warehousing services and the integration of the sharing economy (Elia et al., 2024). This paradigm shift leverages digital platforms to optimize underutilized assets, enhance operational efficiency, and address the rapid fluctuations of the e-commerce landscape (Tornese et al., 2020; Xenou et al., 2021; Parodos et al., 2022).

E-commerce has accelerated these changes, with collaborative consumption models exemplified by platforms like Airbnb and Uber demonstrating the value of shared resources in logistics (Tornese et al., 2020). These models offer flexibility and scalability, enabling providers to meet rising delivery expectations while addressing operational inefficiencies (Pazour and Unnu, 2018). In Europe, the proliferation of instant delivery services underscores the growing consumer preference for speed, creating opportunities for shared operations to reduce environmental impacts and improve efficiency (Xenou et al., 2021).

This evolution signals a broader reorientation within the sector, where shared, digitized logistics systems are becoming essential to meet the dynamic demands of modern commerce (Tornese et al., 2020). By exploring the intersection of e-commerce growth, on-demand platforms, and the sharing economy, this segment highlights the factors driving the expansion of on-demand warehousing services.

2.1.1 From Sharing Economy to Industrial Sharing in Logistics

The sharing economy (SE) remains a concept under active academic debate, with definitions varying across disciplines. Muñoz and Cohen (2018) describes it as “*an economic system enabling intermediated exchanges of goods and services to optimize underutilized resources in society.*” In the logistics sector, “on-demand logistics” has traditionally been associated with “instant delivery” services, a trend accelerated by the rapid growth of the e-commerce economy. Building on this, Elia et al. (2024) highlights the transformative impact of SE models and e-commerce on logistics, where demand has shifted toward smaller, more frequent handling units and expanded distribution networks. This shift aligns with broader societal trends prioritizing access over ownership, particularly in logistics, where immediate service fulfillment has become critical (Alkhatib et al., 2015).

The SE’s defining feature within logistics is its emphasis on collaboration, enabling companies and individuals to share assets such as warehouses, transportation fleets, and parking through digital platforms. This contrasts with the on-demand economy’s focus on immediate, time-sensitive resource fulfillment (Xenou et al., 2021). Together, these models promote sustainable practices by shifting the emphasis from asset ownership to optimized utilization (Tornese et al., 2020; Elia et al., 2024).

Furthermore, broader adoption faces challenges, including the absence of a standardized framework and a lack of cohesive definitions (Acquier et al., 2017). Despite these obstacles, the core principle of leveraging underutilized resources through digital platforms remains pivotal for driving innovation and efficiency in modern supply chains (Elia et al., 2024).

This evolution has driven the decentralization of warehouse operations, transitioning from large, capital-intensive facilities to flexible, distributed models (Tornese et al., 2020). On-demand platforms exemplify this shift, leveraging crowd-shipping and crowd-sourcing to mobilize underutilized vehicles and storage spaces, reducing fixed costs and enhancing supply chain resilience (Carbone et al., 2017). However, these models rely heavily on robust digital infrastructure and face challenges in managing demand fluctuations, particularly for SMEs with limited capital and platform access (Unnu and Pazour, 2019).

2.1.2 The Shift Towards On-Demand Warehousing Solutions

The sharing economy's influence on logistics is most evident in crowd-shipping, where informal couriers fulfill transportation needs via digital platforms (Elia et al., 2024). Yet, shared storage services remain underexplored despite their potential to address seasonal demand fluctuations and optimize resource utilization (Rogers et al., 2020).

As urbanization intensifies and space becomes increasingly scarce, innovations like Automated Storage and Retrieval Systems (ASRS) aim to optimize warehousing in densely populated areas (Rogers et al., 2020). However, traditional warehousing models often face inefficiencies during periods of low demand, underscoring the need for flexible, technology-driven solutions (Rogers et al., 2020; Xenou et al., 2021).

Historically, logistics networks relied on in-house distribution systems or long-term partnerships with third-party logistics (3PL) providers, structured around fixed commitments and precise forecasts (Tornese et al., 2020; Correia and Melo, 2022). While these models provided stability, they often lacked the flexibility required to navigate market volatility. Critics contend that traditional logistics service providers remain tethered to outdated, relying on rigid contracts that limit their capacity to evolve with shifting supply chain demands (Gnoni and Tornese, 2023).

ODW represents a paradigm shift, offering short-term, scalable storage solutions that cater to fluctuating demand. Businesses benefit from reduced rigidity, while asset owners monetize underutilized resources (Tornese et al., 2020). This shift from long-term outsourcing to agile, tactical operations underscores ODW's potential to meet the needs of modern supply chains (Xenou et al., 2021). However, challenges such as technological integration, infrastructure readiness, and trust among stakeholders remain critical hurdles to its widespread adoption (Gnoni and Tornese, 2023; Elia et al., 2024).

2.1.3 Navigating Challenges in the Sharing Economy

Despite its transformative potential, the sharing economy within the logistics sector faces several significant hurdles that can impede its full realization, such as :

- *Infrastructure Demands:* High-quality infrastructure and reliable digital platforms are prerequisites for effective implementation (Carbone, 2021).
- *Standardization Gaps:* The absence of a universally accepted definition and a cohesive framework for sharing economy models in logistics, which are critical for its

broader acceptance and integration, creates inconsistencies and scalability issues across regions (Parodos et al., 2022; Elia et al., 2024).

- *Operational Complexity*: Variations in development approaches and operational philosophies complicate adoption and undermine standardization efforts (Carissimi and Creazza, 2022).

Overcoming these challenges demands a grasp of sharing economy dynamics, emphasizing partnerships, standardized models, and advanced technologies to streamline processes and build trust. This approach enables logistics companies to navigate complexities and fully leverage the sharing economy’s potential (Carbone, 2021; Xenou et al., 2021; Elia et al., 2024).

2.2 Current Warehousing and the Need for Alternative Solutions

E-commerce retailers confronted with limited warehouse capacity have traditionally had a few options. One approach is constructing new warehouses or expanding existing infrastructure, which requires considerable capital investment (Unnu and Pazour, 2019). Alternatively, retailers can lease warehouse space from traditional operators or third-party logistics providers (3PLs). However, these approaches demand significant capital investment, limiting flexibility for businesses in need of adaptable storage solutions, and often entail long-term contractual commitments, making them less viable for retailers seeking flexible storage solutions (Ceschia et al., 2022). The final option for e-commerce retailers is to utilize on-demand warehousing capabilities (Lahy et al., 2022).

This section examines common warehousing models, analyzes the varying cost structures associated with each, and highlights the need for alternative solutions. It highlights how optimal strategies vary based on operational requirements and strategic objectives, focusing on the trade-offs between cost, flexibility, and control in supply chain management decisions.

2.2.1 Common Warehousing Models

The warehouse has transcended its traditional role as a mere storage facility to become a critical component of business success (Jum’a and Basheer, 2023), driven by the complexities of today’s competitive business environment, where a warehouse’s functionality is not limited to inventory storage but extends to managing value-added services (Ekren et al., 2023). Jum’a and Basheer (2023) reinforces this notion, suggesting that well-orchestrated warehousing activities can significantly enhance customer value—a sentiment and bolster supply chain competitiveness as echoed by Strøm et al. (2023). Building on Tornese et al. (2020) comprehensive typology, Table 2.1 summarizes key warehousing models. Each model differs in cost, control, and flexibility, catering to varied operational needs.

Private Warehouses offer high control and customization but require significant investment and are less adaptable to demand fluctuations. Contracted models include *Dedicated Warehouses*, providing tailored services for single clients but necessitating long-term commitments, and *Shared Warehouses*, which enhance cost-efficiency by accommodating multiple clients at the cost of reduced control. *Public Warehouses* provide flexibility with

Table 2.1: Types of Warehouse Models and Their Primary Differences*Source: Tornese et al. (2020)*

Warehouse type	Business model	Owner of Facility	Space utilization	Fee service type	Commitment period
Private Aarehouse	Owned	Private company	Only items of the company	Internal cost	Long term (investment costs)
Contracted Dedicated Warehouse	Outsourced	3PL	Items of a single customer	Flat + variable fee	Long (e.g., 3-5 years)
Contracted Shared Warehouse	Outsourced	3PL	Items of different customers	Flat + variable fee	Long (e.g., 1-2 years)
Public Warehouse	Outsourced	3PL	Items of different customers	Based on the actual service level	Short (e.g., one month)
Pooled Warehouse	Consortium	Private companies	Only items of the participating partner companies	Shared internal cost	Long term (investment costs)
On-Demand Warehouse	Mixed through a platform company	Private companies	Items of the lender company and of different on-demand customers	Based on the actual service level	Short (e.g., one month)

short-term agreements but may face capacity limitations due to their first-come, first-serve approach (Tornese et al., 2020).

Pooled Warehouses exemplify collaborative logistics, enabling consortium members to share resources, though they require long-term commitment and collective decision-making. Meanwhile, *On-Demand Warehousing* leverages digital platforms to match underutilized assets with demand, offering agility and scalability without traditional commitments (Lahy et al., 2022).

In synthesizing these insights, Unnu and Pazour (2019) argue that as companies navigate the decision-making process regarding distribution strategies, the choice among these models depends on balancing operational control, cost, financial outlay, service levels, and the agility required to adapt to market dynamics.

2.2.2 Varying Cost Structures of Alternative Warehouse Strategies

Comparison of Distribution Center Alternatives

The study by Unnu and Pazour (2019) compares the cost structures and characteristics of three main warehousing strategies: *Self-Distribution*, *Third-Party Logistics (3PL) Providers*, and *On-Demand Warehousing (ODW)*. Each model offers distinct advantages and challenges, as summarized in Table 2.2.

Self-Distribution provides greater control and trust with lower operational costs per

Table 2.2: Comparison of Distribution Center Alternatives*Source: Unnu and Pazour (2019)*

	Advantages	Disadvantages
Self Distribution	• Low operational costs per pallet if operated at high capacity utilization • Trust and control	• High investment costs and the longest commitment • Not adaptable to demand variability and volatility • Long start-up period
3PL	• More flexible than self-distribution • Shorter start-up period • Much lower initial investments	• Higher operational costs • Start-up period required for contract negotiation • Commitment with binding contracts • Potential trust, quality, and performance issues
On-Demand	• Highest flexibility • No latency between decision and implementation • No initial investments	• Highest unit costs • Minimal control • Potential trust, quality, and performance issues

pallet when operating at full capacity. However, it requires substantial initial investment, long-term commitment, and is less adaptable to fluctuating demand (Unnu and Pazour, 2019).

3PL Providers are more flexible with shorter start-up times and lower initial costs compared to self-distribution. Nevertheless, this model involves higher operational costs, binding contracts, and potential concerns regarding trust and service quality. Furthermore, *On-Demand Warehousing* stands out for its unmatched flexibility, allowing rapid scaling without initial investments. Despite these advantages, it incurs the highest per-unit costs and challenges in maintaining control and consistent service quality (Unnu and Pazour, 2019).

Cost Analysis of Warehouse Strategies

Warehouse cost structures are categorized into *Initial Costs*, *Operational Costs*, *Holding Costs*, and *Handling Costs* (Unnu and Pazour, 2019; Tornese et al., 2020), forming the foundation for evaluating distribution center (DC) strategies. Table 2.3 provides a comparative overview of these cost components across self-distribution, third-party logistics (3PL), and on-demand warehousing (ODW) models.

- *Initial Costs*: These one-time expenses encompass the acquisition or construction of facilities and equipment procurement. Self-distribution entails substantial upfront investment, while on-demand warehousing minimizes these costs by leveraging shared infrastructure (Unnu and Pazour, 2022; Pazour and Unnu, 2018).
- *Operational Costs*: Recurring costs include labor, utilities, and maintenance. Self-distribution and 3PL models often involve fixed monthly fees, whereas on-demand

Table 2.3: Main Cost Types and DC Alternatives

Source: Unnu and Pazour (2019)

DC Alternative	Initial Costs (\$)	Operational Costs (\$/month)	Holding Costs (\$/month*pallet)	Handling Costs (\$/pallet)
Self Distribution	• Construction or acquisition • Equipment (handling, storage, etc.) • Closing costs, due diligence	• Labor (direct labor, common, management, etc.) • Equipment rental (e.g., handling, storage) • Other charges (insurance, outsourced services, etc.)	None	None
3PL	• Monthly contractual payments • Other charges (insurance, outsourced services, etc.)	None	Per pallet costs	Per pallet costs
On-Demand	None	None	Per pallet per month costs	Per pallet costs

warehousing aligns costs with usage, enhancing flexibility (Carbone, 2021; Lahy et al., 2022).

- *Holding Costs:* These storage-related expenses, calculated per unit or volume per month, vary with inventory levels. On-demand warehousing’s pay-per-use model benefits businesses with fluctuating inventory, offering scalable solutions (Unnu and Pazour, 2019).
- *Handling Costs:* Costs tied to the frequency and volume of goods movement are critical for high-throughput businesses. On-demand models charge per transaction, which may increase costs for companies with frequent operations (Unnu and Pazour, 2019).

The analysis demonstrates that the optimal warehousing strategy depends on operational needs and strategic goals. On-demand warehousing excels in flexibility and scalability, requiring no upfront investments, making it ideal for businesses with fluctuating demand. However, its higher per-unit costs may not suit companies with stable, predictable operations or those benefiting from long-term investments (Unnu and Pazour, 2019; Elia et al., 2024). Self-distribution offers cost efficiency and control over time but demands significant initial investment and lacks adaptability. Meanwhile, third-party logistics (3PL) provides a balance of flexibility and lower startup costs, though it entails higher operational expenses and contractual constraints (Unnu and Pazour, 2019).

Ultimately, selecting a warehousing strategy requires balancing cost, control, and flexibility while aligning with broader business objectives, considering factors such as demand variability, capital resources, and desired control over logistics processes (Tornese et al., 2020; Carissimi and Creazza, 2022).

Chapter 3

State of Art Analysis of On-Demand Warehousing

On-demand warehousing (ODW) represents a novel and evolving concept within the logistics sector, offering unparalleled flexibility and scalability for businesses seeking adaptable storage solutions. Yet it remains underexplored in scholarly literature (Gnoni and Tornese, 2023; Elia et al., 2024). Despite the growing adoption of ODW platforms by enterprises primarily based in the United States, European Union, and select Asian economies, a comprehensive academic framework for these business models is still in its nascent stages, also leaving the main implications for businesses unexplored (Lahy et al., 2022).

Scholars such as Pazour and Unnu (2018) and Tornese et al. (2020) have emphasized the need for robust decision-making frameworks to address the complexities of ODW systems. These include capacity allocation, cost structures, and integration into broader supply chain strategies. The lack of established models that support decision-makers leaves critical gaps in understanding ODW's operational dynamics, stakeholder interactions, and long-term viability. This chapter seeks to bridge these gaps by synthesizing existing perspectives and laying the groundwork for structured analysis.

This chapter synthesizes diverse perspectives to present a holistic understanding of ODW as an innovative logistics solution, with a focus on operational dynamics and key stakeholders. It delves into the operational frameworks of ODW platforms, analyzing service offerings and cost-revenue models. Additionally, it examines the potential transition of ODW platforms into integrated 4PL solutions, enabling end-to-end supply chain management. Finally, the chapter evaluates the strategic advantages of ODW, such as flexibility and scalability, alongside its challenges, including cost variability and implementation barriers. This chapter establishes a foundation for a structured approach for analyzing and evaluating ODW within supply chain operations.

To achieve these objectives, the chapter is organized into four sections: Section 3.1 discusses the theoretical frameworks underpinning ODW and its relationship with modern distribution systems. Section 3.2 analyzes the dynamics, service offerings, and cost-revenue models of ODW platforms. Section 3.3 examines the transition from ODW to integrated 4PL solutions, bridging flexibility with holistic supply chain management. Finally, Section 3.4 explores ODW's strategic benefits and limitations, offering insights into its practical adoption and future opportunities.

3.1 Theoretical Frameworks of ODW

There is no universally agreed-upon definition of On-Demand Warehousing (ODW) in the literature. However, Elia et al. (2024) suggests that *"ODW represents a B2B alternative to traditional warehousing strategies, such as leasing or outsourcing offered by third-party logistics providers (3PLs). Facilitated by online third-party platforms, ODW connects suppliers with surplus warehouse space to businesses in need of short-term storage solutions, creating a symbiotic ecosystem"*.

These platforms function as dynamic marketplaces, matching supply with demand in real-time. Suppliers benefit from increased resource utilization and additional revenue streams, while demand-side entities gain access to flexible storage capacity (Tornese et al., 2020; Gnoni and Tornese, 2023).

The research on On-Demand Warehousing (ODW) is still in its early stages, with studies primarily addressing theoretical and operational dimensions. Early conceptualizations by Pazour and Unnu (2018), highlighted ODW's flexibility and efficient resource utilization in volatile demand environments, while Tornese et al. (2020) delved into the operational advantages, challenges, and strategic implications of ODW, proposing a framework highlighting its adaptability and scalability.

Theoretical approaches to digital transformation in logistics were explored by Lahy et al. (2022), who outlined the potential of flexible, on-demand warehousing in enabling scalable and responsive supply chains. Expanding on these foundations, recent studies have tackled various aspects of ODW implementation. Studies like Van der Heide et al. (2020) and Correia and Melo (2022) explored hybrid network integrations and shipment optimizations in shared systems, illustrating how dynamic allocation strategies can enhance logistics performance across varied structures.

Operational investigations have focused on key challenges and opportunities. Unnu and Pazour (2022) addressed dynamic facility location problems, comparing ODW with 3PL and self-distribution strategies, while highlighting risks such as uncertain service availability. Gnoni and Tornese (2023) examined resource allocation from a supplier's perspective, while Lee et al. (2024) addressed inventory and commitment decisions under uncertainty, demonstrating ODW's cost-effectiveness in certain scenarios.

The market-readiness perspective was addressed by Xenou et al. (2021), who analyzed the Greek market for ODW adoption, identifying barriers such as regulatory constraints and digital infrastructure limitations. Similarly, Parodos et al. (2022) used a Business Model Canvas to align ODW strategies with urban mobility needs, emphasizing its integration in smart city logistics. Building on these insights, Elia et al. (2024) conducted a comprehensive trend analysis of ODW as a sharing economy model, outlining its evolution, identifying key enablers, and addressing platform-specific challenges.

While the operational benefits and foundational structures of ODW are gradually being outlined, significant gaps remain in understanding its managerial implications and strategic applications (Correia and Melo, 2022; Gnoni and Tornese, 2023). These areas remain critical for ODW's broader adoption and operational efficiency (Elia et al., 2024). These gaps offer opportunities for further exploration into ODW's strategic and operational dimensions within the logistics sector.

A summary of these studies, methodologies, and findings is presented in Table 3.1, illustrating the evolving academic discourse on ODW.

Table 3.1: Chronological Review of Key Studies on On-Demand Warehousing Models

Author(s)	Methodology	Topic/Focus	Key Findings
Pazour and Unnu (2018)	Conceptual Analysis	Comparative analysis of ODW vs. traditional warehousing	Highlighted flexibility and better resource utilization
Tornese et al. (2020)	Framework Development	Features and business models of ODW	Proposed a general framework for ODW business models
Van der Heide et al. (2020)	Network Modeling	Dynamic shipments in ODW-enabled shared networks	Optimized shipment strategies for various network structures
Xenou et al. (2021)	Market Analysis	Readiness of the Greek market for ODW adoption	Discussed market dynamics and adoption barriers
Unnu and Pazour (2022)	Dynamic Facility Location Model	Evaluating ODW with 3PL and self-distribution strategies	Emphasized ODW's scalability but noted risks of service availability
Parodos et al. (2022)	Business Model Canvas	Analysis of smart city logistics and ODW e-marketplaces	Highlighted strategic alignment with urban mobility needs
Lahy et al. (2022)	Theoretical Analysis	Flexible, on-demand warehousing for digital transformation	Explored integration of ODW in digital supply chains
Ceschia et al. (2022)	Optimization Model	The on-demand warehousing problem	Analyzed optimization strategies for ODW under varying conditions
Gnoni and Tornese (2023)	Dynamic Programming	Resource allocation for ODW platforms from the lender's perspective	Explored space allocation strategies to optimize resource use
Correia and Melo (2023)	Distribution Network Redesign	Hybrid networks integrating ODW	Improved responsiveness to demand changes
Lee et al. (2024)	Mixed Integer Programming	Inventory and commitment decisions in ODW systems	Demonstrated cost-effectiveness under uncertain supply and demand
Elia et al. (2024)	Trend Analysis	Evolution and trends in ODW as a sharing economy model	Identified key enablers and challenges for ODW platforms

3.1.1 On-Demand Warehousing and Distribution Systems

On-Demand Warehousing Actors

As illustrated by Unnu and Pazour (2019), ODW systems involve three pivotal actors, as explained in Figure 3.1 which shows the stakeholder dynamics in On-Demand Warehousing platforms:

- *Supply Owners (Lenders)*: Typically not traditional suppliers, these entities share access to their underutilized resources, such as warehouse space, deriving additional value and possibly attaining a more consistent workload.
- *Demand Requests*: Customers (either individuals or businesses) who do not own the resources, articulate their immediate, often short-term, needs for warehousing resources, generally requiring small resource amounts.
- *Central Mechanism/The Platform*: This third-party organization orchestrates the supply-demand interactions, operating a marketplace that enhances visibility for both suppliers and customers .

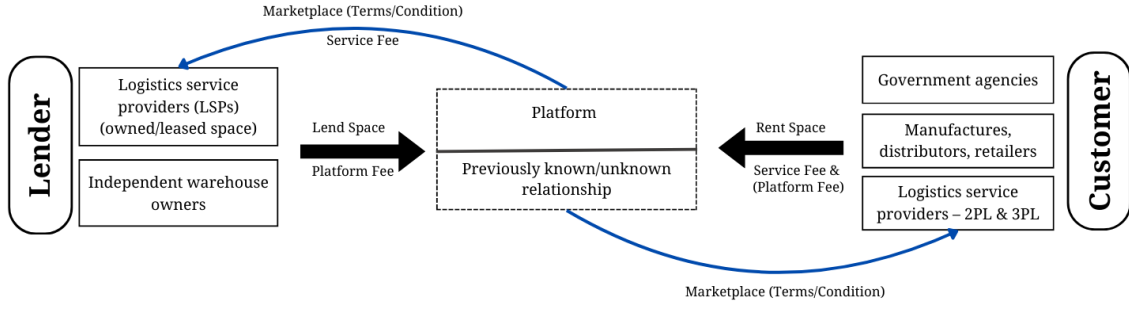


Figure 3.1: Stakeholder Dynamics in On-Demand Warehousing Platforms

Operational Framework of ODW Systems

The operational framework of On-demand distribution systems departs significantly from traditional logistics methods due to several key attributes Pazour and Unnu (2018):

- *Marketplace:* On-demand systems link supply owners with surplus capacity to users, relying on critical mass to balance supply and demand for optimal functionality.
- *Open Market Structure:* These platforms facilitate diverse participation with minimal barriers, using standardized agreements for flexibility and scalability, though they may face inconsistencies in resource availability.
- *Dynamic Capacity:* Capacity depends on voluntary supply-owner participation, necessitating strategies to ensure steady engagement and consistent service quality.
- *Resource Allocation:* Effective coordination matches distributed resources with demand, balancing platform efficiency with supply-owner autonomy to ensure reliable service.
- *Online-to-Offline Integration:* Platforms digitally manage allocation while fulfillment occurs offline through transportation, storage, and order execution, requiring seamless coordination.
- *Technology Utilization:* By leveraging technology, on-demand systems unlock underutilized resources, improving asset utilization and cost-efficiency across logistics networks.

3.2 Dynamics of On-Demand Warehousing Platforms

On-demand warehousing platforms have emerged as pivotal intermediaries in logistics, connecting warehouse owners (lenders) with businesses requiring temporary storage (renters) through digital platforms Pazour and Unnu (2018); Tornese et al. (2020). These platforms enhance visibility, accessibility, and efficiency, addressing seasonal demand fluctuations and fostering resource elasticity in alignment with principles like the Physical Internet (Xenou et al., 2021; Elia et al., 2024).

Central to these platforms is achieving critical mass, where increased participation enhances network effects. Effective platforms accommodate diverse supply capabilities and

evolve services from basic storage to advanced operations like order fulfillment, KPI monitoring, and consulting (Tornese et al., 2020; Elia et al., 2024). Geographical segmentation further influences platform performance and shapes platform selection and service adaptability, with significant activity in the EU, North America, and Southeast Asia (Gnoni and Tornese, 2023).

Figure A.1 in Appendix A outlines the proposed ODW framework, highlighting benefits, cost structures, and service offerings (Tornese et al., 2020).

The platforms typically offer two categories of services: *Physical services* and *Additional services*. *Physical services* include core operations such as pallet-in/pallet-out storage, order fulfillment (e.g., picking, packing, kitting), and e-commerce support, including returns and transportation (Tornese et al., 2020). Meanwhile, *Additional services* include a cloud-based warehouse management system (WMS), inventory tracking, consulting, benchmarking, and specialized services like white-glove installation (Tornese et al., 2020).

Based on the range of services offered, the platforms are categorized into three main groups. *The first group (Level 0)* provides only basic storage services. *The second group (Level 1)* offers additional warehouse operations if required by the renter. *The highest group (Level 2)* offers a comprehensive set of services, including consulting and KPI monitoring, which are not directly managed by the lenders but are facilitated by the platform (Tornese et al., 2020).

As depicted in Figure 3.2, the clusterization of platforms according to the service spectrum is based on the pioneering work by Tornese et al. (2020). This analysis provides an initial classification of on-demand warehousing business models, incorporating a comprehensive review of active platforms as of 2020. While most platforms start at Level 0, they may advance by expanding their services to meet evolving renter demands and market needs (Tornese et al., 2020).

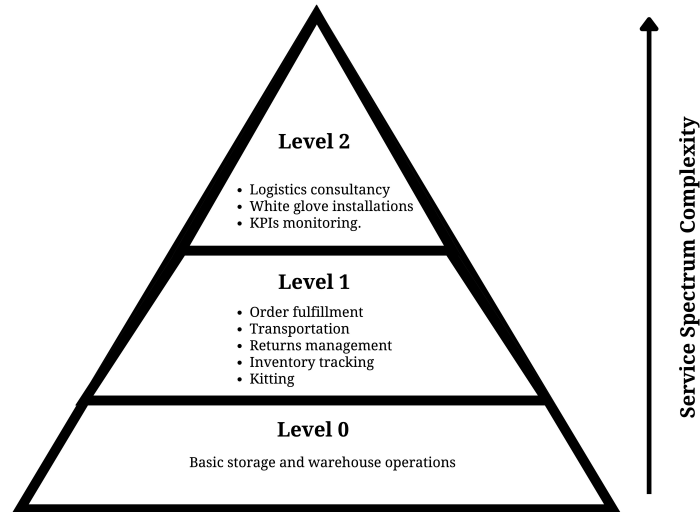


Figure 3.2: Hierarchy of Platform Services According to The Service Spectrum

Source: Tornese et al. (2020)

Accordingly, joining an on-demand platform involves distinct processes for *Renters* and *Lenders*. *Renters* register, agree to terms, and specify space and service requirements, while *Lenders* provide detailed listings of available spaces and services.

3.2.1 Service Offerings of On-Demand Warehousing Platforms

3.3 Building upon the foundational work of Gnoni and Tornese (2023) then (Elia et al., 2024) which endeavors to construct an initial conceptual framework for On-Demand Warehousing, their research meticulously explores operational nuances within the ODW domain. Their analysis of existing ODW platforms, active as of 2023, identifies prevailing trends within this innovative approach to warehousing.

These platforms are characterized by their dynamic cost structures, varying service offerings, and geographical focus. The analysis of 15 platforms reveals a bifurcation, Elia et al. (2024) identified two primary clusters within ODW platforms: *Pure ODW platforms* and *Mixed ODW-4PL platforms*.

Pure ODW platforms operate on a peer-to-peer model, facilitating direct interactions between customers and lenders, akin to sharing economy models like Airbnb, while *Mixed ODW-4PL platforms* blend ODW services with 4PL capabilities. These platforms establish strategic partnerships with lenders, guaranteeing service quality and consistency while broadening their range of services to include end-to-end supply chain management (Elia et al., 2024).

The service spectrum of ODW platforms ranges from basic storage to comprehensive packages, including order fulfillment, inventory management, and value-added services (VAS) like supply chain consulting and KPI monitoring (Gnoni and Tornese, 2023; Elia et al., 2024). Pure ODW platforms like Stockspots and Stowga offer value-added services such as order fulfillment, returns management, kitting, and regulatory compliance for specialized industries (Gnoni and Tornese, 2023).

Meanwhile, mixed ODW-4PL platforms, such as Flexe and Stord, extend their capabilities to include comprehensive supply chain optimization, including inventory management, custom packaging, and transportation (Tornese et al., 2020; Elia et al., 2024). The inclusion of additional services such as cloud-based warehouse management systems (WMS), KPI monitoring, and consulting further enhances the value proposition of these platforms, making them attractive for businesses seeking end-to-end logistics solutions (Elia et al., 2024). However, the lack of service standardization across platforms remains a challenge, particularly for renters requiring uniform service levels across multiple locations.

Elia et al. (2024) also emphasize the geographic disparities in ODW adoption. While the model originated in the U.S., with pioneers like Flexe, it has gained greater traction in Europe, where regulatory frameworks and market conditions have proven more conducive to its growth (Gnoni and Tornese, 2023). Half of the pure ODW platforms analyzed by Elia et al. (2024) are based in Central and Northern Europe, compared to only two in the U.S., indicating a shifting market dynamic. This geographic disparity highlights the importance of understanding regional market conditions and the factors driving the adoption of ODW solutions, such as demand volatility, regulatory support, and customer expectations (Elia et al., 2024).

A notable distinction lies in the platforms' cost models. While most allow lenders to list their spaces without charge, a few platforms require a fee proportional to the invoice, depending on the service type (Rogers et al., 2020; Elia et al., 2024). For customers, costs typically follow a pay-as-you-go approach, with additional platform fees, facilitating either direct transactions or platform-mediated payments (Gnoni and Tornese, 2023).

Notably, regarding regulatory policies and compliance, only one platform, Ware2Go by UPS, conducts audits on lenders to ensure compliance with certain standards before they

can register (Tornese et al., 2020; Elia et al., 2024). A comprehensive summary of ODW platforms analyzed with their main features is provided in Appendix Table A.1.

3.2.2 Prevailing Cost Structures and Revenue Streams in ODW Platforms

The current common cost structures in on-demand warehousing platforms exhibit notable variations. Many pure ODW platforms, as analyzed by Elia et al. (2024), allow lenders to list spaces without fees, generating revenue through customer transaction fees calculated on a weekly or monthly per-pallet basis. This pay-as-you-go model offers financial flexibility. In some cases, such as Warehouse Exchange, both lenders and customers are charged, demonstrating diverse revenue models. Mixed ODW-4PL platforms, by contrast, integrate costs into broader logistics services, consolidating financial obligations into a single managed contract rather than maintaining transactional models (Elia et al., 2024).

For renters, costs typically include a *Storage Fee*, calculated per pallet on a monthly or weekly basis, a *Handling Fee* determined by required services (e.g., receiving, order processing, shipping), and an *Additional Fee* calculated based on the additional services requested by the renter. These fees provide flexibility but differ from traditional warehousing, which involves upfront investments in facilities or long-term leases, incurring higher fixed costs but potentially lower variable costs if capacity aligns with demand (Tornese et al., 2020).

Lenders, on the other hand, face less uniform cost models. Most platforms allow free listings, but platform fees vary, often calculated monthly or per transaction as a percentage or negotiated rate. These details are frequently opaque, revealed only upon registration or inquiry. Platform revenues typically stem from fees paid by renters, though some retain portions of these fees in undisclosed transactions, supporting operational sustainability (Tornese et al., 2020).

The successful adoption of ODW requires strategic adjustments to pricing, service levels, and operations to enhance competitiveness and functionality. Transparent pricing, real-time space availability, and simplified digital interfaces are critical for quick and informed decision-making (Pazour and Unnu, 2018; Elia et al., 2024). Furthermore, ODW promotes sustainable logistics by optimizing underutilized assets, reducing overcapacity, and aligning with environmental goals. Its inherent flexibility also strengthens disaster response capabilities by reallocating resources to urgent needs (Pazour and Unnu, 2018; Xenou et al., 2021).

3.3 Transition from ODW to Integrated 4PL: A Phenomenon

The transition from On-Demand Warehousing (ODW) platforms to integrated Fourth-Party Logistics (4PL) providers marks a significant evolution in the logistics and supply chain industry (Gnoni and Tornese, 2023; Elia et al., 2024). Companies such as Flexe, Stord, and FlowSpace in the U.S., along with their European counterparts, have shifted from offering flexible, short-term storage solutions to providing comprehensive 4PL services. This transformation reflects the growing demand for end-to-end supply chain man-

agement and enhances competitiveness in omnichannel and e-commerce fulfillment (Gnoni and Tornese, 2023).

Mixed ODW-4PL platforms represent a critical stage in this evolution, blending the flexibility of traditional ODW models with the reliability and service breadth of 4PL solutions. These platforms act as direct service providers, delivering storage, distribution, and advanced supply chain capabilities while streamlining communication through a single point of contact. By leveraging extensive networks of verified partners, they ensure consistency, scalability, and high-performance levels, making them suitable for businesses with dynamic logistics needs (Elia et al., 2024).

As summarized in Table 3.2, several ODW platforms have evolved into 4PL providers, focusing on omnichannel fulfillment and supply chain optimization.

Table 3.2: Former ODW Platforms with New Core Businesses

Source: Gnoni and Tornese (2023)

Logistic company (4PL)	Website slogan	Based (founded)	Service offering	Declared Core Business
Flexe	The intersection of logistics and technology	USA (2013)	• E-commerce fulfillment • Inventory management • Order management • Storage & distribution • Integrated software	Omnichannel
Flowspace	Fast, Reliable E-commerce Fulfillment for Omnichannel Brands	USA (2017)	• E-commerce fulfillment • Inventory management • Order management • Network optimization • Integrated software	Omnichannel
Stord	Make Your Supply Chain a Competitive Advantage	USA (2015)	• Storage & distribution • Omnichannel fulfillment • Custom packaging • Cross-docking • Network optimization • Integrated software	Omnichannel
Ware2go (by UPS)	Simplify Your Operations warehousing to delivery	USA (2018)	• Storage & distribution • Fulfillment optimization • Omnichannel fulfillment	Omnichannel
Waredock	The New Era of Green Fulfillment	Scandinavian countries (2019)	• Storage & shipping • E-commerce fulfillment • Omnichannel fulfillment	E-commerce fulfillment

The service offerings of mixed ODW-4PL platforms extend beyond basic storage and handling to include inventory management, supply chain analytics, and network optimization. However, Jum'a and Basheer (2023) notes that focusing exclusively on basic services often yields minimal profit margins due to a lack of differentiation. Integrating Value-Added Services (VAS) allows logistics providers to manage more comprehensive aspects

of their clients' supply chains, securing a competitive advantage and higher profitability. Moreover, by expanding the service range, logistics providers can deepen client relationships and position themselves as essential partners in their client's business strategies.

Under the 4PL model, customers engage with a single provider that coordinates all logistics activities through a standardized and reliable framework. This approach contrasts with the peer-to-peer structure of Pure ODW platforms, which often favored short-term commitments and exhibited variability in service quality. By prioritizing long-term relationships while maintaining scalability and flexibility, Mixed ODW-4PL platforms address the complexities of modern logistics (Gnoni and Tornese, 2023).

3.3.1 Features Positioning of ODW, 3PL, and 4PL

Based on the pioneering work of Gnoni and Tornese (2023) and subsequent insights from Elia et al. (2024), the analysis of ODW and its operational dynamics highlights key distinctions when compared to mixed ODW-4PL, 3PLs, and 4PLs. These distinctions are critical for service users and providers in selecting suitable logistics models as they highlight key differences in their approaches and implications for stakeholders.

As depicted in Table 3.3, Pure ODW platforms excel in flexibility, short-term commitments, and adaptability to sporadic storage needs. However, they often face challenges such as inconsistent service quality, lack of standardization, and limited opportunities for optimization or innovation. Mixed ODW-4PL platforms mitigate these issues by integrating advanced logistics services, quality control, and operational reliability while preserving some flexibility (Elia et al., 2024).

Table 3.3: Comparison Of Features Between Pure ODW , Mixed ODW, 4PLs, and 3PLs

Source: Elia et al. (2024)

Features	Pure ODW Platforms	Mixed ODW-4PLs	4PLs	3PLs
Time to service	Days	Days/weeks	Weeks/months	Weeks/months
Lenders' relationship	Short-term, flexible (involves many lenders)	Medium/long-term (involves many lenders)	Medium/long-term (involves many lenders)	3PL is the only lender
Lenders' reliability	Variable	High (verified lenders)	High (verified lenders)	High
Facilities involved	High (network-based)	High (network-based)	High (network-based)	Low
Service portfolio	Medium variety of logistics services (depending on the lender)	Wide variety of logistics services	Wide variety of logistics services	Wide variety of logistics services
Automation	Not provided	Usually not provided	Can be provided	Can be provided
Inventory tracking	Optional	Guaranteed	Guaranteed	Guaranteed
Time commitment	Weeks	Weeks/months	Months	Months
Capacity granularity	Per pallet	Per pallet	Minimum space required	Minimum space required
Access to scale	High	High	High	Low
Cost structure	Pay-as-you-go	Pay-as-you-go	Flat + variable fee	Flat + variable fee

For customers, mixed ODW-4PL platforms provide access to a broader range of services and standardized performance levels, making them ideal for medium- to long-term logistics needs. Conversely, pure ODW platforms are better suited for businesses requiring temporary, short-term storage solutions with high adaptability. From a lender's perspective, joining a mixed ODW-4PL network requires adherence to predefined quality standards, contrasting with the self-regulated offerings typical of pure ODW platforms. Although this may seem restrictive, it ultimately benefits lenders by ensuring stability in demand and increasing the likelihood of matching with customers (Elia et al., 2024).

In summary, mixed ODW-4PL platforms cater to businesses that prioritize reliability, comprehensive service, and long-term partnerships, while pure ODW platforms serve those needing quick, flexible, and short-term solutions (Elia et al., 2024). This evolution illustrates the logistics sector's adaptive strategies in meeting the complex demands of modern commerce (Gnoni and Tornese, 2023).

3.4 Strategic Granularity and Flexibility in ODW

On-demand warehousing streamlines the search for available space by consolidating offerings on a single platform, thereby enhancing transparency and reducing the time and resources typically spent on securing warehousing. Additionally, the model supports sustainability by enabling closer proximity of warehouse locations to destinations, facilitating the use of more sustainable transportation options, and reducing the need for new storage constructions, thereby benefiting urban livability and planning (Tornese et al., 2020).

Pazour and Unnu (2018) identify three critical factors distinguishing on-demand warehousing from traditional options like new construction and leasing. These factors, illustrated in Figure ?? in the Appendix, provide a framework for evaluating the adaptability of different warehousing models.

1. *Capacity Granularity*: Refers to the smallest unit of storage available.
 - New Construction: Entire facilities (e.g., warehouses) are the minimum units.
 - Leasing: Measured in square feet, offering moderate granularity.
 - On-Demand Warehousing: Operates on a per-pallet basis, offering the highest granularity and allowing companies to scale operations efficiently (Pazour and Unnu, 2018).
2. *Commitment Granularity*: This represents the minimum duration required for a distribution decision.
 - New Construction: Long-term commitments (5+ years) tied to ROI timelines.
 - Leasing: Contracts typically range from 1 to 3 years.
 - On-Demand Warehousing: Monthly commitments, aligning with pay-as-you-go pricing models, provide unmatched flexibility with minimal financial risk (Pazour and Unnu, 2018).
3. *Access to Scale*: This evaluates how efficiently a distribution model meets demand across a geographic area.

- **Traditional Ownership:** Limited locations increase delivery distances, often requiring costly transportation.
- **On-Demand Warehousing:** Leverages a distributed network of resources to reduce delivery times and costs, enhancing scalability without upfront infrastructure investments (Pazour and Unnu, 2018).

Each warehousing option has distinct benefits and trade-offs. New Construction offers low variable costs but requires high utilization and significant fixed investments. Leasing balances cost and flexibility with moderate long-term commitments. On-Demand Warehousing provides unmatched flexibility and scalability with short-term commitments but incurs higher variable costs and operational complexity. However, for modern businesses in a fast-paced environment, a hybrid approach combining multiple strategies may better balance cost, flexibility, and scalability for most companies (Pazour and Unnu, 2018).

3.4.1 Strategic Advantages of ODW for Stakeholders

The discourse on On-Demand Warehousing (ODW) has prominently highlighted its transformative impact on modern supply chain management, presenting a dual perspective on the benefits accrued to both customers and lenders (Tornese et al., 2020; Elia et al., 2024).

- **Advantages for Customers:**

- *Flexibility in Storage Services:* ODW enables capacity and commitment granularity, allowing businesses to adapt their warehousing needs to seasonal market fluctuations and unexpected disruptions. This enhances overall supply chain agility (Tornese et al., 2020; Elia et al., 2024)
- *Access to Scale and Enhanced Market Accessibility:* Customers can strategically select warehouses close to demand points, reducing last-mile delivery costs and times. This expanded network supports rapid scaling across regions, offering an edge over traditional 3PL solutions (Ekren et al., 2023; Elia et al., 2024).
- *Cost-Effectiveness:* The pay-per-use model shifts fixed costs to variable ones, providing an economical option for short-term storage needs (Tornese et al., 2020; Elia et al., 2024). Furthermore, the shift from fixed to variable costs under the ODW model reduces financial risk and increases operational flexibility for customers. This allows them to invest more dynamically in areas like inventory or marketing without the burden of high upfront costs Ekren et al. (2023).
- *Faster Shipping:* Proximity to end points minimizes delivery times, addressing the growing demand for expedited shipping and enhancing customer satisfaction (Ekren et al., 2023; Elia et al., 2024).
- *Sustainability and Urban Planning:* By optimizing the proximity of storage to delivery destinations, ODW supports greener transportation options and minimizes the need for new constructions, benefiting urban development and enhancing livability within densely populated areas (Tornese et al., 2020).

• **Advantages for Lenders:**

- *Maximized Warehouse Capacity and Utilization:* Lenders can monetize surplus capacity, ensuring better resource utilization and generating additional profits (Ekren et al., 2023; Elia et al., 2024).
- *Dynamic Allocation and B2B Connectivity:* Lenders retain flexibility in allocating space on the platform and benefit from streamlined B2B connections, increasing occupancy rates (Tornese et al., 2020; Elia et al., 2024).
- *Larger Warehousing Network:* While primarily a customer benefit, lenders also gain from being part of a larger network, which increases their visibility to potential renters and can lead to higher occupancy rates Ekren et al. (2023).
- *Economic Impact for the Supply Chain:* A comparative analysis suggests that using ODW models can lead to lower total supply chain costs than utilizing traditional 3PL warehousing solutions, making it a financially attractive option for many businesses (Tornese et al., 2020).

Table 3.4: Comparison of Strategic Advantages for Stakeholders in ODW Models

Advantages for Customers	Advantages for Lenders
- High granularity in capacity and commitment allows adaptation to market fluctuations.	- Dynamic space allocation enables response to changing demand.
- Proximity-based storage reduces last-mile delivery costs and improves market reach.	- Increased visibility to potential renters through platform networks.
- Strategic warehouse placement minimizes delivery times and supports expedited shipping.	- Monetizing unused space ensures full utilization of resources and generates profits.
- Pay-per-use pricing reduces financial risk and provides cost-effective short-term storage solutions.	- Broader network participation enhances occupancy rates and revenue stability.
- Streamlined platform-based search simplifies logistics planning and operational flexibility.	- Efficient business matching and negotiation processes improve operational efficiency.
- Access to a larger warehousing network supports rapid scaling of distribution operations across regions.	- Participation in broader networks increases the ability to attract diverse customers.
- Promotes sustainability by supporting green transportation and reducing the need for new constructions.	- Aligns with long-term cost-reduction strategies for logistics operations.

3.4.2 Critical Challenges and Limitations of ODW for Stakeholders

While the advantages of On-Demand Warehousing (ODW) are well documented, its limitations remain underexplored, as highlighted by Gnani and Tornese (2023) and Elia et al. (2024). These limitations span various operational aspects that impact both customers and lenders, presenting critical considerations for businesses adopting ODW solutions.

Recent insights by Tornese et al. (2020) hypothesis' derived from the market analysis suggest that certain companies are transitioning away from the ODW model to address its inherent limitations and to cater to a different customer demographic. We elucidate the significant challenges inherent in ODW models, highlighting the need for businesses to carefully consider these factors when opting for on-demand warehousing solutions in their logistics and supply chain strategies.

- **Challenges for Customers:**

- *Service Standardization*: Diverse offerings without uniform standards on ODW platforms can hinder customers seeking consistent service quality (Elia et al., 2024; Tornese et al., 2020).
- *Limited Control and Visibility*: Short-term relationships reduce oversight of fulfillment processes, often deprioritized by lenders managing their primary operations (Tornese et al., 2020).
- *Short-term Orientation*: ODW platforms are designed for short-term needs, making them unsuitable for businesses requiring consistent, long-term partnerships (Elia et al., 2024).
- *Limited Control and Customization*: Companies using ODW may have to forego certain specific requirements or customizations they could enforce in their facilities or through dedicated long-term partnerships (Ceschia et al., 2022).
- *Lack of Stability and Predictability*: ODW often lacks stability, leading to unpredictability in space availability and costs. Fluctuating demand can result in variable pricing, which may pose budgeting challenges for companies that require consistent cost structures for financial planning (Pazour and Unnu, 2018).
- *Performance Variability and Quality Concerns*: The varying levels of expertise among lenders can lead to a broad spectrum of performance, including potential fulfillment errors (Tornese et al., 2020).
- *Trust and Security Concerns*: ODW models necessitate sharing sensitive information with third parties, raising concerns about data security and the protection of intellectual property. Trusting external providers to handle products correctly and maintain confidentiality is critical yet challenging (Tornese et al., 2020).
- *Operational Integration & Complex Logistics Management*: Managing logistics across decentralized ODW locations and integrating with existing systems poses technical and coordination challenges due to the lack of standardized processes across different ODW providers, and it requires complex IT solutions, training, and potentially significant investment (Gnoni and Tornese, 2023).
- *Platform Dependency*: Reliance on third-party platforms for essential warehousing functions can create a dependency that may be risky if the platform encounters operational or financial difficulties. This dependency may limit negotiation power and the ability to secure favorable terms (Unnu and Pazour, 2022).
- *Economic Scalability and Investment*: While ODW reduces upfront capital investment, it may not provide the economies of scale achievable with larger, dedicated warehousing solutions, particularly for high-volume operations. For businesses with large and consistent warehousing needs, the cost benefits of ODW might diminish as the scale of operations grows, and it may limit how quickly and efficiently a business can scale up or down, especially during peak seasons or unexpected surges in demand (Rogers et al., 2020).

- *Automation Deficiency*: Limited automation capabilities restrict ODW’s appeal for customers requiring high-tech operations (Elia et al., 2024).

Challenges for Lenders:

- *Resource Prioritization*: Balancing on-demand and traditional warehousing customers requires effective prioritization strategies, especially during high resource utilization, complicating allocation and planning (Elia et al., 2024).
- *Demand Uncertainty*: Listing space on ODW platforms does not ensure it will be filled. This inherent uncertainty requires lenders to carefully consider how much space and which services to offer on the platform. Misjudgments in space allocation can lead to underutilization or overcommitment, affecting financial outcomes (Elia et al., 2024).
- *High Concentration of Customer Demand*: Serving many customers simultaneously increases operational complexity and the risk of service disruptions (Elia et al., 2024).
- *Short-Term Orientation*: The transient nature of ODW relationships limits lenders’ ability to engage in long-term operational planning, complicating forecasts and resource allocation for future operational needs effectively (Unnu and Pazour, 2019).
- *Critical Mass Dependency*: ODW platforms rely on achieving a critical mass of supply and demand to ensure variety, availability, profitability, and service efficiency (Pazour and Unnu, 2018).
- *Regulatory Compliance*: Navigating varying regulations across jurisdictions increases complexity and can constrain operational flexibility for lenders operating in multiple regions (Siebrecht et al., 2016).
- *Exposure to Market Rates*: One significant risk associated with dynamic warehousing is the variability of costs due to market conditions. Similar to surge pricing in ride-sharing platforms like Uber, warehousing rates may increase unexpectedly based on demand, unlike fixed-cost models used in traditional warehousing (Siebrecht et al., 2016). (Siebrecht et al., 2016).
- *Reliance on an Unrelated Network*: ODW often relies on a network of warehouses that are not directly related to the retailer but are connected through an electronic marketplace. This outsourcing approach can lead to operational inconsistencies such as order fulfillment errors or practices that do not align with the retailer’s values and objectives (Siebrecht et al., 2016).
- *Pricing Strategy Complexity*: Developing agile pricing models to accommodate variable customer needs and market conditions requires sophisticated strategies and responsiveness (Elia et al., 2024).

Table 3.5: Challenges in ODW Models for Customers and Lenders

Challenges for Customers	Challenges for Lenders
- Service Standardization: Inconsistent service offerings across the platform hinder reliability and quality. - Limited Control and Visibility: Reduced oversight of fulfillment processes leads to operational inefficiencies. - Short-Term Orientation: Dynamic, short-term relationships limit suitability for long-term needs. - Performance Variability: Lenders' varying expertise can lead to fulfillment errors and inconsistent service levels. - Economic Scalability: Cost benefits diminish for large-scale operations requiring consistent capacity. - Platform Dependency: Overreliance on third-party platforms can create risks if the platform fails operationally or financially. - Trust and Security Concerns: Sharing sensitive data and trusting third parties with products raises confidentiality risks. - Operational Complexity: Coordinating logistics across multiple warehouses complicates supply chain management. - Automation Deficiency: Lack of advanced automated solutions limits utility for tech-driven operations.	- Resource Prioritization: Balancing demands of on-demand and traditional customers complicates operations. - Demand Uncertainty: Listing space on the platform does not guarantee occupancy, risking underutilization or overcommitment. - Short-Term Orientation: Limits lenders' ability to engage in long-term planning and forecasting. - High Concentration of Demand: Managing simultaneous requests from multiple customers increases complexity. - Critical Mass Dependency: Platforms require balanced supply and demand to maintain viability. - Regulatory Compliance: Meeting diverse jurisdictional regulations impacts operational flexibility. - Exposure to Market Rates: Dynamic pricing models increase costs unpredictably during peak demand. - Reliance on Unrelated Networks: Decentralized services risk inconsistencies in quality and operational alignment. - Pricing Strategy Complexity: Developing dynamic pricing strategies to meet variable market demands adds an operational burden.

Chapter 4

Methodology

The primary aim of this research is to develop a comprehensive decision-making framework for optimizing the utilization of on-demand warehousing (ODW) in supply chain management. Building upon prior analyses, this study employs a Comparative Static Model to systematically evaluate the interplay between demand variability, cost parameters, and capacity configurations. By integrating theoretical insights with quantitative, data-driven analysis, the research provides a robust and actionable framework for strategic planning.

An extensive review of existing literature on ODW was conducted to establish a contextual foundation and identify critical gaps. Key themes emerged from this analysis:

- **Decision-Making Frameworks:** The literature underscores the importance of data-driven models to guide decisions on capacity allocation, cost trade-offs, and service prioritization, yet such frameworks are underdeveloped for ODW.
- **Quantitative Modeling Gap:** While qualitative studies highlight the potential benefits and challenges of ODW, there is a scarcity of quantitative models that simulate real-world scenarios to analyze trade-offs and provide actionable insights.
- **Operational Dynamics and Contextual Factors:** The interdependencies between demand variability, cost structures, and capacity constraints remain underexplored, particularly in high-variability and uncertain demand environments.

By systematically addressing these themes, the study identifies critical gaps in understanding the operational dynamics of ODW. These insights form the basis for developing the Comparative Static Model used in this research, which evaluates fixed capacity configurations and their impact on profitability, service levels, and resource allocation. The model provides decision-makers with a quantitative framework to navigate the complexities of ODW implementation and enhance supply chain resilience.

4.1 Quantitative Modeling Framework

To address the identified gaps and provide a data-driven decision-making framework, a robust simulation model was developed:

4.1.1 Comparative Static Model

The *Comparative Static Model* evaluates fixed capacity combinations under varying demand and cost conditions. It provides insights into strategic planning by analyzing the system's performance under controlled, single-period scenarios. This model enables decision-makers to assess trade-offs between service levels, costs, and profitability.

- **Purpose:**

- Evaluate the impact of demand variability and cost parameters on capacity decisions.
- Identify optimal capacity configurations to balance service levels, costs, and profitability across stakeholders.

- **Key Features:**

- *Demand Scenarios:* Simulates low, high, and extreme demand variability to assess system robustness and adaptability.
- *Cost Sensitivity Analysis:* Analyzes the effect of varying cost parameters (e.g., ODW usage fees, unmet demand penalties) on operational performance.
- *Capacity Evaluation:* Systematically examines fixed private warehousing and ODW capacities to explore trade-offs and identify cost-effective configurations.

- **Performance Metrics:**

- Average profits, service levels, and unmet demand costs across stakeholders.
- Economic breakdowns to highlight key trade-offs and inform decision-making.

4.2 Rationale for the Comparative Static Model

The Comparative Static Model was chosen for its ability to provide clear insights into system performance under varying conditions, making it ideal for evaluating long-term capacity decisions. By focusing on single-period settings, the model eliminates the complexities of dynamic adaptation, allowing for a targeted analysis of specific cost and capacity trade-offs. Table 4.1 highlights the distinctions and contributions of the Comparative Static Model.

Table 4.1: Key Characteristics of the Comparative Static Model

Aspect	Comparative Static Model
Timeframe	Focuses on fixed, one-time snapshots of system performance.
Focus	Sensitivity to specific parameters such as cost structures, capacity configurations, and demand variability.
Output	Identifies risks, economic trade-offs, and optimal configurations under varying conditions.
Purpose	Provides a framework for long-term strategic planning and risk assessment.
Simulation Approach	Uses systematic capacity sweeps and Monte Carlo trials to explore parameter ranges comprehensively.

4.2.1 Key Considerations in Model Development

- **Demand Variability:** Scenarios representing low, high, and extreme variability simulate real-world fluctuations, from stable markets to volatile demand spikes. These scenarios are essential to evaluate the robustness of warehousing strategies under varying conditions.
- **Stochastic Demand Behavior:** The model incorporates stochastic demand variations to simulate random market behavior, ensuring a realistic representation of real-world uncertainty and enabling better strategic insights.
- **Capacity Configurations:** Incremental adjustments in private and on-demand capacities are tested systematically to identify optimal configurations for different scenarios and service-level objectives.
- **Cost Sensitivity:** Sensitivity analyses on key cost parameters, such as ODW usage fees and unmet demand penalties, highlight economic trade-offs and inform decision-making.
- **Prioritization Strategies:** Scenarios with and without prioritization assess the impact of strategic capacity allocation rules on profitability, service levels, and equity between stakeholders.

4.3 Contributions of the Comparative Static Model

- **Scenario-Based Analysis:** The model evaluates profitability, service levels, cost efficiency, and unmet demand penalties across multiple stakeholders under distinct demand variability scenarios, offering scenario-specific insights.
- **Decision-Making Framework:** By quantifying the impact of demand variability and cost structures on capacity allocation, the model supports data-driven decisions on private and on-demand warehousing investments.
- **Cost-Risk Trade-Off Analysis:** The model highlights trade-offs between capacity decisions, service-level improvements, and associated risks, enabling decision-makers to balance profitability with operational resilience.
- **Policy and Prioritization Impact:** The analysis reveals that prioritization policies significantly influence system performance, particularly under high variability scenarios. Tailored policies dynamically adjust resource allocation based on real-time demand patterns and cost thresholds.
- **Framework Validation:** The model demonstrates the effectiveness of ODW strategies through quantitative simulations and performance metrics, bridging theoretical insights with practical applications.
- **Capacity Optimization Insights:** The results emphasize diminishing returns in service levels and profitability beyond specific capacity thresholds guiding efficient capacity investments.

Chapter 5

Model Development

5.1 Model Overview

This chapter presents a quantitative framework to analyze strategic and operational decisions in an on-demand warehousing (ODW) environment. The framework captures interactions between key stakeholders, including:

- Entities with private warehouses.
- Entities without private warehouses.
- Third-party logistics (3PL) providers.
- On-demand warehousing (ODW) providers.

By formalizing these relationships, the model evaluates how capacity investment decisions, demand variability, and cost structures influence profitability, service levels, and resource allocation.

5.2 Objectives of the Model

The primary objectives of the model are to:

- Formalize the decision-making processes of stakeholders using private warehousing, 3PL services, and ODW solutions.
- Analyze the responses of stakeholders to stochastic demand variability and service-level constraints.
- Evaluate the impact of cost structures, prioritization strategies, and capacity adjustments on profitability and operational performance.
- Identify optimal capacity configurations and trade-offs between cost efficiency and service levels under varying demand and cost conditions.
- Provide actionable insights for decision-makers to optimize warehousing strategies in dynamic and static scenarios.

5.3 Notation and Variables

This section provides an overview of the key stakeholders, variables, parameters, and constraints used in the model. A summary is presented in Table 5.1, with additional details on assumptions and cost structures in subsequent sections.

Table 5.1: Summary of Notations and Variables

Notation	Description
Entity Notations	
n_1	Entities with private warehousing capacity.
n_2	Entities without private warehousing capacity.
T_{PL}	Third-party logistics provider offering reserved capacity.
ODW	On-demand warehousing service provider for excess capacity.
Decision Variables	
W_p	Private warehousing capacity invested by n_1 .
$w_{TPL,1}$	Capacity reserved by n_1 with the 3PL provider.
$w_{TPL,2}$	Capacity reserved by n_2 with the 3PL provider.
W_{ODW}	Total capacity invested by the ODW provider.
Random Variables	
X_1	Realized demand for n_1 in Period 1, following distribution F_1 .
X_2	Realized demand for n_2 in Period 1, following distribution F_2 .
Parameters	
C_p^{cap}	Investment cost per unit of private warehousing capacity.
c_p^{use}	Usage cost per unit of private warehousing capacity.
C_{TPL}^{cap}	Investment cost per unit of capacity for 3PL.
c_{TPL}^{res}	Reservation cost per unit of capacity with 3PL.
c_{TPL}^{use}	Usage cost per unit of demand served by 3PL.
C_{ODW}^{cap}	Investment cost per unit of capacity for ODW.
c_{ODW}^{use}	Usage cost per unit of demand served by ODW.
ϕ	Penalty cost per unit of unmet demand.
p_1	Selling price per unit for n_1 .
p_2	Selling price per unit for n_2 .
Allocation Variables	
q_p	Quantity fulfilled using private capacity for n_1 .
$D_{TPL,1}$	Quantity allocated to 3PL by n_1 .
$D_{ODW,1}$	Quantity allocated to ODW by n_1 .
U_{n_1}	Unmet demand for n_1 .
$D_{TPL,2}$	Quantity allocated to 3PL by n_2 .
$D_{ODW,2}$	Quantity allocated to ODW by n_2 .
U_{n_2}	Unmet demand for n_2 .

This model employs a structured set of notations and variables to facilitate the optimization of ODW strategies. These notations are organized into five main categories:

- **Key Stakeholders:** The primary actors in this model are entities with or without

private warehousing, 3PL providers, and ODW providers.

- **Decision Variables:** Represent key capacities and allocations determined within the optimization process.
- **Random Variables:** Capture uncertainty in demand across different entities, reflecting the dynamic nature of ODW.
- **Parameters:** Include costs, selling prices, and penalty terms, which define the economic structure of the model.
- **Allocation Variables:** Define quantities fulfilled, allocated, or left unmet for different entities and warehousing providers.

Figure 5.1 illustrates the sequential process flow of demand fulfillment for the two entities. The diagram provides a clear visualization of the decision-making process, capacity constraints, and the key stakeholders, including 3PL providers and ODW providers.

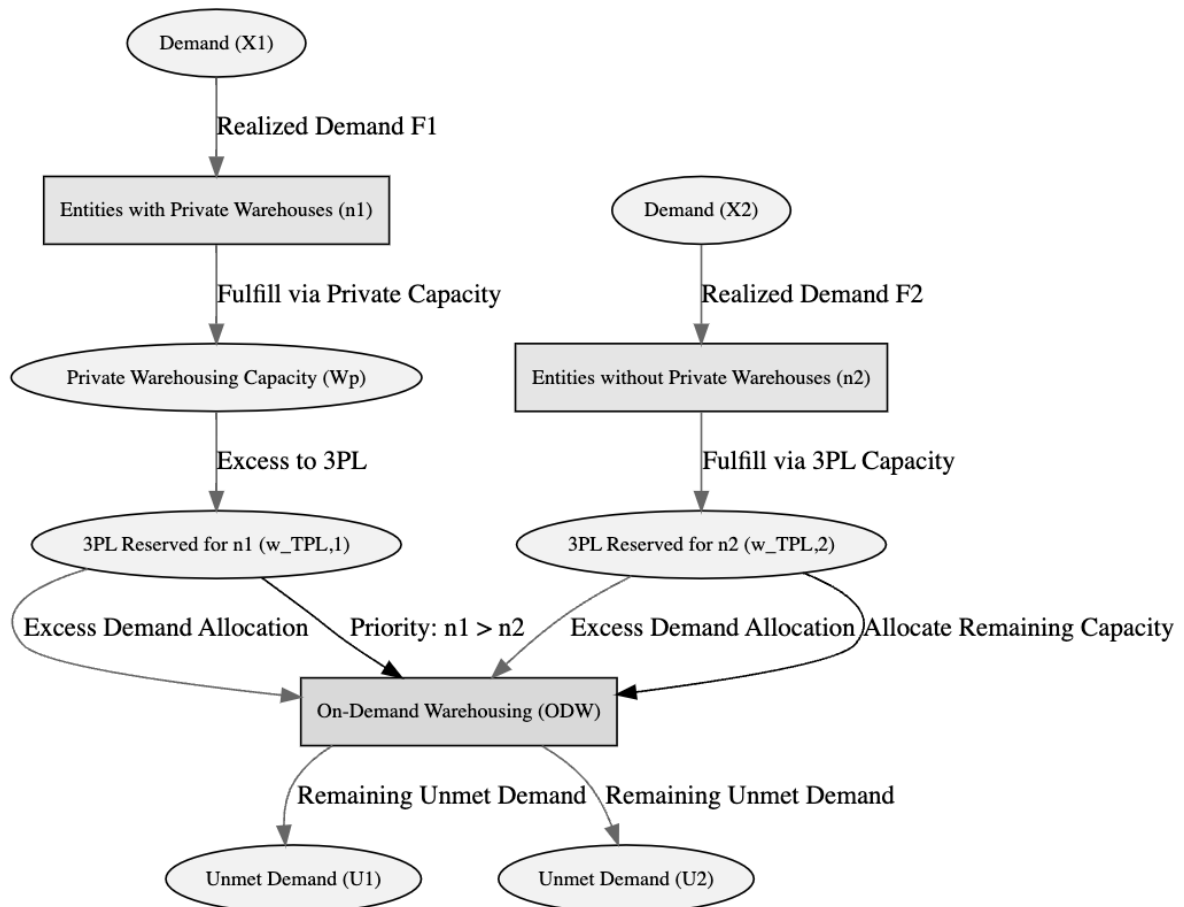


Figure 5.1: Demand Fulfillment and Capacity Allocation Flow.

5.4 Model Assumptions

To construct a tractable and insightful model, we make the following assumptions:

1. Time Horizon:

The model operates over a defined time horizon consisting of two primary periods:

- **Period 0 (Investment Phase):** During this phase, capacity investment decisions are made for W_p , w_{TPL} , and W_{ODW} . These decisions determine the foundational capacity available for subsequent operations.
- **Period 1 (Operational Phase):** Demand is realized, and resources are allocated to fulfill demand based on the pre-defined capacities.

In the *Multi-Period Model* investments are periodically adjusted across multiple cycles based on demand patterns and performance to enable adaptive resource optimization, while in the *Comparative Static Model*, it assumes fixed capacity investments in Period 0, evaluated over a single operational cycle without adjustments or carry-over.

Two modeling approaches are explored to account for capacity decisions over time:

- **Dynamic Model:** Capacity investments are periodically adjusted across multiple cycles based on demand patterns and performance, reflecting a recurring cost structure and enabling adaptive resource optimization.
- **Static Model:** Capacity investments made in Period 0 are fixed and evaluated over a single operational cycle (Period 1), with no adjustments or carry-over. This assumes a one-time investment and system reset for each evaluation.

2. Demand:

- Random demand variables, X_1 and X_2 , are defined for two entities and follow known distributions, F_1 and F_2 , respectively.

3. The decision variables are non-negative:

The decision variables in the model, including private warehousing capacity (W_p), reserved 3PL capacities for entities with ($w_{TPL,1}$) and without ($w_{TPL,2}$) private warehouses, and total ODW capacity (W_{ODW}), are constrained to be non-negative (≥ 0).

4. Cost Structure:

- **Private Warehouse Costs:**
 - Usage Cost (c_p^{use})
 - Capacity Investment Cost (C_p^{cap})
- **3PL Costs:**
 - Reservation Cost (c_{TPL}^{res})
 - Usage Cost (c_{TPL}^{use})
 - Capacity Investment Cost (C_{TPL}^{cap})

- **ODW Costs:**
 - Usage Cost ($c_{\text{ODW}}^{\text{use}}$)
 - Capacity Investment Cost ($C_{\text{ODW}}^{\text{cap}}$):
- **Penalty Cost for Unmet Demand (ϕ)**

5. Capacity Allocation Rules and Priority Hierarchy:

Demand allocation follows a sequential process:

- (a) Entities with private warehouses (n_1) allocate demand first to private capacity, then to reserved 3PL capacity, and finally to on-demand warehousing (ODW).
- (b) Entities without private warehouses (n_2) allocate demand first to reserved 3PL capacity, then to ODW.
- (c) If ODW capacity is insufficient:
 - Priority is given to n_1 .
 - Remaining ODW capacity is allocated to n_2 .
 - If demand still exceeds capacity, allocation is done proportionally based on the magnitude of unmet demand or according to pre-defined business rules.

6. Capacity Constraints:

- Total capacity available from 3PL and ODW providers is limited.
- Unmet demand results in lost sales and incurs penalty costs.

5.5 Demand Fulfillment Process

The demand fulfillment process is formalized as follows:

5.5.1 Entities with Private Warehouses (n_1)

Entities with private warehouses allocate demand sequentially:

$$q_p = \min(X_1, W_p) \quad (\text{Private Capacity Allocation}) \quad (5.1)$$

$$D_{\text{TPL},1} = \min(w_{\text{TPL},1}, \max(0, X_1 - q_p)) \quad (\text{3PL Allocation}) \quad (5.2)$$

$$D_{\text{ODW},1} = \min(D_{\text{ODW},1}^{\text{alloc}}, \max(0, X_1 - q_p - D_{\text{TPL},1})) \quad (\text{ODW Allocation}) \quad (5.3)$$

The unmet demand for n_1 is:

$$U_{n_1} = X_1 - (q_p + D_{\text{TPL},1} + D_{\text{ODW},1}) \quad (5.4)$$

5.5.2 Entities without Private Warehouses (n_2)

Entities without private warehouses allocate demand as follows:

$$D_{\text{TPL},2} = \min(w_{\text{TPL},2}, X_2) \quad (\text{3PL Allocation}) \quad (5.5)$$

$$D_{\text{ODW},2} = \min(D_{\text{ODW},2}^{\text{alloc}}, \max(0, X_2 - D_{\text{TPL},2})) \quad (\text{ODW Allocation}) \quad (5.6)$$

Unmet demand for n_2 is:

$$U_{n_2} = X_2 - (D_{\text{TPL},2} + D_{\text{ODW},2}) \quad (5.7)$$

5.6 Allocations and Capacity Constraints

For 3PL Provider The total demand allocated to the 3PL provider cannot exceed its total capacity:

$$D_{\text{TPL},1} + D_{\text{TPL},2} \leq w_{\text{TPL}} \quad (5.8)$$

where $w_{\text{TPL}} = w_{\text{TPL},1} + w_{\text{TPL},2}$.

Since 3PL capacities are pre-reserved, the constraint is automatically satisfied.

For ODW Provider Let:

$$D_{\text{ODW}}^{\text{total}} = D_{\text{ODW},1} + D_{\text{ODW},2} \quad (5.9)$$

The capacity constraint is:

$$D_{\text{ODW}}^{\text{total}} \leq W_{\text{ODW}} \quad (5.10)$$

If $D_{\text{ODW}}^{\text{total}} \leq W_{\text{ODW}}$, all demand can be fulfilled by the ODW provider.

If $D_{\text{ODW}}^{\text{total}} > W_{\text{ODW}}$, we need to allocate the available capacity according to a priority rule (see Section 5).

5.7 Cost and Revenue Structures

This section formalizes the revenue, costs, and profit functions for each stakeholder in the ODW environment.

5.7.1 Entities with Private Warehouses (n_1)

Revenue The total revenue for n_1 is:

$$R_{n_1} = p_1 \times (q_p + D_{\text{TPL},1} + D_{\text{ODW},1}). \quad (5.11)$$

Costs

- **Private Warehouse Investment Cost:**

$$C_P = C_p^{\text{cap}} \times W_p. \quad (5.12)$$

- **3PL Costs:**

$$C_{\text{TPL},1}^{\text{res}} = c_{\text{TPL}}^{\text{res}} \times w_{\text{TPL},1} \quad (\text{Reservation Cost}) \quad (5.13)$$

$$C_{\text{TPL},1}^{\text{use}} = c_{\text{TPL}}^{\text{use}} \times D_{\text{TPL},1} \quad (\text{Usage Cost}) \quad (5.14)$$

- **ODW Usage Cost:**

$$C_{\text{ODW},1}^{\text{use}} = c_{\text{ODW}}^{\text{use}} \times D_{\text{ODW},1} \quad (5.15)$$

- **Penalty Cost for Unmet Demand:**

$$C_{\text{penalty},1} = \phi \times U_{n_1} \quad (5.16)$$

Profit The total profit for n_1 is:

$$\Pi_{n_1} = R_{n_1} - C_P - C_{\text{TPL},1}^{\text{res}} - C_{\text{TPL},1}^{\text{use}} - C_{\text{ODW},1}^{\text{use}} - C_{\text{penalty},1} \quad (5.17)$$

5.7.2 Entities without Private Warehouses (n_2)

Revenue The total revenue for n_2 is:

$$R_{n_2} = p_2 \times (D_{\text{TPL},2} + D_{\text{ODW},2}) \quad (5.18)$$

Costs

- **3PL Costs:**

$$C_{\text{TPL},2}^{\text{res}} = c_{\text{TPL}}^{\text{res}} \times w_{\text{TPL},2} \quad (\text{Reservation Cost}) \quad (5.19)$$

$$C_{\text{TPL},2}^{\text{use}} = c_{\text{TPL}}^{\text{use}} \times D_{\text{TPL},2} \quad (\text{Usage Cost}) \quad (5.20)$$

- **ODW Usage Cost:**

$$C_{\text{ODW},2}^{\text{use}} = c_{\text{ODW}}^{\text{use}} \times D_{\text{ODW},2} \quad (5.21)$$

- **Penalty Cost for Unmet Demand:**

$$C_{\text{penalty},2} = \phi \times U_{n_2} \quad (5.22)$$

Profit The total profit for n_2 is:

$$\Pi_{n_2} = R_{n_2} - C_{\text{TPL},2}^{\text{res}} - C_{\text{TPL},2}^{\text{use}} - C_{\text{ODW},2}^{\text{use}} - C_{\text{penalty},2} \quad (5.23)$$

5.7.3 3PL Provider

Revenue and Costs The revenue and total cost for the 3PL provider are:

$$R_{\text{TPL}} = c_{\text{TPL}}^{\text{res}} \times w_{\text{TPL}} + c_{\text{TPL}}^{\text{use}} \times (D_{\text{TPL},1} + D_{\text{TPL},2}) \quad (5.24)$$

$$C_{\text{TPL}} = C_{\text{TPL}}^{\text{cap}} \times w_{\text{TPL}} \quad (5.25)$$

Profit The profit for the 3PL provider is:

$$\Pi_{\text{TPL}} = R_{\text{TPL}} - C_{\text{TPL}} \quad (5.26)$$

5.7.4 ODW Provider

Revenue and Costs The revenue and total cost for the ODW provider are:

$$R_{\text{ODW}} = c_{\text{ODW}}^{\text{use}} \times (D_{\text{ODW},1} + D_{\text{ODW},2}) \quad (5.27)$$

$$C_{\text{ODW}} = C_{\text{ODW}}^{\text{cap}} \times W_{\text{ODW}} \quad (5.28)$$

Profit The profit for the ODW provider is:

$$\Pi_{\text{ODW}} = R_{\text{ODW}} - C_{\text{ODW}} \quad (5.29)$$

5.8 Unmet Demand and Penalty Costs

Unmet demand results in lost sales for the entities and may also incur penalty costs.

- For n_1 :

$$U_{n_1} = X_1 - (q_p + D_{\text{TPL},1} + D_{\text{ODW},1}) \quad (5.30)$$

Note that $U_{n_1} \geq 0$.

- For n_2 :

$$U_{n_2} = X_2 - (D_{\text{TPL},2} + D_{\text{ODW},2}) \quad (5.31)$$

Note that $U_{n_2} \geq 0$.

Penalty Costs

- For n_1 :

$$C_{\text{penalty},1} = \phi \times U_{n_1} \quad (5.32)$$

- For n_2 :

$$C_{\text{penalty},2} = \phi \times U_{n_2} \quad (5.33)$$

Chapter 6

Mathematical Analysis and Validation

This chapter presents the mathematical foundations of the proposed models. We derive the equilibrium conditions and first-order conditions (FOCs) for profit maximization, ensuring the solutions are optimal. To validate the models, we analyze the concavity of the profit functions and confirm the dimensional consistency of the equations.

An equilibrium represents a state where no stakeholder can unilaterally improve their profit by adjusting capacity investments or allocation decisions. The following sections derive and analyze the optimization problems for all stakeholders: entities with private warehouses (n_1), entities without private warehouses (n_2), 3PL providers, and ODW providers.

6.1 Equilibrium Conditions and Optimization Problems

The equilibrium conditions are derived by solving the profit maximization problems for each stakeholder. The general form of the optimization problem is:

$$\max_z E[\Pi] \quad \text{subject to: } z \geq 0, \quad (6.1)$$

where z represents the decision variables (e.g., capacities), and $E[\Pi]$ is the expected profit. Each stakeholder's problem is defined below.

6.1.1 Entities with Private Warehouses (n_1)

Objective Function Entity n_1 seeks to maximize its expected profit:

$$\max_{W_p, w_{\text{TPL},1}} E[\Pi_{n_1}] \quad (6.2)$$

Expected Profit Function: The expected profit for n_1 is:

$$\begin{aligned}
E[\Pi_{n_1}] &= E[R_{n_1}] - C_p - C_{\text{TPL},1}^{\text{res}} - E[C_{\text{TPL},1}^{\text{use}}] \\
&\quad - E[C_{\text{ODW},1}^{\text{use}}] - E[C_{\text{penalty},1}] \\
&= p_1 \cdot E[q_p + D_{\text{TPL},1} + D_{\text{ODW},1}] - c_p W_p \\
&\quad - c_{\text{TPL}}^{\text{res}} w_{\text{TPL},1} - c_{\text{TPL}}^{\text{use}} \cdot E[D_{\text{TPL},1}] \\
&\quad - c_{\text{ODW}}^{\text{use}} \cdot E[D_{\text{ODW},1}] - \phi \cdot E[U_{n_1}]
\end{aligned} \tag{6.3}$$

Constraints:

$$W_p \geq 0 \tag{6.4}$$

$$w_{\text{TPL},1} \geq 0 \tag{6.5}$$

6.1.2 Entities without Private Warehouses (n_2)

Objective Function Entity n_2 seeks to maximize its expected profit:

$$\max_{w_{\text{TPL},2}} E[\Pi_{n_2}] \tag{6.6}$$

Expected Profit Function: The expected profit for n_2 is:

$$\begin{aligned}
E[\Pi_{n_2}] &= E[R_{n_2}] - C_{\text{TPL},2}^{\text{res}} - E[C_{\text{TPL},2}^{\text{use}}] \\
&\quad - E[C_{\text{ODW},2}^{\text{use}}] - E[C_{\text{penalty},2}] \\
&= p_2 \cdot E[D_{\text{TPL},2} + D_{\text{ODW},2}] - c_{\text{TPL}}^{\text{res}} w_{\text{TPL},2} \\
&\quad - c_{\text{TPL}}^{\text{use}} \cdot E[D_{\text{TPL},2}] - c_{\text{ODW}}^{\text{use}} \cdot E[D_{\text{ODW},2}] \\
&\quad - \phi \cdot E[U_{n_2}]
\end{aligned} \tag{6.7}$$

Constraints:

$$w_{\text{TPL},2} \geq 0 \tag{6.8}$$

6.1.3 3PL Provider

Objective Function The 3PL provider seeks to maximize its expected profit:

$$\max_{w_{\text{TPL}}} E[\Pi_{\text{TPL}}] \tag{6.9}$$

Expected Profit Function:

$$\begin{aligned}
E[\Pi_{\text{TPL}}] &= E[R_{\text{TPL}}] - C_{\text{TPL}} \\
&= c_{\text{TPL}}^{\text{res}} \cdot w_{\text{TPL}} + c_{\text{TPL}}^{\text{use}} \cdot E[D_{\text{TPL},1} + D_{\text{TPL},2}] \\
&\quad - c_{\text{TPL}}^{\text{cap}} \cdot w_{\text{TPL}}
\end{aligned} \tag{6.10}$$

Constraint:

$$w_{\text{TPL}} \geq w_{\text{TPL},1} + w_{\text{TPL},2} \tag{6.11}$$

6.1.4 ODW Provider

Objective Function The ODW provider seeks to maximize its expected profit:

$$\max_W E [\Pi_{\text{ODW}}] \quad (6.12)$$

Expected Profit Function:

$$\begin{aligned} E [\Pi_{\text{ODW}}] &= E [R_{\text{ODW}}] - C_{\text{ODW}} \\ &= c_{\text{ODW}}^{\text{use}} \cdot E [D_{\text{ODW},1} + D_{\text{ODW},2}] \\ &\quad - c_{\text{ODW}}^{\text{cap}} \cdot W_{\text{ODW}} \end{aligned} \quad (6.13)$$

Constraint:

$$W_{\text{ODW}} \geq 0 \quad (6.14)$$

6.2 First-Order Conditions and Optimality

To find the equilibrium, we derive the first-order conditions (FOCs) for each stakeholder's optimization problem and analyze the concavity of the expected profit functions.

6.2.1 Entities with Private Warehouses (n_1)

Deriving FOCs We take partial derivatives of $E [\Pi_{n_1}]$ with respect to W_p and $w_{\text{TPL},1}$.

With respect to W_p :

$$\frac{\partial E [\Pi_{n_1}]}{\partial W_p} = p_1 \frac{\partial E [q_p]}{\partial W_p} - c_p - \phi \frac{\partial E [U_{n_1}]}{\partial W_p} \quad (6.15)$$

Since $q_p = \min(X_1, W_p)$ and $U_{n_1} = X_1 - (q_p + D_{\text{TPL},1} + D_{\text{ODW},1})$, the derivatives depend on the probability distribution of X_1 .

With respect to $w_{\text{TPL},1}$:

$$\frac{\partial E [\Pi_{n_1}]}{\partial w_{\text{TPL},1}} = -c_{\text{TPL}}^{\text{res}} + (p_1 - c_{\text{TPL}}^{\text{use}}) \frac{\partial E [D_{\text{TPL},1}]}{\partial w_{\text{TPL},1}} - \phi \frac{\partial E [U_{n_1}]}{\partial w_{\text{TPL},1}} \quad (6.16)$$

Solving for Optimal W_p and $w_{\text{TPL},1}$ The optimal values of W_p and $w_{\text{TPL},1}$ are those that satisfy the FOCs:

$$\frac{\partial E [\Pi_{n_1}]}{\partial W_p} = 0, \quad \frac{\partial E [\Pi_{n_1}]}{\partial w_{\text{TPL},1}} = 0 \quad (6.17)$$

6.2.2 Entities without Private Warehouses (n_2)

Deriving FOCs We take the partial derivative of $E [\Pi_{n_2}]$ with respect to $w_{\text{TPL},2}$.

$$\frac{\partial E [\Pi_{n_2}]}{\partial w_{\text{TPL},2}} = -c_{\text{TPL}}^{\text{res}} + (p_2 - c_{\text{TPL}}^{\text{use}}) \frac{\partial E [D_{\text{TPL},2}]}{\partial w_{\text{TPL},2}} - \phi \frac{\partial E [U_{n_2}]}{\partial w_{\text{TPL},2}} \quad (6.18)$$

Solving for Optimal $w_{\text{TPL},2}$ Set the FOC to zero:

$$\frac{\partial E[\Pi_{n2}]}{\partial w_{\text{TPL},2}} = 0 \quad (6.19)$$

6.2.3 3PL Provider

Deriving FOC Assuming the 3PL provider decides on total capacity w_{TPL} :

$$\frac{\partial E[\Pi_{\text{TPL}}]}{\partial w_{\text{TPL}}} = c_{\text{TPL}}^{\text{res}} - C_{\text{TPL}}^{\text{cap}} \quad (6.20)$$

Since the 3PL provider's expected profit is linear in w_{TPL} , the optimal capacity depends on whether $c_{\text{TPL}}^{\text{res}} > C_{\text{TPL}}^{\text{cap}}$.

Optimal Capacity

- If $c_{\text{TPL}}^{\text{res}} > C_{\text{TPL}}^{\text{cap}}$, the 3PL provider will invest in as much capacity as is demanded (up to constraints).
- If $c_{\text{TPL}}^{\text{res}} \leq C_{\text{TPL}}^{\text{cap}}$, the provider may not invest in additional capacity.

6.2.4 ODW Provider

Deriving FOC

$$\frac{\partial E[\Pi_{\text{ODW}}]}{\partial W_{\text{ODW}}} = c_{\text{ODW}}^{\text{use}} \frac{\partial E[D_{\text{ODW}}^{\text{total}}]}{\partial W_{\text{ODW}}} - C_{\text{ODW}}^{\text{cap}} \quad (6.21)$$

However, since $D_{\text{ODW}}^{\text{total}}$ is constrained by W_{ODW} , the derivative $\frac{\partial E[D_{\text{ODW}}^{\text{total}}]}{\partial W_{\text{ODW}}}$ depends on the probability of capacity being fully utilized.

Optimal Capacity Solving $\frac{\partial E[\Pi_{\text{ODW}}]}{\partial W_{\text{ODW}}} = 0$ provides the optimal W_{ODW} .

6.3 Concavity and Convexity Analysis

The concavity of the expected profit functions ensures that the solutions obtained from the FOCs are optimal. The second-order condition (SOC) for concavity is:

$$\frac{\partial^2 E[\Pi]}{\partial z^2} < 0 \quad \forall z, \quad (6.22)$$

where z represents the decision variables.

Since exact analytical solutions may be intractable due to stochastic demand, numerical simulations validate the concavity by checking the second derivatives and observing profit behavior around the optimal points.

Chapter 7

Simulation and Analysis

7.1 Comparative Static Model

We developed a *Comparative Static Model* using the R programming language to evaluate warehousing operations under fixed capacity assumptions. The model analyzes the impact of demand variability and cost structures on key performance metrics, including profits and service levels. The implementation of this methodology in R is detailed in Appendix B.1.

7.1.1 The Motivation

The Comparative Static Model provides a systematic framework for analyzing predefined capacities and demand patterns, offering insights into stakeholder performance under stable conditions while enabling stress testing of demand variability and cost parameters. This model explores:

- **Demand Variability:** Analyzes the effect of changes in average demand levels (μ_1, μ_2) and demand variability (σ_1, σ_2) on profits and service levels.
- **Cost Sensitivity:** Examines how cost structures, including penalties for unmet demand, usage fees, and investment costs, influence profitability and stakeholder outcomes.
- **Allocation Strategies:** Evaluates scenarios with and without prioritization for specific customer segments to assess the impact of allocation rules on system performance.

7.1.2 Parameters and Assumptions

Prices and Costs

- **Selling Prices:**
 - $p_1 = 100$ (per unit) for n_1 customers and $p_2 = 120$ (per unit) for n_2 customers.
- **Costs:**

- *Private Warehousing Cost* $c_p = 10$ per unit of capacity.
- *3PL Services*:
 - * Reservation fee $c_{\text{TPL_res}} = 15$ per unit.
 - * Usage fee $c_{\text{TPL_use}} = 20$ per unit of goods stored and handled.
 - * Capacity investment cost $c_{\text{TPL_cap}} = 8$ per unit for 3PL expansions.
- *ODW Services*:
 - * Usage cost $c_{\text{ODW_use}} = 25$ (per unit) for on-demand warehousing services.
 - * Capacity investment cost $C_{\text{ODW_cap}} = 30$ per capacity unit.
- **Penalty for Unmet Demand** ($\phi = 50$): Cost imposed per unit of demand that cannot be fulfilled.

Demand Parameters

- **Stochastic Demand:** Customer demands X_1 and X_2 follow normal distributions:

$$X_1 \sim \mathcal{N}(\mu_1, \sigma_1^2), \quad X_2 \sim \mathcal{N}(\mu_2, \sigma_2^2),$$

ensuring a random component for demand fluctuations.

- **Mean Demands:** Base mean levels are $\mu_1 = 500$ for n_1 and $\mu_2 = 300$ for n_2 .
- **Variability:** Standard deviations $\sigma_1 = 50$ and $\sigma_2 = 40$ capture normal demand fluctuations. The high-variability multiplier (κ) simulates riskier or uncertain scenarios by scaling σ_1 and σ_2 . For instance, $\kappa = 2$ represents higher variability, while $\kappa = 4$ indicates extreme variability.

Capacity Parameters

- **Private Warehousing Capacity:** Fixed capacities $W_p \in \{100, 150, 200, 250, 300, 350, 400\}$ are allocated for n_1 .
- **On-Demand Warehousing Capacity:** Fixed capacities $W \in \{100, 150, 200, 250, 300, 350, 400\}$ are allocated for on-demand services.
- **3PL Reserved Capacities:** $w_{\text{TPL1}}, w_{\text{TPL2}} \in [50, 200]$ units represent dynamically allocated medium-term contracted capacities for n_1 and n_2 .

7.1.3 Simulation Settings

- **Scenarios:** Four demand scenarios are simulated:
 - *Low Variability:* $\sigma_1 = 50, \sigma_2 = 40$.
 - *High Variability:* $\sigma_1 = 100, \sigma_2 = 80$.
 - *Extreme Variability:* $\sigma_1 = 200, \sigma_2 = 160$.
 - *Mixed Scenario:* Demand variability fluctuates dynamically across samples, with $\sigma_1 \sim \mathcal{U}(50, 100)$ and $\sigma_2 \sim \mathcal{U}(40, 80)$.

- **Monte Carlo Iterations:** $N = 1000$ samples are generated for each scenario, providing robust average performance metrics.
- **Prioritization Scenarios:** Two strategies are considered:
 - *With Prioritization:* n_1 customers receive priority for ODW allocations.
 - *Without Prioritization:* ODW allocations are shared proportionally between n_1 and n_2 .

7.1.4 Model Mechanics

For each scenario, the following steps are performed:

- **Demand Generation:** Stochastic demands X_1 and X_2 are generated for n_1 and n_2 based on their respective scenarios.
- **Service Level (SL) Evaluation:** Service levels are computed as:

$$SL_{n_1} = \frac{\text{Allocated Demand}_{n_1}}{X_1}, \quad SL_{n_2} = \frac{\text{Allocated Demand}_{n_2}}{X_2}.$$
- **Cost and Profit Calculation:** Revenues and costs are computed for n_1 , n_2 , and the ODW provider, considering:
 - Fixed costs for reserved capacities.
 - Variable costs for actual usage.
 - Penalties for unmet demand.

Scenario Evaluation: Each scenario is evaluated across all configurations to derive average service levels, profits, and unmet demand costs.

7.1.5 Summary of Results

Simulation results for the static model are summarized in Table 7.1, showcasing average profits and service levels across scenarios. The extended results are provided in Table C.1 in Appendix C.

Table 7.1: Summary of the Comparative Static Model Results Across Scenarios

Scenario	Prioritization	σ_1	σ_2	Π_{n_1}	Π_{n_2}	$\text{Net}_{ODW} \text{ Cost}$	SL_{n_1}	SL_{n_2}
low	With	50	40	40804.20	26041.42	2892.19	1.00	0.97
low	Without	50	40	40336.66	26583.78	2892.19	0.99	0.98
high	With	100	80	40744.41	22778.60	3139.76	1.00	0.91
high	Without	100	80	39023.32	24775.07	3139.76	0.98	0.95
extreme	With	200	160	38725.60	16727.02	3380.47	0.98	0.82
extreme	Without	200	160	35338.58	20655.96	3380.47	0.95	0.89
mixed	With	U(50, 100)	U(40, 80)	40749.23	24401.77	3074.23	1.00	0.95
mixed	Without	U(50, 100)	U(40, 80)	39783.49	25522.03	3074.23	0.99	0.97

7.2 Introduction to Configurations and Policies

The performance and adaptability of supply chain systems are profoundly influenced by the configuration of key parameters such as private warehousing capacity (W_p), on-demand warehousing capacity (W_{ODW}), and third-party logistics (3PL) reserved capacities ($w_{TPL,1}$ and $w_{TPL,2}$). These configurations play a pivotal role in determining the allocation of resources, cost efficiency, and service levels across the supply chain. Additionally, the implementation of specific policies, such as prioritization versus non-prioritization in the allocation of on-demand warehousing (ODW) resources, introduces a dynamic layer of decision-making that affects equity, profitability, and resilience under varying demand scenarios.

Prioritization policies provide n_1 (the primary entity) with preferential access to ODW resources, ensuring higher service levels and reduced unmet demand penalties. Conversely, non-prioritization policies adopt a proportional sharing strategy, aiming to balance resource allocation between n_1 and n_2 (secondary entities). This trade-off creates a complex interplay between maximizing system-wide profitability and achieving equitable service levels. The examination of these configurations and policies within different demand scenarios, including low, high, and extreme variability, offers critical insights into optimizing supply chain performance.

7.3 Optimal Configurations for n_1 and n_2

Configurations that maximize profits for n_1 and n_2 while maintaining acceptable service levels were identified. These optimal configurations were determined by analyzing simulation outcomes across different capacity allocations and cost parameters.

7.3.1 Optimal Configurations for n_1

The configurations for n_1 highlight top-performing scenarios based on two key criteria:

- **Profitability:** Configurations are selected from the top 10% of results with the highest Π_{n_1} .
- **Service Level:** Configurations maintain a minimum SL_{n_1} of 95%, ensuring operational efficiency and customer satisfaction.

7.3.2 Optimal Configurations for n_2

The optimal configurations for n_2 are selected using the following criteria:

- **Service Level:** Configurations achieve a minimum SL_{n_2} of 90%.
- **Profitability Ranking:** Configurations consider Π_{n_1} to reflect the interconnected nature of system performance.

The Tables 7.2 and 7.3 showcase a subset of optimal configurations for n_1 and n_2 across different scenarios. The extended Table C.2 and C.3 in Appendix C, provide 40 configurations, offering a detailed view of service level and profitability variations.

Table 7.2: Summary of the Top Configurations for n_1

Scenario	W_p	W_{ODW}	$w_{TPL,1}$	$w_{TPL,2}$	$C_{ODW,1}^{use}$	Π_{n_1}	SL_{n_1}
extreme	400	400	50	50	4623.73	41657.54	1
extreme	400	400	50	75	4974.17	41657.54	1
extreme	400	400	50	200	6797.01	41657.54	1
extreme	400	400	75	75	5154.69	41494.12	1
high	400	400	50	50	4397.59	42480.39	1
high	400	400	50	75	4897.04	42480.39	1
high	400	350	50	100	4144.36	42468.48	1
high	400	400	50	175	7131.25	42480.39	1
low	400	250	50	50	1380.88	43035.33	1
low	400	250	50	75	1540.87	43035.33	1
low	400	250	50	100	1783.59	43035.33	1
low	400	250	50	175	3086.76	43035.33	1
mixed	400	350	50	50	3155.85	42893.08	1
mixed	400	350	50	75	3613.26	42893.08	1
mixed	400	350	50	100	4122.14	42893.08	1
mixed	400	350	50	175	5825.69	42893.08	1

Table 7.3: Summary of the Top Configurations for n_2

Scenario	W_p	W_{ODW}	$w_{TPL,1}$	$w_{TPL,2}$	$C_{ODW,2}^{use}$	Π_{n_2}	SL_{n_2}
extreme	400	400	150	175	7125.44	26199.79	0.99
extreme	400	400	175	150	6869.21	26333.02	0.98
extreme	400	400	175	200	7736.60	26268.73	0.99
extreme	400	400	200	150	7033.72	26467.62	0.99
high	400	400	150	50	5315.02	27686.92	0.99
high	400	400	175	75	6041.83	27755.62	1.00
high	400	400	200	50	5543.08	27940.08	0.99
high	400	400	200	75	6201.97	27684.85	1.00
low	300	400	200	50	5213.27	28122.29	1.00
low	350	400	150	50	5213.27	28122.29	1.00
low	350	400	175	50	5458.81	28150.91	1.00
low	400	400	125	50	5458.81	28150.91	1.00
mixed	400	400	200	50	5708.27	27779.90	1.00
mixed	400	400	125	50	5296.73	27831.13	1.00
mixed	400	400	175	75	6195.70	27812.93	1.00
mixed	400	350	200	50	4192.97	27802.36	1.00

7.4 Sensitivity Analysis with Additional Parameters

The baseline results were obtained using fixed cost parameters for the ODW usage cost ($C_{\text{ODW}}^{\text{use}}$) and the unmet demand penalty (ϕ). To extend the analysis and evaluate the robustness of the system, a cost sensitivity analysis with additional scenarios and parameters was conducted to capture a broader range of market conditions. The purpose of this extension is to examine how changes in key cost parameters impact system performance, including profits (Π_{n_1}, Π_{n_2}) and service levels (SL_{n_1}, SL_{n_2}).

The following cost parameters were varied systematically:

- $C_{\text{ODW}}^{\text{use}}$: Evaluated at increments of \$2.5 within the range \$20 to \$30.
- ϕ : Varied in increments of 5, covering a range between 40 and 60.

The summary of results presented in Table 7.4 offers valuable insights into the system's flexibility, illustrating how variations in cost parameters impact key performance metrics. The extended results are provided in Table C.4 in Appendix C.

Table 7.4: Summary of the Sensitivity Analysis for ODW and Unmet Demand Penalties

Scenario	$C_{\text{ODW}}^{\text{use}}$	ϕ	Π_{n_1}	Π_{n_2}	SL_{n_1}	SL_{n_2}
low	20.0	40	41023.01	27235.17	1.00	0.98
high	20.0	40	41508.33	23971.95	1.00	0.92
extreme	20.0	40	39546.29	17610.27	0.98	0.81
mixed	20.0	40	41504.04	25160.43	1.00	0.94
low	20.0	45	41057.82	26960.36	1.00	0.98
high	20.0	45	41364.99	23621.84	1.00	0.91
extreme	20.0	45	39461.12	17453.40	0.98	0.82
mixed	20.0	45	40657.20	25764.29	1.00	0.95
low	20.0	50	41221.91	26936.85	1.00	0.98
high	20.0	50	41165.45	24006.81	1.00	0.92
extreme	20.0	50	39546.78	17796.43	0.99	0.83
mixed	20.0	50	41051.81	25556.47	1.00	0.95
low	20.0	55	41026.37	26924.77	1.00	0.98
high	20.0	55	41255.25	23586.28	1.00	0.92

Chapter 8

Results and Analysis

This section presents an in-depth analysis of profitability, service levels, and policy analysis under different demand and warehousing scenarios. The results provide critical insights into capacity management decisions and the strategic use of ODW.

8.1 Profitability Analysis Across Scenarios

The analysis of private warehousing capacity (W_p) and its impact on profitability (Π_{n_1} and Π_{n_2}) across different demand scenarios provides crucial insights into the role of capacity investments in supply chain performance. Key findings are presented below.

8.1.1 Profitability Variability Across Scenarios

Figure 8.1 illustrates the variability in profitability for n_1 across different scenarios as a function of W_p . The boxplot reveals several key trends:

- Profitability increases with W_p for all scenarios, but the rate of increase diminishes as W_p approaches higher values (e.g., $W_p = 300$ to 400).
- The "extreme" scenario exhibits the largest variability in profitability, highlighting the sensitivity of n_1 to capacity decisions under highly volatile demand conditions.
- In contrast, the "low" and "mixed" scenarios demonstrate more stable profitability distributions, indicating reduced sensitivity to W_p changes.

Figure 8.2 provides a heatmap representation of average profitability (Π_{n_1}) across W_p values and scenarios:

- In the "extreme" scenario, profitability is more sensitive to changes in W_p , with sharp increases observed up to $W_p = 300$. Beyond this point, the returns diminish.
- For the "low" scenario, the heatmap confirms that moderate W_p values (e.g., $W_p = 250$ to 300) are sufficient to maintain high profitability without over-investing in capacity.
- The "mixed" and "high" scenarios display intermediate behaviors, suggesting a balance between capacity investments and operational flexibility.

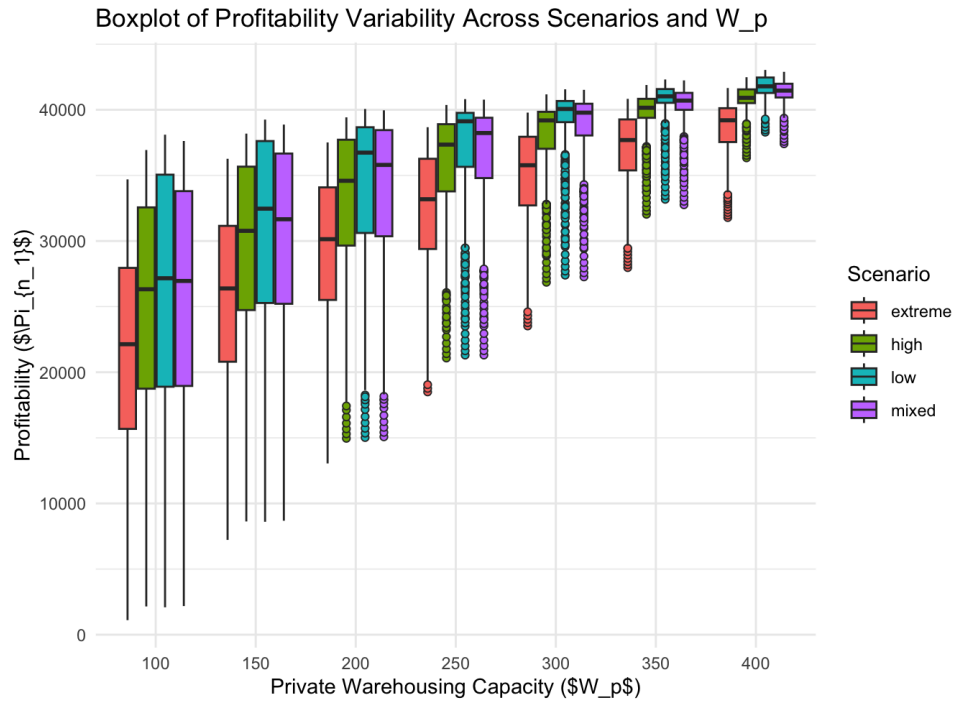


Figure 8.1: Boxplot of Profitability Variability Across Scenarios and W_p

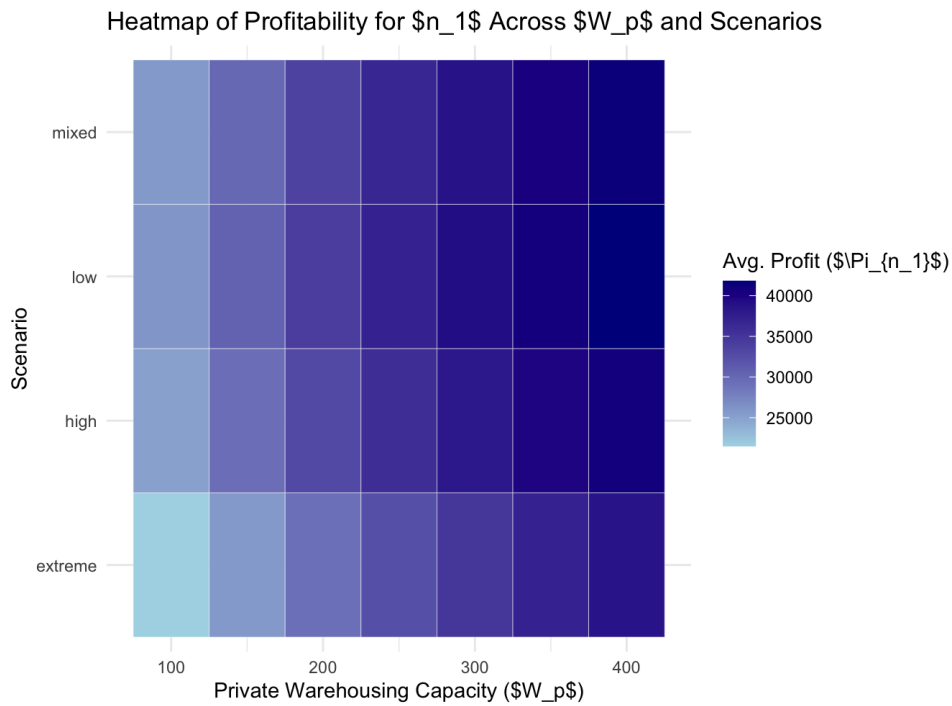


Figure 8.2: Heatmap of Profitability for n_1 Across W_p and Scenarios

8.1.2 Critical Thresholds for ODW Usage Costs

The profitability analysis highlights critical thresholds for ODW usage costs ($C_{ODW,use}$). While profitability remains stable across moderate costs, it drops significantly at higher

costs (beyond 9,000). To maintain profitability, it is essential to identify and monitor these thresholds. Policies that prioritize ODW allocations in configurations with lower W_p and W_{ODW} can help stabilize service levels during demand surges. Such policies ensure a more resilient and balanced system when faced with unpredictable demand variability.

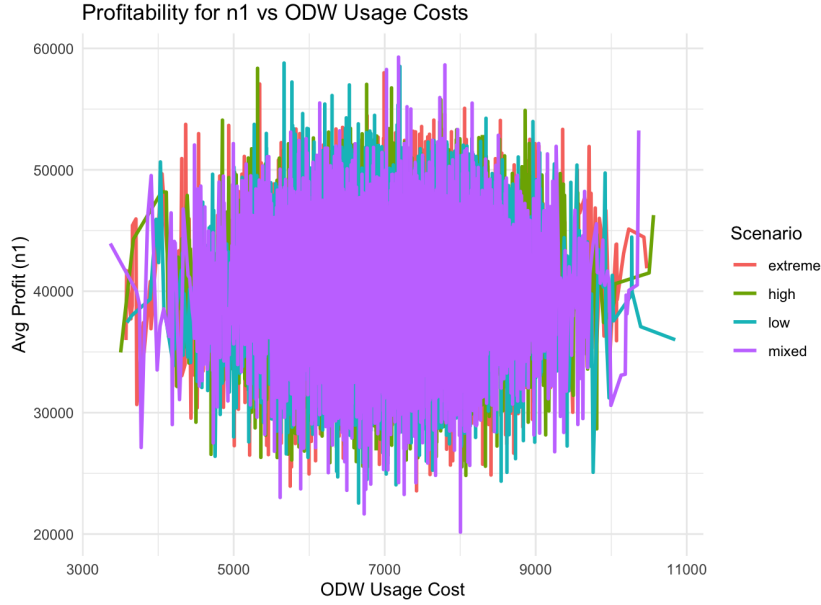


Figure 8.3: Profitability for n_1 vs ODW Usage Costs

8.1.3 Insights on Capacity Thresholds

Figure 8.4 highlights the diminishing returns for n_1 profitability as W_p increases.

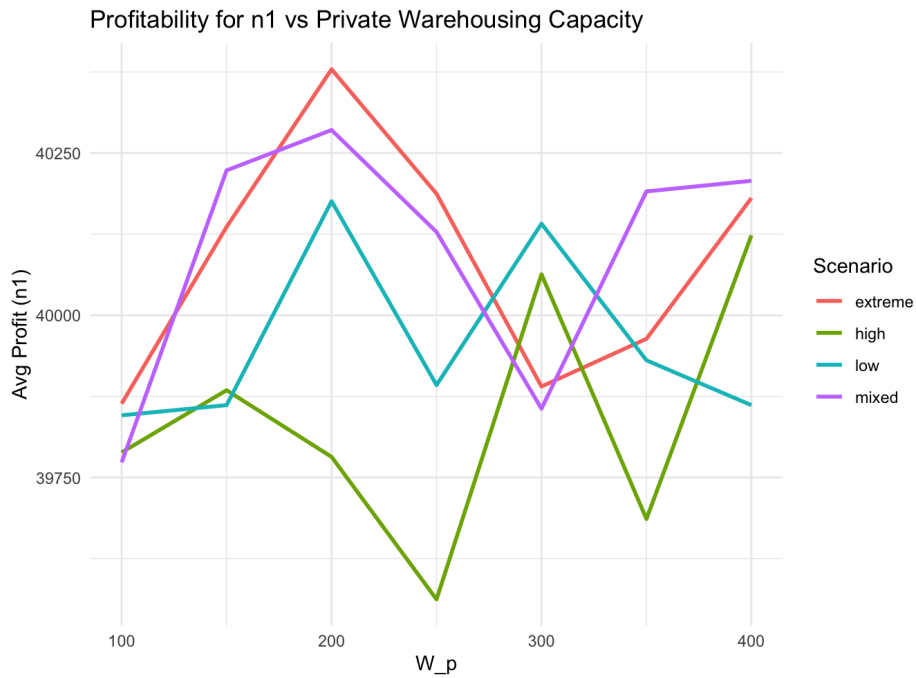


Figure 8.4: Profitability for n_1 vs Private Warehousing Capacity

The analysis of profitability versus W_p reveals diminishing marginal returns for n_1 as W_p increases, particularly beyond $W_p = 300$. This suggests that decision-makers should carefully balance investments in W_p to avoid over-allocation, as the added cost of private warehousing may outweigh its benefits. A cost-benefit analysis is recommended to determine optimal W_p levels under varying scenarios, such as "low" versus "extreme" demand conditions. By strategically allocating W_p , supply chain systems can achieve a balance between cost efficiency and service level performance.

8.1.4 Distribution of Profit for n_2 Across Scenarios

The boxplot in Figure 8.5 illustrates the distribution of profits for n_2 under different demand scenarios ("extreme," "high," "low," and "mixed"). This analysis provides insights into the profitability variations and the impact of demand variability on n_2 's performance.

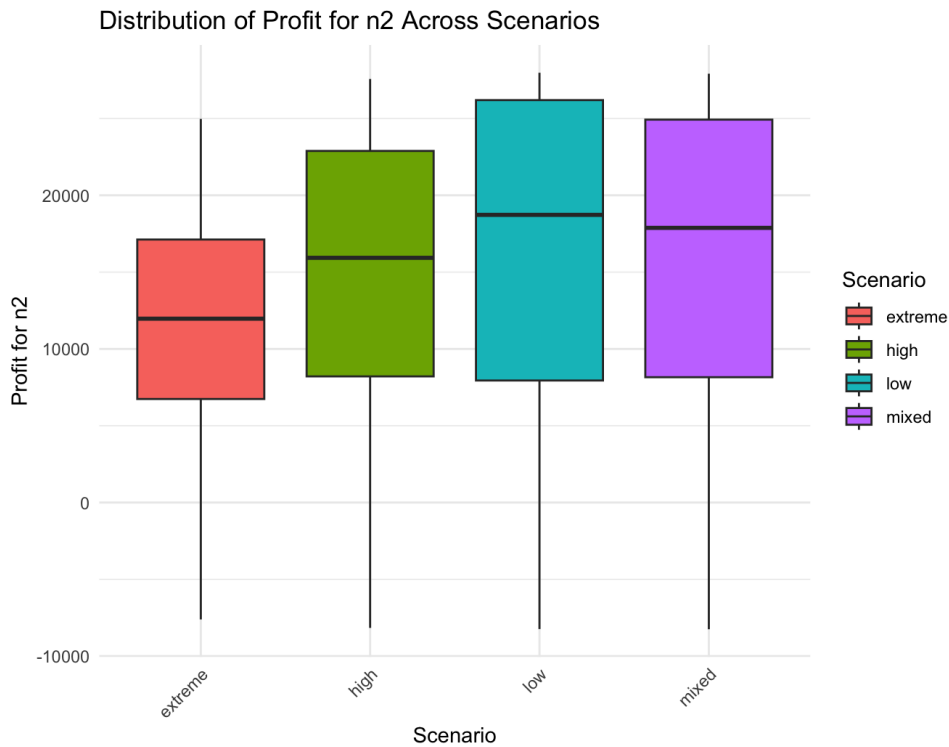


Figure 8.5: Distribution of Profit for n_2 Across Scenarios

Insights:

- **Extreme Scenario:** The "extreme" scenario exhibits the lowest median profit for n_2 , with a median value slightly above \$10,000. The interquartile range (IQR) is relatively small compared to other scenarios, indicating lower variability in profitability.
- **High Scenario:** In the "high" scenario, the median profit for n_2 increases significantly, approaching \$15,000. The IQR is larger than in the "extreme" scenario, suggesting higher variability in profitability. This variability reflects the impact of increased demand, which can either benefit n_2 through higher resource utilization or lead to inefficiencies if demand exceeds capacity.

- **Low Scenario:** The "low" scenario achieves the highest median profit for n_2 , exceeding \$20,000. The IQR is also the largest among all scenarios, indicating substantial variability. This scenario benefits from stable demand conditions, which allow for more efficient resource allocation. However, the wide range of profits suggests that n_2 's performance is sensitive to small fluctuations in demand and capacity allocation.
- **Mixed Scenario:** The "mixed" scenario displays a median profit comparable to the "low" scenario, slightly exceeding \$20,000. The IQR is slightly narrower than in the "low" scenario, indicating a moderate level of variability. This scenario reflects a balance between stability and demand fluctuations, allowing n_2 to maintain high profitability while managing variability more effectively.

Key Observations:

- **Profit Variability:** The "low" and "mixed" scenarios exhibit the highest profits and the largest variability, highlighting n_2 's ability to capitalize on stable demand conditions. In contrast, the "extreme" and "high" scenarios demonstrate lower profits and reduced variability, reflecting the challenges of managing demand volatility.
- **Outliers:** The presence of negative profit outliers in the "extreme" and "high" scenarios underscores the risk of unmet demand penalties and resource inefficiencies. These outliers suggest the need for adaptive policies to mitigate profit losses under volatile conditions.
- **Scenario-Specific Strategies:** The analysis indicates that n_2 benefits most from stable demand conditions, as seen in the "low" and "mixed" scenarios. Strategies that optimize resource allocation and minimize inefficiencies in volatile scenarios can help improve n_2 's profitability and reduce variability.

8.1.5 Profitability Analysis Insights

These insights provide a robust framework for aligning capacity decisions with scenario-specific profitability trends, ensuring sustainable and equitable supply chain performance.

- **Impact of W_p :** Increasing W_p leads to higher profits for n_1 , primarily due to reduced unmet demand penalties and improved resource utilization. However, diminishing returns are observed beyond $W_p = 300$, indicating an optimal capacity threshold for maximizing profitability without incurring excessive costs.
- **Effect of Demand Variability:**
 - *Low Scenario:* Profitability remains stable with minimal fluctuation, highlighting the lower costs associated with unmet demand and consistent resource allocation.
 - *High and Extreme Scenarios:* Profitability exhibits significant variability and declines, driven by higher unmet demand penalties and the challenges of resource allocation under volatile conditions.
 - *Mixed Scenario:* Profitability fluctuates between stable and volatile outcomes, depending on the specific demand realizations within the scenario. This underscores the need for adaptable policies to address varying demand patterns.

8.1.6 Scenario Summaries and Baseline Comparisons

Table 8.1 provides an overview of multiple scenarios, each characterized by distinct mean demands (μ_1, μ_2) and variability (σ_1, σ_2). It also distinguishes between scenarios with ODW availability and baseline scenarios where ODW is not accessible. This comprehensive summary illustrates how changes in demand conditions and capacity structures affect outcomes.

Table 8.1: Summary of Results by Scenario with μ and σ Parameters

Scenario	μ_1	μ_2	σ_1	σ_2	Π_{n_1}	Π_{n_2}	SL_{n_1}	SL_{n_2}
extreme	500	300	200 (4*50)	160 (4*40)	33025.77	11747.25	0.93	0.72
extreme_NoODW	500	300	200	160	24993.31	462.39	0.82	0.51
high	500	300	100 (50*2)	80 (40*2)	36484.42	14829.97	0.96	0.74
high_NoODW	500	300	100	80	29703.45	1835.68	0.85	0.45
low	500	300	50	40	37429.98	15885.48	0.96	0.75
low_NoODW	500	300	50	40	31203.33	1867.80	0.86	0.42
mixed	500	300	U(50, 100)	U(40, 80)	37036.37	15360.41	0.96	0.74
mixed_NoODW	500	300	U(50,100)	U(40,80)	30470.81	2050.70	0.85	0.44

As demand variability intensifies (e.g., from *low* to *extreme* scenarios), profits and service levels generally decline. Notably, scenarios without ODW capacity (e.g., *low_NoODW*, *high_NoODW*) exhibit substantially lower profits and service levels, underscoring ODW's role as a strategic buffer against uncertainty. The *mixed* scenario, with variable σ_1 and σ_2 , highlights the importance of flexibility and adaptive capacity management in mitigating unpredictable demand patterns.

8.2 Service Level Analysis Across Scenarios

This section examines the impact of On-Demand Warehousing on service levels for n_1 and n_2 under varying capacities and demand scenarios. The analysis illustrates the service levels for n_1 and n_2 with and without ODW, highlighting key trends and observations.

8.2.1 Analysis of Service Levels for n_1

This section explores the service levels (SL_{n_1}) across scenarios ("extreme," "high," "low," and "mixed") and private warehousing capacities (W_p), with and without ODW. The Figure 8.6 was used to highlight general trends across scenarios, while scatter plots Figure A.2 were used for detailed variability analysis in the Appendix A.3.

Insights:

- **High Service Levels Across Scenarios** Service levels for n_1 generally exceed 85% across all scenarios. This stability reflects n_1 's reliance on private warehousing capacity (W_p) and prioritization policies. Both "With ODW" and "Without ODW" configurations show consistently high service levels, though the difference between the two configurations varies by scenario and capacity.

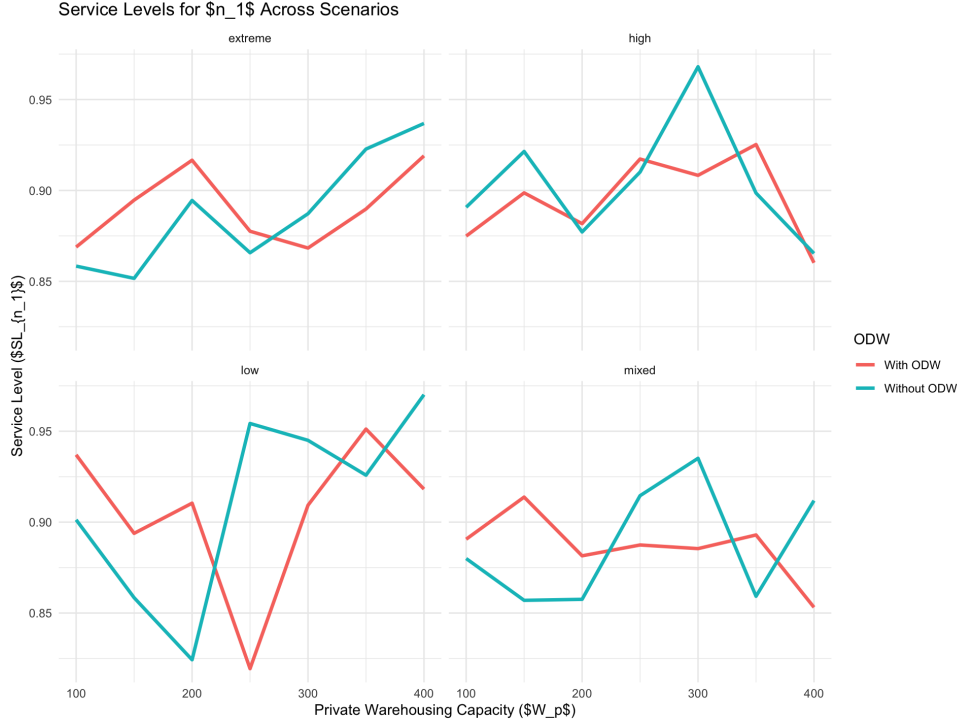


Figure 8.6: Line Plot: Service Levels for n_1 Across Scenarios (With vs Without ODW)

- Impact of ODW on Service Levels** The impact of ODW is evident in certain configurations but remains modest overall, as evidenced by the overlap of "With ODW" and "Without ODW" points in the scatter plot and the proximity of lines in the line plot. The "With ODW" configuration often provides slightly higher service levels, particularly at lower values of W_p . This suggests that ODW acts as a useful contingency mechanism, especially when private capacity is limited. However, as W_p increases, the gap between "With ODW" and "Without ODW" diminishes, indicating that private capacity is the primary driver of n_1 's performance.
- Variability in Extreme and Mixed Scenarios:** These scenarios exhibit more pronounced variability in service levels, particularly for lower W_p values. For example, in the "extreme" scenario, the "With ODW" configuration stabilizes service levels, whereas the "Without ODW" configuration shows noticeable dips.
- Diminishing Returns on Private Capacity (W_p)** Increasing W_p beyond 300 results in diminishing returns for service levels. In all scenarios, service levels plateau near 95% as W_p reaches its upper range. This indicates that further investment in private capacity provides minimal additional benefit, particularly when ODW is available as a contingency.

Key Observations:

- Private Capacity Dominates:** Service levels for n_1 are primarily driven by private warehousing capacity (W_p). ODW acts as a secondary measure, providing slight improvements in service levels in scenarios with high variability or limited private capacity.

- **Scenario-Specific Role of ODW:** ODW plays a more significant role in the "extreme" and "mixed" scenarios, where demand variability is higher. In contrast, its impact is negligible in the "low" and "high" scenarios, where private capacity alone ensures stable service levels.
- **Efficiency Considerations:** For decision-makers, investing in private capacity up to a threshold (~ 300) is effective, but additional investments beyond this point yield diminishing returns. ODW can complement this strategy by providing flexibility and resilience during demand surges or extreme variability.

8.2.2 Diminishing Returns for n_1 Service Levels

Figure 8.7 illustrates the marginal improvements in SL_{n_1} as W_p increases. The graph demonstrates the relationship between additional capacity and the corresponding service level improvements, highlighting the point at which returns diminish.

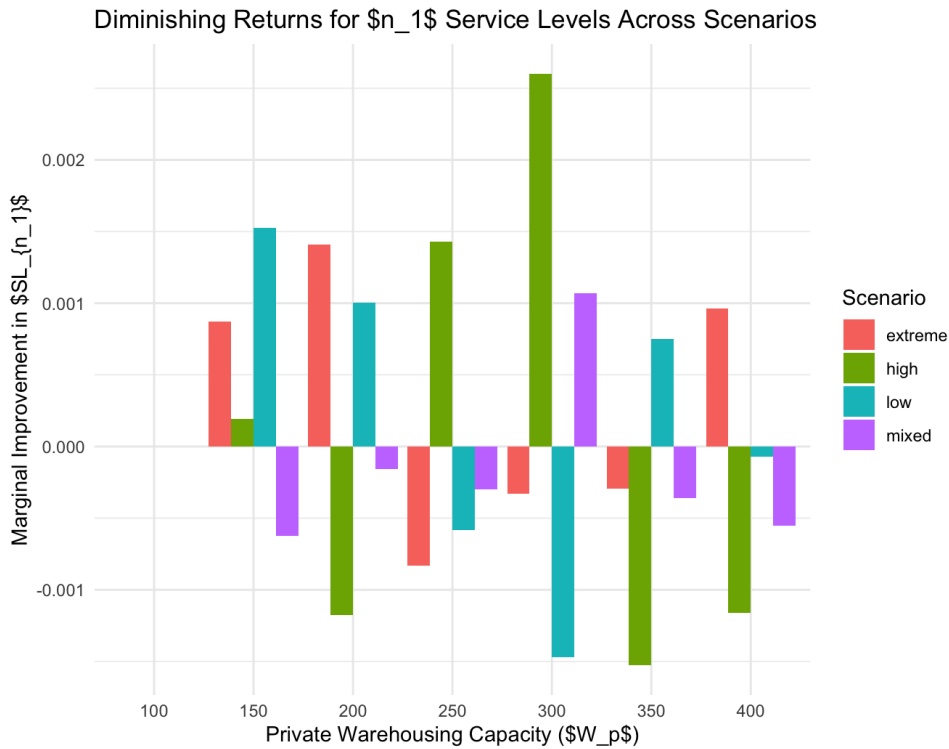


Figure 8.7: Diminishing Returns for n_1 Service Levels

Insights:

- **Diminishing Returns:** Across all scenarios, increasing W_p leads to diminishing returns in service levels. The marginal improvement consistently decreases as W_p approaches 400.
- **Scenario-Specific Observations:**
 - **Extreme Scenario:** Marginal improvements are generally positive but small across all W_p . This indicates that service levels in the "extreme" scenario benefit incrementally from higher W_p , but the gains are limited.

- **High Scenario:** A significant positive spike is observed at $W_p = 300$, indicating a noticeable improvement in service levels at this capacity. However, beyond $W_p = 300$, diminishing returns become pronounced, with negative marginal improvements appearing at $W_p = 400$.
- **Low Scenario:** Marginal improvements are inconsistent, with positive gains at lower W_p (100–200) and diminishing returns or negative values beyond $W_p = 250$. This suggests that W_p beyond 250 provides little benefit in the "low" scenario.
- **Mixed Scenario:** Variability is highest in this scenario. Marginal improvements alternate between positive and negative values, reflecting the unpredictable nature of demand variability in "mixed" conditions. Positive gains are observed at $W_p = 200$ and $W_p = 300$, but diminishing returns set in beyond $W_p = 350$.

Key Observations:

- **Optimal Capacity (W_p):** For most scenarios, $W_p = 300$ represents a critical turning point where service levels achieve significant improvements. Beyond this point, the marginal gains become negligible or negative, indicating that further investment in W_p may not be cost-effective.
- **Scenario Variability:** The "mixed" scenario demonstrates the highest variability, highlighting the importance of flexible strategies such as on-demand warehousing (ODW) to handle demand fluctuations.
- **Efficiency of Private Warehousing:** The "low" and "high" scenarios suggest that private warehousing alone can maintain high service levels up to a certain threshold ($W_p \approx 250\text{--}300$), beyond which additional capacity does not yield proportional benefits.

8.2.3 Service Levels for n_2 Across Scenarios

Figures 8.9, 8.8, and A.3 in Appendix A.3. The analysis investigates the variance, stability, and distribution of SL_{n_2} , providing deeper insights into the behavior of service levels under different capacity and demand conditions.

Insights:

Distribution of Service Levels (SL_{n_2}):

- Figure 8.8 shows that SL_{n_2} follows a relatively uniform distribution across all scenarios, with most values concentrated between 0.85 and 1.00.
- The extreme scenario exhibits a slightly wider distribution, reflecting greater variability in service levels under volatile demand conditions.
- In contrast, low and mixed scenarios demonstrate narrower distributions, indicating higher consistency in service levels.

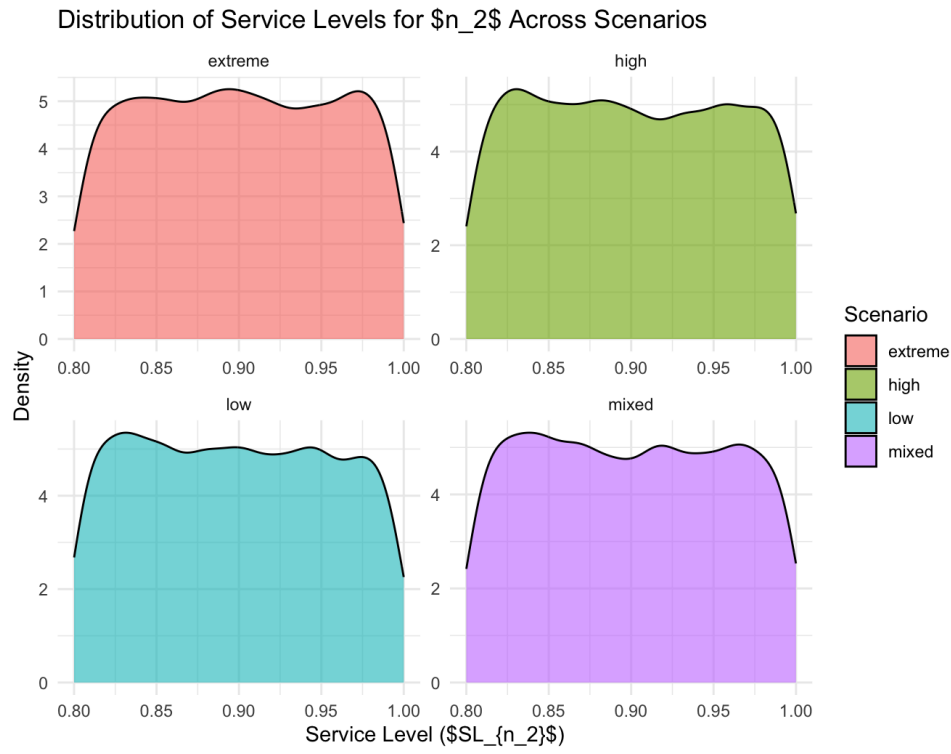


Figure 8.8: Distribution of Service Levels for n_2 Across Scenarios.

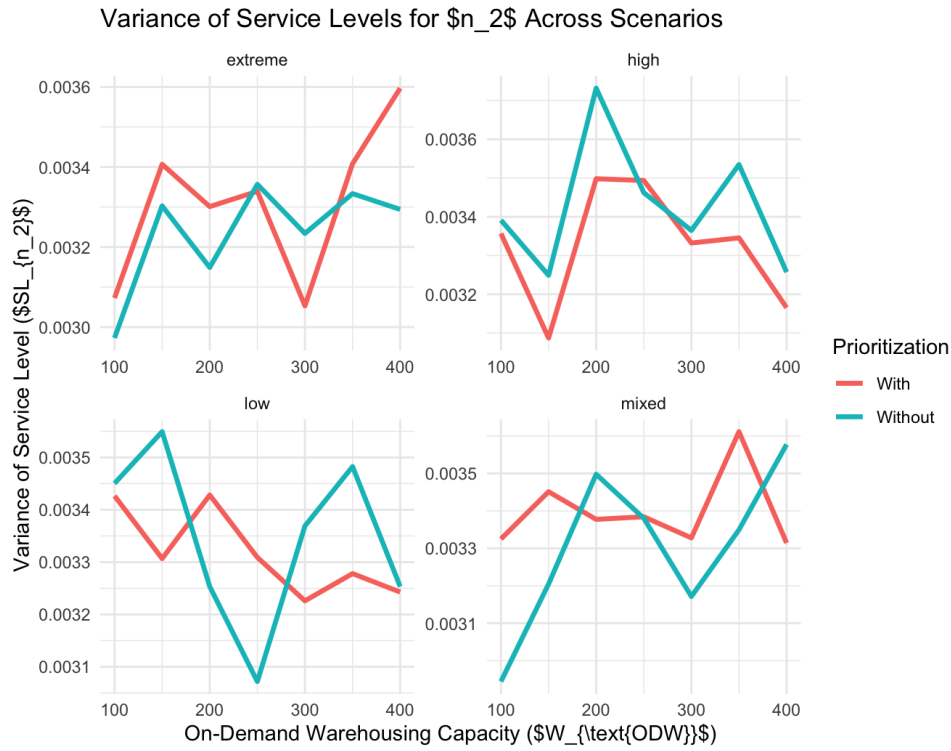


Figure 8.9: Variance of Service Levels for n_2 Across Scenarios (W_{ODW}).

- **Variance of Service Levels (SL_{n_2}):**

- **Extreme Scenario:** As shown in Figure 8.9, variance increases significantly at higher ODW capacities ($W_{\text{ODW}} > 300$). This indicates potential inefficiencies in allocation strategies under highly volatile demand conditions.
- **High Scenario:** Variance fluctuates as capacity increases, with sharp peaks around $W_{\text{ODW}} \approx 200$. This highlights the challenge of balancing capacity with demand under moderately variable conditions.
- **Low and Mixed Scenarios:** Variance remains stable across all capacities, indicating limited impact of capacity adjustments on SL_{n_2} under stable or moderately variable demand conditions.

- **Stability of Service Levels (SL_{n_2}):**

- Figure A.3 demonstrates that service level stability is generally high across all scenarios, with minimal differences between prioritization strategies ("With ODW" and "Without ODW").
- Stability is slightly lower in extreme scenarios compared to low and mixed scenarios, reflecting the challenges of maintaining consistent performance under high variability.
- The stability index is comparable across prioritization strategies, suggesting that both approaches perform similarly in terms of service level consistency.

Key Observations:

- **Scenario-Specific Trends:** Extreme and high variability scenarios exhibit greater variance and wider distributions, while low variability scenarios are characterized by stability and uniformity in service levels.
- **Effectiveness of ODW:** The results suggest that ODW capacities are most effective in stabilizing service levels under extreme and high scenarios but offer limited benefits in low or mixed scenarios.
- **Capacity Optimization:** Variance and stability analysis underscore the importance of capacity-specific optimization. Over-provisioning ODW beyond $W_{\text{ODW}} > 300$ yields diminishing returns in most scenarios.

To summarize, the inclusion of ODW does not consistently improve service levels for n_2 across all scenarios. While ODW shows promise in stabilizing service levels in "high" scenarios, its impact is less pronounced in "low" and "mixed" scenarios and may introduce inefficiencies in "extreme" scenarios due to allocation dynamics. This highlights the importance of scenario-specific deployment and optimization of ODW resources.

8.3 Cost Sensitivity Analysis: Results and Insights

This section provides an in-depth examination of cost sensitivity results derived from variations in ODW usage costs ($C_{\text{ODW}}^{\text{use}}$) and penalty costs (ϕ) across multiple demand scenarios. Table 8.2 focuses specifically on the impact of penalty costs (ϕ), highlighting their influence on key performance metrics. Additionally, Table 8.3 offers a more comprehensive analysis by considering the interactions between $C_{\text{ODW}}^{\text{use}}$ and ϕ .

8.3.1 System Performance (Focus on ϕ)

Table 8.2: Summary of the Cost Sensitivity Analysis for ODW (Focus on ϕ)

Scenario	$C_{\text{ODW}}^{\text{use}}$	ϕ	Π_{n_1}	Π_{n_2}	SL_{n_1}	SL_{n_2}
low	20	40	41078.76	27001.50	1.00	0.98
high	20	40	40975.59	24016.55	1.00	0.92
extreme	20	40	39677.53	17813.42	0.99	0.83
mixed	20	40	41163.88	25299.53	1.00	0.94
low	20	45	41023.01	27193.39	1.00	0.98
high	20	45	41506.89	23825.92	1.00	0.92
extreme	20	45	39466.49	17205.54	0.98	0.81
mixed	20	45	41503.47	25054.07	1.00	0.94
low	20	50	41057.82	26921.99	1.00	0.98
high	20	50	41363.49	23462.24	1.00	0.91
extreme	20	50	39385.61	17069.64	0.98	0.82
mixed	20	50	40657.09	25678.56	1.00	0.95

From Table 8.2, it is evident that n_1 consistently maintains high profitability across all scenarios, with profits exceeding \$39,000 even as penalty costs (ϕ) increase.

- **Profitability of n_1 :** For lower ODW usage costs (e.g., $C_{\text{ODW}}^{\text{use}} = 20$) and moderate penalties ($\phi = 40, 50, 60$), n_1 demonstrates exceptional resilience.
 - In the "mixed" scenario, n_1 achieves the highest profitability (\$41,163.88) at $\phi = 40$, underscoring the robustness of private warehousing systems in addressing variations in unmet demand penalties.
- **Sensitivity of n_2 :** Conversely, on-demand warehousing (n_2) shows greater sensitivity to demand variability and cost parameters (e.g., moving from "low" to "extreme").
 - Profitability for n_2 declines more sharply under high-variability scenarios where unmet demand penalties exacerbate losses.
 - For example, in the "extreme" scenario with $C_{\text{ODW}}^{\text{use}} = 20$ and $\phi = 60$, profits drop to \$16,198.87, highlighting the impact of demand volatility on non-private warehousing performance.
- **Service Levels:**
 - Service levels for n_1 (SL_{n_1}) consistently remain at or near 100% across all scenarios, even under extreme demand conditions. This highlights the system's capacity to prioritize private customer demand effectively.
 - On the other hand, service levels for n_2 (SL_{n_2}) are slightly lower, declining more noticeably in high-variability scenarios. For instance, SL_{n_2} drops to 0.83 in the "extreme" scenario with $\phi = 40$, reflecting challenges in meeting non-private demand under volatile conditions.

The system demonstrates resilience to moderate increases in both ODW usage costs ($C_{\text{ODW}}^{\text{use}}$) and penalty costs (ϕ). While increasing ϕ slightly reduces profitability, especially in "extreme" and "mixed" scenarios, the declines are modest. Service levels for both n_1 and n_2 remain robust, indicating the effectiveness of prioritization policies and the overall system's ability to adapt to cost fluctuations.

From a managerial perspective, these findings emphasize the strategic value of ODW as a flexible buffer to address demand fluctuations, particularly when $C_{\text{ODW}}^{\text{use}}$ and ϕ remain within moderate ranges. Additionally, the findings suggest that moderate increases in penalty or ODW usage costs do not drastically compromise either profitability or service performance. However, the greater sensitivity of n_2 to cost increases and demand variability suggests that supplementary strategies—such as dynamic pricing, pre-negotiated contracts, or increased safety stock—may be necessary to mitigate risks and enhance system performance.

8.3.2 System Performance (Focus on both $C_{\text{ODW}}^{\text{use}}$ and ϕ)

Table 8.3 examines variations in both $C_{\text{ODW}}^{\text{use}}$ and ϕ assesses their combined effects on performance metrics in order to provide a nuanced understanding of how $C_{\text{ODW}}^{\text{use}}$ and ϕ collectively influence Π and SL_n . The key findings are summarized as follows:

Table 8.3: Summary of the Cost Sensitivity Analysis (Focus on both $C_{\text{ODW}}^{\text{use}}$ and ϕ)

Scenario	$C_{\text{ODW}}^{\text{use}}$	ϕ	Π_{n_1}	Π_{n_2}	SL_{n_1}	SL_{n_2}
low	20	50	40539.36	25116.68	1.00	0.97
high	20	50	40059.08	22193.39	1.00	0.92
extreme	20	60	37317.71	16198.87	0.99	0.85
mixed	20	50	40505.38	23098.68	1.00	0.94
low	25	50	40249.46	25200.46	1.00	0.98
high	25	50	40731.04	21785.56	1.00	0.91
extreme	25	50	38127.83	15662.14	0.98	0.82
mixed	25	50	40427.63	23440.29	1.00	0.95
low	30	60	40478.05	25096.90	1.00	0.98
high	30	60	39803.55	22302.19	1.00	0.93
extreme	30	60	38088.96	15315.35	0.98	0.84
mixed	30	50	40110.63	23348.37	1.00	0.95

- **Low Scenario: Stability and Profitability**

- The Low Scenario consistently achieves the highest profits and near-perfect service levels ($SL_{n_1} = 1.00$, $SL_{n_2} = 0.98$), demonstrating remarkable stability under low variability conditions.

- **Extreme Scenario: Challenges and Sensitivity**

- The Extreme Scenario faces significant challenges, with the lowest profits and service levels ($SL_{n_2} \leq 0.85$), highlighting its high sensitivity to demand variability.

- Higher penalty costs (ϕ) further reduce profits in this scenario. However, service levels remain robust ($SL_{n_1} \geq 0.98$, $SL_{n_2} \geq 0.82$), demonstrating the system's flexibility despite unfavorable conditions.
- **Profitability Trends for n_1 and n_2 :**
 - Profits for n_1 remain stable across all scenarios.
 - Profits for n_2 , however, decline significantly, particularly in the Mixed and Extreme Scenarios. This decline reflects n_2 's higher sensitivity to ODW usage costs (C_{ODW}^{use}) and variability.
- **Mixed Scenario: Balancing Performance**
 - The Mixed Scenario strikes a balance between profitability and service levels, effectively managing variability and costs.
- **High Scenario: Robust Service Levels with Slight Profit Reductions**
 - The High Scenario maintains strong service levels ($SL_{n_1} = 1.00$, $SL_{n_2} \approx 0.92$).
 - However, slight profit reductions for n_2 are observed as C_{ODW}^{use} increases.
- **Key Observations:**
 - The Low and High Scenarios exhibit strong resilience to changes in both C_{ODW}^{use} and ϕ , ensuring stable performance.
 - In contrast, the Extreme Scenario remains highly sensitive to these cost changes, leading to reduced profitability and performance.

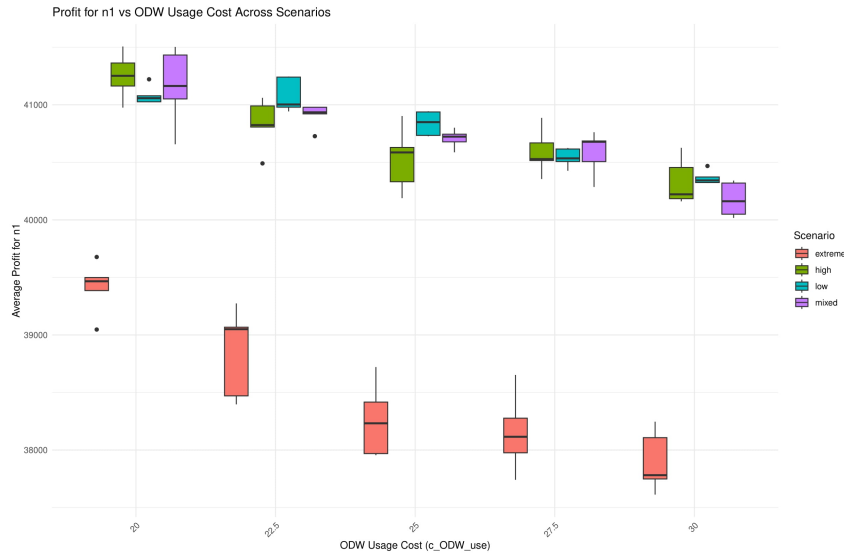


Figure 8.10: Profit for n_1 vs ODW Usage Cost Across Scenarios

Figure 8.10 visualizes the sensitivity of n_1 's profitability to ODW usage costs across scenarios. Profitability for n_1 experiences marginal declines (less than 5%) as C_{ODW}^{use} increases, particularly in 'extreme' scenarios. The 'extreme' scenarios exhibit a decline

in profitability of over 15% for n_2 as ϕ increases, compared to more stable performance in 'low' and 'mixed' scenarios reflecting the interplay between penalty costs and demand variability.

In summary, the results indicate that the system demonstrates resilience to moderate increases in penalty costs ($\phi = 40\text{--}60$) and ODW usage costs ($C_{\text{ODW}}^{\text{use}} = 20\text{--}30$), particularly under 'low' and 'mixed' scenarios. Profits and service levels remain stable, particularly for n_1 , suggesting that prioritization policies are effective.

8.4 Configuration and Prioritization Policies

The analysis of optimal configurations reveals significant scenario-specific impacts on profits and service levels, highlighting the interplay between system parameters and demand conditions. Key findings from the simulations are summarized as follows:

8.4.1 Optimal Configurations and Policy Impact

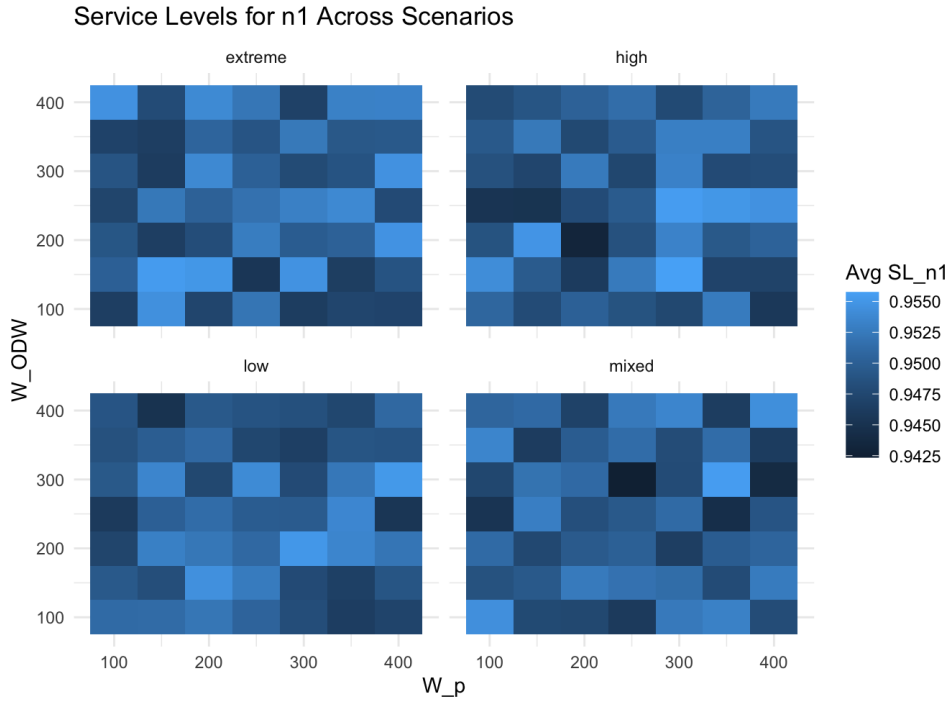


Figure 8.11: Service Levels for $n1$ Across Scenarios

For the "low" demand scenario, configurations with $W_p = 400$ and $W_{\text{ODW}} = 250$ or 300 effectively balance costs and service levels. These configurations achieved high service levels ($SL_{n1} = 1$) for $n1$, with the highest profitability ($\Pi_{n1} = 43,035$) at $W_{\text{ODW}} = 250$. In contrast, the "extreme" demand scenario required higher W_p and W_{ODW} capacities to mitigate unmet demand penalties and maintain profitability. Configurations such as $W_p = 400$ and $W_{\text{ODW}} = 400$ proved optimal, yielding significant increases in Π_{n1} (41,658) while maintaining $SL_{n1} = 1$.

The heatmap analysis of service levels (SL_{n_1}) across W_p and W_{ODW} highlights the variability in achieving high service levels under extreme conditions. This variability underscores the importance of identifying configurations that maximize service levels for both n_1 and n_2 under unpredictable demand. Policies prioritizing ODW in configurations with lower W_p and W_{ODW} can stabilize service levels during surges, ensuring a resilient system. Adaptive policies that prioritize n_1 during extreme scenarios while balancing resources for n_2 are crucial for overall system efficiency. Equitable prioritization policies are essential to reduce unmet demand for n_2 and foster a more inclusive supply chain system.

8.4.2 Policy Impact on Service Levels and Profitability for n_1

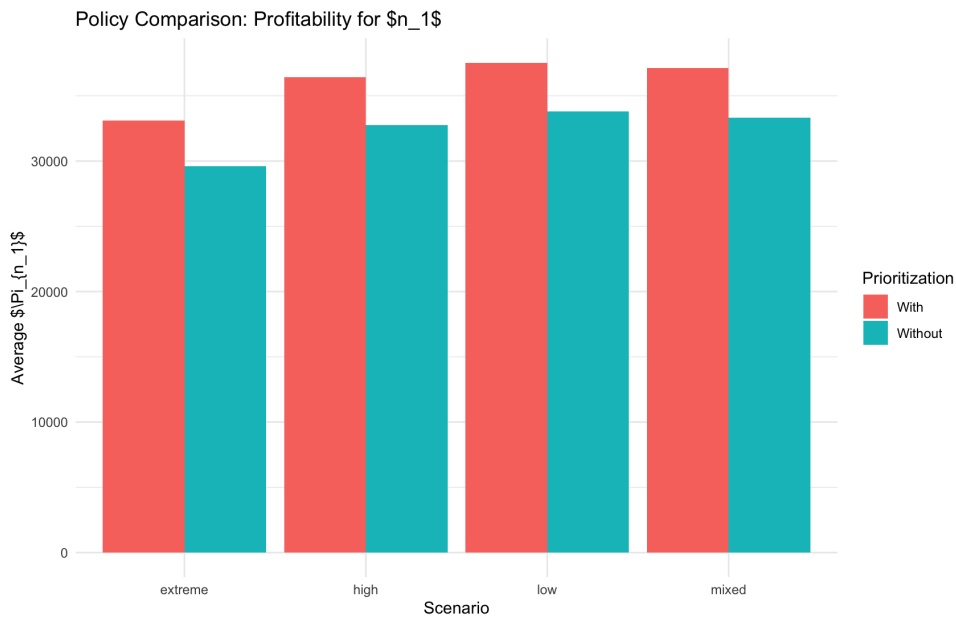


Figure 8.12: Policy Comparison: Profitability for n_1 Across Scenarios

The analysis in Figure 8.12 illustrates the impact of prioritization policies on the profitability (Π_{n_1}) for n_1 across four scenarios: "extreme," "high," "low," and "mixed." The graph provides valuable insights into the role of prioritization in shaping profitability outcomes under varying demand conditions and capacity configurations.

Insights:

- Prioritization Benefits Across All Scenarios:** Across all four scenarios, the "With Prioritization" configuration consistently yields higher profitability for n_1 compared to the "Without Prioritization" configuration. The difference is most pronounced in the "extreme" scenario, where the complexity of demand variability amplifies the benefits of prioritization policies. This trend highlights the effectiveness of prioritization in ensuring optimal resource allocation for n_1 .

- **Scenario-Specific Variations:**

- **Extreme Scenario:** The profitability gap between the two configurations is widest in the "extreme" scenario. This is likely due to prioritization policies stabilizing n_1 's performance amidst high demand fluctuations, which otherwise result in inefficiencies in the "Without Prioritization" case.
 - **High Scenario:** In the "high" scenario, the prioritization policy provides a moderate profitability advantage. However, the margin is less pronounced than in the "extreme" scenario, suggesting that n_1 's performance is less sensitive to prioritization when demand variability is lower.
 - **Low Scenario:** The "low" scenario demonstrates a smaller yet consistent profitability benefit from prioritization, reflecting the robustness of n_1 's performance under stable demand conditions.
 - **Mixed Scenario:** The "mixed" scenario shows a balanced profitability advantage for the "With Prioritization" configuration, reflecting the adaptability of prioritization policies in environments characterized by moderate demand variability.
- **Consistent Performance for n_1 :** The results indicate that prioritization policies provide a systematic advantage across all scenarios, ensuring consistently higher profitability for n_1 . This underscores the importance of integrating prioritization into resource allocation frameworks, particularly in environments with high demand variability.
 - **Efficiency Implications:** The profitability trends observed suggest that prioritization not only enhances n_1 's financial performance but also contributes to overall system efficiency by minimizing unmet demand penalties and optimizing capacity utilization.

Key Observation: Prioritization policies play a critical role in enhancing the profitability of n_1 across diverse scenarios. While the benefits are most pronounced in high variability scenarios such as "extreme," they remain significant across all demand conditions. This highlights the strategic importance of incorporating prioritization mechanisms into supply chain decision-making to achieve optimal financial and operational performance.

8.4.3 Diminishing Returns for n_1 Service Levels with Prioritization

Figure 8.13 illustrates the marginal improvements in service levels (SL_{n_1}) as on-demand warehousing capacity (W_{ODW}) increases across four scenarios: "extreme," "high," "low," and "mixed." The analysis compares the "With Prioritization" and "Without Prioritization" configurations, highlighting key trends in diminishing returns and prioritization effects.

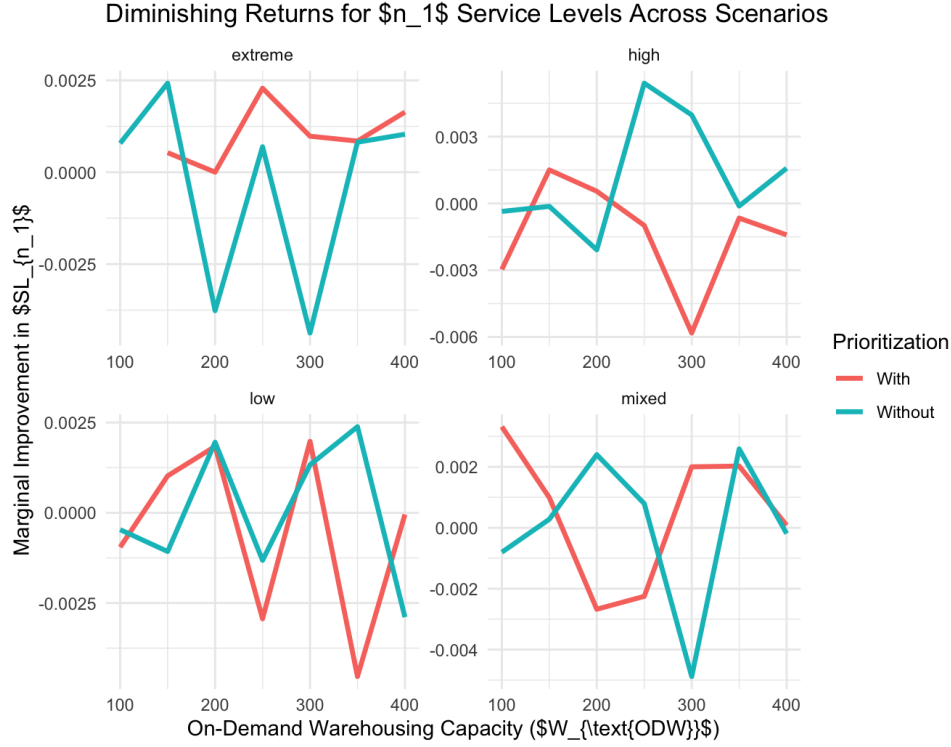


Figure 8.13: Diminishing Returns for SL_{n_1} Across Scenarios

Insights:

- **Diminishing Returns Across Scenarios:**

- Across all scenarios, marginal improvements in service levels decline as W_{ODW} increases. This reflects the principle of diminishing returns, where additional capacity contributes less to improving service levels as existing capacity becomes sufficient.
- Negative marginal improvements are observed at certain capacity levels, particularly in the "high" and "mixed" scenarios, indicating inefficiencies or over-provisioning at higher W_{ODW} .

- **Scenario-Specific Observations:**

- **Extreme Scenario:** Both "With" and "Without Prioritization" configurations show small yet consistent marginal improvements, with noticeable dips at $W_{ODW} = 200$ and $W_{ODW} = 300$. Prioritization slightly stabilizes service levels in this scenario, reducing the variability of marginal improvements.
- **High Scenario:** The "Without Prioritization" configuration exhibits a sharp positive spike at $W_{ODW} = 300$, followed by negative marginal improvements at $W_{ODW} = 400$. This indicates that prioritization helps to smooth out abrupt changes, ensuring more consistent performance.
- **Low Scenario:** Marginal improvements are inconsistent for both configurations, with peaks at $W_{ODW} = 200$ and $W_{ODW} = 300$. This suggests that the low demand scenario benefits less from additional ODW capacity, with prioritization having minimal impact.

- **Mixed Scenario:** The "mixed" scenario demonstrates the highest variability, with alternating positive and negative marginal improvements across W_{ODW} . The prioritization configuration shows smoother trends compared to the "Without Prioritization" configuration, reflecting its ability to mitigate extreme fluctuations.

- **Role of Prioritization:**

- Prioritization provides a stabilizing effect across most scenarios, reducing the variability of marginal improvements. This is particularly evident in the "high" and "mixed" scenarios, where the "With Prioritization" configuration demonstrates more consistent trends.
- In scenarios with high demand variability (e.g., "extreme" and "mixed"), prioritization helps to mitigate inefficiencies by ensuring equitable allocation of ODW resources.

- **Efficiency Considerations:**

- For decision-makers, the results suggest that W_{ODW} should be capped at 300 in most scenarios to avoid inefficiencies. Beyond this threshold, diminishing returns and negative marginal improvements indicate that additional capacity provides minimal benefits.
- Prioritization should be considered as a strategic mechanism to enhance resource allocation and improve service level consistency in scenarios with high variability.

Key Observation: While W_{ODW} plays a critical role in improving SL_{n_1} , diminishing returns highlight the need for capacity optimization. Prioritization enhances the effectiveness of ODW by stabilizing service levels and mitigating variability, particularly in scenarios with high demand fluctuations.

8.4.4 Prioritization Policies and Service Levels for n_2 Across Scenarios

Figures 8.14 and 8.15 analyze the impact of prioritization policies on the service levels (SL_{n_2}) for n_2 across various scenarios. These figures compare the performance of 3PL Reserved Capacity ($w_{TPL,2}$) and On-Demand Warehousing (ODW) Capacity (W_{ODW}) under prioritization ("With") and non-prioritization ("Without") policies, providing deeper insights into their effectiveness across different demand conditions.

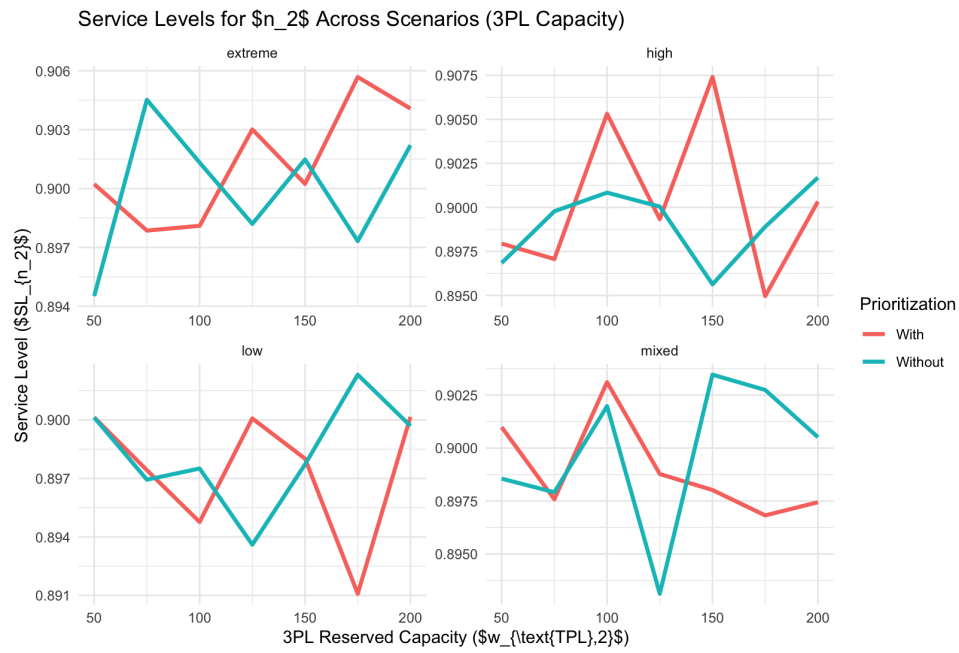


Figure 8.14: Service Levels for n_2 Across Scenarios (3PL Reserved Capacity $w_{\text{TPL},2}$)



Figure 8.15: Service Levels for n_2 Across Scenarios (ODW Capacity w_{ODW})

Insights:

- **Impact of 3PL Reserved Capacity ($w_{\text{TPL},2}$):**

- In the **extreme** scenario, significant fluctuations are observed across both prioritization settings. Prioritization ("With") generally leads to higher service levels at intermediate capacities (e.g., $w_{\text{TPL},2} \approx 150$), but non-prioritization ("Without") surpasses it at lower and higher capacities, indicating challenges in handling highly variable demand with rigid allocation mechanisms.
- In the **high** scenario, prioritization consistently outperforms non-prioritization at most capacity levels, particularly around $w_{\text{TPL},2} = 100$. This highlights the stabilizing role of prioritization in addressing unmet demand under moderately variable conditions.
- For the **low** scenario, differences between prioritization and non-prioritization are negligible, suggesting that stable demand mitigates the necessity for advanced allocation mechanisms.
- In the **mixed** scenario, prioritization shows marginal benefits at $w_{\text{TPL},2} \approx 150$, but non-prioritization often provides comparable or better performance, highlighting the need for adaptive allocation strategies in moderately variable demand environments.

- **Impact of ODW Capacity (W_{ODW}):**

- In the **extreme** scenario, non-prioritization consistently outperforms prioritization, suggesting inefficiencies in prioritization mechanisms under highly variable demand conditions.
- In the **high** scenario, prioritization marginally improves performance at $W_{\text{ODW}} \approx 200$, but diminishing returns are observed as capacity increases beyond $W_{\text{ODW}} = 300$. This underscores the need for capacity optimization under moderate demand variability.
- For the **low** scenario, service levels for both prioritization and non-prioritization remain almost identical, reaffirming the limited utility of ODW under stable demand conditions.
- In the **mixed** scenario, non-prioritization frequently yields higher service levels, particularly at $W_{\text{ODW}} > 250$. This indicates that dynamic allocation strategies may introduce inefficiencies in moderate demand environments.

- **General Observations Across Scenarios:**

- **Prioritization Benefits:** While prioritization stabilizes service levels in high-demand variability scenarios, it introduces inefficiencies in extreme and mixed scenarios, suggesting the need for flexible allocation strategies.
- **Capacity Sensitivity:** Service levels improve with increasing 3PL or ODW capacities, but diminishing returns occur beyond $w_{\text{TPL},2} > 150$ or $W_{\text{ODW}} > 300$. This highlights the need for capacity-specific optimization.

- **Scenario-Specific Impact:** The inclusion of ODW capacity offers substantial benefits in high variability scenarios but has minimal impact in stable or moderately variable scenarios.

Key Observation: Prioritization and ODW capacities must be tailored to the specific demand variability of each scenario. While prioritization improves service levels under high variability, it often introduces inefficiencies in extreme and mixed scenarios, underscoring the importance of dynamic, scenario-specific resource allocation strategies.

8.5 Policy Analysis

The comparison of prioritization and non-prioritization policies reveals key insights into equitable resource distribution and profitability. Prioritization ensures that n_1 maintains high service levels and profitability across demand scenarios, particularly in "extreme" conditions where variability is pronounced. However, the minimal differences in service levels between prioritization and non-prioritization for n_1 ($SL_{n_1} \approx 0.95$) suggest that prioritization may not be necessary in stable or low-demand scenarios. Non-prioritization policies, while slightly improving service levels for n_2 , do not significantly impact overall equity due to the negligible differences observed in SL_{n_2} .

Table 8.4: Overview of Profitability and Service Level Metrics Across Scenarios

Scenario	Prioritization	Π_{n_1}	Π_{n_2}	SL_{n_1}	SL_{n_2}
Extreme	With	40,116	20,060	0.950	0.901
Extreme	Without	40,056	20,020	0.950	0.900
High	With	39,860	20,087	0.949	0.900
High	Without	39,823	19,962	0.950	0.899
Low	With	40,077	19,960	0.950	0.897
Low	Without	39,840	19,989	0.950	0.898
Mixed	With	40,100	20,014	0.950	0.899
Mixed	Without	40,090	20,065	0.950	0.900

The "extreme" demand scenario presents unique challenges due to high variability and unmet demand penalties. In such conditions, the profitability for n_1 is highly sensitive to resource allocation, with prioritization yielding a policy impact of 60 units for n_1 compared to 40 units for n_2 . This indicates that adaptive policies prioritizing n_1 can mitigate disparities and maximize overall system efficiency.

The policy analysis highlights critical thresholds for $C_{ODW,use}$ and W_p , respectively. The stability of profitability at moderate costs and capacities, followed by sharp declines at higher thresholds, underscores the importance of scenario-specific configurations. These findings underscore the importance of tailoring policies based on the demand scenario. While prioritization offers marginal benefits in extreme conditions, decision-makers must carefully evaluate its necessity to ensure balanced resource distribution without compromising profitability.

Chapter 9

Recommendations

This section consolidates the key insights from the preceding analyses into practical, data-driven recommendations for decision-makers. By aligning operational capacities, on-demand warehousing (ODW), and cost structures with specific demand scenarios, organizations can optimize both profitability and service levels for stakeholders.

9.1 Prioritizing Private Capacity and ODW Thresholds

- **Private Warehousing Capacity (W_p):** The results consistently indicate that increasing W_p beyond approximately 300 units yields diminishing returns in both profitability (Π_{n_1}) and service levels (SL_{n_1}). Decision-makers should therefore invest in W_p up to this threshold but avoid excessive allocations that fail to improve performance proportionally.
- **On-Demand Warehousing Usage Cost ($C_{\text{ODW}}^{\text{use}}$):** Simulations reveal that moderate ODW usage costs (e.g., \$20–\$30) do not critically erode profits or service levels for private (i.e., n_1) customers; however, once $C_{\text{ODW}}^{\text{use}}$ surpasses specific cutpoints (e.g., \$30–\$35), on-demand warehousing ceases to offer significant cost advantages. Clear internal guidelines or renegotiated ODW contracts should keep usage fees below these cutpoints.
- **Penalty Costs (ϕ) and Unmet Demand Exposure:** Sensitivity analyses indicate that higher ϕ disproportionately affects non-private (n_2) entities under volatile scenarios (e.g., “extreme”), while n_1 remains relatively robust. Managers should consider scenario-based penalty reductions or alternative capacity buffers (e.g., partial ODW contracts) to mitigate risks for n_2 .
- **Demand Variability Scenarios:** In “low” or “mixed” scenarios, stable demand requires only moderate ODW or TPL capacity to maintain high service levels. In contrast, “extreme” scenarios demand a combination of higher W_p and strategic ODW usage to weather surges and avoid severe unmet-demand penalties.

9.1.1 Dynamic ODW Activation Policies

- **Scenario-Based ODW Deployment:** Activate ODW capacity only when forecasts or real-time indicators project volatility beyond the capacity of existing W_p . In stable periods, reduce or deactivate ODW usage to contain costs.
- **Adaptive Prioritization:** Regularly review and refine activation thresholds for ODW based on real-time performance metrics, including service levels, unmet demand penalties, and capacity utilization. In the same time, use predictive demand models to anticipate variability and optimize ODW deployment timing and scale.
- **Flexible Cost-Sharing Strategies:** If $C_{\text{ODW}}^{\text{use}}$ or ϕ shift substantially, organizations should renegotiate ODW usage fees or partial capacity guarantees to ensure demand surges do not undermine system profitability.

9.1.2 Equity Versus Profit Trade-Offs

- **Balancing Service Levels for n_1 and n_2 :** While n_1 experiences near-perfect service levels by design, modest adjustments in prioritization significantly improve n_2 service levels, especially under moderate or high variability. Managers should adopt an approach that balances equity (i.e., more capacity for n_2) with overall system profitability.
- **Cost-Effectiveness:** In many scenarios, increasing W_p capacity alone can achieve high service levels for n_1 . Integrating ODW capacity beyond roughly 300–350 units does not substantially enhance system performance, indicating an upper bound for cost-effective expansions.

9.2 Managerial Implications for Industry Practitioners

9.2.1 Operational Flexibility and Cost-Benefit Trade-Offs

- **Dynamic Resource Allocation Policies:** Adjust ODW activation dynamically based on scenario-specific demand patterns to maximize cost efficiency and service level performance.
- **Balancing Efficiency vs. Resilience:** The model shows that *overinvesting* in private capacity or ODW capacity beyond these thresholds ($W_p \approx 350$, $W_{\text{ODW}} \approx 300$) yields diminishing returns. Practitioners should weigh the cost of idle capacity against the benefits of reduced unmet demand penalties.
- **Coordination with 3PLs:** For moderate usage-cost ranges (\$20–\$30), strong 3PL or ODW partnerships are cost-effective in handling short-term demand spikes. At higher costs, renegotiations or partial capacity reservations become critical.

9.2.2 Scenario-Specific Strategies and Long-Term Planning

- **Low and Mixed Demand Environments:** Managers can lean on private capacity alone, limiting ODW usage to sporadic surges. Keep ODW contracts flexible rather than locked in at fixed usage rates.
- **High Variability (High / Extreme):** Proactively secure adequate ODW or TPL capacity, ensuring cost thresholds are not exceeded. For severe “extreme” conditions, capacity expansions above 300 units become essential to maintain high service levels and avoid steep penalties.
- **Innovation in Prioritization Rules:** The minimal margin of difference between “With” and “Without” prioritization in stable contexts suggests managers can experiment with balanced or rotating priority systems. In extremely volatile scenarios, a robust priority policy for n_1 clearly preserves profitability.

9.3 Policy Guidelines

Based on the analysis, the following policy guidelines are proposed to optimize resource allocation and decision-making:

1. **Prioritization Activation:** Prioritization policies should be activated during “high” or “extreme” demand scenarios where n_1 ’s service levels and profitability are slightly enhanced. In stable or low-demand scenarios, proportional allocation can be employed to balance resources more equitably.
2. **Monitoring ODW Costs:** Establish critical thresholds for $C_{\text{ODW,use}}$, ensuring that ODW usage costs remain below levels where profitability declines sharply. Implement subsidies or cost-sharing mechanisms if costs exceed these thresholds during high-demand periods. This ensures sustained profitability and system efficiency.
3. **Strategic Capacity Investments:** Invest in W_p resources up to the point of diminishing returns (e.g., $W_p = 300$) and prioritize additional investments in W_{ODW} to handle demand variability more flexibly, especially under extreme scenarios.
4. **Equity Policies:** While prioritization policies favor n_1 , non-prioritization strategies marginally improve n_2 ’s service levels (e.g., SL_{n_2} improves from 0.899 to 0.900 in “high” scenarios) without significantly reducing n_1 ’s performance (SL_{n_1} remains consistent at 0.950). Decision-makers should develop equitable resource distribution strategies that balance n_1 ’s profitability with n_2 ’s access to ODW resources.
5. **Scenario-Specific Configurations:** Tailor configurations based on scenario demands, emphasizing higher W_p and W_{ODW} capacities during extreme scenarios to mitigate unmet demand penalties and balanced allocations for lower-demand scenarios to maximize efficiency.

These guidelines provide a structured approach for decision-makers to enhance supply chain performance while maintaining equity and resilience across diverse operational scenarios.

9.4 Integrated Decision Framework for On-Demand Warehousing (ODW)

This section consolidates two complementary approaches for deciding whether and when to deploy On-Demand Warehousing (ODW):

1. **Scenario-Based Triggers:** Where usage of ODW is recommended or discouraged according to specific *scenario definitions* (e.g., *low*, *mixed*, *high*, *extreme*) derived from the model’s assumptions on demand variability (σ_1, σ_2) and cost structures.
2. **Metric-Based Triggers:** Where a set of *universal rules* (e.g., service-level falling below 0.8, profitability difference exceeding 5%, or ODW marginal cost being lower than penalty cost) directly indicate the need for ODW, regardless of scenario labels.

By combining both, decision makers can *first* identify which scenario they are most likely facing and *then* verify that scenario’s recommended thresholds while still retaining the flexibility to respond to real-time changes in costs and service levels.

9.4.1 Scenario-Based Triggers

Table 9.1 reproduces an example of how each scenario can be linked to specific usage cost cutpoints, penalty thresholds, and recommended actions for ODW activation. These guidelines assume that (1) managers have identified themselves as “low,” “mixed,” “high,” or “extreme” demand cases based on observed standard deviations (σ_1, σ_2), and (2) approximate capacity ranges have been computed from prior analysis.

Table 9.1: Scenario-Based Triggers for ODW Deployment

Scenario	Demand Variability	ODW Usage Cost Trigger	Penalty ϕ Trigger	Recommended Action
Low	$\sigma_1 = 50, \sigma_2 = 40$ (stable)	$C_{\text{ODW}}^{\text{use}} < \$30$	$\phi \leq 50$	<i>ODW optional.</i> Deploy only if surges arise, or if usage costs remain well below penalty.
Mixed	σ_1 in $[50-100]$, σ_2 in $[40-80]$	$C_{\text{ODW}}^{\text{use}} < \$32$	$\phi \leq 55$	Deploy ODW if $W_p < 300$ to handle intermittent spikes.
High	$\sigma_1 = 100, \sigma_2 = 80$	$C_{\text{ODW}}^{\text{use}} < \$35$	$\phi \leq 60$	Activate ODW if $W_p < 250$ or if usage cost under \$35.
Extreme	$\sigma_1 \approx 200, \sigma_2 \approx 160$	$C_{\text{ODW}}^{\text{use}} \leq \$30$	$\phi \leq 55$	<i>Essential</i> if $W_p < 350$; advanced policies recommended for large surges.

- **Low Scenario:** On-demand warehousing is not strictly necessary when $W_p \geq 250$; however, managers can keep ODW on standby in case of sudden surges or as a cost-buffer if $C_{\text{ODW}}^{\text{use}}$ remains below \$30.

- **Mixed Scenario:** Intermittent demand spikes may occur. Activating ODW at $W_p < 300$ ensures risk mitigation without over-investment, provided usage costs remain below \$32.
- **High Scenario:** If $\phi \leq 60$ and usage costs remain moderate (\$30–\$35), deploying ODW helps cover surges when $W_p \approx 200$ –250. Larger W_p alone can suffice for stable periods.
- **Extreme Scenario:** The highest variability demands both robust private capacity ($W_p \approx 300$ –350) and carefully monitored ODW usage costs to ensure profitability. Exceeding these triggers under extreme volatility sharply reduces n_2 profitability and sometimes lowers n_1 performance.

Interpretation: Under stable (low) demand, the necessity of ODW is minimal unless usage costs are particularly low. Under extreme demand ($\sigma_1 = 200$), ODW often becomes “essential,” especially when private capacity W_p is capped at 300–350. This approach is intentionally *scenario-centric*, providing a quick lens for managers to align decisions with the recognized environment.

9.4.2 Metric-Based Triggers

While scenario-based triggers are practical for *planning* at a strategic level, day-to-day or short-term fluctuations may call for more *direct performance metrics* to decide if ODW is beneficial:

- **Profitability Difference:** If

$$\Pi_{n_2}^{(\text{With ODW})} - \Pi_{n_2}^{(\text{No ODW})} > 5\%$$

(or some user-defined margin), then ODW usage is justified.

Example: In the “extreme” scenario, if profitability for n_2 increases by 10% due to ODW, the decision maker should use ODW.

- **Service Level Deviation:** If SL_{n_2} falls below 0.80 (or a manager-specified threshold) in real time, ODW is triggered to avoid unmet demand penalties and maintain customer satisfaction. *Example:*

- If $SL_{n_2}^{\text{Without ODW}} < 0.8$, ODW becomes essential to ensure customer satisfaction and avoid unmet demand penalties.
- *For Instance:* For n_1 , if SL_{n_1} remains consistent at or above 0.95 without ODW, additional investments in ODW for n_1 are unnecessary.

- **Marginal Cost vs. Penalty:** If $C_{\text{ODW,use}} < \phi$, then paying for ODW usage is cheaper than incurring unmet demand. This is especially pertinent in high or extreme scenarios where ϕ can be large.

Example:

- If $C_{\text{ODW,use}} < \phi$, ODW usage is cost-effective.

– *For Instance:* For $\phi = 50$, if $C_{\text{ODW,use}} = 25$, ODW is a cost-effective solution.

- **Demand Variability Surpassing Private Capacity:** If actual demand surges beyond the “optimal” W_p (e.g., $W_p^{\text{opt}} = 300$) in a single period, ODW can be *activated dynamically*.

Clear Cut: Use ODW in scenarios with high demand variability (e.g., “extreme” and “mixed” scenarios) where private warehousing capacity cannot handle surges efficiently. In other words, use ODW when private warehousing (W_p) is fully utilized, and demand still exceeds available capacity.

Example:

- If $W_p^{\text{Optimal}} < \text{Demand Peak}$, ODW is necessary to prevent unmet demand.
- *For Instance:* In “high” or “extreme” scenarios, if $W_p = 300$ but demand peaks at 400, ODW can be deployed to bridge the gap.

- **Trade-Off Ratio for Equity vs. Profit:**

$$\text{Ratio} = \frac{\Delta SL_{n_2}}{\Delta \Pi_{n_1}} \quad (\text{With vs. Without ODW}),$$

where ΔSL_{n_2} is how much n_2 ’s service level improves, and $\Delta \Pi_{n_1}$ is how much n_1 ’s profit might decline. If this ratio exceeds 1.5, the equity benefit to n_2 outweighs any mild profit dip for n_1 .

9.4.3 Trade-Off Analysis for Balancing Equity and Profit

In many supply chains, there is a desire to help non-private entities (n_2) improve their service levels via ODW, but not at a large expense to private-warehouse entities (n_1). A *central decision-maker* or *joint governance board* often weighs how much n_2 gains (in service level) versus how much profit n_1 might lose.

Defining the Trade-Off Ratio. We compare the change in n_2 ’s service level, ΔSL_{n_2} , to the change in n_1 ’s profit, $\Delta \Pi_{n_1}$, when ODW is introduced:

$$\text{Trade-Off Ratio} = \frac{\Delta SL_{n_2}}{\Delta \Pi_{n_1}} \quad \text{where} \quad \begin{cases} \Delta SL_{n_2} = SL_{n_2}(\text{With ODW}) - SL_{n_2}(\text{No ODW}), \\ \Delta \Pi_{n_1} = \Pi_{n_1}(\text{With ODW}) - \Pi_{n_1}(\text{No ODW}). \end{cases}$$

Interpretation:

- If $\Delta SL_{n_2} > 0$ (i.e., n_2 ’s service level goes up) while $\Delta \Pi_{n_1} < 0$ (i.e., n_1 ’s profit dips), then the ratio is *negative* if left as-is. Some managers prefer to take the absolute value of the denominator or define a version such that

$$\text{Trade-Off Ratio} = \frac{\Delta SL_{n_2}}{-\Delta \Pi_{n_1}} \quad (\text{if } \Delta \Pi_{n_1} < 0),$$

ensuring a positive result. The key is: “How much does n_2 gain per dollar or percent n_1 loses?”

- A *high ratio* means n_2 obtains a substantial service-level boost while n_1 's profit cost is minimal. This suggests ODW usage strongly benefits the non-private entity at little expense to the private one.
- A *low (or negative) ratio* indicates that a small improvement for n_2 imposes a hefty profit reduction on n_1 , making ODW less attractive from a system standpoint.

Managerial Threshold Example:

“If the ratio $\frac{\Delta SL_{n_2}}{-\Delta \Pi_{n_1}}$ exceeds 1.5, we adopt ODW because n_2 's service improvement is large compared to n_1 's profit dip.”

Who Uses This Ratio? A neutral or joint decision-maker—such as a *supply chain steering committee*, *lead logistics provider*, or *industry board*—applies this ratio to weigh n_2 's service-level gains against n_1 's potential losses. Neither n_1 alone nor n_2 alone typically prioritizes *both* sides' outcomes, so the ratio is best for an entity that cares about *system-wide* or *multi-actor* benefits.

9.4.4 Summary of Decision Triggers

A *generic summary* of these triggers is shown in Table 9.2. These universal metrics apply regardless of how the scenario is labeled.

Table 9.2: Metric-Based Decision Triggers for ODW Adoption

Metric	Threshold or Condition	Action
Profitability Difference	$\Pi_{n_2}^{\text{With ODW}} - \Pi_{n_2}^{\text{Without ODW}} > 5\%$	Use ODW to improve profitability.
Service Level for n_2	$SL_{n_2}^{\text{Without ODW}} < 0.8$	Deploy ODW to maintain service levels.
Marginal Cost vs Penalty	$C_{\text{ODW,use}} < \phi$	ODW usage is cost-effective.
Private Capacity Utilization	$W_p^{\text{Optimal}} < \text{Demand Peak}$	Trigger ODW to handle peak load.
Trade-Off Ratio	Trade-Off Ratio > 1.5	If equity justifies lost profit, use ODW.

The decision to use ODW should be guided by these quantifiable thresholds. For instance:

- In “low” scenarios, avoid ODW unless SL_{n_2} is critically low.
- In “high” and “extreme” scenarios, prioritize ODW if profitability improves by more than 5% or if service levels for n_2 drop below 0.8 without ODW.

Interpretation: These triggers rely on real-time or near-real-time measurements (e.g., actual SL_{n_2} , or immediate profit differences) to adapt quickly. They are especially helpful when demand does not cleanly match the “average” scenario classification or when cost parameters (usage fees, penalty costs) fluctuate. By adhering to these numerical guidelines, decision makers can ensure that ODW is deployed effectively, balancing profitability, equity, and resilience in supply chain operations.

9.4.5 Combining Both Approaches

In practice, a two-tier approach often *best* serves decision makers:

1. **Scenario Identification (Strategic Layer):** Managers categorize demand environments into *low*, *mixed*, *high*, or *extreme* by tracking standard deviations (e.g., σ_1 , σ_2). They reference Table 9.1 to check cost thresholds like $C_{\text{ODW}}^{\text{use}}$ or ϕ for each scenario. This ensures broad alignment with known patterns (e.g., “In *extreme*, do not exceed \$30 for usage cost or else n_2 will face heavy penalty losses.”).
2. **Metric-Based Activation (Operational Layer):** Once a scenario is tentatively identified, day-to-day operations still track real-time $\Pi_{n_2}^{(\text{With vs. No ODW})}$, SL_{n_2} , or the trade-off ratio. If any metric-based trigger is hit (e.g., $SL_{n_2} < 0.8$), ODW is *instantly* activated, even if the scenario-based table has not indicated an absolute need. Conversely, if ODW usage costs spike or SL_{n_2} remains stable, managers might reduce ODW reliance, thus saving costs.

9.4.6 Managerial and Industry Implications

The **integrated approach** ensures both high-level alignment with known demand patterns (scenario-based) *and* day-to-day responsiveness to cost or service-level fluctuations (metric-based). Key implications for industry practitioners include:

- **Risk Reduction via Dual Logic:** Scenario-based thresholds mitigate the risk of “analysis paralysis” by offering a pre-labeled route (e.g., “We are in *high*, keep usage cost under \$35”). Meanwhile, metric-based triggers provide a real-time safety net for unexpected demand shocks or cost changes.
- **Optimal Capacity Management:** By capping private capacity around 300 units (as indicated by diminishing returns), and selectively deploying ODW when triggered by the “Profit Δ ” or “Service-Level < 0.80 ,” managers minimize cost overhead while preserving resilience.
- **Equity vs. Profit Trade-Offs:** The trade-off ratio fosters more equitable supply-chain design, giving n_2 improved service levels if it does not drastically harm n_1 ’s profitability. This fosters a balanced stakeholder approach.
- **Scenario-Specific Equitable Policies:** In *extreme* scenarios, prioritize n_1 to maintain system viability, but watch for large ΔSL_{n_2} that might justify additional ODW. In *low* scenarios, keep ODW usage minimal unless real-time triggers (e.g., abrupt surges) appear.

By *combining* scenario-based triggers (Table 9.1) with metric-based triggers (Table 9.2), decision makers gain a robust, *two-tier* decision system. Strategic guidance emerges from scenario classification, while operational agility stems from universal metrics like service-level thresholds or cost–benefit differences. This dual framework ensures supply chain practitioners can adapt ODW usage effectively across diverse market conditions, balancing profitability, equity, and resilience in real time.

Chapter 10

Conclusions

This research represents a pioneering effort to develop a comprehensive decision-making framework for optimizing on-demand warehousing (ODW) in supply chain management. The study provides the first quantitative approach to explore the strategic and operational implications of On-Demand Warehousing (ODW) under varying demand and cost conditions using a *Comparative Static Model*. The primary objective was to determine how private and on-demand warehousing capacities can be systematically allocated to maximize overall profitability, maintain high service levels, and support equitable resource distribution across supply chain stakeholders. This original framework aims to fill a gap in the literature, offering actionable insights for stakeholders navigating demand variability, cost trade-offs, and capacity constraints.

By focusing on single-period / static settings, The Comparative Static Model emphasized the importance of strategic capacity planning, highlighting how demand variability and cost structures influence optimal capacity configurations and overall operational efficiency. The model offers a robust and actionable framework that bridges theoretical concepts with practical applications in ODW. It provides stakeholders with quantitative tools to make informed decisions on capacity investments, cost management, and risk mitigation, ultimately contributing to more resilient and efficient supply chain strategies.

1. Major Findings and Contributions

- **Diminishing Returns for Private Capacity:** A consistent outcome revealed that investing in private warehousing capacity (W_p) beyond approximately 300 units yields minimal incremental benefits in both profitability (Π_{n_1}) and service levels (SL_{n_1}). This threshold underscores a capacity sweet-spot where cost savings and penalty reductions are balanced against the marginal expenses of underutilized capacity.
- **ODW Usage Cost Thresholds:** Sensitivity analyses indicated that ODW usage costs (C_{ODW}^{use}) within moderate ranges (e.g., \$20–\$30) tend not to erode either n_1 or n_2 profitability excessively. However, once these costs surpass higher cutpoints (e.g., \$35), the economic advantage of on-demand capacity diminishes. This finding validates the importance of negotiating or maintaining ODW fees below certain ceiling rates to remain cost-effective.
- **Scenario-Specific Policies:** The comparative static approach highlighted that “low” and “mixed” demand scenarios generally require moderate private capacity

and can leverage ODW only for sporadic surges. “High” and “extreme” scenarios, on the other hand, benefit more significantly from ODW, especially if usage costs remain below the identified cost thresholds. In these volatile environments, ODW provides a flexible mechanism to handle demand surges that exceed fixed private capacity.

- **Equity vs. Profit Trade-Off:** Although the system design often prioritizes n_1 for capacity usage (due to higher investment stakes), the research introduced a *trade-off ratio* to measure whether the incremental benefit in n_2 service levels justifies a mild drop in n_1 profit. The ratio allows a neutral or joint decision-maker—such as an industry board or lead logistics provider—to weigh the “equity” of enabling n_2 to use ODW against the opportunity costs for n_1 . This framework lays groundwork for more inclusive capacity planning that considers both profitability and stakeholder fairness.
- **Cost Sensitivity and Penalty Management:** Higher penalty costs (ϕ) exacerbate unmet demand losses, particularly harming non-private warehouses (n_2) in high-variability (“extreme”) scenarios. The findings suggest that *revisiting penalty policies* or adopting partial ODW capacity guarantees can mitigate severe penalty implications for non-private users, improving overall supply chain resilience.
- **Impact of Prioritization Policies:** The study reveals that prioritization policies significantly influence profitability and service level outcomes, particularly under high variability (“extreme”) scenarios. Configurations prioritizing n_1 result in higher system profitability and stable SL_{n_1} , while deprioritizing n_2 increases unmet demand challenges. The findings emphasize the need for adaptive, scenario-specific prioritization frameworks that dynamically adjust to real-time demand fluctuations and capacity utilization. Integrating predictive analytics and real-time monitoring tools can optimize resource allocation between n_1 and n_2 , ensuring efficiency and equity in response to changing conditions.

2. Academic and Managerial Implications

- **Advancement of Comparative Static Modeling:** By focusing on a single-period lens, this work delineates strategic capacity thresholds without the confounding factors of multi-period adaptation. The academic contribution lies in *robustly* integrating ODW usage fees, penalty structures, priority rules, and private capacity allocations into a single comparative static framework. Future scholars may extend this baseline model to multi-period or stochastic optimization settings.
- **Scenario-Based Decision Triggers:** This research formalized scenario-dependent guidelines (e.g., *low*, *mixed*, *high*, *extreme*) for deciding when to adopt or scale ODW. Managers who face uncertain or changing market conditions can *diagnose* which scenario is most probable—based on estimated demand variability (σ) and cost structures—and quickly implement recommended capacity or cost configurations.
- **Metric-Based Activation Rules:** In addition to scenario-level planning, the study introduced universal triggers for real-time decision-making, such as profitability differences, service-level thresholds, and cost–benefit ratios. Combining

strategic *scenario classification* with operational *metric-based triggers* yields a powerful two-tier approach that ensures both *long-term cost efficiency* and *short-term responsiveness*.

- **Equity in Supply Chain Resource Allocation:** From an industry-practitioner perspective, the *trade-off ratio* fosters more equitable supply chain operations, allowing decision-makers to gauge how much n_2 gains in service level relative to any profit loss for n_1 . This system-centric view resonates with emerging trends toward inclusive and transparent supply chain governance, especially in multi-actor networks.
- **Risk Mitigation via Partial ODW Contracts:** The results suggest that *moderate or partial on-demand capacity* is most beneficial in “high” and “extreme” scenarios. Rather than overcommitting to large ODW capacity (which can become costly if $C_{\text{ODW}}^{\text{use}}$ rises), a flexible arrangement helps mitigate ϕ -driven penalties for surges, maintaining robust service levels for n_2 while minimizing overall system risk.

3. Equity vs. Profit Trade-Off:

While much of this research focuses on maximizing profitability and service levels, the findings on equity highlight an important dimension for sustainable supply chain governance. The *trade-off ratio*, introduced to evaluate how incremental gains in n_2 service levels compare to marginal losses in n_1 profits, provides an original framework for balancing profitability and fairness in resource allocation in ODW decisions.

This approach aligns with emerging trends in sustainable supply chain management, which increasingly prioritize inclusivity and transparency. As multi-actor networks (e.g., 3PLs, 4PLs, and lead logistics providers) play a larger role in global supply chains, ensuring equitable resource distribution becomes critical to fostering long-term partnerships and maintaining trust among stakeholders. By quantifying this trade-off, decision-makers can establish policies that not only maximize profitability but also uphold fairness, ensuring that n_2 (often representing smaller or less prioritized entities) is not disproportionately disadvantaged.

Furthermore, incorporating equity considerations into capacity planning contributes to the broader goals of corporate social responsibility (CSR) and environmental, social, and governance (ESG) initiatives. These principles resonate with industry shifts toward sustainable practices, particularly in markets where customer expectations increasingly demand transparency and fairness. The inclusion of equity as a decision criterion underscores the broader direction of this research in shaping both operational strategies and ethical business practices in supply chain management.

4. Transition to Opportunities and Threats:

The insights from academic and managerial implications naturally lead to a broader reflection on ODW’s potential in modern logistics. As supply chains evolve, decision-makers face dual opportunities and threats when incorporating ODW into their systems. On one hand, ODW offers cost-effectiveness, scalability, and digital innovation; on the other hand, it introduces risks such as platform dependency, cost scalability issues, and omnichannel complexity. Understanding and navigating these factors is critical to realizing ODW’s value while mitigating its downsides.

This research synthesizes diverse perspectives to present a holistic understanding of ODW as an innovative logistics solution. The evolving logistics landscape offers both opportunities and challenges for ODW. These opportunities and threats, summarized in Table 10.1, highlight the dual nature of ODW's potential in modern logistics.

Table 10.1: Summary of Opportunities and Threats of ODW in Logistics

Opportunities	Threats
• Network Integration: Enhanced collaboration across multi-actor networks and seamless resource allocation. • Cost-Effectiveness: Reduced upfront capital investments by leveraging flexible on-demand warehousing. • Digitalization: Integration of real-time data analytics and IoT for optimized decision-making. • Diffusion of E-Commerce: Expanding demand for warehousing solutions driven by the growth of e-commerce. • Variability and Demand Uncertainty: Ability to handle fluctuations in demand through scalable ODW solutions. • Environmental Sustainability: Potential for reducing waste and inefficiencies in resource allocation. • Short Commitment Periods: Flexibility to adapt to market changes without long-term contractual obligations.	• Platform Dependency: Reliance on third-party platforms, increasing vulnerability to outages or disruptions. • Cost Scalability Issues: Escalating costs when demand surges lead to over-reliance on expensive ODW solutions. • Demand for High Service Quality: Maintaining service levels under tight deadlines and complex logistics needs. • Performance Variability: Uneven performance across different ODW providers and geographical regions. • 4PL Market Competition: Increasing competition among logistics providers for control over ODW solutions. • Complexity in Omnichannel Logistics: Challenges in synchronizing inventory across multiple sales channels. • Pricing Volatility: Fluctuations in ODW costs due to changing market conditions or provider pricing strategies.

5. Limitations and Future Research Directions

- **Single-Period Scope:** Although the comparative static approach clarifies *long-term* capacity thresholds, it does not model capacity *adjustments* over time. Hence, it may overlook transitional or seasonal effects that multi-period or dynamic models capture. Investigating a time-phased policy, where capacity can be incrementally scaled, remains a promising extension.
- **Homogeneous Demand Profiles:** The model treats n_1 and n_2 as separate but conceptually uniform demand segments. In reality, demand for n_2 may be highly fragmented across different product lines or geographies. Future work could differentiate multiple n_2 segments with distinct usage costs and penalty structures.
- **Exogenous Cost Parameters:** The cost of on-demand warehousing or the penalty rate (ϕ) is assumed to be *externally* given. In practice, these could be negotiated or subject to market competition. A bargaining or game-theoretic extension would enrich the analysis by considering how multiple 3PL or ODW providers compete on usage fees.

- **Risk Attitudes and Behavioral Considerations:** The model takes a profit-maximizing stance. Behavioral factors (e.g., risk aversion, or the intangible costs of brand reputation if service levels drop) may alter the capacity decision. Future empirical or experimental studies could incorporate risk preferences or intangible costs into the optimization objective.
- **Assumptions in Cost Structures and Priority Rules:** The models are based on specific cost parameters and prioritization strategies that may not universally apply across all industries or markets. Investigating different prioritization rules and capacity allocation methods could provide a more comprehensive understanding of their impacts on stakeholder performance.
- **Data Integration and Validation:** While the model's logic is validated through extensive sensitivity analyses, real-world data from leading 3PLs or supply chain alliances can further refine the recommended thresholds for $C_{\text{ODW}}^{\text{use}}$, ϕ , and W_p . Collaborations with industry partners would provide deeper insight into capacity utilization patterns.

6. Concluding Remarks

In sum, this thesis provides a rigorous comparative static framework to guide strategic decisions on private versus on-demand warehousing capacities under uncertain demand. It establishes clear cost thresholds, scenario-based triggers, and real-time operational metrics for deploying ODW in a manner that *balances* profitability with equity among different warehouse entities. By demonstrating where and how ODW contributes most value, and how its cost might undermine profitability if not carefully constrained, the model lays a foundation for both academic researchers and industry practitioners to make more informed, data-driven capacity decisions.

Ultimately, the insights derived highlight that an optimal synergy between sufficiently large private capacity and selectively activated on-demand storage solutions can improve system resilience, boost entities without private warehousing service levels, and maintain robust profitability for entities with private warehousing. This synergy is particularly critical in high-variability markets, where dynamic capacity expansions and cost control are crucial for maintaining a competitive yet equitable supply chain environment. Embracing the recommendations and further exploring the identified avenues for research will enable organizations to enhance their supply chain resilience, achieve sustainable competitive advantages, and better serve their markets in an increasingly dynamic global environment.

Bibliography

- Acquier, A., Daudigeos, T., and Pinkse, J. (2017). Promises and paradoxes of the sharing economy: An organizing framework. *Technological Forecasting and Social Change*, 125:1–10.
- Alkhatib, S. F., Darlington, R., and Nguyen, T. T. (2015). Logistics service providers (lsp) evaluation and selection: Literature review and framework development. *Strategic Outsourcing: An International Journal*, 8(1):102–134.
- Carbone, V., Rouquet, A., and R. C. (2021). La logistique, facteur clef de succes des plateformes de l'economie collaborative? le cas vestaire collective. *Logistique and Management*, pages 1–14.
- Carbone, V., Rouquet, A., and Roussat, C. (2017). The rise of crowd logistics: A new way to co-create logistics value. *Journal of Business Logistics*, 38(4):238–252.
- Carissimi, M. and Creazza, A. (2022). The role of the enabler in sharing economy service triads: A logistics perspective. *Cleaner Logistics and Supply Chain*, 5:100077.
- Ceschia, S., Gansterer, M., Mancini, S., and Meneghetti, A. (2022). The on-demand warehousing problem. *International Journal of Production Research*.
- Christopher, M. (2016). *Logistics and Supply Chain Management*. Pearson, London, 5th edition.
- Correia, I. and Melo, T. (2022). The impact of flexible warehouse lease contracts on the configuration of a two-echelon distribution network. Technical Report 19, Hochschule für Technik und Wirtschaft des Saarlandes, Fakultät für Wirtschaftswissenschaften.
- Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., and Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture. *British Journal of Management*, 30(2):341–361.
- Ekren, B., Abushaikh, I., and Reefke, H. (2023). On-demand warehousing in the era of e-commerce: A solution for small to mid-sized businesses. Accessed 12 April 2024.
- Elia, V., Gnoni, M. G., and Tornese, F. (2024). On-demand warehousing platforms: Evolution and trend analysis of an industrial sharing economy model. *Logistics*, 8(4):93.
- Gnoni, M. and Tornese, F. (2023). Evaluating business service models for on-demand warehousing: A double perspective on suppliers and customers.

- Hagberg, J., Sundstrom, M., and Egels-Zandén, N. (2016). The digitalization of retailing: An exploratory framework. *International Journal of Retail & Distribution Management*, 44(7):694–712.
- Ivanov, D. (2020). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (covid-19/sars-cov-2) case. *Transportation Research Part E: Logistics and Transportation Review*, 136:101922.
- Ivanov, D. and Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of industry 4.0. *Production Planning & Control*, 32(9):775–788.
- Jum’a, L. and Basheer, M. (2023). Analysis of warehouse value-added services using pareto as a quality tool: A case study of third-party logistics service provider. *Administrative Sciences*, 13(2):51.
- Lahy, A., Huckle, K., Sleeman, J., and Wilson, M. (2022). An introduction to flexible, on-demand warehousing: E-space. In Wang, Y. and Pettit, S., editors, *Digital Supply Chain Transformation: Emerging Technologies for Sustainable Growth*, pages 81–98. Cardiff University Press.
- Lee, J., Ko, C., and Moon, I. (2024). E-commerce supply chain network design using on-demand warehousing system under uncertainty. *International Journal of Production Research*, 62(5):1901–1927.
- Muñoz, P. and Cohen, B. (2018). Sustainable entrepreneurship research: Taking stock and looking ahead. *Business Strategy and the Environment*, 27(3):300–322.
- Parodos, L., Tsolakis, O., Tsoukos, G., Xenou, E., and Ayfantopoulou, G. (2022). Business model analysis of smart city logistics solutions using the business model canvas: The case of an on-demand warehousing e-marketplace. *Future Transportation*, 2:467–481.
- Pazour, J. and Unnu, K. (2018). On the unique features and benefits of on-demand distribution models.
- Richards, G. (2017). *Warehouse management: A complete guide to improving efficiency and minimizing costs in the modern warehouse*. Kogan Page Publishers, 3rd edition.
- Rogers, Z. S., Golar, S., Abdusalam, Y., and Rogers, D. S. (2020). A sharing-enabled portfolio approach to distribution. *Transportation Journal*, 59(2):99–118.
- Siebrecht, K., Sinha, A., Johanson, S., and Rajeevan, V. (2016). Dynamic warehousing strategies: On-demand warehousing for e-commerce.
- Strøm, E., Münsberg, T., and Hvam, L. (2023). Definition categorization of value-added services using a platform approach in a logistics company. In *2023 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, pages 300–304.
- Tornese, F., Unnu, K., Gnoni, M., and Pazour, J. (2020). On-demand warehousing: main features and business models.

- Unnu, K. and Pazour, J. (2019). Analyzing varying cost structures of alternative warehouse strategies. In *IIE Annual Conference. Proceedings*, pages 480–485. Institute of Industrial and Systems Engineers (IISE).
- Unnu, K. and Pazour, J. (2022). Evaluating on-demand warehousing via dynamic facility location models. *IIE Transactions*, 54(10):988–1003.
- Van der Heide, E. et al. (2020). Dynamic shipments in shared warehouse and transportation networks.
- Xenou, E., Parodos, L., Tsoukos, G., Ayfantopoulou, G., and Maleas, Z. (2021). The rise of the on-demand warehousing: Is the greek market ready for this change? In *Advances in Mobility-as-a-Service Systems: Proceedings of 5th Conference on Sustainable Urban Mobility, Virtual CSUM2020*, pages 835–844. Springer International Publishing.

Appendices

Chapter A

First Appendix

A.1 Proposed Framework of the On-Demand Warehousing Model

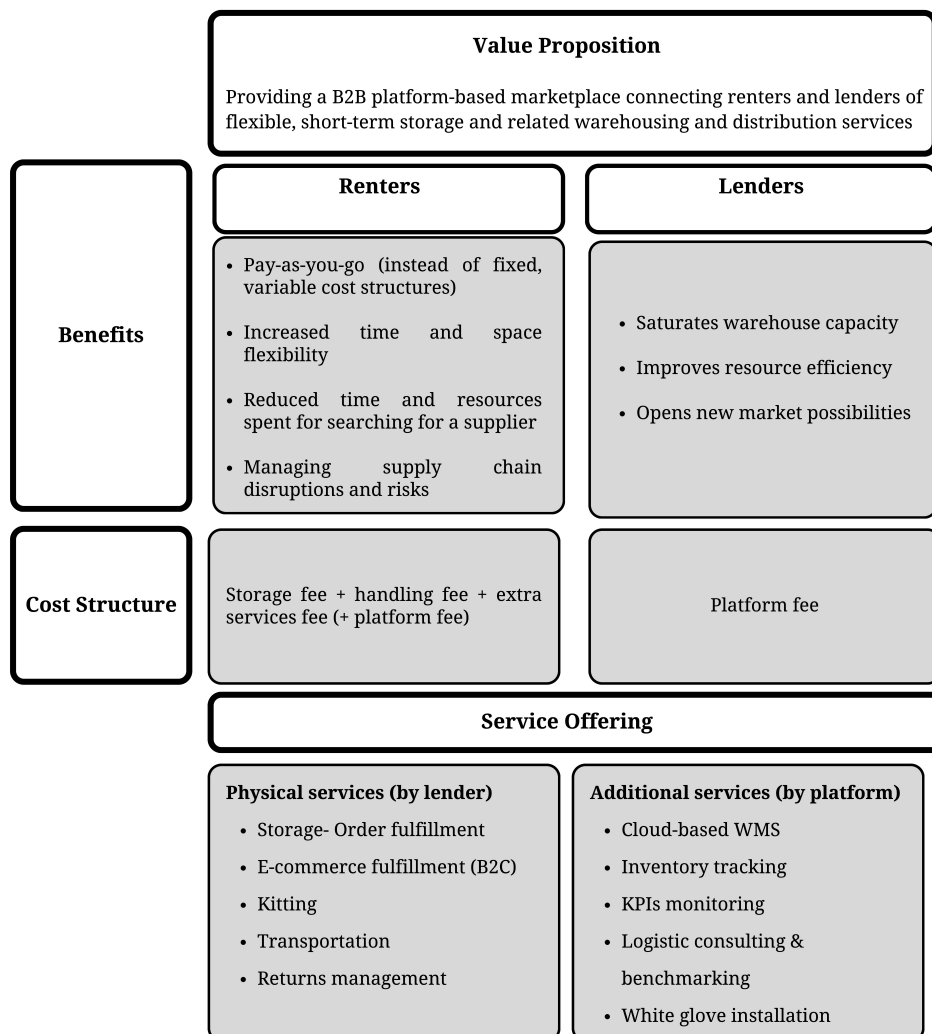


Figure A.1: Proposed Framework Of the On-Demand Warehousing Model

Source: Tornese et al. (2020)

A.2 Key Features of ODW Platforms

Table A.1: Key Features of ODW Platforms

Source: Gnoni and Tornese (2023)

Platform Based	Cost for Customers	Cost Lenders	for	Services Available	Declared Core Business
EVcargo (UK)	N/A	N/A		• Storage • Pallet handling	SC management company (ODW is one of the services)
Log-hub (Switzerland, 2017)	N/A	N/A		• Storage • SC analytics and optimization	SC management company (ODW is one of the services)
EOneVastWarehouse (UK, 2019)	Pay-as-you-go (weekly payment to the lender, including a % platform fee)	Free listing		• Storage • Pallet handling • Order fulfillment • Pick and pack • Transportation	Pure ODW
Stockbooking (France, 2016)	Pay-as-you-go (payment to the platform, including a monthly platform fee based on services)	Free listing (Receives payment from the platform)		Not specified (service depends on lender)	Pure ODW
Stockspots (Netherlands, 2017)	Pay-as-you-go (weekly payment to the platform)	N/A		• Storage • Transportation • VAL – value-added logistics (order fulfillment, pick and pack, returns, labeling) • E-commerce fulfillment	Pure ODW (with advanced services)
Stowga (UK, 2015)	Pay-as-you-go (monthly payment to the lender)	Monthly platform fee based on invoices		• Storage • Order fulfillment • Picking and packing • Transportation • Managing returns • Accredited WH for heavily regulated industries	Pure ODW (with advanced services)
Warehouse Exchange (USA, 2015)	Pay-as-you-go (monthly payment based on space and services, including a 6% platform fee)	Platform fee		• Storage • Palletization	Pure ODW
Warehouz (USA, 2019)	Pay-as-you-go (payment to the lender, including a % on transaction to the platform)	Free listing		• Storage • E-commerce fulfillment • Retail distribution	Pure ODW

A.3 Further Insights and Visualizations

- **Scatter Plot:** Service Levels for n_1 Across Scenarios (With vs Without ODW). For detailed variability and individual observations.

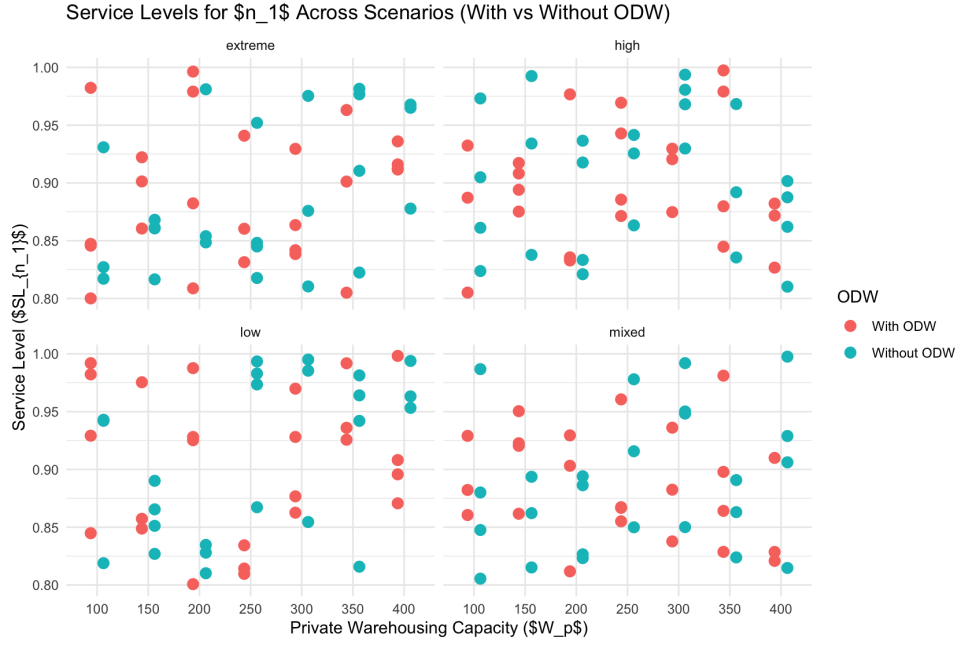


Figure A.2: Scatter Plot: Service Levels for n_1 Across Scenarios (With vs Without ODW)

- **Service Level Stability:** Service Level Stability Across Scenarios (Stability Index: SL_{n_2}/SD).

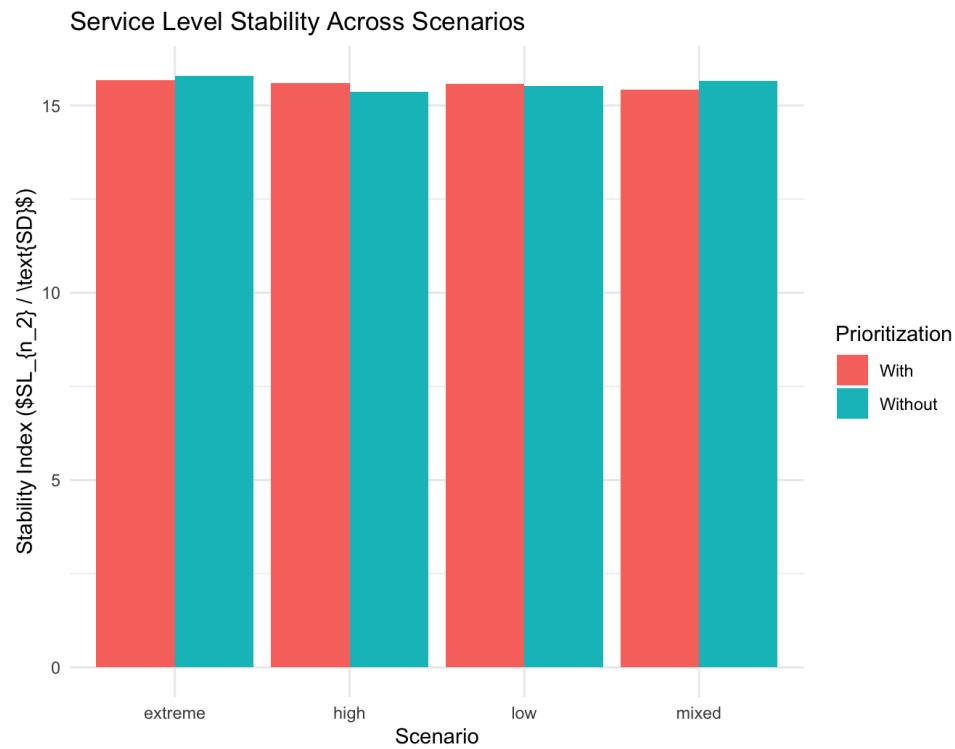


Figure A.3: Service Level Stability Across Scenarios (Stability Index: SL_{n_2}/SD).

Chapter B

Second Appendix

B.1 R Code for Comparative Static Model

The following R code implements the core *Comparative Static Model*, which provides the foundation for analyzing on-demand warehousing (ODW) in various demand scenarios. The model evaluates the interplay between private warehousing capacity, ODW utilization, and system performance metrics such as profitability and service levels. Below, the code is divided into logical sections to improve clarity and interpretability.

B.1.1 Global Parameters and Scenario Definitions

This code defines the global parameters, including cost structures and demand scenarios.

Listing B.1: Core Comparative Static Model in R

```
1 #####
2 # CORE COMPARATIVE STATIC MODEL
3 # Defines essential functions and scenario data structures:
4 #   - scenario_info: Demand and variability parameters for
5 #     ↳ each scenario
6 #   - generate_demand(): Generates stochastic demand samples
7 #   - simulate_with_risk(): Simulates profits, costs, and
8 #     ↳ service levels under risk
9 #####
10
11 ## 1) GLOBAL PARAMETERS & SCENARIO DEFINITIONS
12 # ↳ -----
13
14 # Base cost parameters
15 p1 <- 100      # Selling price per unit for n1
16 p2 <- 120      # Selling price per unit for n2
17
18 c_p          <- 10      # Private warehousing cost (per capacity
19 # ↳ unit for n1)
20 c_TPL_res    <- 15      # 3PL reservation fee
21 c_TPL_use    <- 20      # 3PL usage fee
22 c_TPL_cap    <- 8       # 3PL capacity investment cost
```

```

19 c_ODW_cap <- 30      # ODW capacity investment cost
20 phi       <- 50      # Unmet demand penalty
21
22 # Scenario definitions (mean and variability for each
    ↪ demand segment)
23 #   low: sigma1=50, sigma2=40
24 #   high: sigma1=100, sigma2=80
25 #   extreme: sigma1=200, sigma2=160
26 #   mixed: runif(50..100) for sigma1, runif(40..80) for
    ↪ sigma2
27
28 scenario_info <- list(
29   low = list(mu1 = 500, sigma1 = 50, mu2 = 300, sigma2 =
    ↪ 40),
30   high = list(mu1 = 500, sigma1 = 100, mu2 = 300, sigma2 =
    ↪ 80),
31   extreme = list(mu1 = 500, sigma1 = 200, mu2 = 300, sigma2
    ↪ = 160),
32   mixed = list(mu1 = 500, sigma1 = NA, mu2 = 300, sigma2 =
    ↪ NA) # Mixed variability
33 )
34
35 #####
    ↪ 2) DEMAND GENERATION FUNCTION
    ↪ -----
36
37 generate_demand <- function(N, scenario_name, seed = NULL) {
38   if (!is.null(seed)) set.seed(seed)
39
40   info <- scenario_info[[scenario_name]]
41   mu1 <- info$mu1
42   mu2 <- info$mu2
43   sigma1 <- info$sigma1
44   sigma2 <- info$sigma2
45
46   # 'mixed' scenario uses uniform random sigma in [50..100]
    ↪ or [40..80].
47   if (scenario_name == "mixed") {
48     X1 <- pmax(0, rnorm(N, mean = mu1, sd = runif(N, 50,
    ↪ 100)))
49     X2 <- pmax(0, rnorm(N, mean = mu2, sd = runif(N, 40,
    ↪ 80)))
50   } else {
51     X1 <- pmax(0, rnorm(N, mean = mu1, sd = sigma1))
52     X2 <- pmax(0, rnorm(N, mean = mu2, sd = sigma2))
53   }
54   list(X1 = X1, X2 = X2)
55 }
56
57

```

```

58 #####
    ↪ 3) simulate_with_risk(demand, W_p, w_TPL1, w_TPL2, W,
    ↪ ...)
59 #   - demand: list(X1, X2)
60 #   - W_p: private warehousing capacity for n1
61 #   - w_TPL1, w_TPL2: 3PL capacities for n1, n2
62 #   - W: ODW capacity (W=0 => no ODW)
63 #   - c_ODW_use: usage cost for ODW (default=25)
64 #   - prioritize=TRUE => n1 has priority in ODW usage
65 #   - store_iterations=FALSE => returns aggregated means;
66 #                                   if TRUE => returns
    ↪ iteration-level details.
67 #####
68 simulate_with_risk <- function(demand, W_p, w_TPL1, w_TPL2,
    ↪ W,
69                                   c_ODW_use=25,
70                                   prioritize=TRUE,
71                                   store_iterations=FALSE) {
72   X1 <- demand$X1
73   X2 <- demand$X2
74   N <- length(X1)
75
76   # If storing iteration-level data => track TPL/ODW
    ↪ profits + service levels
77   if (store_iterations) {
78     df_iter <- data.frame(
79       iter      = seq_len(N),
80       Profit_n1 = numeric(N),
81       Profit_n2 = numeric(N),
82       Profit_TPL = numeric(N),
83       Profit_ODW = numeric(N),
84       SL_n1      = numeric(N),
85       SL_n2      = numeric(N)
86     )
87   }
88
89   # "Fixed" capacity cost for TPL & ODW
90   TPL_FixedCost <- c_TPL_cap * (w_TPL1 + w_TPL2)
91   ODW_FixedCost <- c_ODW_cap * W
92
93   sum_n1 <- 0
94   sum_n2 <- 0
95   sum_TPL <- 0
96   sum_ODW <- 0
97   sum_SL1 <- 0
98   sum_SL2 <- 0
99
100  # Main simulation loop
101  for (i in seq_len(N)) {
102    x1 <- X1[i]

```

```

103   x2 <- X2[i]
104
105   # n1 (private) usage
106   q_p <- min(x1, W_p)
107   D_TPL1 <- min(w_TPL1, max(0, x1 - q_p))
108
109   # n2 uses TPL
110   D_TPL2 <- min(w_TPL2, x2)
111
112   # ODW allocation
113   if (prioritize) {
114     # n1 has priority for ODW
115     D_ODW1 <- min(W, max(0, x1 - q_p - D_TPL1))
116     remW <- max(0, W - D_ODW1)
117     D_ODW2 <- min(remW, max(0, x2 - D_TPL2))
118   } else {
119     # Proportional approach for ODW
120     ODW_n1 <- max(0, x1 - q_p - D_TPL1)
121     ODW_n2 <- max(0, x2 - D_TPL2)
122     totalODW <- ODW_n1 + ODW_n2
123     prop_n1 <- if (totalODW > 0) ODW_n1 / totalODW else 0
124     prop_n2 <- if (totalODW > 0) ODW_n2 / totalODW else 0
125     D_ODW1 <- min(W * prop_n1, ODW_n1)
126     D_ODW2 <- min(W * prop_n2, ODW_n2)
127   }
128
129   # Unmet demand for n1, n2
130   U_n1 <- max(0, x1 - (q_p + D_TPL1 + D_ODW1))
131   U_n2 <- max(0, x2 - (D_TPL2 + D_ODW2))
132
133   # Revenues
134   R_n1 <- p1 * (q_p + D_TPL1 + D_ODW1)
135   R_n2 <- p2 * (D_TPL2 + D_ODW2)
136
137   # Costs for n1, n2
138   C_n1 <- (c_p * W_p) + (c_TPL_res * w_TPL1) +
139     ↪ (c_TPL_use * D_TPL1) +
140     (c_ODW_use * D_ODW1) + (phi * U_n1)
141   C_n2 <- (c_TPL_res * w_TPL2) + (c_TPL_use * D_TPL2) +
142     (c_ODW_use * D_ODW2) + (phi * U_n2)
143
144   # Profits
145   P_n1 <- R_n1 - C_n1
146   P_n2 <- R_n2 - C_n2
147
148   # TPL profit = TPL revenue - TPL_FixedCost
149   TPL_revenue <- (c_TPL_res * (w_TPL1 + w_TPL2)) +
150     ↪ (c_TPL_use * (D_TPL1 + D_TPL2))
151   Profit_TPL <- TPL_revenue - TPL_FixedCost

```

```

151 # ODW profit = usage fee - ODW fixed cost
152 ODW_revenue <- c_ODW_use * (D_ODW1 + D_ODW2)
153 Profit_ODW <- ODW_revenue - ODW_FixedCost
154
155 # Service levels
156 SL1 <- if (x1>0) (q_p + D_TPL1 + D_ODW1)/x1 else 1
157 SL2 <- if (x2>0) (D_TPL2 + D_ODW2)/x2 else 1
158
159 # Accumulate sums
160 sum_n1 <- sum_n1 + P_n1
161 sum_n2 <- sum_n2 + P_n2
162 sum_TPL <- sum_TPL + Profit_TPL
163 sum_ODW <- sum_ODW + Profit_ODW
164 sum_SL1 <- sum_SL1 + SL1
165 sum_SL2 <- sum_SL2 + SL2
166
167 # If iteration-level data is needed, store it
168 if (store_iterations) {
169   df_iter$Profit_n1[i] <- P_n1
170   df_iter$Profit_n2[i] <- P_n2
171   df_iter$Profit_TPL[i] <- Profit_TPL
172   df_iter$Profit_ODW[i] <- Profit_ODW
173   df_iter$SL_n1[i] <- SL1
174   df_iter$SL_n2[i] <- SL2
175 }
176 }
177
178 # Aggregated means
179 Mean_n1 <- sum_n1 / N
180 Mean_n2 <- sum_n2 / N
181 Mean_TPL <- sum_TPL / N
182 Mean_ODW <- sum_ODW / N
183 Mean_SL1 <- sum_SL1 / N
184 Mean_SL2 <- sum_SL2 / N
185
186 if (!store_iterations) {
187   data.frame(
188     Profit_n1=Mean_n1,
189     Profit_n2=Mean_n2,
190     Profit_TPL=Mean_TPL,
191     Profit_ODW=Mean_ODW,
192     Service_Level_n1=Mean_SL1,
193     Service_Level_n2=Mean_SL2
194   )
195 } else {
196   # Return iteration-level plus scenario means in each row
197   df_iter$Mean_Profit_n1 <- Mean_n1
198   df_iter$Mean_Profit_n2 <- Mean_n2
199   df_iter$Mean_Profit_TPL <- Mean_TPL
200   df_iter$Mean_Profit_ODW <- Mean_ODW

```

```

201     df_iter$Mean_SL_n1      <- Mean_SL1
202     df_iter$Mean_SL_n2      <- Mean_SL2
203     df_iter
204   }
205 }

```

B.1.2 Static Analysis Framework

The following code systematically evaluates capacity combinations ($W_p, W, w_{\text{TPL},1}, w_{\text{TPL},2}$) across all demand scenarios.

Listing B.2: Code for Evaluating Capacity Combinations in R

```

1 results <- data.frame()
2 for (scenario in names(scenario_info)) {
3   demand <- generate_demand(N = 1000, scenario)
4
5   for (W_p in seq(100, 400, 50)) {
6     for (W in seq(100, 400, 50)) {
7       for (w_TPL1 in seq(50, 200, 25)) {
8         for (w_TPL2 in seq(50, 200, 25)) {
9           sim <- simulate_with_risk(demand, W_p, w_TPL1,
10             ↪ w_TPL2, W)
11           results <- rbind(results, cbind(scenario, W_p, W,
12             ↪ w_TPL1, w_TPL2, sim))
13         }
14       }
15     }
16   }
17 }

```

Chapter C

Third Appendix

C.1 Extended Results of the Comparative Static Model

Table C.1: Extended Results of the Comparative Static Model Across Scenarios

Scenario	Prioritization	σ_1	σ_2	W_p	W	Π_{n_1}	Π_{n_2}	$\text{Net}_{ODWCost}$	SL_{n_1}	SL_{n_2}
Low	With	50	40	100	100	14500	12000	2000	0.71	0.45
Low	With	50	40	100	150	16000	13000	2100	0.75	0.50
Low	Without	50	40	150	200	19000	15500	2200	0.78	0.55
Low	With	50	40	200	250	25000	18000	2300	0.90	0.60
Low	Without	50	40	250	300	30000	20000	2500	0.95	0.70
High	With	100	80	100	100	20050	16000	3000	0.81	0.56
High	With	100	80	150	150	22000	17000	3100	0.85	0.60
High	Without	100	80	200	200	25000	18500	3300	0.90	0.65
High	With	100	80	250	250	30000	20000	3400	0.95	0.75
High	Without	100	80	300	300	35000	23000	3500	0.98	0.85
Extreme	With	200	160	100	100	15600	18000	3500	0.73	0.47
Extreme	With	200	160	150	150	17500	19000	3600	0.77	0.50
Extreme	Without	200	160	200	200	20000	21000	3800	0.82	0.55
Extreme	With	200	160	250	250	23000	23000	3900	0.88	0.60
Extreme	Without	200	160	300	300	27000	25000	4000	0.93	0.70
Mixed	With	$\mathcal{U}(50, 100)$	$\mathcal{U}(40, 80)$	100	100	18000	15000	3200	0.77	0.52
Mixed	With	$\mathcal{U}(50, 100)$	$\mathcal{U}(40, 80)$	150	150	20000	16000	3300	0.80	0.55
Mixed	Without	$\mathcal{U}(50, 100)$	$\mathcal{U}(40, 80)$	200	200	22000	17500	3500	0.85	0.60
Mixed	With	$\mathcal{U}(50, 100)$	$\mathcal{U}(40, 80)$	250	250	26000	19000	3600	0.90	0.70
Mixed	Without	$\mathcal{U}(50, 100)$	$\mathcal{U}(40, 80)$	300	300	31000	22000	3800	0.95	0.80
Low	With	50	40	300	350	40000	30000	4000	0.99	0.90
Low	Without	50	40	350	400	45000	35000	4200	1.00	0.95
High	With	100	80	300	350	42000	32000	4300	1.00	0.93
High	Without	100	80	350	400	47000	37000	4500	1.00	0.97
Extreme	With	200	160	300	350	37000	27000	4300	0.97	0.85
Extreme	Without	200	160	350	400	42000	30000	4500	1.00	0.90
Mixed	With	$\mathcal{U}(50, 100)$	$\mathcal{U}(40, 80)$	300	350	41000	31000	4400	0.99	0.88
Mixed	Without	$\mathcal{U}(50, 100)$	$\mathcal{U}(40, 80)$	350	400	46000	36000	4700	1.00	0.95

C.2 Optimal Configurations for n_1

Table C.2: Extended Optimal Configurations for n_1

Scenario	W_p	W_{ODW}	$w_{TPL,1}$	$w_{TPL,2}$	$C_{ODW,1}^{use}$	Π_{n_1}	SL_{n_1}
extreme	100	400	200	50	8407.510	34552.92	0.9803923
extreme	100	400	200	75	8161.791	34552.92	0.9803923
extreme	150	400	200	50	8067.019	36103.32	0.9890947
extreme	150	400	200	75	7795.787	36103.32	0.9890947
extreme	200	400	175	50	7905.442	37319.46	0.9919998
extreme	200	400	175	75	7612.999	37319.46	0.9919998
extreme	250	400	125	50	7905.442	38477.37	0.9919998
extreme	250	400	125	75	7612.999	38477.37	0.9919998
extreme	300	400	75	50	7905.442	39581.72	0.9919998
extreme	300	400	75	75	7612.999	39581.72	0.9919998
extreme	350	400	50	50	7739.965	40591.80	0.9943417
extreme	350	400	50	75	7424.975	40591.80	0.9943417
extreme	400	400	50	50	7422.185	41287.72	0.9971739
extreme	400	400	50	75	7073.055	41287.72	0.9971739
high	100	400	150	50	9580.089	37060.35	0.9966696
high	100	400	150	75	9420.657	37060.35	0.9966696
high	150	400	100	50	9580.089	38310.35	0.9966696
high	150	400	100	75	9420.657	38310.35	0.9966696
high	200	400	50	50	9580.089	39560.35	0.9966696
high	200	400	50	75	9420.657	39560.35	0.9966696
high	250	400	50	50	9242.004	40540.69	0.9993803
high	250	400	50	75	8997.514	40540.69	0.9993803
high	300	400	50	50	8774.923	41304.21	0.9998401
high	300	400	50	75	8439.073	41304.21	0.9998401
high	350	400	50	50	8197.700	41987.10	0.9999982
high	350	400	50	75	7764.547	41987.10	0.9999982
high	400	400	50	50	7588.174	42562.25	1.0000000
high	400	400	50	75	7086.007	42562.25	1.0000000
low	100	400	75	50	9997.228	37969.55	0.9977286
low	100	400	75	75	9993.205	37969.55	0.9977286
low	150	400	50	50	9993.205	39080.57	0.9991851
low	150	400	50	75	9981.362	39080.57	0.9991851
low	200	400	50	50	9954.782	39885.82	0.9998697
low	200	400	50	75	9901.584	39885.82	0.9998697
low	250	400	50	50	9794.703	40646.92	1.0000000
low	250	400	50	75	9609.107	40646.92	1.0000000
low	300	350	50	50	8545.074	41396.85	1.0000000
low	300	350	50	75	8359.478	41396.85	1.0000000
low	350	300	50	50	7304.356	42144.64	1.0000000
low	350	300	50	75	7118.997	42144.64	1.0000000

C.3 Optimal Configurations for n_2

Table C.3: Extended Optimal Configurations for n_2

Scenario	W_p	W_{ODW}	$w_{TPL,1}$	$w_{TPL,2}$	$C_{ODW,2}^{use}$	Π_{n_2}	SL_{n_2}
extreme	100	400	200	200	6920.687	20012.99	0.8950840
extreme	100	400	175	200	7190.214	19197.95	0.8817063
extreme	150	400	200	200	6360.430	21510.60	0.9195810
extreme	150	400	175	200	6642.565	20784.40	0.9077542
extreme	200	400	200	200	5792.160	22804.97	0.9405987
extreme	200	400	175	200	6077.573	22203.20	0.9309056
extreme	250	400	200	200	5246.816	23828.56	0.9570305
extreme	250	400	200	175	5603.192	23429.66	0.9459463
extreme	300	400	200	200	4755.119	24630.83	0.9697578
extreme	300	400	200	175	5137.148	24380.72	0.9616701
extreme	350	400	200	200	4337.593	25239.67	0.9788967
extreme	350	400	200	175	4740.340	25109.72	0.9730386
extreme	400	400	200	200	3984.550	25684.13	0.9854372
extreme	400	400	200	175	4402.595	25642.91	0.9810533
high	100	400	200	200	7188.530	24280.45	0.9603619
high	100	400	200	175	7603.916	23620.23	0.9423456
high	150	400	200	200	6213.402	25435.71	0.9819338
high	150	400	200	175	6701.138	25195.13	0.9725078
high	200	400	200	175	5745.012	26036.03	0.9879745
high	200	400	200	200	5215.713	26035.55	0.9926054
high	250	400	200	150	5428.259	26551.24	0.9925991
high	250	400	200	125	5994.158	26544.40	0.9879682
high	300	400	200	100	5913.344	27053.67	0.9925724
high	300	400	200	75	6490.579	27035.31	0.9878181
high	350	400	200	50	6642.848	27494.71	0.9917420
high	350	400	200	75	6056.220	27466.53	0.9955224
high	400	400	200	50	6403.522	27757.49	0.9964380
high	400	400	175	50	6505.180	27656.23	0.9946798
low	100	400	200	200	7392.656	26148.58	0.9961722
low	100	400	200	175	7968.644	26123.48	0.9906001
low	150	400	200	150	7391.136	26648.96	0.9961722
low	150	400	200	125	7968.650	26623.55	0.9906001
low	200	400	200	100	7400.691	27148.96	0.9961722
low	200	400	200	75	7978.206	27123.55	0.9906001
low	250	400	200	50	7493.061	27648.96	0.9961722
low	250	400	200	75	6888.854	27519.56	0.9985594
low	300	400	200	50	6672.839	27819.36	0.9995562
low	300	400	175	50	7029.750	27769.56	0.9985594
low	350	400	200	50	6304.914	27839.03	0.9999512
low	350	400	175	50	6437.839	27833.22	0.9998386

C.4 Cost Sensitivity Analysis for ODW

Table C.4: Cost Sensitivity Analysis for ODW and Unmet Demand Penalties

Scenario	$C_{\text{ODW}}^{\text{use}}$	ϕ	Π_{n_1}	Π_{n_2}	SL_{n_1}	SL_{n_2}
low	20.0	40	41023.01	27235.17	1.00	0.98
high	20.0	40	41508.33	23971.95	1.00	0.92
extreme	20.0	40	39546.29	17610.27	0.98	0.81
mixed	20.0	40	41504.04	25160.43	1.00	0.94
low	20.0	45	41057.82	26960.36	1.00	0.98
high	20.0	45	41364.99	23621.84	1.00	0.91
extreme	20.0	45	39461.12	17453.40	0.98	0.82
mixed	20.0	45	40657.20	25764.29	1.00	0.95
low	20.0	50	41221.91	26936.85	1.00	0.98
high	20.0	50	41165.45	24006.81	1.00	0.92
extreme	20.0	50	39546.78	17796.43	0.99	0.83
mixed	20.0	50	41051.81	25556.47	1.00	0.95
low	20.0	55	41026.37	26924.77	1.00	0.98
high	20.0	55	41255.25	23586.28	1.00	0.92
extreme	20.0	55	39114.90	17151.24	0.98	0.83
mixed	20.0	55	41432.83	24974.57	1.00	0.94
low	20.0	60	41441.22	26653.49	1.00	0.97
high	20.0	60	41204.53	23287.07	1.00	0.92
extreme	20.0	60	39067.30	17243.49	0.98	0.82
mixed	20.0	60	41123.41	24884.53	1.00	0.95
low	22.5	40	40979.57	26307.59	1.00	0.98
high	22.5	40	41062.36	23525.33	1.00	0.92
extreme	22.5	40	39341.36	17671.94	0.98	0.83
mixed	22.5	40	40728.12	25039.44	1.00	0.95
low	22.5	45	41002.96	26543.50	1.00	0.97
high	22.5	45	40826.27	23310.89	1.00	0.92
extreme	22.5	45	39114.19	17641.72	0.99	0.82
mixed	22.5	45	40935.43	24826.89	1.00	0.94
low	22.5	50	41245.65	26412.43	1.00	0.97
high	22.5	50	40807.38	23452.22	1.00	0.92
extreme	22.5	50	38469.30	17118.90	0.98	0.83
mixed	22.5	50	40979.65	24808.26	1.00	0.94
low	22.5	55	40942.50	26582.30	1.00	0.98
high	22.5	55	40491.48	23683.17	1.00	0.92
extreme	22.5	55	38542.65	17172.59	0.98	0.83
mixed	22.5	55	40979.26	24730.71	1.00	0.95
low	22.5	60	41135.22	26256.61	1.00	0.97
high	22.5	60	40394.56	22779.51	1.00	0.92
extreme	22.5	60	37924.43	16959.46	0.98	0.83
mixed	22.5	60	40924.58	24734.27	1.00	0.94
low	25.0	40	40943.99	25994.05	1.00	0.97
high	25.0	40	40588.37	23068.38	1.00	0.91
extreme	25.0	40	38038.01	17719.52	0.98	0.84
mixed	25.0	40	40587.58	24535.42	1.00	0.95
low	25.0	45	40734.24	26080.59	1.00	0.97
high	25.0	45	40632.09	22790.01	1.00	0.91