

Title:

*Behavioral Inventory Management: Supply Uncertainty, Policy
Choice, and Stockout Responses*

Cumulative Dissertation

to obtain the academic degree of a
„Doctor rerum oeconomicarum (Dr. rer. oec.)“
according to doctoral degree regulations 2024

at the University of Hamburg Business School
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Hamburg, July 1, 2026

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Date of Disputation: 23.09.2026

Danksagung

Allem voran gilt mein besonderer Dank Guido Voigt, der mich als Erstbetreuer und über viele Jahre hinweg auch als Vorgesetzter stets unterstützt hat. Er hat sich stets Zeit für meine Fragen genommen und mir wertvolles Feedback gegeben. In Phasen des Erfolgs ebenso wie bei Rückschlägen wusste ich stets, dass ich auf seine Unterstützung und seine hilfreichen Rückmeldungen zu meiner Forschung zählen konnte.

Ebenso möchte ich meinem Zweitbetreuer Malte Fliedner herzlich danken, wie auch allen Professorinnen und Professoren des Schwerpunkts, die mir über die Jahre hinweg wertvolle Anregungen und konstruktive Rückmeldungen für meine Forschung gegeben haben.

Auch Florian E. Sachs möchte ich herzlich danken. Ohne seine Expertise und seine Unterstützung in unserer Zusammenarbeit wäre das Paper „Behavioral Aspects of Uncertain Arrival Times in Inventory Decisions“ in dieser Form nicht möglich gewesen. Darüber hinaus danke ich allen Kolleginnen und Kollegen aus unserem Schwerpunkt und insbesondere vom LSCM-Lehrstuhl. Über die Jahre hinweg standen sie mir mit Rat und Tat, einem offenen Ohr, hilfreichen Ratschlägen und wertvollen Erfahrungen zur Seite und haben damit wesentlich zu einem angenehmen und fruchtbaren Arbeitsumfeld beigetragen.

Schließlich möchte ich meinen Freundinnen und Freunden, meiner Familie und insbesondere meiner Frau von Herzen danken. Sie haben mich auf diesem Weg durch Höhen und Tiefen begleitet, mir Rückhalt gegeben und mich immer wieder ermutigt.

Vielen Dank!

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1 Synopsis

1.1 Motivation

Inventory management has gained renewed importance in recent years. Since the post Covid inflationary period, interest rates have increased substantially. Although central bank key interest rates peaked in 2023, they remain above the levels observed in most of the period following the financial crisis of 2008 in both the euro area and the United States (Statista, 2026a,b). Higher interest rates increase the opportunity cost of capital tied up in inventory and therefore make inventory holding more expensive. At the same time, lost sales and service levels remain central managerial concerns. The survey evidence presented in this dissertation confirms that store switching and no purchase account for a sizable share of consumer responses to stockouts and exceed postponement in the observed product categories, which points to the relevance of lost sales relative to full backlogging assumptions. Stockouts also create costs beyond the immediate loss of a sale. Fitzsimons (2000) shows that stockouts reduce satisfaction with the decision process and increase the likelihood of future store switching. Anderson et al. (2006) show in a catalog retailing context that stockouts reduce customer satisfaction, increase cancellation rates, and decrease future demand. These findings highlight the continued importance of effective inventory management for firms.

The second motivation for this dissertation is the behavioral nature of inventory decisions. Over the last few decades, behavioral operations management has shown that human decisions often deviate systematically from normative models. Decision makers are subject to bounded rationality (Simon, 1955) and to biases such as anchoring on mean demand in order decisions (Schweitzer and Cachon, 2000). Modern software systems provide automated decision support for many inventory management tasks, but human decision makers often override recommendations or choose not to use them. Such behavior creates room for biases and bounded rationality to affect operational decisions (Gino and Pisano, 2008). Fisher and Raman (1996) provide an example of the potential value of analytical decision support in inventory management. In their study of a fashion apparel company, the application of a newsvendor model substantially improved profitability. This dissertation builds on this general argument by showing further settings in which bounded rationality affects inventory outcomes. The findings underline the importance of using appropriate decision support tools in inventory management and of designing these tools with human decision making in mind.

The first paper studies how the representation and decision space of inventory policies affect human decision making and short run performance. The second paper examines stochastic lead times as an exogenous source of operational uncertainty over which firms often have limited control. The third paper investigates consumer responses to stockouts and provides information for inventory model specification, since the choice between lost sales, backlogging, and substitution assumptions depends on how consumers react when products are unavailable. The three papers connect behavioral decision making within the focal firm and on the supply side with behavioral responses on the demand side.

Based on these considerations, this dissertation addresses three complementary questions in behavioral inventory management. First, it examines whether different inventory policies and their decision spaces lead to different managerial decisions, even when the policies are operationally similar. Second, it analyzes how stochastic lead times affect ordering behavior in dynamic inventory decisions. Third, it investigates how consumers respond to stockouts and how these responses can be used to evaluate inventory model assumptions such as lost sales, backlogging, and substitution. These questions follow the inventory process from supply side uncertainty to internal policy choice and finally to customer responses after product unavailability.

The remainder of this synopsis provides the conceptual background and positions the dissertation within behavioral operations management. It then outlines the methodology, discusses the main findings, and concludes with limitations, future research directions, and overall implications.

1.2 Conceptual background and positioning in the literature

Inventory management has traditionally been studied through analytical models that derive optimal or heuristic solutions under specific assumptions about demand, supply, and costs. Their practical value depends on several conditions. Decision makers must have access to the relevant models, they must rely on them instead of replacing them with their own judgment, and the behavioral assumptions embedded in the models must correspond sufficiently well to actual behavior.

Behavioral operations management addresses these issues by studying how human decision makers behave in operational settings and how their decisions deviate from normative predictions. On the one hand, this literature documents biases and behavioral effects that explain why human decisions often differ from optimal benchmarks. On the other hand, it shows why analytical decision support and automated systems can improve operational performance when human judgment is affected by bounded rationality. A central insight from this literature is that decision makers often do not implement optimal policies, even when the decision environment is clearly described and incentives are provided. In inventory management, this has been shown most prominently in the newsvendor literature, which documents systematic deviations from the optimal order quantity and identifies effects such as anchoring on mean demand and pull to center behavior (Schweitzer and Cachon, 2000; Bostian et al., 2008; Bolton and Katok, 2008). Chapter 2 examines whether the representation and decision space of inventory policies affect human parameter selection. Classical inventory theory provides conditions under which reorder point and Kanban policies can be compared as equivalent or nearly equivalent inventory systems (Axsäter, 2006). Behavioral operations management has examined framing effects in related inventory contexts. Closely related evidence comes from Stangl and Thonemann (2017), who show that equivalent inventory metrics can lead to different decisions depending on how they are framed. The decision task in Chapter 2 is also related to repeated inventory experiments in which decisions have a multi period structure but remain independent across rounds. Katok et al. (2008)

and Pan et al. (2020) show that decision makers deviate from optimal decisions in such settings under order up to and economic order quantity policies. Related behavioral evidence on multidimensional decisions is provided by Kocabıyıkoglu et al. (2016) and Ramachandran et al. (2018), who study price setting newsvendor problems. Chapter 2 adds to these streams by directly comparing reorder point and Kanban policies from a decision making perspective and by examining how differences in inventory policies and their feasible decision spaces affect choices in a repeated, independent, and multidimensional inventory decision task.

The paper discussed in Chapter 3 concerns supply side uncertainty, specifically exogenous lead time uncertainty. Classical inventory management has considered uncertain lead times for a long time, for example in the work of Hadley and Whitin (1963). Behavioral inventory management has largely studied decision settings with constant lead times. This focus allows researchers to isolate specific behavioral mechanisms, as in the experimental literature on the bullwhip effect and dynamic ordering decisions (Sterman, 1989; Croson et al., 2014; Wu and Katok, 2006; Cui et al., 2015). Exogenous lead time uncertainty has received less attention in behavioral inventory experiments, although empirical evidence shows that uncertain lead times occur frequently in practice. Disney et al. (2016), for example, document stochastic lead times in global logistics. Ancarani et al. (2013) provide experimental evidence on inventory decisions under lead time uncertainty, but their setting includes endogenous and exogenous sources of lead time variation as well as bullwhip dynamics. This leaves open the question of how decision makers respond to purely exogenous lead time uncertainty in a single echelon setting. Chapter 3 addresses this gap by isolating exogenous lead time uncertainty in such a setting. It thereby extends behavioral inventory management beyond demand uncertainty and highlights the role of supply side uncertainty in human decision making. The paper discussed in Chapter 4 concerns consumer behavior after stockouts. Inventory models often represent product unavailability through assumptions such as full backlogging, lost sales, or substitution, but the behavioral validity of these assumptions depends on how consumers actually respond when a preferred product is unavailable. Consumers may substitute within the store, postpone the purchase, switch stores, or abandon the purchase entirely. A substantial empirical literature studies these responses, but much of the evidence is based on data from the 2000s or earlier (Zinn and Liu, 2001; Corsten and Gruen, 2003; Sloot et al., 2005; van Woensel et al., 2007; Miranda, 2008). Chapter 4 therefore revisits this literature with contemporary survey data and focuses especially on Corsten and Gruen (2003) and Sloot et al. (2005), which serve as central points of comparison for stockout response patterns in fast moving consumer goods. Since the data underlying these studies were collected, retail environments, consumer demographics, and product assortments have changed substantially. This demand side perspective complements the two managerial decision making studies, since Chapters 2 and 3 examine how decision makers set inventory parameters and order quantities, while Chapter 4 analyzes how consumers respond when products are unavailable.

This dissertation is positioned at the intersection of behavioral operations management

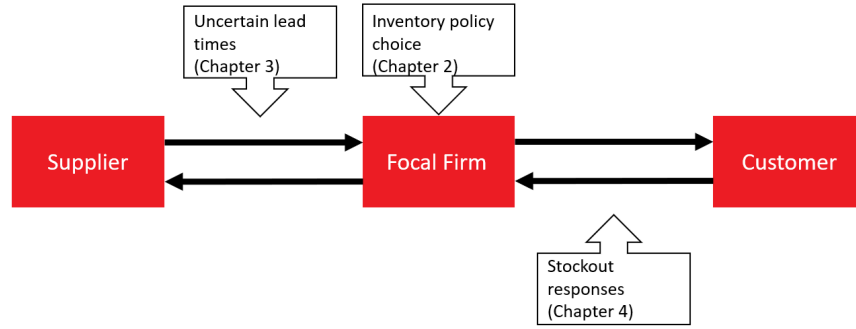


Figure 1.1: Positioning of the dissertation along the supply chain

and inventory management. It studies behavioral factors that affect inventory systems along the supply chain. Figure 1.1 summarizes the positioning of the dissertation within a simplified supply chain. The arrows on the top represent the downstream flow of goods, while the arrows on the bottom represent information and monetary flows up the supply chain. The three papers examine behavioral factors that affect the focal firm's inventory management from different directions. Chapter 3 examines behavioral responses to supply side uncertainty in the flow of goods from suppliers to the focal firm. Chapter 2 examines how the internal representation of inventory policies affects decision making within the focal firm. Chapter 4 examines customer responses to stockouts and their implications for demand side inventory assumptions. This combined perspective shows that behavioral inventory management is relevant not only for individual order decisions, but also for the design, evaluation, and modeling of inventory systems along the supply chain.

1.3 Methodology

The dissertation uses behavioral experiments and survey evidence to study inventory decisions and stockout behavior. The laboratory experiments provide controlled decision environments in which specific behavioral mechanisms can be isolated. The surveys provide broader evidence from larger or more targeted samples and make it possible to study initial decisions without feedback as well as consumer responses outside the laboratory. Since the dissertation focuses on behavioral inventory management, these empirical approaches are central for observing how decision makers and consumers behave under different inventory related conditions.

All experiments and surveys were programmed in the Python based software oTree (Chen et al., 2016). The laboratory experiments were conducted at the WiSo Forschungslabor of the University of Hamburg, and participants were recruited using hroot (Bock et al., 2014). Across the managerial decision studies, observed behavior is compared with benchmark values derived from analytical or simulation based procedures. These benchmarks provide reference points for evaluating deviations from profit maximizing or cost minimizing decisions. In the consumer response study, contemporary stockout responses are compared with earlier empirical findings, particularly Corsten and Gruen

(2003) and Sloot et al. (2005).

Chapter 2 contains two studies on decision making under reorder point and Kanban policies. Study 1 is a laboratory experiment in which participants choose inventory parameters under one of the two inventory policies. Participants receive feedback over repeated decision rounds, which makes it possible to analyze both initial differences between policies and learning over time. The main purpose of this study is to examine whether the employed inventory policy affects parameter choices and profit performance, even when the policies are operationally similar.

Study 2 in Chapter 2 is a preregistered survey conducted in an undergraduate operations management course. Participants choose inventory parameters for several products with varying demand means and standard deviations. In contrast to the laboratory experiment, participants do not receive feedback between decisions. This design makes it possible to study initial parameter choices across different demand environments and to examine whether the decision patterns observed in the laboratory experiment persist without learning.

Chapter 3 uses laboratory experiments to study ordering decisions under different lead time regimes. Participants make repeated order decisions in a continuous inventory setting and are assigned to treatments with constant lead times, stochastic lead times, or dynamic lead times known in advance. This design allows the dissertation to isolate the behavioral effect of exogenous lead time uncertainty and to examine whether providing information about future lead times changes ordering behavior. The experiment also collects self reported measures of stress and related emotions in order to assess how participants experience the different decision environments.

Chapter 4 uses an online survey conducted via Prolific to study consumer responses to stockouts in the U.S. fast moving consumer goods market. The survey consists of two parts. First, participants report experienced stockouts and indicate the product category, whether the purchase was planned, and how they responded. Second, participants answer hypothetical stockout questions for preselected product categories. The survey also collects demographic information and measures of shopping behavior. The main purpose is to compare contemporary consumer stockout responses with earlier evidence and to relate these responses to inventory model assumptions.

All methods used in this dissertation are designed to observe human decision making in inventory related contexts. They differ in the degree of control and feedback provided to participants. The laboratory experiments create controlled decision environments with feedback, while the surveys are used to study decisions without feedback or to collect responses from larger and more diverse samples. The experiments allow for the identification of behavioral mechanisms under controlled conditions, while the surveys broaden the empirical scope by testing decision patterns in different settings and by capturing consumer responses in a representative sample.

1.4 Results and discussion

The results of the three papers show that behavioral factors affect inventory management at several points of the supply chain. The first two papers demonstrate that managerial decisions are sensitive to the representation and complexity of the inventory problem. The third paper shows that consumer responses to product unavailability are central for the behavioral validity of inventory model assumptions. For the contexts studied in this dissertation, the findings further support the view that inventory performance depends not only on analytical models and benchmark policies, but also on how decision makers and consumers behave within inventory systems.

Chapter 2 shows that reorder point and Kanban systems can lead to systematically different decisions, even when the policies are analytically equivalent or nearly equivalent, because they differ in representation and feasible decision space. Participants choose higher reorder points and lower order quantities under Kanban than under the reorder point policy. These differences are particularly pronounced in early decisions and lead to significant short run profit differences. Although the profit difference diminishes quickly as participants learn, differences in reorder points and order quantities persist. The second study in Chapter 2 provides evidence on the behavioral mechanism behind these differences. Participants appear to interpret the two decision dimensions differently across policies. Under the reorder point policy, decision parameters are interpreted more additively, while under Kanban they are interpreted more multiplicatively. This difference interacts with the structure of the decision space. The Kanban policy restricts the feasible set of parameter combinations and excludes many poorly performing choices that remain possible under the reorder point policy. This restriction appears to be an important driver of both the observed parameter differences and the initial performance advantage under Kanban.

Chapter 3 shows that stochastic lead times increase costs compared to constant lead times, even after adjusting for differences in benchmark performance. The cost increase is linked to less aggressive inventory corrections. Under stochastic lead times, participants adjust less strongly to inventory imbalances, which contributes to stronger inventory fluctuations and can result in higher inventories, backlogs, or both. The results also show that participants report higher stress when facing supply uncertainty.

The dynamic lead time treatment in Chapter 3 provides additional insight into the role of information. In this treatment, participants have perfect knowledge about future lead times. This removes uncertainty while preserving the dynamic nature of lead times. The additional information reduces reported stress and leads to lower backlogs, but it does not significantly reduce total costs compared to the stochastic lead time treatment. Participants use the information to anticipate longer lead times, but this tends to shift costs from backlogs to inventory holdings rather than reduce costs overall. These findings show that providing information about future lead times alone is not necessarily sufficient to improve inventory performance.

Chapter 4 shows that substitution remains the dominant consumer response to stockouts in fast moving consumer goods. At the same time, postponement is relatively rare

and represents the smallest response category. This finding is important because postponement is the response most closely related to backlogging assumptions. Store switching and no purchase account for a substantial share of stockout responses, which underlines the relevance of lost sales in inventory models. The results also indicate that some stockout response patterns have changed compared to earlier evidence from the early 2000s. In particular, the role of hedonic goods appears to differ from earlier findings, and response distributions have changed significantly for some product categories. These findings support the need for updated consumer response evidence when evaluating inventory model assumptions.

Figure 1.1 illustrates how the three papers relate to different behavioral interfaces around the focal firm. Chapter 3 shows that uncertainty in the flow of goods from suppliers to the focal firm affects managerial ordering behavior. Chapter 2 shows that the internal choice and structure of inventory policies affect parameter decisions within the focal firm. Chapter 4 shows that customer responses to stockouts affect the interpretation of product unavailability and therefore the assumptions used in inventory models. This demand side evidence also links back to Chapter 2, where the inventory setting is modeled with lost sales. Chapter 4 supports the relevance of this modeling assumption for fast moving consumer goods, since store switching and no purchase exceed postponement in the observed product categories. The three papers show that behavioral inventory management is relevant along the supply chain and not only within isolated ordering decisions.

A common pattern across the three papers is that behavioral effects are not merely random deviations from optimal behavior. Policies and their feasible decision spaces change how decision makers interpret and select parameters. Lead time uncertainty changes how decision makers correct inventory imbalances. Stockout situations reveal systematic consumer responses that determine whether product unavailability should be modeled as substitution, postponement, store switching, or lost sales. The dissertation therefore shows that inventory models and decision support systems should not only optimize given assumptions, but also account for the behavioral processes through which these assumptions and decisions arise.

1.5 Limitations and future research

Several overarching limitations of this dissertation provide opportunities for future research. Paper specific limitations are discussed in the corresponding chapters. First, the participants in the experimental studies and in the survey in Chapter 2 were students. Prior research suggests that students and managers do not necessarily differ significantly in their performance in newsvendor decisions (Bolton et al., 2012). This finding provides some support for the use of student samples in behavioral inventory experiments. Nevertheless, the decision tasks examined in Chapters 2 and 3 are more complex than the standard newsvendor problem. It therefore remains an open question whether experienced managers would show the same behavioral patterns under more complex inventory policies or stochastic lead times.

Second, the empirical methods used in this dissertation emphasize internal validity. The laboratory experiments and survey based decision tasks are designed to isolate specific behavioral mechanisms, such as policy structure, the aggressiveness of inventory corrections, and consumer responses to specific stockout situations. This controlled design makes it possible to identify behavioral effects while holding other factors constant. At the same time, the results do not directly show how strongly these effects would influence inventory decisions in practical firm environments. Future research could therefore examine similar behavioral mechanisms in field settings or with professional decision makers.

Third, this dissertation studies behavioral effects on inventory management from several perspectives, but it does not quantify all operational cost implications that may arise from these effects in practice. For example, Chapter 4 shows that consumer stockout responses differ from full backlogging assumptions, but the dissertation does not simulate how an inventory policy based on full backlogging would perform compared with a policy that incorporates the observed distribution of stockout responses. Similarly, the behavioral deviations identified in Chapters 2 and 3 are evaluated relative to experimental benchmarks, but their implications for larger operational systems remain outside the scope of this dissertation.

These limitations point to several avenues for future research. Future studies could test whether the behavioral patterns observed in this dissertation also arise among professional inventory managers and in richer operational environments. Another promising direction is to integrate the empirical behavioral findings into inventory optimization models and simulation studies. Such work could quantify how the choice and structure of inventory policies, stochastic lead time behavior, and consumer stockout responses affect costs, service levels, and inventory decisions in more realistic systems. Finally, future research could examine how decision support systems, training interventions, or automated inventory tools can reduce the behavioral inefficiencies documented in this dissertation.

1.6 Conclusion

This dissertation shows that operations management, and inventory management as one of its central fields, is shaped by the behavior of actors along the supply chain. Human decision makers are subject to bounded rationality, biases, and behavioral effects that influence inventory decisions and inventory outcomes. The dissertation extends the understanding of these effects across three empirical contexts. Chapter 2 shows that analytically similar inventory policies can lead to different decisions when they are represented through different parameters. Chapter 3 shows that stochastic lead times reduce the effectiveness of inventory corrections and increase the stress experienced by decision makers. Chapter 4 shows that consumer responses to stockouts are essential for assessing whether assumptions such as lost sales, backlogging, and substitution reflect actual behavior.

The overall implication is that firms should account for behavioral factors when designing,

implementing, and evaluating inventory systems. These factors should not be considered only at one isolated point, but along the supply chain. The findings suggest that decision support systems and automated tools can be valuable when human decisions are affected by bounded rationality. The results on inventory policies and their decision spaces show that the structure of inventory decisions can influence parameter choices and short run performance. The results on stochastic lead times show that supply uncertainty increases the gap between benchmark solutions and human decisions. The results on consumer stockout responses show that inventory models can benefit from assumptions that reflect actual customer behavior. The dissertation highlights the importance of behaviorally informed inventory management and supports the development of decision support tools that account for both managerial decision making and consumer responses.

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2 Chapter 2

Points and Cards - A behavioral view of decision making under equivalent order policies

Alexander Daniels, Guido Voigt

Abstract

Many inventory decisions are made by humans and are influenced by behavioral effects. These effects can lead to losses through stockouts or excessive inventory. This study examines behavioral influences on decision making under the widely used reorder policy and Kanban. The two policies behave similarly and become equivalent under lost sales and when multiple reorders are allowed.

To test differences in decision making between the policies, we conduct two studies. Study 1 is a between-subject laboratory experiment in which participants decide on the order quantity and reorder point, or on the number of containers and units per container, over 15 decision periods. The results show significant differences between the two policies, particularly in early decisions. Under periodic Kanban, participants choose lower order quantities but higher reorder points compared to decisions under the reorder policy. These differences diminish over time as participants learn.

Study 2 is a survey that collects initial decisions without feedback. The results indicate that participants anchor their decisions on the mean demand. Under the reorder policy, decision parameters are combined additively, whereas under Kanban they are combined multiplicatively. In interaction with the respective decision spaces, this leads to systematic initial differences between the policies and explains the patterns observed in Study 1.

Keywords: Behavioral Operations Management, Inventory management, Decision making, Framing, Behavioral Experiment

2.1 Introduction

Since 2022, interest rates have increased substantially, raising the cost of capital and, consequently, the cost of holding inventory. This development renews managerial attention to effective inventory management. Historically, the average out of stock rate is approximately 8.3% across firms (Corsten and Gruen, 2003). Stockouts are detrimental for several reasons. Beyond reputational damage, sales are frequently not backlogged. In grocery retailing, for example, approximately 85% of stockout situations result in lost sales (Corsten and Gruen, 2005).

Although modern enterprise resource planning systems provide automated decision support for a wide range of inventory policies, human decision makers often override

system recommendations or turn them off entirely. Such overrides create room for behavioral biases and bounded rationality (Gino and Pisano, 2008). Understanding how behavioral factors affect inventory decisions therefore remains highly relevant.

In this study, we explore decision making under two commonly used inventory policies. Our focus lies on Kanban systems, which are compared to reorder point policies. The Kanban system, originally popularized through its implementation at Toyota (Sugimori et al., 1977), has become a widely adopted replenishment mechanism. Kanban and reorder policies, particularly the (r, Q) policy, are among the most commonly used inventory control rules and are especially suitable for medium- and low-priority items with relatively short lead times (Axsäter, 2006; Tamjizad and Mirmohammadi, 2015; Tomaszewska, 2023). Under specific conditions, these policies can be formulated to be operationally equivalent, although their parameterizations imply different feasible decision spaces (Axsäter, 2006), which allows for a controlled comparison. Because the Kanban policy restricts the set of feasible parameter combinations, decision makers face a smaller and structurally different decision space compared to the reorder point policy. Prior research suggests that reorder policies can outperform Kanban in direct comparisons (Axsäter and Rosling, 1994), whereas findings favoring Kanban are often attributed to work in process constraints inherent in the system design (Krajewski et al., 1987). We examine whether observed performance differences are purely operational or whether behavioral factors systematically influence decision making under these two inventory policies.

This study examines how decision makers select inventory parameters under two equivalent inventory policies and how their choices systematically differ across policy framings. Such framing effects are a known source of differences in otherwise equivalent situations in behavioral operations management (Kocabiyikoglu et al., 2015; Stangl and Thonemann, 2017).

To investigate these differences, we collect decision data in two studies. Study 1 takes place in a controlled laboratory setting. Observed decisions are evaluated relative to theoretical profit maximizing benchmarks and compared across the two equivalent policy structures.

Prior research in behavioral operations management demonstrates that decision makers frequently deviate from profit optimal benchmarks in single echelon, multi period inventory settings due to bounded rationality (Katok et al., 2008; Su, 2008). Consistent with this literature, we observe systematic deviations from the optimal policy and differences in ordering behavior across policies. These behavioral differences translate into statistically significant profit differences in the early decisions of the experiment. We also observe learning effects, as performance gaps diminish after only a few decision rounds when participants gain experience.

Under the reorder policy, decision makers anchor on the additive structure of the decision parameters and combine the reorder point and order quantity dimensions. In contrast, under the Kanban system, participants interpret the parameters multiplicatively, which leads to distinct choices between policies.

Motivated by these findings, we conduct Study 2 to assess the robustness of the observed effects. We conduct a survey in which participants choose initial inventory parameters without receiving feedback. This design allows us to test whether the additive and multiplicative patterns persist under alternative demand parameters characterized by varying means and standard deviations. The survey takes place in an undergraduate operations management course. The results confirm that the initial findings are robust across different demand environments.

Overall, our evidence suggests that although reorder point policies are theoretically equivalent to Kanban systems and perform at least equally well under optimal settings, boundedly rational decision makers achieve higher profits in the early decisions when setting parameters within the Kanban framework. These differences arise because decision makers anchor on mean demand, interpret decision parameters differently across policies, and operate within structurally different decision spaces. As a consequence, Kanban decisions tend to generate higher inventory levels but lower lost sales compared to reorder point policies, a pattern that contrasts with the common perception that Kanban systems are associated with lower inventory levels. Classical Kanban systems, unlike reorder point systems, require physical containers, Kanban cards, and in some cases adjustments to production processes. These investments occur upfront, i.e., before receiving system feedback. In this light, our results show that decision biases without feedback have substantial cost effects and it is worthwhile to consider decision support tools, e.g. simulations studies before making such investment.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the theoretical framework. Section 4 presents the experimental design of Study 1. Section 5 reports the results of Study 1. Section 6 presents the design of Study 2. Section 7 reports the results of Study 2. Section 8 concludes with managerial implications and directions for future research.

2.2 Related Literature

2.2.1 Positioning Within Behavioral Operations Research

Behavioral research on inventory decision making begins more than two decades ago with the seminal experimental study of the newsvendor model by Schweitzer and Cachon (2000). Their findings provide clear evidence that decision makers systematically deviate from profit maximizing benchmarks. This work lays the foundation for the behavioral operations management literature on order decisions, particularly in single period settings.

A related but distinct stream of research examines multi period decision making in the context of the bullwhip effect, often studied using variants of the beer distribution game (Croson and Donohue, 2006; Croson et al., 2014; Sterman, 1989; Balvers et al., 2023). While this work relates to order up to policies that are closely related to reorder policies, the present study is conceptually closer to the single period inventory setting, as each decision in our experimental design is independent of previous decisions.

2.2.2 The Newsvendor Literature

In their laboratory experiment, Schweitzer and Cachon (2000) demonstrate that participants systematically deviate from optimal order quantities due to demand chasing and anchoring on the mean of the demand distribution, an effect commonly referred to as pull to center. This deviation is replicated in numerous studies. For example, Bolton and Katok (2008) confirm the persistence of systematic deviations while documenting learning effects over repeated decision rounds. The pull to center effect becomes one of the central behavioral regularities in the newsvendor literature (Bostian et al., 2008; Benzion et al., 2008; Bolton and Katok, 2008; Schweitzer and Cachon, 2000).

Researchers propose several theoretical explanations for these deviations. One possible explanation is prospect theory to account for asymmetric risk attitudes and reference dependence in ordering decisions (Long and Nasiry, 2015). Another stream models behavior through bounded rationality and quantal response frameworks (Su, 2008; Ubøe et al., 2017; Yamini, 2021). These studies demonstrate that even in structurally simple single period environments, human decision makers consistently depart from normative choices.

2.2.3 Independent Order Decisions Beyond the Newsvendor

Despite extensive work on single period problems, behavioral evidence on other inventory decision tasks remains limited (Perera et al., 2020). This gap is relevant for our setting because, in contrast to the newsvendor model, both Kanban and reorder point policies are multi period, even if policy parameters are only set once and decisions are independent, as every decision simulates 365 days.

Pan et al. (2020) investigate behavioral influences in an economic order quantity setting, where participants adjust order quantities across cycles under deterministic demand. Consistent with the newsvendor literature, participants fail to select profit optimal parameters. Learning effects over time are also documented (Pan et al., 2020, 2022), mirroring findings in repeated newsvendor experiments (Bolton and Katok, 2008).

Katok et al. (2008) study service level agreements under an order up to policy designed to ensure independence between choices. They show that pull to center effects persist even in this structured environment and that longer review periods improve efficiency. Similarly, Becker-Peth et al. (2020) demonstrate that budget cycles and short term focus distort multi period inventory decisions, leading participants to undervalue starting inventory levels.

2.2.4 Multidimensional Decision Tasks

The decision problem studied here is inherently multidimensional and requires simultaneous consideration of two policy parameters.

Ramachandran et al. (2018) show that participants perform better when price and quantity decisions are made simultaneously rather than sequentially and that richer feedback improves efficiency. They also document anchoring on both dimensions, with

prices anchored on production cost and quantities anchored on mean demand. Similarly, Kocabiyikoglu et al. (2016) compare single dimensional and multidimensional newsvendor settings. They find that in multidimensional contexts, participants anchor on chosen quantities and adjust prices to manage demand, which suggests that cognitive processing differs across decision structures.

2.2.5 Framing Effects in Operational Decisions

Our study builds on framing research by comparing two operationally equivalent inventory policies presented under different structural representations. Similar framing comparisons appear in supply chain contracting contexts. For instance, Katok and Wu (2009) show that buyback and revenue sharing contracts, though theoretically equivalent under certain conditions, generate different initial behavioral responses that converge with experience. Zhang et al. (2016) document systematic preferences between revenue sharing and buyback contracts depending on the critical ratio.

Framing effects also appear in inventory related contexts. Kocabiyikoglu et al. (2015) find that structurally equivalent revenue management and newsvendor problems yield significant differences in order quantities. Stangl and Thonemann (2017) and Kirshner and Moritz (2023) show that linear versus multiplicative framing of equivalent inventory metrics leads to significant differences in decisions. More broadly, framing effects are well documented across decision domains. For example, Larrick and Soll (2008) demonstrate that alternative representations of fuel efficiency generate systematic biases in consumer choice.

Collectively, this literature suggests that representational differences, even when mathematically equivalent, significantly influence decision outcomes. Our study extends this insight by examining whether equivalent Kanban and reorder policies induce systematically different parameter choices and performance outcomes.

2.3 Analytical Background

2.3.1 Reorder Policy

We consider a lost sales inventory system with independent and identically distributed normally distributed demand $D_t \sim \mathcal{N}(\mu, \sigma^2)$ with known parameters μ and σ . We assume zero lead times such that replenishment decisions affect inventory within the same monitoring interval T . The monitoring interval is fixed and identical across periods.

Under the reorder policy, specifically the $(r, n \cdot Q, T)$ policy, a periodic variant of the (r, Q) policy that allows for multiple orders within the same period, hereafter denoted as ROP, the decision maker chooses a reorder point r and an order quantity Q , both restricted to positive integers. At the end of each monitoring interval, if the inventory position y_t satisfies $y_t \leq r$, an integer number of orders n_t of size Q is placed such that the replenishment condition in Equation (1) holds.

In each period, profit p_t is determined by revenue from satisfied demand SI_t minus

ordering costs, lost sales costs, and inventory holding costs as shown in (2). We denote the revenue per unit by rev , fixed ordering cost by A , lost sales penalty by π , holding cost per unit by h , lost sales by ls_t , end of period inventory by I_t , and mean inventory by MI_t . Profit, satisfied demand, lost sales, ending inventory, and mean inventory are calculated using Equations (2) to (6), where D_t denotes demand in period t .

$$r < y_t + n_t Q \leq r + Q \quad (1)$$

$$\text{Profit}_t(r, Q) = SI_t(r, Q) \cdot rev - n_t(r, Q) \cdot A - ls_t(r, Q) \cdot \pi - MI_t(r, Q) \cdot h \quad (2)$$

$$SI_t(r, Q) = D_t - ls_t(r, Q) \quad (3)$$

$$ls_t(r, Q) = (D_t - I_{t-1}(r, Q) + n_{t-1}(r, Q) \cdot Q)^+ \quad (4)$$

$$I_t(r, Q) = (I_{t-1}(r, Q) + n_{t-1}(r, Q) \cdot Q - D_t)^+ \quad (5)$$

$$MI_t(r, Q) = \frac{I_{t-1}(r, Q) + n_{t-1}(r, Q) \cdot Q + I_t(r, Q)}{2} \quad (6)$$

2.3.2 Kanban Policy

Under the periodic Kanban policy, hereafter Kanban, the decision maker selects the number of containers c and the number of units per container Q . Kanban can be represented as an equivalent reorder policy via the transformation in Equation (7).

$$r = (c - 1) \cdot Q \quad (7)$$

For any decision parameters c and Q we can calculate the respective value of r . The equations (1) through (6) can be used to define the Kanban with r and Q .

2.3.3 Choice Set Comparison

When decision variables are restricted to positive integers, not all ROP parameter combinations can be represented within Kanban. Rearranging Equation (7) yields Equation (8), which expresses the number of units per container as a function of the reorder point and the number of containers. This formulation allows us to characterize the feasible decision set under Kanban.

Under ROP, the number of possible decisions equals $r_{\max} \cdot Q_{\max}$, where $r_{\max}$ denotes the maximum value of the reorder point and $Q_{\max}$ the maximum value of the order quantity. Under Kanban, the number of feasible choices, denoted as Kanban choices K , is calculated using equation (9). If $c = 1$ were allowed, which would imply $r = 0$, an additional $Q_{\max}$ combinations would have to be added to K .

The resulting differences in decision set sizes are illustrated with examples of different values for $r_{\max}$ and $Q_{\max}$ in Appendix 2.B.

$$Q = \frac{r}{c - 1} \quad (8)$$

$$K = \sum_{Q=1}^{Q_{\max}} \left\lfloor \frac{r_{\max}}{Q} \right\rfloor \quad (9)$$

Even though the two policies are theoretically equivalent, integer constraints generate meaningful differences in the available decision space. Moreover, Kanban is only operationally meaningful when $c \geq 2$, since $c = 1$ implies $r = 0$, which leads to lost sales whenever positive demand occurs after depletion within the monitoring interval. For $c \geq 2$, Equation (7) implies that $r \geq Q$. Consequently, parameter combinations with $r > 0$ and $Q > r$ that are feasible under ROP cannot occur under Kanban. The restriction therefore removes a specific region of the ROP decision space and results in a smaller feasible decision set under Kanban.

2.4 Study 1

2.4.1 Experimental Design

2.4.1.1 Experimental Protocol The experiment is programmed in the Python based software oTree (Chen et al., 2016). Participants are recruited from a pool of graduate and undergraduate students at the University of Hamburg using hroot (Bock et al., 2014). Experimental sessions take place in the Research Laboratory of the University of Hamburg.

The study consists of two experimental phases. The first phase takes place in April 2023 with recruitment from a pool of 2552 registered participants. The second phase takes place in February 2024 with recruitment from a pool of 2366 participants. Data for the reorder policy in the high order cost setting stem from the first phase, while all other treatments are conducted in the second phase. Participants are seated in separate cabins without interaction and without information about other participants' decisions or outcomes. Treatments are randomly assigned at the individual level. All monetary values are presented in equivalent currency units (ECU). Participants receive written instructions and a detailed scenario description that remain accessible throughout the experiment. As shown in Table 2.1, 115 participants take part in the study. Three participants were excluded from the analysis because they did not adjust their parameters despite repeatedly receiving negative profit feedback. In addition, six individual decisions were excluded because the combined decision parameter, defined as $r + Q$ under ROP and $c \cdot Q$ under Kanban, exceeded ten times the corresponding profit-maximizing benchmark value. These observations were classified as outliers and removed from the analysis.

Participants could ask questions during the session, which were answered individually and privately. Before the payoff relevant task, participants are able to complete a trial

run with different parameters to familiarize themselves with the interface. Participants must pass a quiz on the inventory model before proceeding to the main task. A built in calculator allows participants to compute profits for given demand realizations and starting inventories under specific parameter choices. After completing the decision task, participants answer demographic questions, questions on their experience in the experiment, and a cognitive reflection test. In the main task, participants in our between-subject design choose either an order quantity and a reorder point under the reorder policy or the number of containers and units per container under Kanban. The objective is to maximize profits. After each decision, participants receive detailed feedback including profits, revenues, realized costs, demand realizations, and a graphical representation of inventory levels and lost sales. Screenshots of the settings, decision, results and visualization screens are provided in Appendix 2.A. Each participant completes 15 independent decisions. Each session lasts approximately 60 minutes.

To reduce demand chasing and risk aversion, each decision parameter setting is evaluated over 365 demand realizations framed as days of one year. Longer monitoring intervals are shown to improve stability of decisions (Katok et al., 2008). Within each simulated year, events occur in the following order:

- Orders from the previous period arrive and are added to the inventory.
- Starting inventory is determined.
- Demand is realized and subtracted from inventory.
- Revenue is generated from satisfied demand and lost sales are recorded.
- New orders are placed based on the current inventory and the chosen parameters.
- Costs are calculated.

To ensure independence across decisions, inventory is reset before each of the 15 decisions. Each decision begins with 20 warm up periods that generate a randomized starting inventory conditional on the chosen parameters. This procedure prevents spillover effects and ensures that decisions are independent from each other.

2.4.1.2 Parameters and Treatment Variables Table 2.1 summarizes the treatment structure and sample sizes. The first treatment variable is the order cost. In the high order cost condition, the fixed ordering cost equals $A = 20$. In the low order cost condition, it equals $A = 0.55$. The second treatment variable is the policy framing, that is reorder policy versus Kanban. The parameters are identical across treatments except for the order cost. Holding costs are $h = 5$ per unit of mean inventory per period, lost sales cost is $\pi = 30$ per unit, and revenue is $rev = 20$ per unit sold. Demand is independent and normally distributed with $D \sim \mathcal{N}(140, 40^2)$ and is restricted to integer realizations.

To allow for a meaningful comparison between policies, we implement settings with relatively low order costs and comparatively high inventory costs. Parameter values are

chosen such that expected profit maximizing reorder points are substantially larger than optimal order quantities. This ensures that optimal decisions of both policies are close.

Table 2.1: Treatment structure and sample sizes

Policy	Order cost	Sample size
Reorder policy	High	27 (29)
Kanban	High	26 (27)
Reorder policy	Low	30 (30)
Kanban	Low	29 (29)

Because the lost sales inventory problem does not admit a general analytical solution (Bijvank and Vis, 2011), we determine profit maximizing parameters using simulation based optimization methods, consistent with related studies (Diaz and Ezell, 2012). The simulated expected profit maximizing values are reported in Table 2.2. We do not observe exact equivalence of profit-maximizing parameters across policies within the predefined integer parameter space considered in this study. The largest deviation between optimal order quantities occurs under low order costs with 12.5 percent and under high order costs with 8.2 percent. Differences in optimal reorder points amount to 1.09 percent and 1.79 percent, respectively. Differences in simulated profits remain below 0.5 percent in both cases.

Table 2.2: Simulated expected profit maximizing parameters

Policy	Order cost	Optimal Q	Optimal r	Simulated profit
Reorder policy	High	61	165	2020
Kanban	High	56	168	2013
Reorder policy	Low	16	184	2088
Kanban	Low	14	182	2086

2.4.1.3 Incentives Participants received a show-up fee of 4.00 EUR. In addition, they earned a performance-based bonus proportional to the profits generated in the decision task. The average performance-based bonus amounted to 8.24 EUR.

2.4.2 Results

The results are structured in three parts. Section 4.2.1 compares decisions and performance across policies. Section 4.2.2 examines the influence of the choice set on decisions. Section 4.2.3 analyzes learning effects. Unless stated otherwise, all reported significance tests are non-parametric Mann–Whitney U tests conducted at the participant level using individual averages across the relevant decision periods.

2.4.2.1 Comparison of Decisions Between the Policies Table 2.3 reports descriptive statistics for both policies across all decisions and order cost treatments. The reorder point r for Kanban is calculated using Equation (7). In this table, and in all subsequent references, inventory cost, order cost, lost sales cost, and profits are

reported as simulated expected values calculated in the benchmark simulation rather than realized values.

Table 2.3: Descriptive statistics by policy

		ROP	Kanban
Mean (SD)	Order quantity Q	83.4 (56.6)	26.2 (20.6)
	Reorder point r	148.5 (46.2)	192.6 (58.6)
	Inventory cost	649.1 (225.2)	707.7 (293.1)
	Order cost	35.1 (61.8)	70.5 (87.1)
	Lost sales cost	372.4 (382.8)	230.1 (223.5)
	Expected profit	1487.3 (560.2)	1630.4 (403.3)
Median	Order quantity Q	74.4	20.0
	Reorder point r	149.7	180.0
	Inventory cost	652.5	631.7
	Order cost	5.3	15.0
	Lost sales cost	235.3	153.8
	Expected profit	1728.3	1778.7

Table 2.3 illustrates substantial differences in parameter choices across policies. Figure 2.1 further supports this finding by showing median order quantities and mean reorder points across treatments, compared to their respective profit-maximizing benchmarks. In both order cost treatments, the order quantity Q is significantly lower under Kanban than under ROP. The mean order quantity in the high (low) order cost treatment equals 66.89 (98.25) under ROP and 28.75 (23.90) under Kanban. These results confirm significant differences in both cases ($p < 0.001$).

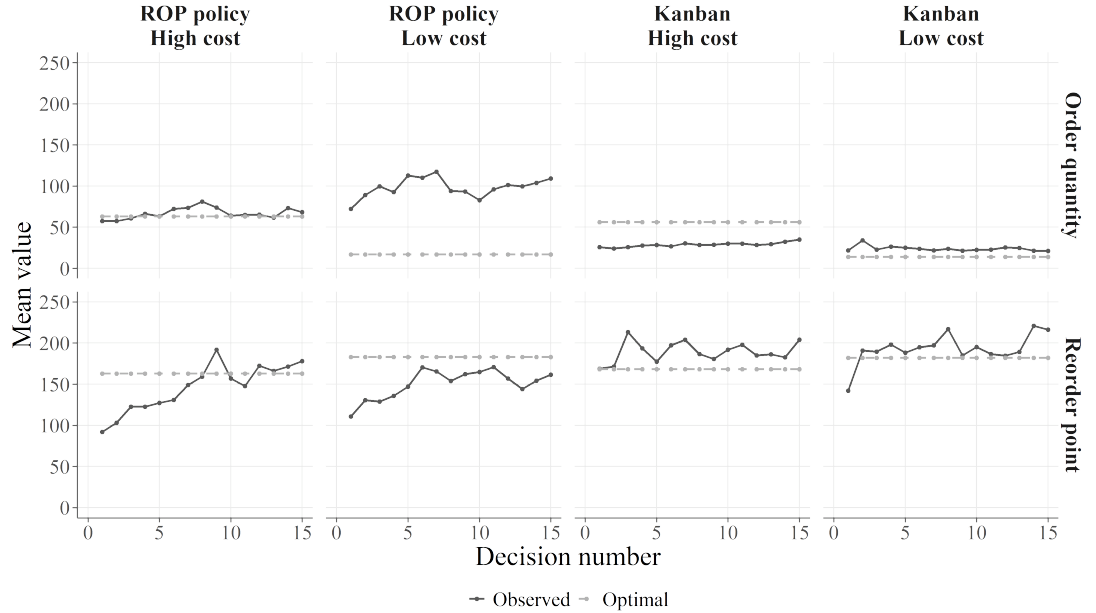


Figure 2.1: Observed and optimal order quantity and reorder point across treatments and decisions.

For the reorder point r , we observe the opposite pattern. Using Equation (7) to derive the implied reorder point under Kanban, participants choose significantly higher values

compared to ROP in both cost settings. The average reorder point in the high (low) order cost treatment equals 146.11 (150.50) under ROP and 189.39 (195.10) under Kanban. These differences are significant at ($p < 0.01$) in both treatments.

Despite these substantial differences in parameter choices, the resulting cost structures are more similar. Inventory costs are higher under Kanban but do not differ significantly overall. When restricting the analysis to the first five decisions, inventory costs are significantly higher under Kanban in the high order cost treatment ($p < 0.05$). This difference disappears in later decisions and is not observed under the low order cost treatment. When pooling both order cost treatments, the difference in early decisions becomes more pronounced ($p < 0.01$). Descriptive statistics for the first five decisions are reported in Appendix 2.C.

Lost sales costs exhibit a complementary pattern. Under high order costs, lost sales costs are significantly higher under ROP ($p < 0.05$) in both the first five decisions and across all decisions. In the low order cost treatment, the direction remains the same, but the difference is not statistically significant at any point. When pooling both order cost treatments, the difference remains weakly significant ($p < 0.1$). Order costs are consistently higher under Kanban, reflecting the higher order quantities chosen under ROP. Because order costs are small relative to inventory and lost sales costs, their impact on total costs remains limited.

No significant difference in expected profits is detected between policies at the participant level using a non parametric test, even when restricting the analysis to the first five decisions. The limited profit differences despite substantial parameter deviations from the optimum, particularly under Kanban, suggest that participants navigate the two-dimensional decision space effectively. Figure 2.2 shows that although container choices under Kanban often deviate from the profit-maximizing benchmark, participants adjust the number of units per container such that expected profits remain close to optimal levels. Under ROP, a similar pattern can be observed, although it is less pronounced. While participants approach near-optimal parameter choices in later decisions under the high order cost treatments, Figure 2.1 shows that under ROP participants partially compensate for high order quantities by selecting slightly lower reorder points, even in later decisions.

2.4.2.2 Influence of the Choice Set Persistent differences between the calculated r and Q values are observed throughout the experiment. To better understand the source of these differences, we examine how participants allocate values across the two decision parameters. Specifically, we analyze which parameter receives the larger value within a decision. We refer to this parameter as the dominant parameter. The magnitude of these differences is illustrated in Tables 2.4. Detailed information on the first five decisions can be found in Appendix 2.D. Across all decisions, participants choosing Q as the dominant parameter under the reorder policy earn substantially lower expected profits than those choosing r as the dominant parameter. This difference is particularly pronounced in early decisions.

Under the reorder policy, 87% of decisions satisfy $r \geq Q$, while 13% satisfy $r < Q$. In

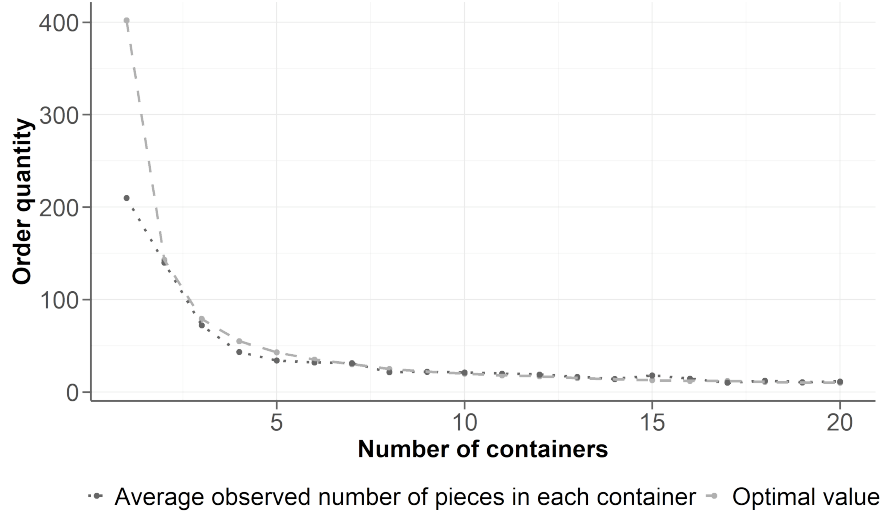


Figure 2.2: Average units per container vs. number of containers

the first decision this share is lower, with 79% of participants choosing $r \geq Q$ and 21% choosing $r < Q$. Under Kanban, 34% of decisions satisfy $c \geq Q$ while 66% satisfy $c < Q$. These results indicate that a non-trivial share of reorder policy decisions use Q as the dominant parameter, resulting in parameter combinations that lie outside the feasible decision space of Kanban.

Despite this difference in parameter setting, we observe no significant differences in the sum $r + Q$ between participants who choose r or Q as their dominant parameter under ROP. A similar result is obtained under Kanban when comparing the product of the parameters $c \cdot Q$. This suggests that participants anchor their decisions on a similar target level and distribute this level across parameters rather than optimizing each parameter independently.

The consequences of this parameter allocation differ across policies because the policy structures translate parameter combinations differently into inventory positions. Under Kanban, the multiplicative structure constrains the resulting parameter combinations. Swapping the dominant parameter therefore has only a limited effect on the implied reorder point. For example, with $Q = 30$ and $c = 10$, swapping the parameters changes the implied reorder point from 270 to 290.

Under the reorder policy, the same behavior leads to substantially larger deviations. Using parameters in a similar ratio with $Q = 67$ and $r = 201$, swapping the dominant parameter reduces the reorder point by 134. The ordering of the parameters therefore has a much larger impact on expected profits under the reorder policy.

Consistent with this mechanism, expected profits in the first decision are significantly higher for participants who choose r as the dominant parameter compared to those who choose Q as the dominant parameter ($p < 0.01$). No such difference is observed under Kanban ($p = 0.93$). The share of decisions with Q as the dominant parameter decreases over the course of the experiment, indicating learning. Differences are most pronounced in early decisions, as shown in Appendix 2.D. Even in the final decision, expected profits remain significantly lower for participants choosing Q as the dominant

parameter under ROP ($p < 0.01$).

In Study 2 we investigate the parameter setting mechanism more directly by eliciting initial parameter choices without feedback.

Table 2.4: Summary statistics for decisions between dominant decision parameters

		ROP ($Q > r$)	ROP ($Q \leq r$)	Kanban ($Q > c$)	Kanban ($Q \leq c$)
Mean (SD)	Q	122.4 (85.9)	73.0 (41.4)	31.5 (21.7)	11.9 (4.9)
	r	109.2 (60.2)	158.9 (35.7)	191.8 (59.7)	192.0 (42.0)
	Profit	960.6 (602.8)	1627.7 (461.3)	1616.0 (415.8)	1681.5 (329.5)
Median	Q	97.3	72.3	24.3	10.4
	r	114.5	162.5	179.5	188.1
	Profit	982.8	1795.0	1779.0	1778.7

2.4.2.3 Learning Effects and Bounded Rationality Performance differences between policies are more pronounced in early decisions and diminish over time. Figure 2.3 illustrates the development of expected profits across decisions.

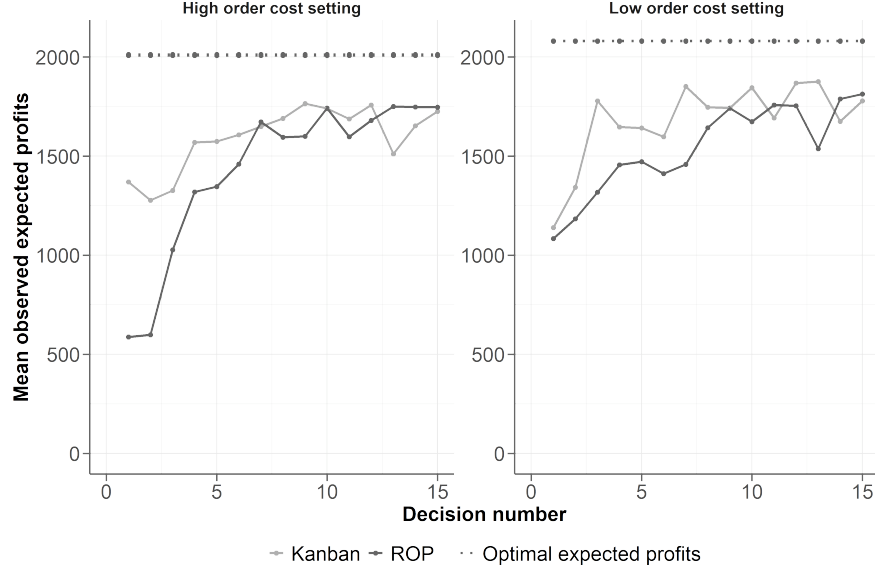


Figure 2.3: Observed expected profits across decisions

To analyze these dynamics more formally, we estimate a random-effects panel regression with robust standard errors using expected profit as the dependent variable. The regression specification is given by Equation (10).

$$\begin{aligned}
\text{Expected Profit}_{it} = & \alpha_i + \beta_1 \text{Policy}_i + \beta_2 \text{Decision}_{1-5,it} \\
& + \beta_3 \text{Decision}_{6-10,it} + \beta_4 (\text{Policy}_i \times \text{Decision}_{1-5,it}) \\
& + \beta_5 (\text{Policy}_i \times \text{Decision}_{6-10,it}) + \beta_6 \text{CRT}_i \\
& + \beta_7 (\text{CRT}_i \times \text{Decision}_{1-5,it}) + \beta_8 (\text{CRT}_i \times \text{Decision}_{6-10,it}) \\
& + v_i + \varepsilon_{it}.
\end{aligned} \tag{10}$$

The regression Table 2.5 results confirm that expected profits are significantly lower in

Table 2.5: Random Effects Panel Regression: Expected Profit

	All Treatments	High Order Cost	Low Order Cost
Constant	1628.35*** (80.33)	1546.19*** (114.22)	1710.07*** (111.59)
Policy	-16.73 (70.46)	34.65 (96.42)	-59.56 (101.85)
Decisions 1–5	-299.93** (95.31)	-216.69 (159.65)	-363.36*** (105.34)
Decisions 6–10	-9.79 (61.63)	65.88 (96.32)	-89.76 (72.37)
Policy × Decisions 1–5	-309.22** (118.78)	-474.21* (204.58)	-167.12 (126.89)
Policy × Decisions 6–10	-94.62 [•] (56.91)	-106.94 (78.54)	-88.31 (82.66)
CRT	152.73 [•] (83.36)	196.04 [•] (113.80)	103.95 (119.70)
CRT × Decisions 1–5	57.95 (124.14)	-65.67 (211.99)	145.22 (131.43)
CRT × Decisions 6–10	-18.64 (63.78)	-78.68 (90.39)	50.50 (86.47)
Overall R^2	0.082	0.119	0.057
Observations	1674	791	883

Notes: Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [•] $p < 0.1$. Policy dummy: 1 = ROP, 0 = Kanban. CRT dummy: 1 if at least two cognitive reflection test questions are answered correctly.

the first five decisions under the reorder point policy relative to Kanban. The negative interaction between Policy and $Decisions_{1-5}$ indicates that the initial disadvantage of the reorder policy is larger in early decisions. As decisions progress, this difference diminishes and becomes statistically insignificant.

The evidence suggests rapid learning across both policies. Under ROP, reorder points initially have low values and gradually increase toward the profit-maximizing region. Under Kanban, container choices adjust only moderately over time. Additional non-parametric tests comparing early and late decisions confirm significant upward adjustments of reorder points under ROP but not for containers under Kanban (see Appendix 2.F).

One reason for the rapid convergence is the experimental design. Each decision simulates 365 demand realizations, which substantially reduces stochastic noise and allows participants to systematically adjust parameters toward more profitable configurations. As a result, initial differences in expected profits become indistinguishable in later decisions. Cost structures across policies follow similar dynamics. While early decisions show differences in inventory and lost-sales costs, these differences diminish as participants gain experience. Random-effects panel regressions examining expected inventory costs and expected lost-sales costs are reported in Appendix 2.E. The results confirm the patterns observed in the main analysis.

While decision parameters remain distinct, learning quickly reduces performance differences, resulting in comparable profit levels across policies. These findings highlight the role of policy framing in shaping initial decisions.

2.5 Study 2

2.5.1 Experimental Design

2.5.1.1 Experimental Protocol The survey for Study 2 was preregistered, including outlier criteria, treatments, and hypotheses (<https://aspredicted.org/94zv9t.pdf>). The experiment was programmed using the Python-based platform oTree (Chen et al.,

2016). Participants were undergraduate students enrolled in an operations management course and received course credit for participation.

The study was conducted in December 2025. A total of 89 participants completed the experiment out of 300 enrolled students. Seventeen participants were removed according to the preregistered outlier criteria. Each participant completed only one treatment. Participants were told that they take the role of an inventory manager deciding the inventory parameters for sixteen products with different demand parameters. They received detailed written instructions about their assigned policy, including an example. The instructions, example, and decision interface are provided in Appendix 2.G. After this, the main task began. At the end, participants completed a demographic questionnaire as well as questions about their order decisions.

2.5.1.2 Task Participants chose inventory parameters for sixteen products with different demand characteristics. Demand followed a normal distribution with varying mean and standard deviation combinations (see Appendix 2.H). The order of the demand parameters was randomized for each participant.

In contrast to Study 1, participants did not receive any feedback between decisions. This eliminates learning effects and allows us to observe initial parameter choices under varying demand parameters.

2.5.1.3 Parameters and Treatments All parameters besides the demand correspond to the high-order-cost setting of Study 1. The survey is between subject and consisted of two treatments reflecting ROP and Kanban.

2.5.1.4 Hypothesis Development To understand initial order decisions, we examine how participants interpret the two decision dimensions of the inventory policies. Under the reorder point policy (ROP), we expect participants to interpret the parameters additively. Under Kanban, we expect participants to interpret the parameters multiplicatively, consistent with Equation (7). In both cases, we expect decision makers to anchor their parameter choices on the mean demand, as documented for one-dimensional inventory decisions in the newsvendor literature (Bostian et al., 2008; Benzion et al., 2008; Bolton and Katok, 2008; Schweitzer and Cachon, 2000).

H1: Under the reorder point policy, the sum of the order quantity and reorder point is closer to the mean demand than the product of these parameters.

H2: Under the Kanban policy, the product of the number of containers and the quantity per container is closer to the mean demand than the sum of these parameters.

Consistent with the results of Study 1, we expect that participants anchor their parameter choices on the mean demand and distribute this target level across the decision parameters. Under the reorder point policy this anchor is distributed additively between Q and r , while under Kanban it is distributed multiplicatively between Q and c . As a result, the two policies should generate systematically different parameter choices even when decision makers anchor on the same demand level.

H3: The order quantity under the reorder point policy is higher than the quantity per container under the Kanban policy.

H4: The calculated reorder point under Kanban is higher than the reorder point under the reorder point policy.

2.5.2 Results

Study 2 examines how participants set initial inventory parameters under changing mean values and standard deviations without feedback. This allows us to assess whether the patterns observed in Study 1 persist across different demand environments in the absence of learning. For clarity, figures display only the Kanban profit-maximizing benchmark.

2.5.2.1 Mean Anchoring The hypotheses above assume that participants anchor their decisions on the mean demand under both the reorder point policy and the Kanban policy. In the following, we test this assumption to verify whether mean anchoring is present in both policy framings.

In contrast to the classical newsvendor setting, we do not implement a low-profit condition. Our test therefore focuses on whether decision parameters systematically align with the mean demand across different demand environments. This test builds on the well-documented presence of mean anchoring in inventory decision making. At the same time, it does not fully rule out alternative explanations such as risk aversion, which could produce similar ordering behavior.

Following Bostian et al. (2008), we estimate Equation (11), where x_t denotes the observed decision parameter, defined as $r + Q$ under ROP and $c \cdot Q$ under Kanban in period t . The variable μ_t denotes the mean demand in the respective decision scenario, x_t^* the profit-maximizing value of x_t , α the adjustment parameter capturing the degree of adjustment from the mean demand toward the optimal value, and ϵ_t a zero-mean error term. If $x_t = x_t^*$, then $\alpha = 1$, while if $x_t = \mu_t$, then $\alpha = 0$. Thus, $\alpha = 1$ corresponds to full adjustment to the optimal benchmark, whereas $\alpha = 0$ indicates complete anchoring on the mean demand. Note: $\alpha = 1$ only reflects the optimal level of the aggregated parameter x_t and does not imply that the individual parameters are chosen optimally. Different combinations of r and Q can yield different profit outcomes, such that even choosing the optimal value of $r + Q$ does not necessarily correspond to the overall profit-maximizing solution.

To obtain participant-level estimates of α , we estimate Equation (11) separately for each participant using ordinary least squares without a constant term, such that the estimated slope coefficient corresponds to α . The resulting estimates are summarized and tested against the benchmark values of 0 and 1 using two-sided Wilcoxon signed-rank tests.

$$x_t = \mu_t + \alpha(x_t^* - \mu_t) + \epsilon_t \quad (11)$$

For both policies, α lies significantly above zero (Wilcoxon signed-rank tests, two-sided: $p < 0.001$), indicating that decisions systematically deviate from the mean demand

benchmark. At the same time, the estimated adjustment parameters are, on average, below the optimal value of $\alpha = 1$ under both policies. This is consistent with insufficient adjustment from the mean and thus mean anchoring. The deviation from 1 is statistically significant under Kanban ($p < 0.01$), while it is not significant under the reorder point policy ($p = 0.19$). Figure 2.4 illustrates the distribution of α across policies. The

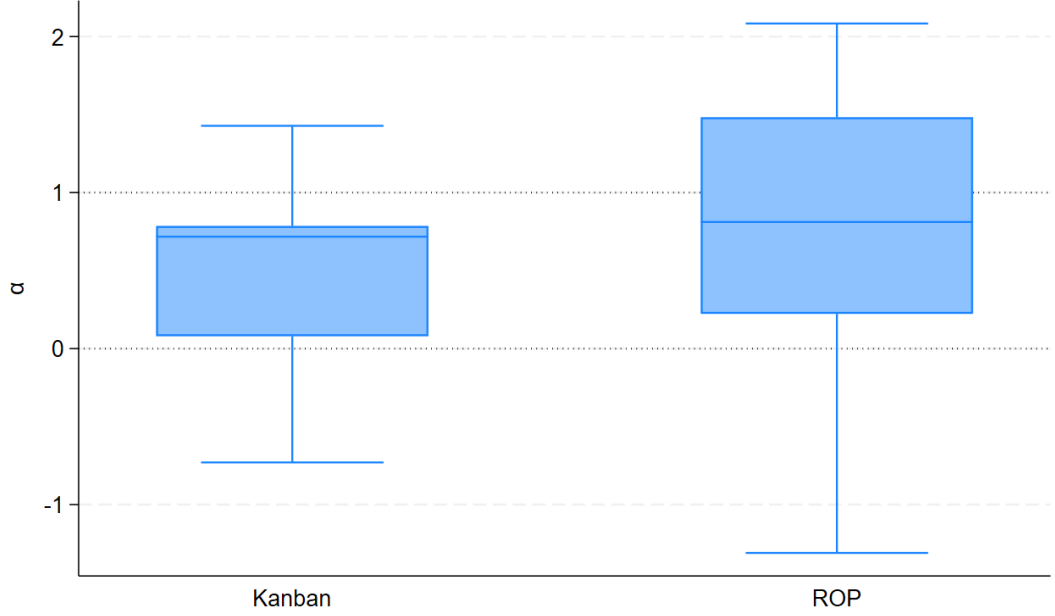


Figure 2.4: Boxplot of the estimated α by policy. Outliers are not shown.

distribution under the reorder point policy is substantially more dispersed, indicating less consistent adjustment behavior. In contrast, estimates under Kanban are more concentrated, with the exception of a few outliers. Summary statistics and the full distribution, including outliers, are reported in Appendix 2.I.

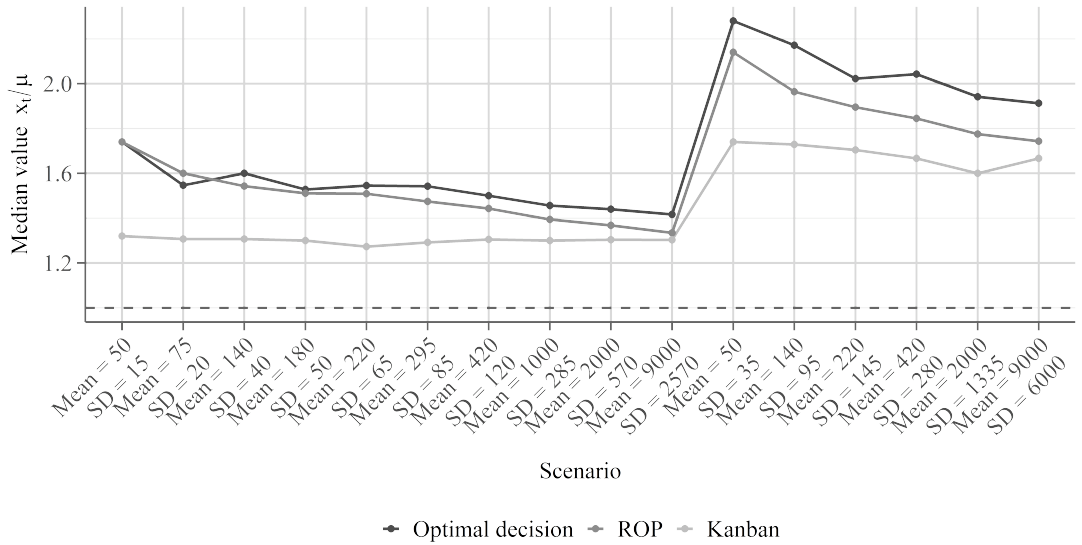


Figure 2.5: Normalized aggregate inventory decisions.

Figure 2.5 illustrates the median value of x_t scaled by μ_t , such that a value of 1 on the y-axis corresponds to the mean demand. The figure shows that decisions generally lie between the mean demand and the profit-maximizing benchmark. In this aggregated representation, both policies yield median values of x_t close to the profit-maximizing benchmark, with the reorder point policy appearing slightly closer.

Figure 2.6 illustrates the individual parameters, with Q shown in the upper panel and r in the lower panel, also scaled by μ_t . The differences suggested by Hypotheses 3 and 4 emerge at this level. These differences are consistent across all demand conditions and show that Kanban parameters are more closely aligned with the profit-maximizing parameters, primarily because decisions under ROP tend to undershoot optimal reorder points and overshoot order quantities.

2.5.2.2 Multiplicative and Additive Structure In the present study, 82% of decisions under ROP use Q as the dominant parameter. This higher share compared to Study 1 may be attributed to the absence of a trial task and feedback. Under Kanban, 86% of decisions also use Q as the dominant parameter. This ratio remains stable across demand environments and contributes to the more pronounced differences in the choices of Q and r between the policies compared to Study 1. As discussed in Study 1, decisions in which Q is the dominant parameter perform worse when anchoring occurs at the mean demand.

Overall, participants interpret ROP parameters additively and Kanban parameters multiplicatively. Under ROP, order quantities tend to be relatively large while reorder points are comparatively small. Under Kanban, order quantities are smaller and the implied reorder points larger. While the one-dimensional aggregation suggests limited differences between policies, the two-dimensional breakdown reveals systematic differences in parameter choices consistent with the results from Study 1.

Having established that decision makers anchor their choices on the mean demand, we now test whether the parameters are combined additively under ROP and multiplicatively under Kanban as predicted by H1 and H2.

To test H1 and H2, we measure the relative distance of decision parameters from the mean demand. For the reorder point policy:

$$\left| \frac{ROP_{i,t} + Q_{i,t}}{\mu_t} - 1 \right| \quad (12)$$

$$\left| \frac{ROP_{i,t} \cdot Q_{i,t}}{\mu_t} - 1 \right| \quad (13)$$

For Kanban, replacing ROP with the number of containers c :

$$\left| \frac{c_{i,t} + Q_{i,t}}{\mu_t} - 1 \right| \quad (14)$$

$$\left| \frac{c_{i,t} \cdot Q_{i,t}}{\mu_t} - 1 \right| \quad (15)$$

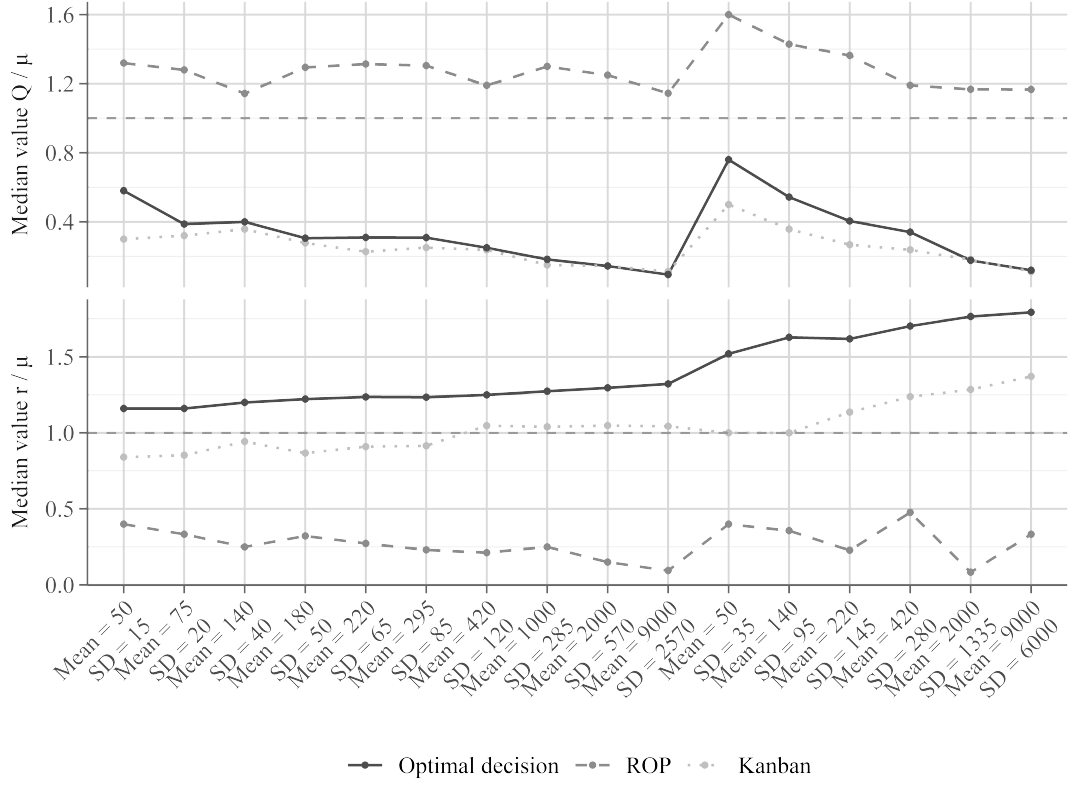


Figure 2.6: Normalized aggregate inventory decisions.

All tests are conducted at the participant level using one-sided Wilcoxon signed-rank tests.

For H1, the additive measure under ROP is significantly closer to zero than the multiplicative measure (one-sided Wilcoxon signed-rank test, $p < 0.001$), supporting additive interpretation under ROP.

For H2, the multiplicative measure under Kanban is significantly closer to zero than the additive measure (one-sided Wilcoxon signed-rank test, $p < 0.1$). The effect appears weaker for low mean values, where additive and multiplicative combinations produce more similar results. The same test yields strong significance if we remove the lowest 3 mean levels (one-sided Wilcoxon signed-rank test, $p < 0.01$).

2.5.2.3 Policy Parameters We confirm H3 (one-sided Wilcoxon signed-rank test, $p < 0.001$) and H4 (one-sided Wilcoxon signed-rank test, $p < 0.001$). Order quantities under ROP exceed quantities per container under Kanban, and implied reorder points under Kanban exceed reorder points under ROP.

Taken together, the results of Study 2 support the interpretation derived from Study 1. Participants anchor their decisions on mean demand under both policies, but they interpret the decision parameters differently. Under the reorder point policy, parameters tend to be combined additively, whereas under Kanban they are interpreted multiplicatively. When combined with the structural differences in the feasible decision space, these interpretations imply that the choice of the dominant parameter has much stronger

consequences under the reorder point policy than under Kanban. Consequently, the same anchor can produce larger reorder points and smaller order quantities under Kanban than under the reorder point policy. This mechanism explains the initial differences in achieved profits observed in Study 1.

2.6 Discussion, Limitations, and Managerial Implications

Inventory items managed through Kanban or reorder point (ROP) systems are typically classified as B- or C-items. Although these items are individually less critical than A-items, they constitute the majority of stock-keeping units and account for a substantial share of total inventory costs. From a purely operational perspective, reorder point systems should therefore perform at least as efficiently as Kanban systems when differences in work-in-process constraints are minimized.

Our empirical study shows that Kanban systems may lead to better initial outcomes as the structure of the policy restricts the feasible decision space and eliminates many low-profit parameter combinations. Our findings show that behavioral factors influence parameter selection even when structural differences between the policies are largely removed. By constructing a lost-sales environment in which profit-maximizing solutions are close across policies, we eliminate most operational advantages of either system. Nevertheless, we observe systematic differences in parameter choices. Participants under Kanban consistently select smaller order quantities and higher implied reorder points than participants under the reorder point policy.

Performance differences are most pronounced in early decisions. Under Kanban, participants find more profitable parameter combinations more quickly, whereas participants under ROP initially choose less profitable combinations before adjusting through learning. These differences are largely driven by the structure of the decision space. The Kanban policy restricts feasible parameter combinations to regions that are more closely aligned with profitable solutions, reducing the likelihood of poorly performing parameter choices.

Study 2 further clarifies the behavioral mechanism underlying these results. When feedback and learning are removed, decision makers under both policies anchor their decisions on the mean demand. Participants interpret the parameters differently across policies. Under the reorder point policy, decision parameters tend to be interpreted additively, while under Kanban they are interpreted multiplicatively. Because the Kanban structure links containers and units per container through their multiplicative relationship, anchoring on the mean demand produces parameter combinations that tend to imply higher reorder points than under the reorder point policy. The anchoring itself is therefore not the reason for Kanban's better performance. Instead, the structure of the policy translates similar anchors into more favorable parameter combinations. Even after repeated decisions, parameter differences between policies persist, suggesting that behavioral influences are not fully eliminated through learning. These findings indicate that differences between Kanban and reorder point systems are not purely operational but also behavioral in nature. Consequently, policies that are operationally

equivalent can still lead to systematically different decision behavior and short-run performance outcomes.

2.6.1 Limitations

Several limitations should be acknowledged.

First, in Study 1 each decision simulated 365 demand realizations, effectively implying yearly adjustment intervals. In practice, inventory parameters can typically be revised more frequently. Different results might emerge if parameters could be adjusted after each shorter decision cycle, as suggested by Katok et al. (2008).

Second, the number of decision rounds may have been insufficient to fully capture convergence toward satisficing solutions. Although learning slowed over time, many participants continued adjusting parameters in later rounds, suggesting that decision makers were still exploring the decision space.

Third, participants in both studies were university students. Although the newsvendor literature documents behavioral differences between students and managers (Bolton and Katok, 2008; Bolton et al., 2012; Moritz et al., 2013), it remains unclear whether these findings generalize to more complex multi-period decision environments.

Finally, although the dominant parameter mechanism explains a large share of the observed behavioral differences, some structural differences in parameter choices remain even after accounting for dominant parameter choices and learning effects. In particular, order quantities under ROP remain systematically higher than quantities per container under Kanban. One possible explanation is path dependency arising from initial choices. A rigorous test of this hypothesis is beyond the scope of this study. Future research may explore the behavioral mechanisms underlying these remaining differences.

2.6.2 Managerial Implications

The main managerial implication of this study concerns early decision performance when inventory systems are newly implemented or assigned to decision makers with limited experience.

In such situations, Kanban systems may lead to better initial outcomes because the structure of the policy restricts the feasible decision space to parameter combinations that are closer to profitable solutions. By limiting the set of feasible choices, Kanban reduces the cognitive complexity of parameter selection and lowers the risk of poorly performing initial decisions.

When demand and cost parameters remain stable over time, learning reduces these differences. As decision makers gain experience, performance under both policies converges and long-run profit differences become negligible. Consequently, switching inventory policies in stable environments may provide limited benefits relative to the potential transition costs.

Implementing a Kanban system requires physical changes, such as the introduction of containers and scanning systems, which involve upfront investment costs. These initial advantages are therefore likely to be outweighed by the associated implementation costs,

making a transition to Kanban primarily attractive in environments with high cost levels or consistently changing demand.

Overall, this study highlights that even equivalent inventory policies can lead to systematically different decision behavior and short-run performance outcomes. Understanding how policy framing and decision space structure influence parameter selection may therefore be important when designing inventory control systems and decision support tools.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

Author Contributions

[blinded for review]

Funding Sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation Process

During the preparation of this work, the author(s) used ChatGPT to assist with sentence formulation and bug fixing in R code and LaTeX. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix

2.A Experiment Study 1

You will now start the payoff relevant task. Please check the changes in the scenario.

Instructions and scenario

You can let the text show and disappear by clicking on the blue buttons.

Setting

Scenario

Example

Payoff

Calculator

Setting

In the following task you will take the role of an inventory manager in a large retail company. Your task is to determine the reorder point as well as the number of units in each order for a product. The demand for this product follows a normal distribution with constant mean and standard deviation.

After every inventory decision a year passes before you review the inventory and make a new decision. You will be in charge of the inventory for a total of 15 years. Your goal is to maximize your profits which result from Revenues minus Costs.

What happens to demand that cannot be satisfied on the same day?

Demand that cannot be satisfied on the same day will be lost.

Which variables can be influenced?

You will be able to decide the point under which a reorder is placed in your warehouse as well as the amount of pieces which are reordered.

Please note: There can be multiple reorders on one day. Please check the Example for further information.

When are new orders placed?

If the inventory is below the reorder point at the end of a day, one or more orders are placed until the orders in addition to the inventory are larger than the reorder point, which arrive in the morning of the following day.

The costs consist of three parts.

- The shortage cost: Has to be paid for each unit of demand that you were not able to satisfy. Consider it to be the goodwill loss of customers expressed in monetary terms.
- Ordering Cost: The ordering cost is the number of orders at the end of each day multiplied by the order cost.
- Inventory cost: Is calculated for each day by the average inventory multiplied by the inventory cost per day and per unit. The average inventory is calculated as the middle of the starting plus ending inventory of each day.

Please note: The starting inventory (1st day of the 365 days) is random and independent of earlier decisions.

Next

Figure 2.7: Settings page for ROP treatment

You will now start the payoff relevant task. Please check the changes in the scenario.

Instructions and scenario

You can let the text show and disappear by clicking on the blue buttons.

Setting

Scenario

Example

Payoff

Calculator

Setting

In the following task you will take the role of an inventory manager in a large retail company. Your task is to determine the number of containers as well as the number of units in each container for a product. The demand for this product follows a normal distribution with constant mean and standard deviation.

After every inventory decision a year passes before you review the inventory and make a new decision. You will be in charge of the inventory for a total of 15 years. Your goal is to maximize your profits which result from Revenues minus Costs.

What happens to demand that cannot be satisfied on the same day?

Demand that cannot be satisfied on the same day will be lost.

Which variables can be influenced?

You will be able to decide the amount of containers in your warehouse as well as the amount of pieces in each of these containers.

When are new containers ordered?

If at least one of these containers is completely empty at the end of a day, an order in the number of empty containers is placed, which arrives in the morning of the following day.

The costs consist of three parts.

- The shortage cost: Has to be paid for each unit of demand that you were not able to satisfy. Consider it to be the goodwill loss of customers expressed in monetary terms.
- Ordering Cost: The ordering cost is the number of containers that have to be ordered at the end of each day multiplied by the order cost.
- Inventory cost: Is calculated for each day by the average inventory multiplied by the inventory cost per day and per unit. The average inventory is calculated as the middle of the starting plus ending inventory of each day.

Please note: The starting inventory (1st day of the 365 days) is random and independent of earlier decisions.

Next

Figure 2.8: Settings page for Kanban treatment

You will now start the payoff relevant task. Please check the changes in the scenario.

Instructions and scenario

You can let the text show and disappear by clicking on the blue buttons.

Setting Scenario Example Payoff Calculator

Example

In the following you will find a short example of how your daily profits will be calculated:

Exemplary inventory decisions:

- Reorder point: 40 units.
- Reorder quantity: 10 units.

Exemplary Inventories:

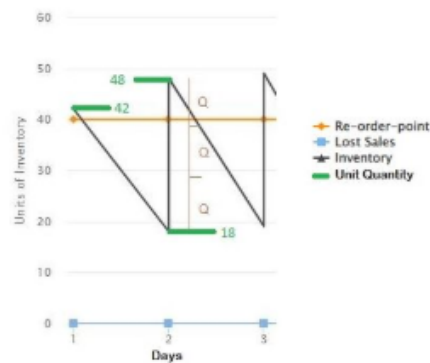
- Starting inventory: 42 units
- Demand realization of the day: 24 units
- Inventory at the end of the day: Starting inventory – demand realization = $42 - 24 = 18$

Cost:

- Total Order cost: Orders x order cost = $3 \times 0.55 = 1.65$ ECU
 - 3 orders are placed that have 10 units in each. As such, 30 units will be ordered. The starting inventory of the next day is 48 units.
- Total Inventory cost: Average inventory x inventory cost = $30 \times 5 = 150$ ECU
 - Average Inventory: The middle of the starting inventory + ending inventory = $(42+18)/2 = 30$ units
- Total Shortage cost: Unmet demand x shortage cost = $0 \times 30 = 0$ ECU (all demand was satisfied)

Revenue and Profit:

- Total Revenue: Demand x revenue per piece = $24 \times 20 = 480$ ECU
- Total Profit: Total revenue – total ordering cost – total inventory cost – total shortage cost = $480 - 1.65 - 150 - 0 = 328.35$ ECU



Next

Figure 2.9: Example page for ROP treatment

You will now start the payoff relevant task. Please check the changes in the scenario.

Instructions and scenario

You can let the text show and disappear by clicking on the blue buttons.

Setting

Scenario

Example

Payoff

Calculator

Example

In the following you will find a short example of how your daily profits will be calculated:

Exemplary inventory decisions:

- Number of containers: 5 containers.
- Number of units in each container: 10 units.

Exemplary Inventories:

- Starting inventory: 42 units
- Demand realization of the day: 24 units
- Inventory at the end of the day: Starting inventory – demand realization = $42 - 24 = 18$

Cost:

- Total Order cost: Orders x order cost = $3 \times 0.55 = 1.65$ ECU
 - 3 reorders are placed to replace the empty containers with new containers that have 10 units in each. As such, 30 units will be ordered. The starting inventory of the next day is 48 units.
- Total Inventory cost: Average inventory x inventory cost = $30 \times 5 = 150$ ECU
 - Average Inventory: The middle of the starting inventory + ending inventory = $(42+18)/2 = 30$ units
- Total Shortage cost: Unmet demand x shortage cost = $0 \times 30 = 0$ ECU (all demand was satisfied)

Revenue and Profit:

- Total Revenue: Demand x revenue per piece = $24 \times 20 = 480$ ECU
- Total Profit: Total revenue – total ordering cost – total inventory cost – total shortage cost = $480 - 1.65 - 150 - 0 = 328.35$ ECU



Next

Figure 2.10: Example page for Kanban treatment

Inventory decisions

Please input your ordering decisions for the next year. You can find your last decisions in the table below.

Your ordering decisions in year 1/ 15	
Reorder Point	165 Units
Reorder Quantity	61 Units

Please input your preferred reorder point:

Please input your preferred reorder quantity:

[Next](#)

Instructions and scenario

You can let the text show and disappear by clicking on the blue buttons.

[Setting](#)[Scenario](#)[Example](#)[Payoff](#)[Calculator](#)

Figure 2.11: Decision page for ROP treatment

Inventory decisions

Please input your ordering decisions for the next year. You can find your last decisions in the table below.

Your ordering decisions in year 1 / 15	
Container	4 containers
Units per Container	56 Units

Please input your preferred number of containers:

Please input the number of units that should be in each container?

[Next](#)

Instructions and scenario

You can let the text show and disappear by clicking on the blue buttons.

[Setting](#)[Scenario](#)[Example](#)[Payoff](#)[Calculator](#)

Figure 2.12: Decision page for Kanban treatment

Decision overview

On this page, you will find all necessary information concerning the last 365 days. Please consider the provided information carefully before continuing to the next page.

What do you want to do?

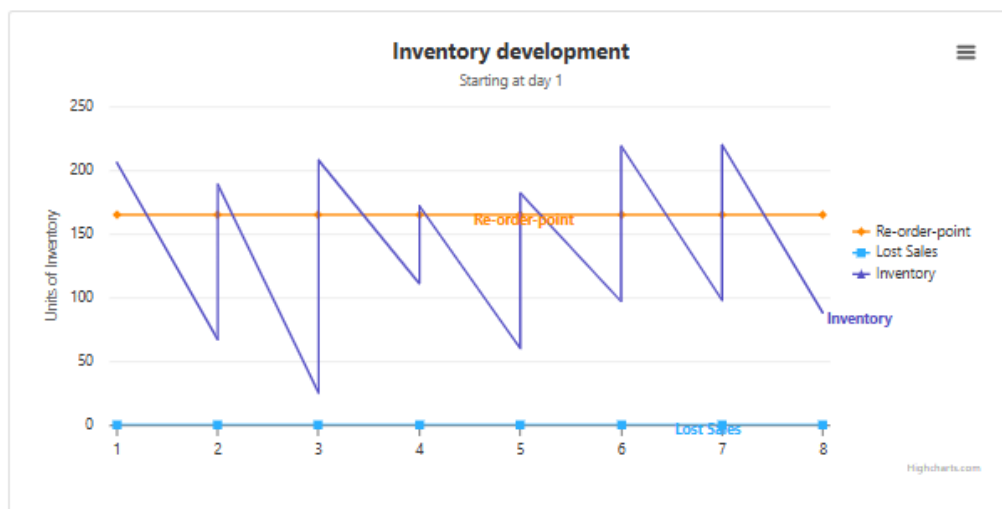
Proceed to next year

Table with average daily values

Table with your ordering decisions

Graphic for week 1

Next



Instructions and scenario

You can let the text show and disappear by clicking on the blue buttons.

Setting

Scenario

Example

Payoff

Calculator

Payoff relevant scenario

Scenario	Values
Shortage cost	30 ECU
Ordering cost	0.55 ECU
Inventory cost	5 ECU
Revenue per sold unit	20 ECU
Mean	140 units
Standard deviation	40 units

Figure 2.13: Visualization and Feedback page for ROP treatment

Decision overview

On this page, you will find all necessary information concerning the last 365 days. Please consider the provided information carefully before continuing to the next page.

What do you want to do?

Table with average daily values

Table with your ordering decisions

Graphic for week 1

Next

Average daily values of the last 365 days			
Unmet demand	1.55 units	Shortage cost	46.36 ECU
Ordered containers	2.41 containers	Ordering cost	1.32 ECU
Average inventory	130.91 units	Inventory cost	654.53 ECU
		Total cost	702.21 ECU
Sold units	134.8 units	Revenue	2696.05 ECU
		Profit	1993.84 ECU

Instructions and scenario

You can let the text show and disappear by clicking on the blue buttons.

Setting

Scenario

Example

Payoff

Calculator

Figure 2.14: Feedback page for Kanban treatment

Decision overview

On this page, you will find all necessary information concerning the last 365 days. Please consider the provided information carefully before continuing to the next page.

What do you want to do?

Table with average daily values

Table with your ordering decisions

Graphic for week 1

Next

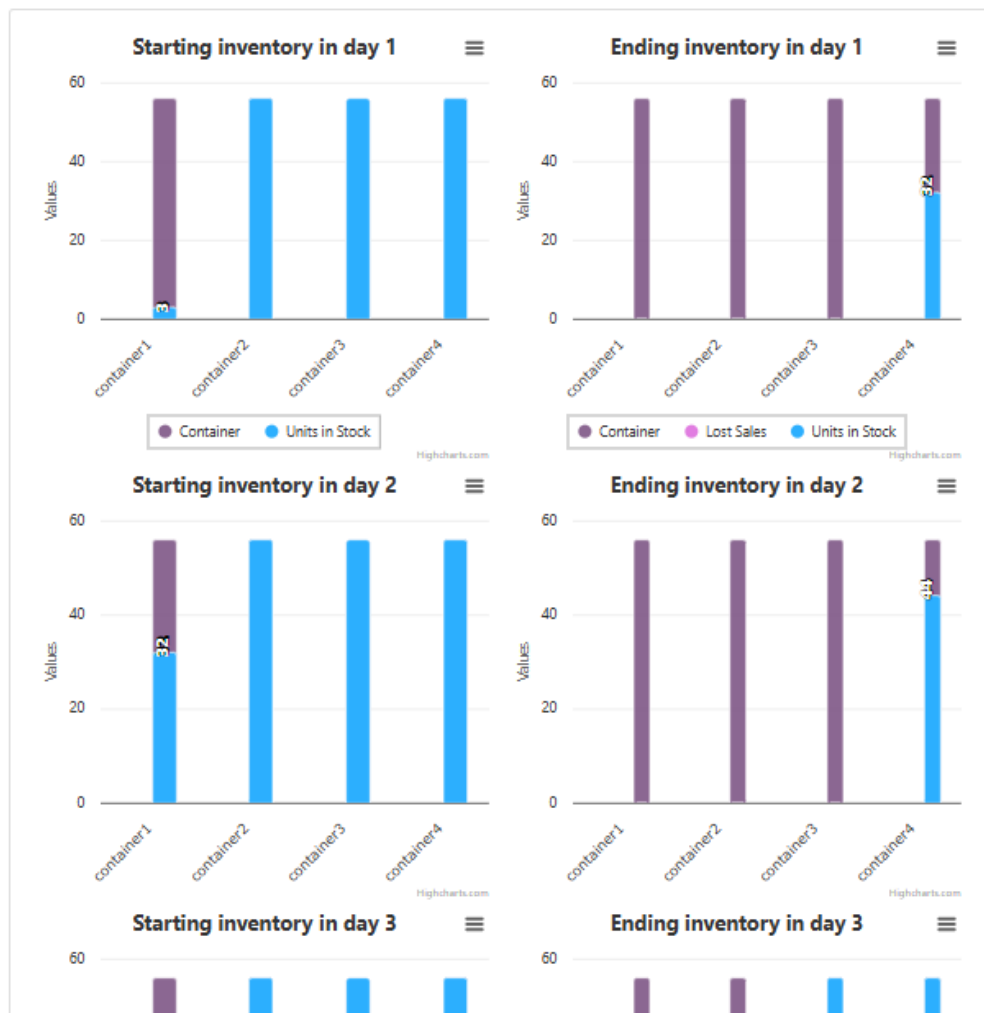


Figure 2.15: Visualization page for Kanban treatment

2.B Choice Set Comparison

Table 2.6: Comparison of possible decision sets under ROP and Kanban

$Q_{\max}$	$r_{\max}$	ROP	Kanban
10	10	100	27
50	50	2500	207
75	75	5625	381
100	100	10000	482
140	140	19600	719
140	200	28000	1038
200	200	40000	1098
1000	1000	1000000	7069
9000	9000	81000000	83358

2.C Descriptive statistics of early decisions

Table 2.7: Summary statistics for decisions 1–5 by policy

		ROP	Kanban
Mean (SD)	Order quantity Q	77.8 (67.5)	26.1 (23.2)
	Reorder point r	122.4 (57.7)	182.7 (75.9)
	Inventory cost	534.4 (323.1)	671.9 (375.6)
	Order cost	34.3 (53.5)	71.2 (86.0)
	Lost sales cost	646.8 (669.9)	353.3 (376.0)
	Expected profit	1145.5 (950.2)	1460.1 (586.6)
Median	Order quantity Q	65.0	19.0
	Reorder point r	120.0	166.0
	Inventory cost	461.9	580.8
	Order cost	3.6	13.6
	Lost sales cost	448.7	205.0
	Expected profit	1539.4	1679.0

2.D Summary statistics for the first five decisions

Table 2.8: Summary statistics for decisions 1–5 by policy and cost setting

		ROP ($Q > r$)	ROP ($Q \leq r$)	Kanban ($Q > c$)	Kanban ($Q \leq c$)
Mean (SD)	Q	131.0 (108.2)	63.7 (43.6)	31.8 (24.9)	11.0 (3.6)
	r	82.6 (85.8)	133.0 (43.1)	177.6 (82.5)	196.5 (54.6)
	Profit	314.7 (1216.2)	1367.1 (735.4)	1415.8 (624.6)	1578.1 (468.9)
Median	Q	92.3	53.0	22.2	11.0
	r	57.5	129.0	158.7	189.4
	Profit	381.7	1675.2	1682.4	1679.0

Table 2.9: Random Effects Panel Regression: Expected Lost Sales Cost

	Full Model	High Order Cost	Low Order Cost
Constant	235.788*** (54.521)	303.891*** (87.167)	163.954** (58.896)
Policy	37.351 (48.413)	32.384 (67.269)	34.332 (67.540)
Decisions 1–5	160.489* (64.536)	18.987 (94.457)	288.449*** (80.484)
Decisions 6–10	-23.903 (49.353)	-87.481 (68.747)	40.917 (67.960)
Policy $\times$ Decisions 1–5	261.819** (91.562)	410.816** (145.257)	140.085 (107.156)
Policy $\times$ Decisions 6–10	65.223 (49.850)	90.416 [•] (48.514)	47.427 (84.869)
CRT	-104.723 [•] (58.878)	-218.930* (86.263)	7.898 (72.604)
CRT $\times$ Decisions 1–5	31.798 (90.843)	234.925 (144.353)	-141.348 (105.937)
CRT $\times$ Decisions 6–10	40.596 (54.815)	110.897 [•] (60.482)	-30.527 (89.008)
Overall R^2	0.105	0.175	0.065
Observations	1674	791	883

Notes: Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [•] $p < 0.1$. Policy dummy: 1 = ROP, 0 = Kanban. CRT dummy: 1 if at least two cognitive reflection test questions are answered correctly.

2.E Cost Regressions

$$\begin{aligned}
\text{Expected Lost-sales Cost}_{it} = & \alpha_i + \beta_1 \text{Policy}_i + \beta_2 \text{Decision}_{1-5,it} \\
& + \beta_3 \text{Decision}_{6-10,it} + \beta_4 (\text{Policy}_i \times \text{Decision}_{1-5,it}) \\
& + \beta_5 (\text{Policy}_i \times \text{Decision}_{6-10,it}) + \beta_6 \text{CRT}_i \\
& + \beta_7 (\text{CRT}_i \times \text{Decision}_{1-5,it}) + \beta_8 (\text{CRT}_i \times \text{Decision}_{6-10,it}) \\
& + v_i + \varepsilon_{it}.
\end{aligned} \tag{16}$$

$$\begin{aligned}
\text{Expected Inventory Cost}_{it} = & \alpha_i + \beta_1 \text{Policy}_i + \beta_2 \text{Decision}_{1-5,it} \\
& + \beta_3 \text{Decision}_{6-10,it} + \beta_4 (\text{Policy}_i \times \text{Decision}_{1-5,it}) \\
& + \beta_5 (\text{Policy}_i \times \text{Decision}_{6-10,it}) + \beta_6 \text{CRT}_i \\
& + \beta_7 (\text{CRT}_i \times \text{Decision}_{1-5,it}) + \beta_8 (\text{CRT}_i \times \text{Decision}_{6-10,it}) \\
& + v_i + \varepsilon_{it}.
\end{aligned} \tag{17}$$

Table 2.10: Random Effects Panel Regression: Expected Inventory Cost

	Full Model	High Order Cost	Low Order Cost
Constant	708.971*** (52.978)	622.486*** (55.247)	803.856*** (84.174)
Policy	-15.569 (48.494)	-30.238 (70.843)	6.683 (61.305)
Decisions 1–5	28.506 (75.626)	175.396 (122.014)	-116.425 (77.470)
Decisions 6–10	45.138 (56.100)	69.609 (65.953)	21.813 (92.567)
Policy × Decisions 1–5	-119.487• (68.141)	-192.902* (96.502)	-67.764 (90.578)
Policy × Decisions 6–10	-3.488 (53.266)	-21.628 (64.483)	9.296 (83.606)
CRT	13.351 (52.309)	138.421* (68.015)	-118.447 (74.314)
CRT × Decisions 1–5	-111.258 (73.339)	-326.122** (106.305)	90.476 (88.925)
CRT × Decisions 6–10	-51.660 (57.261)	-110.527• (64.802)	-0.001 (97.412)
Overall R^2	0.029	0.074	0.024
Observations	1674	791	883

Notes: Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, • $p < 0.1$. Policy dummy: 1 = ROP, 0 = Kanban. CRT dummy: 1 if at least two cognitive reflection test questions are answered correctly. High Order Cost corresponds to $oct = 0$; Low Order Cost corresponds to $oct = 1$.

2.F Additional Tests of Parameter Adjustments

We test for differences in reorder point choices between the first five and last five decisions at the participant level using Wilcoxon signed-rank tests.

Results are as follows:

- Kanban, High Order Cost: $p = 0.35$
- Kanban, Low Order Cost: $p = 0.15$
- ROP, High Order Cost: $p < 0.001$
- ROP, Low Order Cost: $p < 0.001$

These results confirm significant upward adjustment of reorder points over time under ROP, but not under Kanban.

2.G Experimental study 2

Setting

Thank you for joining this survey!

In this task, you are the inventory manager of a large retail company. Your job is to decide:

- **Reorder point** – when to place a new order
- **Order quantity** – the size of each order

You will make these decisions for **16 products**. The products differ only in their expected demand distribution. Your goal is to maximize profit, which equals revenue minus costs. The products differ only in their demand distribution.

Your goal is to maximize profit, which equals revenue minus costs.

Key information

- Demand is random and follows a normal distribution.
- If demand exceeds inventory, the extra demand is lost.

Reordering rule

At the end of each day, if the inventory is below the reorder point, the system automatically places orders.

- Each order is for the order quantity you chose (the order size).
- Multiple orders may be placed if one order is not enough to bring the inventory above the reorder point.
- An ordering cost is charged for each order placed, not for each unit ordered.
- All orders arrive the next morning.

Costs

- **Shortage cost:** charged per unit of unmet demand
- **Ordering cost:** An ordering cost is charged for each order placed, not for each unit inside.
- **Inventory cost:** based on the average daily inventory multiplied by the cost per unit

You can review this information anytime by clicking the blue **Setting** button on future pages.

Next

Figure 2.16: Settings page for ROP treatment

Setting

Thank you for joining this survey!

In this task, you are the inventory manager of a large retail company. Your job is to decide:

- **Number of containers** – how many containers to keep in the warehouse
- **Units per container** – the size of each container

You will make these decisions for **16 products**. The products differ only in their expected demand distribution. Your goal is to maximize profit, which equals revenue minus costs. The products differ only in their demand distribution.

Your goal is to maximize profit, which equals revenue minus costs.

Key information

- Demand is random and follows a normal distribution.
- If demand exceeds inventory, the extra demand is lost.

Reordering rule

At the end of each day, if one or more containers are completely empty, the system automatically places new orders.

- Each empty container triggers one new container to be ordered.
- An ordering cost is charged for each container ordered, not for each unit inside.
- All ordered containers arrive the next morning.

Costs

- **Shortage cost:** charged per unit of unmet demand
- **Ordering cost:** charged per container ordered
- **Inventory cost:** based on the average daily inventory multiplied by the cost per unit

You can review this information anytime by clicking the blue **Setting** button on future pages.

Next

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Figure 2.17: Settings page for Kanban treatment

Example

This example shows how profit is calculated using your inventory policy.

Inventory decisions

- Reorder point: 40 units
- Order quantity: 10 units (the size of each order)

Inventories

- Starting inventory: 42 units
- Demand during the day: 24 units
- Ending inventory: 18 units ($42 - 24$)

At the end of the day, the inventory (18) is below the reorder point (40). The system therefore places new orders until inventory is above 40:

- Three orders placed, each of 10 units → total 30 units ordered
- Each order adds an ordering cost
- Next day's starting inventory: $18 + 30 = 48$ units

Cost and profit parameters

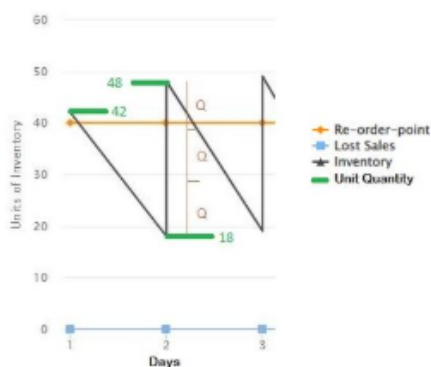
- Shortage cost: 30 ECU per unit
- Ordering cost: 20 ECU per order
- Inventory cost: 5 ECU per unit (average inventory)
- Revenue per sold unit: 20 ECU

Cost calculation

- Ordering cost: $3 \times 0.55 = 60$ ECU
- Inventory cost: $(42 + 18) / 2 \times 5 = 150$ ECU
- Shortage cost: $0 \times 30 = 0$ ECU

Revenue and profit

- Revenue: $24 \times 20 = 480$ ECU
- Profit: $480 - 60 - 150 - 0 = 270$ ECU



In the graph, the inventory drops below the reorder point and triggers three orders, each of 10 units. All arrive the next morning, bringing the inventory back above the reorder point to 48.

You can revisit this example anytime by clicking the blue **Example** button on future pages.

Next

Figure 2.18: Example page for ROP treatment

Example

This example shows how profit is calculated using your Kanban policy.

Inventory decisions

- Number of containers: 5
- Units per container: 10 (the size of each container)

Inventories

- Starting inventory: 42 units
- Demand during the day: 24 units
- Ending inventory: 18 units (42 – 24)

At the end of the day, some containers are empty. The system places new orders for each empty container:

- Three empty containers replaced with full ones (10 units each)
- Total 30 units ordered
- Each container adds one ordering cost
- Next day's starting inventory: 18 + 30 = 48 units

Cost and profit parameters

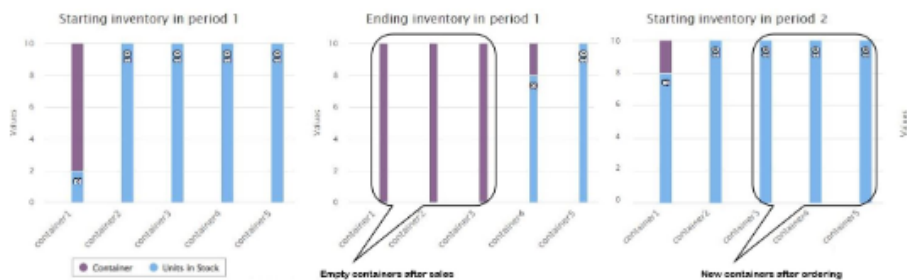
- Shortage cost: 30 ECU per unit
- Ordering cost: 20 ECU per container ordered
- Inventory cost: 5 ECU per unit (average inventory)
- Revenue per sold unit: 20 ECU

Cost calculation

- Ordering cost: $3 \times 0.55 = 60$ ECU
- Inventory cost: $(42 + 18) / 2 \times 5 = 150$ ECU
- Shortage cost: $0 \times 30 = 0$ ECU

Revenue and profit

- Revenue: $24 \times 20 = 480$ ECU
- Profit: $480 - 60 - 150 - 0 = 270$ ECU



In the graph, three containers become empty and are replaced. Each container ordered adds one time the ordering cost. All arrive the next morning, bringing the inventory to 48.

You can revisit this example anytime by clicking the blue **Example** button on future pages.

Next

Figure 2.19: Example page for Kanban treatment

Inventory decisions

For the 1. product we have the following data from the following table. Please take a moment and read the details about the product carefully.

Details for product No. 1	Values
Shortage cost	30 €
Ordering cost	20 €
Inventory cost	5 €
Revenue per sold unit	20 €
Mean	220.0 units →
Standard deviation	65.0 units →

Please input your ordering decisions for the 1. product.

Please input your preferred reorder point:

Please input your preferred reorder quantity:

Next

Instructions and scenario

You can show or hide each section by clicking on the blue buttons below.

Setting

Example

Payoff

Normal Distribution

Figure 2.20: Decision page for ROP treatment

Inventory decisions

For the 1 . product we have the following data from the following table. Please take a moment and read the details about the product carefully.

Details for product No. 1	Values
Shortage cost	30 €
Ordering cost	20 €
Inventory cost	5 €
Revenue per sold unit	20 €
Mean	295.0 units →
Standard deviation	85.0 units →

Please input your ordering decisions for the 1 . product.

Please input your preferred number of containers:

Please input the number of units that should be in each container?

Next

Instructions and scenario

You can show or hide each section by clicking on the blue buttons below.

Setting

Example

Payoff

Normal Distribution

Figure 2.21: Decision page for Kanban treatment

2.H Means and corresponding standard deviations for Study 2

Table 2.11: Means and corresponding standard deviations

Mean	σ
50	15
75	20
140	40
180	50
220	65
295	85
420	120
1000	285
2000	570
9000	2570
50	35
140	95
220	145
420	280
2000	1335
9000	6000

2.I Distribution of the Adjustment Parameter α

Table 2.12: Summary statistics of the adjustment parameter α by policy

	Kanban	ROP
Mean	0.953	0.824
Median	0.717	0.811
SD	1.941	1.044

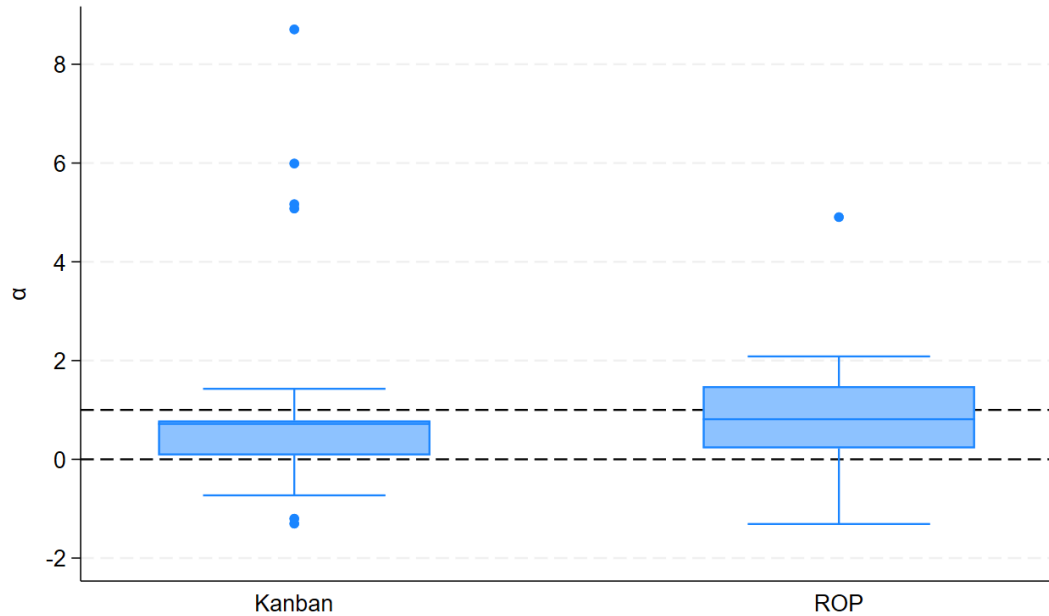


Figure 2.22: Boxplot of the adjustment parameter α by policy, including outliers

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3 Chapter 3

Behavioral Aspects of Uncertain Arrival Times in Inventory Decisions

Alexander Daniels, Guido Voigt, Florian E. Sachs

Abstract

Temporal uncertainty in lead times is common in supply chains, yet most behavioral inventory research assumes constant lead times. To address this gap, we examine how stochastic lead times influence inventory decision-making in a single-echelon system with stochastic demand. We report two laboratory studies comparing constant and stochastic lead time environments. Study 1 contrasts constant and stochastic lead times and shows that supply-side uncertainty reduces the aggressiveness of inventory corrections, leading to higher inventories, backlogs, or both, which subsequently increase costs. Study 2 examines an intervention in which participants are informed of future lead times. While this information reduced reported stress and improved subjective experience, it did not significantly lower costs. Instead, participants deviated from the order-up-to framework by ordering more before longer lead times, reducing backlogs but increasing holding costs. Across all treatments, supply line inventory is consistently undervalued. The findings highlight how bounded rationality shapes order decisions under lead-time uncertainty and suggest that investments in automated decision-support tools may be even more beneficial than under the common assumption of constant lead times.

Keywords: Behavioral Operations Management, Inventory management, Decision making, Stochastic lead times, Behavioral experiment

3.1 Introduction

Although the supply side has stabilized following the COVID-19 pandemic, stockouts and inventory costs remain a major concern for firms. As of July 2025, the U.S. Census Bureau (2025) reports inventories valued at USD 2.666 trillion in manufacturing and trade, while the IHL Group (2023) estimates global stockout costs at USD 1.77 trillion. These figures, along with high interest rates and easy online substitutions, underscore the necessity of well-managed inventories. Many inventory decisions are still made by managers instead of automated systems. As a result, they are subject to risk aversion or bounded rationality (Kahneman and Tversky, 1979; Simon, 1955). Bounded rationality influences inventory decisions, as documented in newsvendor experiments where decision makers diverge systematically from optimal policies (Su, 2008). Biases such as demand anchoring (Bolton and Katok, 2008; Schweitzer and Cachon, 2000) further exemplify deviations from rationality that can impact supply chain performance.

Supply uncertainty contributes to excess inventories, stockouts, and influences managerial decisions (Hofstra et al., 2024). It can stem from uncertainty in supply quantity or lead times. This study focuses on stochastic lead times, a pervasive feature of global supply chains. Disney et al. (2016) illustrate this by documenting the stochastic nature of lead times on container routes between the U.S. and China. Arrivals that deviate from expectations, whether premature or delayed, magnify inventory volatility. These fluctuations result in excessive stock levels during early arrivals and backlogs during delays, thereby raising total supply chain costs. Inventory models confirm that even under optimal policies, stochastic lead times result in higher costs than constant lead times (Bollapragada et al., 2004; Robinson et al., 2001; Srinivasan et al., 2011). Experimental studies have similarly examined supply uncertainty, most commonly arising from quantity rationing, partial or late fulfillment, and inventory record inaccuracy, rather than exogenous lead time variability (Hofstra et al., 2024; Gurnani et al., 2014; Xue et al., 2022; Haeussler et al., 2021). Experimental evidence further suggests that changes in sourcing and allocation structures, as well as enhanced information use, are possible managerial responses to mitigate supply risk (Xue et al., 2022).

Compared to supply quantity uncertainty, lead-time uncertainty has received less attention in the literature on behavioral operations management. An exception is Ancarani et al. (2013), who find that stochastic lead times influence ordering in the beer game, creating systematic behavioral differences from constant lead times. When lead times are stochastic, decision makers face a more complex problem than under constant lead times, as they must anticipate uncertainty in both demand and replenishment timing. This study investigates how boundedly rational managers respond to such temporal uncertainties. Prior work suggests that inventory decisions are often based on the gap between current and target inventory. The rate at which this gap is closed, referred to as the aggressiveness of inventory corrections, depends on perceived risk (Croson et al., 2014). In addition, decision makers tend to underweight the supply line inventory when placing orders, meaning they do not fully take into account the inventory that is already on order but not yet received. This behavior, often referred to as supply line underweighting, leads to excessive ordering and amplifies inventory fluctuations (Croson and Donohue, 2006; Sterman, 1989).

Research on supply uncertainty primarily examines how boundedly rational decision makers behave under the dynamic conditions of the bullwhip effect, characterized by strongly increasing order variances and endogenous lead times that depend on the supply of higher echelons. While bullwhip research centers on amplification mechanisms that describe how small demand changes grow larger upstream through behavioral and structural factors, studying exogenous uncertainties addresses uncontrollable variability that supply chains must absorb, a core focus of classical inventory theory (Porteus, 2002). These perspectives are complementary rather than substitutive because endogenous amplification builds on exogenous variability, so both coexist in real supply chains. Understanding systems under exogenous uncertainty provides benchmarks and foundations for analyzing more complex settings with endogenous effects. Moreover,

risk mitigation strategies differ distinctly. Bullwhip mitigation emphasizes information sharing, collaborative forecasting, vendor-managed inventory, coordination contracts, or coordination stock to mitigate order amplification. In contrast, managing exogenous supply-side uncertainty relies on operational levers such as ordering policies or lead-time forecasting, which are essential even in perfectly coordinated supply chains. Even when such uncertainties are exogenous rather than amplified internally, they still generate substantial cost implications for firms operating under otherwise stable supply conditions.

This study examines how behavioral factors, specifically the aggressiveness of inventory corrections and the underweighting of supply-line information, influence decision making under constant and stochastic lead times. To do this, we design a single-echelon experiment without supply-quantity risk, comparing constant lead times to a setting with stochastic lead times uniformly distributed between zero and two periods. Parameters are selected so that the optimal order-up-to level remains the same across treatments, allowing us to isolate the effect of temporal supply uncertainty.

Even in the absence of bullwhip dynamics, decision makers fail to select cost-efficient order quantities and generate substantial excess costs under exogenously given lead-time uncertainty. Against this background, we examine how ordering behavior differs across lead-time regimes. While target inventory levels do not vary significantly between treatments, participants adjust toward these targets less aggressively under stochastic lead times, which results in higher overall costs. These patterns suggest that stochastic lead times increase decision complexity, making it more difficult for boundedly rational decision makers to correct inventory imbalances in a timely manner. In contrast to multi-echelon findings reported by Ancarani et al. (2013), we find no evidence that stochastic lead times affect the degree of supply line underweighting.

After observing that stochastic lead times increase costs by adding complexity to inventory decisions, we examine whether this effect can be mitigated by providing information on future lead-times. In practice, lead-time distributions are typically estimated from average values in historical order data (Lingitz et al., 2018). Lingitz et al. (2018) apply advanced regression models to historical records to improve lead-time predictions. More recently, research has shifted toward the use of machine-learning approaches, reflecting a growing interest in leveraging such information for operational decision making. For example, Reiners et al. (2025) and Biazon de Oliveira et al. (2021) employ machine-learning models to predict lead times, with Reiners et al. (2025) showing that improved forecasts can reduce capital lock-up by up to 7 percent. In this study, we test how decision makers incorporate this information into their ordering decisions and whether investments in such forecasting capabilities are beneficial when decisions are made by boundedly rational managers. To do so, we conduct a second experiment that introduces an intervention providing perfect information about dynamic future lead-times. This design also allows us to assess whether uncertainty, rather than dynamics, drives changes in ordering behavior.

Our findings indicate that when lead times are known but remain dynamic, participants

anticipate longer risk periods by increasing their order quantities. This reduces backlogs but leads to higher inventories, and overall costs are not significantly lowered. Thus, while decision makers clearly use the additional information, they primarily reallocate rather than reduce costs.

Overall, our work demonstrates that both uncertainty and dynamics in lead times affect ordering behavior and the aggressiveness of participants' inventory corrections towards their desired levels (Sterman, 1989). Section 3.2 reviews the relevant literature, Section 3 describes the experimental design, present the empirical results of the two studies, and Section 6 concludes with a discussion of implications and limitations.

3.2 Related Literature

3.2.1 Single Echelon Studies in Multi-Period Inventory Management under Constant Lead Times

Behavioral research on multiperiod inventory management in single-echelon decision tasks is scarce, with some notable exceptions. Bloomfield and Kulp (2013) show that introducing durability and transit lags reduces the weight participants place on their current inventory positions, leading to less responsive ordering and poorer performance as decision complexity increases. Similarly, Becker-Peth et al. (2020) show that starting inventories are often undervalued and that participants exhibit short-sighted ordering behavior in multiperiod settings with budget cycles. Perera and Fahimnia (2024) show that making relevant information salient improves multi-period ordering performance and profitability. Their results suggest that clear and timely information reduces cognitive burden and enhances decision quality. These studies focus on models with stochastic demand. Pan et al. (2020) and Pan et al. (2022) examine deterministic settings of the economic order quantity model, showing that learning effects emerge over time and that cognitive stress reduces performance, whereas higher cognitive reflection improves it.

3.2.2 Multi Echelon Studies in Multi-Period Inventory Management under Constant Lead Times

The area of behavioral experiments in multi-period decision-making is largely dominated by research on the bullwhip effect, which describes the increase in order variance toward upstream echelons of a supply chain. The seminal work of Sterman (1989) lays the foundation for this stream through the beer distribution game. The bullwhip effect shows an increase in the variance of order towards upper echelons. For a recent overview of behavioral bullwhip literature, we refer to Yang et al. (2021). The bullwhip effect arises from both operational and behavioral causes (Wang and Disney, 2016). Even when all operational causes of the bullwhip effect are eliminated by setting starting parameters and demand so that no bullwhip effect would occur under fully rational behavior, the bullwhip effect persists. In these conditions, participants systematically undervalue their supply lines, meaning they fail to fully consider inventory already on

order but not yet received. As a result, they perceive their inventory levels as too low and place excessive replenishment orders, indicating that behavioral factors influence ordering decisions (Croson and Donohue, 2006).

Much of this literature tests specific biases or behavioral adjustments in the beer distribution game. Cantor and Macdonald (2009) study the impact of problem solving approaches and information in the beer distribution game. Narayanan and Moritz (2015) show that cognitive reflection influences order decisions. Learning effects arise, though they typically require training or communication between echelons (Wu and Katok, 2006). Cui et al. (2015) show that sharing operational information between echelons improves coordination and reduces costs, illustrating that transparency can mitigate behavioral amplification in multi-echelon supply chains. Building on Sterman (1989)’s foundational work, subsequent studies explore additional factors influencing the bullwhip effect. For example, Croson et al. (2014) extend this model by examining perceived risks such as the concern that other decision makers might make poor choices, which they term coordination risk. Their findings suggest that higher perceived coordination risk leads participants to react more aggressively in their inventory adjustments toward target levels. Conversely, increased trust in the competence of managers in other echelons tends to reduce the aggressiveness of these corrections. Moreover, Croson et al. (2014) demonstrate that introducing a higher initial inventory, called coordination stock, can effectively mitigate the bullwhip effect and enhance overall supply chain profits. Additionally, Sterman and Dogan (2015) explore hoarding behaviors in decision-making, characterized by large multi-period orders, and observed that approximately one-third of participants engage in statistically significant hoarding. These findings further illustrate the diverse behavioral biases and strategies that influence order variability in supply chains.

3.2.3 Multi-Echelon Studies under Lead Time Uncertainty

The risk of lead time uncertainty in the context of the bullwhip effect is a topic of various analytical studies (Disney et al., 2016; Kim et al., 2006; Michna et al., 2018; Wang and Disney, 2016, 2017). From a behavioral perspective, Ancarani et al. (2013) show that stochastic lead times influence ordering behavior, resulting in increased backlogs and upstream instability. Haeussler et al. (2021) demonstrate that in a two-echelon experimental setting with capacity-constrained suppliers and load-dependent lead times, order delays lengthen perceived lead times and cause participants to place larger orders, a pattern they term the lead time syndrome. Balvers et al. (2023) examine stochastic lead times in a multi-period model with buyback options and find that participants tend to underestimate lead times and consequently underorder compared to decisions under uncertain review periods, further substantiating the behavioral influence of lead-time uncertainty.

3.2.4 Benchmarks under Stochastic Lead Times with Order Crossing

Hadley and Whitin (1963) present an analytical model for a base-stock inventory policy under stochastic lead times. They assume that replenishment orders are received sequentially and therefore that lead times are non-crossing, arguing that this assumption is reasonable in many practical single-supplier systems where the probability of order crossing is very low. Building on this non-crossing lead-time framework, Ehrhardt (1984) develops a dynamic-programming model for a periodic-review system with stochastic lead times and backorders and proves that the myopic order-up-to policy is optimal under non-crossing stochastic lead times. Janakiraman and Roundy (2004) extend the analysis to lost-sales systems with stochastic, non-crossing lead times and establish the convexity of the expected discounted cost with respect to the order-up-to level. Yuan et al. (2024) show that the base-stock policy becomes asymptotically optimal for lost-sales systems with non-crossing stochastic lead times when the penalty cost for lost sales is large relative to the holding cost. Song et al. (2017) study dual-sourcing systems with endogenous stochastic lead times and derive optimal structural policies that balance regular and expedited supply.

A growing body of research highlights the practical importance of order crossover, where replenishment orders may arrive out of sequence. Disney et al. (2016) show that order crossover is empirically common in global logistics and demonstrate that a proportional order-up-to-level policy can outperform the standard order-up-to rule under such conditions. Zalkind (1978) was among the first to show analytically that base-stock policies are not optimal under stochastic crossing lead times. Subsequent research quantifies the consequences of ignoring crossing lead times for inventory costs and safety-stock requirements. Hayya et al. (2008) and Hayya et al. (2009) show that disregarding crossing lead times can lead to significant underestimation of safety stocks and total inventory cost. Bradley and Robinson (2005) develop tractable approximations for systems with independent stochastic lead times that allow crossing, and Bischak et al. (2014) present an analytical cost model for the order-up-to policy under crossing stochastic lead times. Srinivasan et al. (2011) characterize the optimal policy in the presence of crossing lead times as state-dependent and computationally feasible only for small problem instances. To provide practical alternatives, they introduce two heuristics: the best order-up-to policy, which serves as an efficient benchmark, and the approximate weighted-index policy, which can be readily simulated. More recent studies extend these ideas to broader contexts. Ben-Ammar et al. (2019) optimize multi-period supply planning under stochastic lead times and dynamic demand, and Hansen et al. (2023) incorporate crossing lead times into lost-sales systems with perishable goods. Johansen and Thorstenson (2025) compare inventory systems with non-crossing and independent crossing lead times under compound-Poisson demand and find that when lead times are non-crossing, costs increase with lead-time variability, whereas under independent crossing lead times, costs are largely insensitive to it.

3.3 Experimental Design

This section describes the experimental setup used to collect behavioral ordering data under constant, stochastic, and dynamic lead times.

3.3.1 Experimental Protocol

A total of 107 subjects participated in four sessions, each lasting about 60 minutes. We recruited participants using the hroot software (Bock et al., 2014), from a pool of approximately 2,600 undergraduate and graduate students at the University of Hamburg. Prior research shows that university students and managers exhibit similar behavioral patterns in newsvendor decision tasks, supporting the use of a student sample in our experiment (Bolton et al., 2012). The computerized sessions took place in the university’s research laboratory in January 2025.

We randomly assigned subjects to one of the three treatments, which served as the basis for both Study 1 and Study 2. Upon arrival, the participants were seated in individual cubicles to read the experimental instructions on-screen. The instructions remained accessible throughout the experiment, and the full text is available in Appendix 3.A. After a short reading period, participants could ask clarification questions, which the experimenters answered privately. We prohibited any communication between participants.

Participants completed control questions to verify their understanding of the task before proceeding to the main task. Only those who answered all questions correctly proceeded to the main task.

After completing the main task, participants answered questions about their decision motives and completed a cognitive reflection test, a risk preference test, and self-reports on their mental state, including agitation, fear, challenge, and stress. Although participants knew from the invitation that the session would last about one hour, we did not impose any time limits on order decisions or on completing the questionnaires. We implemented the experiment using the software oTree (Chen et al., 2016).

3.3.2 Sequence of Events

Each period, framed as one week, follows the sequence of events based on Croson et al. (2014) and illustrated in Figure 3.1.

1. Previous orders that are due are received and added to the inventory.
2. The realized stochastic demand is satisfied from the inventory. If the inventory is insufficient, the unmet demand is backlogged.
3. The participant places a new order.

At the beginning of each period, participants receive feedback on their inventory, summarizing the three events above. Before placing a new order, they can view their supply-line inventory, their orders from the previous five periods, and a graph showing the development of their inventory levels over time.

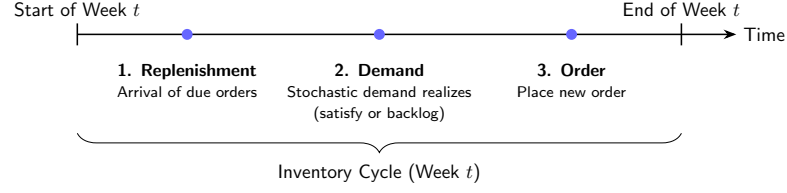


Figure 3.1: Sequence of events

3.3.3 Parameters

Cost parameters follow the standard specification introduced by Sterman (1989) for the beer distribution game, with holding costs set to 0.5 per unit per period and backlog costs set to 1 per unit per period. Because the experiment is single-echelon, no information lag is present.

Customer demand follows a discrete uniform distribution between 0 and 10 units. The instructions illustrate the uniform distribution using a dice-toss example and explicitly inform participants that demand remains stationary and constant throughout the experiment.

The initial state includes an on-hand inventory of two units and a supply line of ten units, split evenly between arrivals in the first and second period. Participants therefore start with an order-up-to level of 12, identical across treatments.

Participants make 49 consecutive order decisions. This number is not disclosed to them in order to prevent end-of-horizon effects. In each period, they receive a fixed budget of 15 experimental currency units. Profit equals this budget minus the costs generated by inventory holdings and backlogs. This budget structure is designed to keep participants in the gain domain rather than facing losses.

3.3.4 Treatment Variables

We employ a between-subject design with three treatments that vary only in the distribution and visibility of lead times seen in Table 3.1. Orders arrive after the realized lead time and are always fulfilled in full. In the constant lead time treatment, orders arrive after a constant lead time of one period. In the stochastic lead time treatment, lead times are independently and identically distributed (i.i.d.) and follow a discrete uniform distribution between 0 and 2 periods. The realized lead time is not known to participants when placing an order. Participants only get to know the realized lead time once the order arrives. Because lead times are restricted to 0, 1, or 2 periods, participants can infer that an order remaining outstanding for two periods will necessarily arrive in the next period.

The dynamic lead-time treatment uses the realizations from the stochastic lead-time treatment to generate a dynamic sequence of deterministic lead times. Participants can observe the lead times of the previous three orders and the upcoming five orders. This information is presented in a table showing the order period, the corresponding lead time, and the arrival period.

Study 1 compares the constant lead-time treatment to the stochastic lead-time treatment, and Study 2 compares the stochastic lead-time treatment to the dynamic lead-time treatment, allowing us to identify the causal effects of different lead-time regimes.

Table 3.1: Changes between treatments in the experiment

Study	Treatment	Lead times	Sample size (incl. outliers)
Study 1	Constant lead times	Constant at 1 period	29 (34)
	Stochastic lead times	Uniformly distributed between 0–2 periods	30 (40)
Study 2	Dynamic lead times	Deterministic sequence between 0–2 periods	29 (33)

3.3.5 Incentives

Earnings combine a fixed participation fee of €5 with performance-based bonuses. The cumulative profit across all decision periods is converted into euros and added to the fixed participation fee. On average, participants earned €15.20, without outliers €17.40. Participants who earned no performance-based bonus were excluded from the analysis, as their realized outcomes placed them in the loss domain (Kahneman and Tversky, 1979). Of the 107 original participants, 19 fall into this category, leaving a final sample of 88 subjects and 4,312 usable decisions.

This exclusion criterion also provides a transparent way to identify extreme observations. The budget was set so that participants should generally remain in the gain domain, so entering the loss domain indicates unusually high cost accumulation relative to the intended range of the task. Although a few participants near the threshold may simply have performed poorly, most excluded cases accumulated costs far above the range observed in the main sample, as shown in Appendix 3.B.

All results remain directionally consistent when these loss-domain participants are included, and any changes in significance are explicitly noted in the results section, supporting the robustness of our findings to their exclusion.

3.3.6 Benchmark Solutions

As a benchmark for the constant lead-time treatment, we use an order-up-to policy, which is optimal for the stationary periodic-review single-echelon inventory model with constant lead times and no fixed ordering costs, following Zipkin (2000).

Srinivasan et al. (2011) show that the optimal ordering policy for inventory systems with stochastic demand and stochastic lead times that allow for order crossing is state-dependent and can be derived by formulating the problem as a Markov decision process. Because solving this process exactly is computationally intensive and yields a complex policy, we adopt the best order-up-to-level policy as a practical and near-optimal approximation. Under their model assumptions, Srinivasan et al. (2011) find that the average cost difference between the best order-up-to-level policy and the optimal state-dependent policy is about 1.4 percent on average and at most 4.2 percent. Given this small performance gap and the widespread use of order-up-to-level policies in practice,

the best order-up-to-level policy provides a realistic benchmark for evaluating human ordering behavior.

To construct the benchmark solution for the dynamic lead-time treatment, we use the same order-up-to benchmark as in the stochastic lead-time treatment. This order-up-to-level policy is myopic and does not condition on the dynamics of lead times. Consequently, the benchmark outcomes for the stochastic lead-time case are the same as those for the deterministic dynamic lead-time case. Since no optimal policy is known to us for the deterministic dynamic lead-time setting with stochastic demand, we use this benchmark as a heuristic rather than an optimal policy, which also allows us to directly compare the treatments.

To evaluate benchmark performance and compare experimental treatments, we simulate inventory dynamics under both constant and stochastic lead-time conditions.

Simulations are conducted in Matlab using 10,000,000 independent replications, each covering 49 decision periods and starting from the same initial conditions as in the experiment. The resulting best order-up-to level is 12 units in both cases, which corresponds to the initial inventory level in the experimental setup. Benchmark values for total cost, average inventory, and backlog are reported in Appendix 3.C .

3.4 Study 1: Constant versus Stochastic Lead Times

In Study 1, we investigate how ordering behavior differs between constant and stochastic lead times in a single-echelon setting. Lead times are framed as customs delays, and participants receive feedback on orders, inventory, and demand at the start of each period.

3.4.1 Realized Cost, Inventories and Emotions

Initially, we compare outcomes across treatments focusing on inventory levels, backlogs, and costs. Table 3.2 reports mean and median values, alongside measures that subtract benchmark performance from the realized values for direct comparability. Throughout this work, we refer to the benchmark adjusted values as cost premium for costs and gaps for inventories and backlogs. On average, both inventories and backlogs are higher under stochastic lead times than under constant lead times. To test for statistical differences, we aggregated performance measures at the participant level and applied Mann-Whitney U (MWU) tests. Inventory and backlog gaps do not differ significantly between treatments (MWU, $p = 0.39$ and $p = 0.54$), whereas the cost premium is significantly higher under stochastic lead times (MWU, $p < 0.05$). Participant-level analysis further shows that high-cost cases are typically driven by extreme imbalances, either large backlogs or large inventories as illustrated in the graphs in Appendix 3.D. These performance differences are consistent with the interpretation that stochastic lead times increase task complexity and, in turn, cognitive stress. To examine this mechanism more directly, we analyze participants' self-reported emotions collected after the experiment. Participants in the stochastic lead-time treatment report stronger negative affect overall, including higher levels of agitation, fear, challenge, and stress

Table 3.2: Descriptive statistics for inventory, backlogs, and costs (SE = standard error of the mean)

		Constant lead time treatment			Stochastic lead time treatment		
		Realized	Benchmark gap	SE	Realized	Benchmark gap	SE
Mean	Inventory	3.89	0.94	2.18	6.12	2.75	4.81
	Backlogs	1.85	0.90	1.85	2.44	1.01	2.12
	Cost	3.79	1.36	1.88	5.50	2.39	2.32
Median	Inventory	3.27	0.32		4.31	0.94	
	Backlogs	1.37	0.42		2.39	0.96	
	Cost	3.36	0.93		4.45	1.34	

compared to those in the constant lead-time treatment. The difference in the combined measure is significant (MWU, $p < 0.10$), and the difference in stress alone is also significant (MWU, $p < 0.10$). These findings indicate that higher task complexity leads to greater cognitive stress, supporting the view that bounded rationality is at play and contributes to reduced decision performance. We next examine ordering behavior in greater detail by estimating a behavioral decision rule following Croson and Donohue (2006).

3.4.2 Decision Rule

We examine the observed performance differences by analyzing how participants translate inventory information into order decisions. Two behavioral dimensions are particularly important for this purpose. Supply line underweighting is closely linked to efficiency losses, as insufficient attention to outstanding orders can amplify inventory fluctuations and increase costs (Sternan, 1989). Likewise, the aggressiveness of inventory corrections determines how quickly participants respond to imbalances, and weak adjustments can result in persistent excess inventories or backlogs (Croson et al., 2014).

We estimate an ordering decision rule adapted from Croson and Donohue (2006). This rule allows us to quantify how aggressively participants adjust their inventories toward desired levels and to what extent they underweight their supply line. For each participant in both treatments, we estimate non-linear least squares regressions with orders as the dependent variable. The regression follows Equation (18) for participant i in period t :

$$O_t^i = \max \left\{ 0, \alpha_0 + \alpha_I I_{t-1}^i + \alpha_B B_{t-1}^i + \alpha_D D_t^i + \alpha_R R_t^i + \alpha_{S1} S1_t^i + \alpha_{S2} S2_t^i + \epsilon_t^i \right\}. \quad (18)$$

Where O_t^i is the order placed by participant i in period t . α_0 is a constant capturing the target order-up-to level, and ϵ_t^i is a mean-zero error term. I_{t-1}^i denotes the positive inventory held in the last period, B_{t-1}^i the backlogs held in the last period. D_t^i is the realized customer demand and R_t^i the units of received orders. Under constant lead times, this always corresponds to $R_t^i = O_{t-2}^i$. Supply line inventory is separated into one-period $S1_t^i$ and two-period $S2_t^i$ outstanding orders. Orders with a lead time of two periods enter $S1_t^i$ after remaining outstanding for one period, and after two periods they are deducted from $S1_t^i$ and added to $S2_t^i$. Under constant lead times, $S2_t^i = 0$. This specification extends the decision rule of Croson and Donohue (2006) to our setting, where stochastic lead times make it necessary to distinguish between orders that are

one versus two periods away from arrival.

We estimate the parameters $\alpha_0, \alpha_I, \alpha_B, \alpha_D, \alpha_R, \alpha_{S1}, \alpha_{S2}$ subject to the constraints $\alpha_I, \alpha_R, \alpha_{S1}, \alpha_{S2} \in [-1, 0]$, $\alpha_D, \alpha_B \in [0, 1]$ and $\alpha_0 \geq 0$. The 95% confidence intervals are obtained using 500 bootstrap replications. Table 3.3 reports mean and median estimates across participants.

Table 3.3: Estimated parameters of the ordering decision rule under constant and stochastic lead times.

(R^2 denotes the pseudo adjusted R^2 . RMSE denotes the root mean square error)

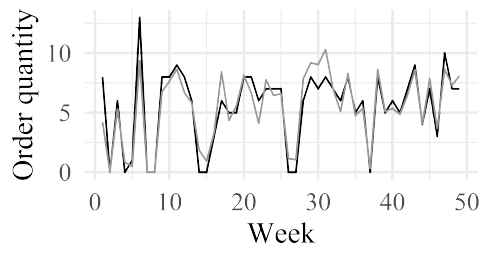
	α_D	α_R	α_B	α_I	α_{S1}	α_{S2}	α_0	R^2	RMSE
<i>Constant lead-time treatment</i>									
Mean	0.59	-0.31	0.36	-0.32	-0.13		5.02	0.53	1.99
Median	0.61	-0.26	0.33	-0.28	-0.10		4.76	0.58	1.93
Mean width of 95%	0.33	0.48	0.60	0.45	0.36		5.61		
Median width of 95%	0.28	0.48	0.61	0.45	0.45		4.94		
<i>Stochastic lead-time treatment</i>									
Mean	0.51	-0.20	0.32	-0.22	-0.13	-0.15	4.87	0.42	2.34
Median	0.56	-0.12	0.23	-0.20	-0.07	-0.15	4.42	0.43	1.97
Mean width of 95%	0.40	0.32	0.47	0.39	0.37	0.41	4.94		
Median width of 95%	0.38	0.27	0.45	0.38	0.37	0.43	4.32		

If participants ordered according to the best order-up-to policy, the estimated parameters would be equivalent across treatments. In this case, participants would fully incorporate the supply line ($\alpha_{S1} = -1$ and $\alpha_{S2} = -1$) and fully account for changes in on-hand inventory ($\alpha_I = -1$), demand ($\alpha_D = 1$), received orders ($\alpha_R = -1$) and backlogs ($\alpha_B = 1$). To achieve the best order-up-to policy, participants further need to set their target inventory to $\alpha_0 = 12$.

Table 3.3 reports the estimated parameters. The model fits the data reasonably well in both treatments, with median pseudo- R^2 values of 0.58 for the constant treatment and 0.43 for the stochastic treatment. Explanatory power is lower under stochastic lead times, reflecting greater heterogeneity in behavior between participants. Figure 3.2 complements this analysis by showing predicted and actual order trajectories for selected participants in each treatment.

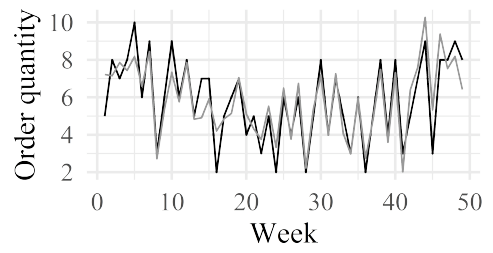
Table 3.3 shows that mean and median values of α_{S1} are slightly lower in the stochastic treatment than in the constant treatment, while α_{S2} values in the stochastic treatment are close to α_{S1} under constant lead times. This pattern is consistent with the fact that both α_{S1} under constant lead times and α_{S2} under stochastic lead times correspond to orders which arrive in the next period. However, Mann–Whitney U tests reveal no statistically significant differences between these coefficients across treatments.

To further examine the extent of supply line underweighting, we also analyze the results at the participant level. For most participants, the 95% confidence intervals of the supply line estimates include zero, suggesting they do not sufficiently consider the supply line when ordering. Only a small minority show significant effects, indicating that few participants consider their supply line when placing orders, with 1 of 29 participants in the constant treatment, 4 of 30 for α_{S1} , and 6 of 30 for α_{S2} in the stochastic treatment exhibiting significant coefficients. The proportion of participants with significant coefficients is higher under stochastic lead times, but these differences



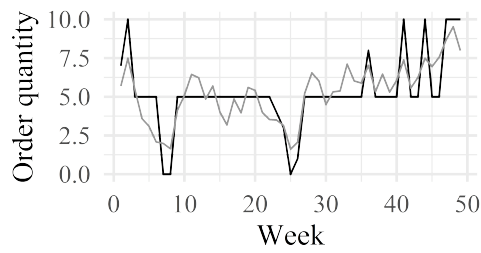
— Order — Prediction

(a)



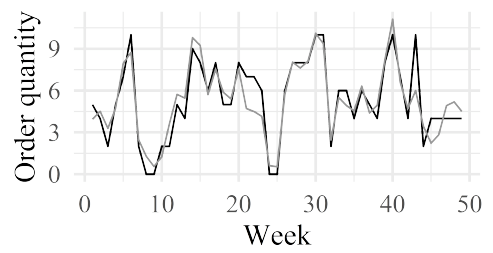
— Order — Prediction

(b)



— Order — Prediction

(c)



— Order — Prediction

(d)

Figure 3.2: Comparison of actual orders and predicted orders from the decision rule for selected participants under constant (left) and stochastic (right) lead times.

are not statistically significant (Fisher’s exact test, $p = 0.35$ for α_{S1} , $p = 0.10$ for α_{S2}). The results indicate pervasive underweighting of the supply line in both treatments. We now turn to the remaining parameters for the inventory α_I , backlogs α_B , and received orders α_R , which capture aggressiveness of inventory corrections. As shown in Table 3.3, all three coefficients are closer to zero under stochastic lead times, indicating weaker adjustments. Differences in α_R (MWU, $p < 0.10$) and α_I (MWU, $p < 0.01$) are statistically significant, while the difference in α_B is not (MWU, $p = 0.27$). When we include outliers, all three parameters become significant.

To capture the aggressiveness of inventory corrections rather than isolated coefficients, we also conducted a multivariate non-parametric test (PERMANOVA) on α_R , α_I , α_B , and α_{S1} jointly. Results show a significant treatment effect on overall adjustment behavior ($p < 0.10$). The multivariate treatment effect remains statistically significant under alternative model specifications. Specifically, we (i) re-estimate the model without the secondary supply line parameter α_{S2} , and (ii) impose structural symmetry by setting $\alpha_{S2} = \alpha_{S1}$ for the constant lead time condition. In both robustness checks, treatment differences remain significant at $p < 0.10$.

These suggest that participants under stochastic lead times corrected inventory gaps less aggressively than under constant lead times, contributing to greater oscillations in on-hand inventory and therefore in a higher cost premium for decision makers.

3.4.3 Qualitative Questionnaire

To better understand the differences in aggressiveness between treatments, we analyze participants’ responses to the open-ended question, adapted from Croson et al. (2014): “What caused your inventory/backlog to behave as it did?”. The following examples illustrate relevant explanations provided by participants:

“I always reacted directly to it, when I had backlog, I bought a lot, when I had inventory I bought less/nothing. But that made my income fluctuate a lot. It would be better to plan ahead - but planning is hard when you don’t know when things will arrive.”

“Sometimes the time that I had to wait for the arrival of my orders didn’t really help me when it came to planning my orders.”

“Randomization in terms of delivery time, if I order too little I may have to wait additional 3 weeks to cover for that, which grows my backlog”

These answers suggest that participants struggle with the additional cognitive stress imposed by stochastic lead times. While they recognized the challenge, they often lacked effective strategies to address it. As a result, participants adjust their orders less aggressively, consistent with our quantitative findings.

3.4.4 Summary and Motivation for Study 2

The results of Study 1 show that supply line underweighting persists throughout our experiment, even in a single-echelon system with relatively short lead times. Unlike

Ancarani et al. (2013), who report less underestimation of the supply line under stochastic lead times, we do not find significant differences in supply line underweighting between stochastic and constant lead times. The introduction of stochastic lead times reduces performance and weakens the aggressiveness of inventory corrections toward the desired inventory level.

Our findings are consistent with Bloomfield and Kulp (2013), who show that added complexity leads decision makers to adjust inventories less aggressively. Participants perceived the stochastic lead-time treatment as more stressful and demanding, which aligns with theories of bounded rationality. As decision environments become more complex, individuals increasingly rely on simplifying heuristics which in turn decreases performance (Gigerenzer and Selten, 2001; Simon, 1955; Su, 2008). This behavioral response does not systematically increase safety stocks. Rather, it produces more extreme inventory positions, with some participants accumulating excess inventory while others incur deeper backlogs compared to the constant lead-time treatment.

Overall, the introduction of additional risk and complexity reduces the aggressiveness of inventory corrections and increases costs. In the next study, we investigate whether removing lead time risk while maintaining dynamic lead times causes decision makers to adjust the aggressiveness of their inventory corrections toward the constant lead time benchmark and, in turn, reduce costs.

3.5 Study 2: Dynamic versus Stochastic Lead Times

Study 2 examines how providing participants with perfect information about dynamic future lead times affects their ordering behavior and costs compared to the stochastic lead-time setting. Prior research shows that sharing information generally improves coordination and performance in supply chains (Cui et al., 2015). Theoretical models further suggest that even reverse information sharing, where suppliers disclose supply-side conditions to downstream partners, can yield efficiency gains under uncertain supply (Harsha et al., 2020). Experimental evidence also shows that while upstream-to-downstream information typically has larger effects, downstream-to-upstream sharing can still improve performance (Sarkar and Kumar, 2015). Although our study uses a single-echelon setting, the dynamic treatment conceptually mirrors upstream-to-downstream information sharing, as participants receive information that would typically originate from a supplier. By providing decision makers with future lead times, the dynamic treatment reduces one dimension of supply uncertainty.

Section 3.5.1 documents a significant reduction in backlogs but no corresponding reduction in total costs. Participants also report significantly lower stress than under the stochastic lead-time treatment. The comparison with the estimated decision rule in Section 3.5.2 reveals no increase in ordering aggressiveness and no significant differences in the rule’s parameters. Insights from the qualitative questionnaire in Section 3.5.3 help explain this pattern. Participants appear to rely on policies that condition on future lead times rather than on a fixed order-up-to level. This behavior leads to larger orders ahead of longer lead times, which reduces backlogs but also increases inventory

holding costs.

3.5.1 Realized Cost, Inventories and Emotions

Table 3.4: Descriptive statistics for inventory, backlogs, and costs (SE = standard error of the mean)

		Dynamic lead-time treatment		Stochastic lead-time treatment	
		Realized	SE	Realized	SE
Mean	Inventory	6.82	5.22	6.12	4.81
	Backlogs	1.72	1.61	2.44	2.12
	Cost	5.13	2.39	5.50	2.32
Median	Inventory	5.20		4.31	
	Backlogs	1.14		2.39	
	Cost	4.11		4.45	

Table 3.4 reports mean and median values for inventory, backlogs, and costs under dynamic and stochastic lead times. We do not report the gap values since we use the same benchmark between the stochastic and dynamic case, as discussed in Section 3.3.6. For a comparison of the benchmark gap and cost premium between all three treatments, please refer to Appendix 3.E.

On average, participants in the dynamic treatment hold more inventory, though the difference is not statistically significant (MWU, $p = 0.29$). In contrast, backlogs are significantly lower under dynamic lead times (MWU, $p < 0.10$). When outliers are included, the backlog difference is no longer significant. This is due to several outlier participants holding very high inventories, which mechanically produce very low backlogs. We find no differences between treatments in order quantities (MWU, $p = 0.51$), achieved order-up-to levels (MWU, $p = 0.28$), or their respective standard deviations. Costs are slightly lower in the dynamic treatment, but the difference is also not statistically significant (MWU, $p = 0.41$). The cost premium also did not differ significantly between the dynamic and constant lead-time treatments (MWU, $p = 0.26$). Appendix 3.F presents examples from the dynamic lead-time treatment that show lower backlog levels, along with the corresponding orders and demand patterns.

Self-reported emotions indicate that participants perceive the dynamic treatment more favorably than the stochastic treatment. They report lower overall negative affect (MWU, $p < 0.05$) and felt less challenged by the task (MWU, $p < 0.05$). Stress levels alone are lower in the dynamic treatment, although the difference fell just short of significance (MWU, $p = 0.10$).

Together, these results suggest that while obtaining perfect information about future lead-times improves participants' subjective experience and appear to reduce backlogs, these benefits are offset by higher inventory holdings and thus did not translate into significantly lower costs in comparison to the stochastic lead-time treatment.

3.5.2 Decision Rule

Since the descriptive analysis reveals only a significant difference in backlogs, we use the nonlinear least squares regression (18) to compare ordering behavior in the dynamic

treatment to the stochastic lead-time treatment. We estimate the regression separately for each participant, and the results are reported in Table 3.5.

Table 3.5: Estimated parameters of the ordering decision rule under dynamic lead times (R^2 denotes the pseudo adjusted R^2 . RMSE denotes the root mean square error)

	α_D	α_R	α_B	α_I	α_{S1}	α_{S2}	α_0	R^{2*}	RMSE
<i>Dynamic lead-time treatment</i>									
Mean	0.45	-0.24	0.28	-0.25	-0.14	-0.26	6.05	0.26	2.74
Median	0.39	-0.18	0.20	-0.20	-0.10	-0.07	5.74	0.26	2.43
Mean width of 95%	0.52	0.42	0.60	0.41	0.44	0.55	6.01		
Median width of 95%	0.46	0.39	0.57	0.38	0.38	0.54	6.00		

Because the intervention removes uncertainty, our initial expectation is that participants' behavior would fall in between that of the stochastic and constant lead-time treatments. However, the explanatory power of the model is substantially lower. The median pseudo- R^2 is only 0.26 in the dynamic treatment, compared to 0.43 in the stochastic treatment and 0.58 in the constant treatment. This drop indicates that the benchmark decision rule captures participants' behavior less accurately when future lead-times are known. Figure 3.3 illustrates this pattern by comparing actual orders and model predictions for two participants: one for whom the decision rule fits closely and another showing large discrepancies between predicted and observed behavior, which are more pronounced under the dynamic treatment. To test supply-line underweighting, we

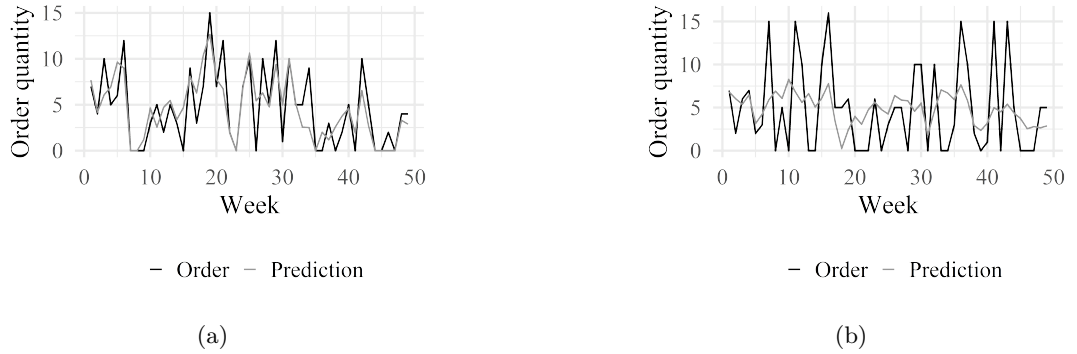


Figure 3.3: Orders and predictions by the decision rule for selected participants under dynamic lead times.

examined the coefficients for α_{S1} and α_{S2} . If participants rely on lead-time information, they might track their supply-line inventory more closely, which would be reflected in higher parameter values compared to the stochastic treatment. Mann–Whitney U tests reveal no statistically significant differences in α_{S1} or α_{S2} between treatments.

At the participant level, only a small minority exhibit significant coefficients in the dynamic treatment, with 4 out of 29 for α_{S1} and 8 out of 29 for α_{S2} . In the stochastic treatment, 4 out of 30 participants show significant α_{S1} coefficients, and 6 out of 30 show significant α_{S2} coefficients. These differences are not statistically significant (Fisher-Exact-Test, $p = 1.00$ for α_{S1} , $p = 0.552$ for α_{S2}).

Participants show a slight reduction in supply-line underweighting, but the differences are marginal and not statistically significant. Thus, participants continue to undervalue

the supply line.

We assess how aggressively participants adjusted their inventories toward their desired inventory level by examining the parameters for inventory α_I , backlogs α_B , and received orders α_R , which capture the aggressiveness of inventory corrections. While supply line parameters also reflect correction dynamics, we analyze them separately.

As shown in Table 3.5, α_I and α_R are directionally further from 0 in the dynamic treatment, while α_B is closer to 0. However, these differences are small and not statistically significant. The only coefficient that differs significantly is the order-up-to level α_0 , which is higher under the dynamic treatment (MWU, $p < 0.10$) and does not directly attribute to aggressiveness.

Consistent with these univariate findings, a non-parametric multivariate test (PERMANOVA) testing α_R , α_I , α_B , α_{S1} , and α_{S2} jointly shows no significant differences in adjustment behavior between dynamic and stochastic conditions ($p = 0.68$). This result suggests that participants did not fundamentally change the aggressiveness of their inventory corrections, contrary to our initial expectation.

3.5.3 Qualitative Questionnaire

To better understand how participants use the lead-time information, we analyze their responses to the open-ended question, “How did you determine what to order?”. Selected answers from participants in the dynamic treatment include:

“I consider the current inventory and lead week of my order, if it is too long to wait i will directly order more (e.g. about 8 or 9), because after then might no inventory anymore”

“I based my decision on th expected demand of 5. I didnt want to have backlog and decided that my inventory should be around 10 if the next shipment arrives the next week. However, if the next shipment wouldnt arrive within the next 3 weeks, the inventory should be around 20 by the start of that 3 week span.”

“depending on the delivery time I placed big orders in the weeks of short delivery time to avoid teh (higher) backlog costs”

These statements show that participants actively incorporate lead-time information. The responses indicate that participants linked longer lead times with longer risk intervals and adjusted by ordering in advance. This behavior is not well captured by decision rule (18), which explains the lower pseudo- R^2 values. Additional support for this interpretation comes from the panel regression results reported in Table 3.6. The panel regression shows that participants in the dynamic-lead-time treatment placed significantly higher orders when current lead times were short and future lead times were longer. To test this effect, we added a dummy variable we termed “anticipation” equals 1 when the current order lead time was 1 period and the next period’s order lead time was 3 periods. This condition occurred in 302 of 1,392 decisions. The random-effects regression was estimated using robust standard errors. These findings quantitatively confirm the

qualitative evidence from the open-ended responses, indicating that participants indeed incorporated lead-time information into their ordering decisions. When the full sample, including all outliers, is used, the effect becomes non-significant as several outlier observations contain extremely large orders.

Table 3.6: Panel regression of order size on hypothesized determinants

	Dynamic lead-time treatment
Constant	3.78*** (0.275)
Inventory position	-0.08*** (0.017)
Demand	0.34*** (0.037)
Supply line	-0.013 (0.034)
Anticipation	0.80* (0.33)
Overall R^2	0.179
Observations (N)	1,392

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$.

3.5.4 Summary

In Study 2, we examined whether providing perfect information about future dynamic lead-times reduces uncertainty and improves ordering performance. Participants in Study 1 reported that stochastic lead times increased cognitive stress and made planning more difficult, reflected in higher cost premiums. Prior research suggests that reducing uncertainty and increasing transparency can improve decision quality (Cui et al., 2015; Kocabiyikoğlu et al., 2024; Perera and Fahimnia, 2024). In our setting participants did not convert the additional information into lower costs and average costs were not significantly lower than in the stochastic lead-time treatment.

If reduced complexity improves decision making we should observe participants adjusting their inventories more aggressively and in a manner closer to the benchmark policy (Bloomfield and Kulp, 2013; Gigerenzer and Selten, 2001; Simon, 1955). The adjustment parameters show no such improvement which indicates that participants do not translate the reduced uncertainty into more effective correction behavior.

The qualitative responses illustrate why. Participants use the information to anticipate longer lead times and reduce backlogs, but they do so by holding higher inventory levels, which increases holding costs. These shifts move costs across categories rather than reducing them.

Taken together, the results of Study 2 show that giving participants information about future lead-times does not generate significant efficiency gains. Participants use the additional information, as reflected in their open-ended responses and higher target inventories, but these adjustments do not increase their aggressiveness of inventory corrections but to anticipate longer risk periods. This primarily shifts costs from backlogs to inventory holdings. As a result, costs are not significantly different from those in the stochastic lead-time treatment.

3.6 Discussion

This work reports results from two experimental studies on uncertainty and dynamicity of supply lead times. Across both studies, we find no systematic differences in supply line underweighting compared to the stochastic lead-time treatment. However, when lead times are stochastic, participants reduce the aggressiveness of inventory corrections. This behavior tends to increase inventories, backlogs, or both, thereby raising costs. When lead times are known but dynamic, participants use the information to anticipate longer risk intervals by ordering more in advance. While this strategy reduces backlogs, it simultaneously increases inventories, leaving overall costs statistically indistinguishable from the stochastic case.

Stochastic lead times thus lead to significant deviations from optimal order policies. For firms, this translates into higher inventory and stockout costs, reinforcing the value of automated inventory management tools and targeted training. Findings from Study 1 highlight that bounded rationality limits decision makers, as greater task complexity diminishes their ability to follow the cost-minimization objective. Even the simplest form of lead-time uncertainty, a uniform distribution between 0 and 2, amplified inefficiencies in both backlogs and inventories. Future work may examine other lead-time distributions observed in practice.

Study 2 tested an intervention in which participants are informed about future lead-times. While such perfect information may not always be feasible, real-time data sharing between supply chain partners is increasingly realistic. Our results show that participants incorporate lead-time information but do not increase the aggressiveness of their inventory corrections. Instead, they shift toward state-dependent ordering policies, which do not generate significant cost reductions in our experiment. Nonetheless, participants report feeling less stressed and challenged, suggesting that even when economic benefits are limited, informational interventions may provide valuable psychological benefits in practice.

Taken together, our findings emphasize that stochastic lead times increase costs because decision makers correct inventory positions less aggressively. While theory often models these settings under assumptions of full rationality, our results show that boundedly rational decision makers behave differently. Even simple forms of temporal uncertainty can therefore create inefficiencies in inventory management. For firms, this translates into higher inventory and stockout costs and highlights the potential value of automated decision-support systems to mitigate these effects. Providing perfect information about future lead times can reduce stress and improve the working conditions of inventory decision makers. However, without further training, such information may lead to excessive inventories and limited cost benefits. Future research should therefore examine whether targeted training or decision-support tools can help decision makers in dynamic settings use lead-time information more effectively and translate it into improved performance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data will be made available in an online repository upon acceptance of the manuscript.

Funding Sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation Process

During the preparation of this work, the author(s) used ChatGPT and Google Gemini to assist with sentence refinement as well as bug fixing in R and $\text{\LaTeX}$ code (including Figure 1). After using these tools, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix

3.A Experimental Instructions

Introduction

As part of experimental research, we want to conduct an experiment today. You can earn money in the process of the experiment. The amount of money depends on your decisions and chance. At the end of the experiment, your earnings will be paid out to you in cash. Your payoff consists of the fixed amount of 6.00 Euro and a variable bonus payment. During the experiment, we will display your currently achieved bonus payment using economic currency units (ECU), whereas 55 ECU equal 1 Euro.

On the next pages, you will find instructions on your task and more information regarding the payoff. You get to the next page by clicking the blue "Next" button.

Please read the instructions on the next page carefully. Good luck!

Figure 3.4: Experimental instructions: initial screen.

Setting

In today's task, you will take on the role as an inventory manager in a large retail company. You will make ordering decisions for a product. In each week, you will decide whether – and if yes – how many items of a product are ordered. You will face a uniformly distributed demand for the product that does not change throughout the experiment. The demand may be at least 0 and at most 10 pieces per week. Each realization has the same probability to be chosen as if you through a 10-sided dice.

After each decision, one week passes before you make another decision. Each week, you can choose a new order quantity. You maximize your profit by minimizing your cost. Your costs are the sum of backlog costs and inventory costs.

- **Backlog Costs:** These need to be paid for each unit of unsatisfied demand that you have at the end of a week. It can be considered the goodwill loss of customers expressed in monetary terms. The backlog costs equal to 1 ECU per unit and week.
- **Inventory Costs:** These are incurred for each item of on-hand inventory at the end of a week. The inventory costs equal to 0.5 ECU per piece and week.

Since only the on-hand inventory or backlog at the end of one week is considered, only one of these costs can occur in a single week.

Demand that cannot be satisfied in the same week will be backlogged. If you have enough inventory on hand, it may be satisfied in future weeks.

Due to variability in the time your truck will be in customs the order will arrive between 1 and 3 weeks, after it is placed. The transit times are uniformly distributed. Each realization has the same probability to be chosen as if you through a 3-sided dice.

The starting inventory at the beginning of the experiment is 2 pieces. In weeks 1 and 2, 5 pieces of inventory will arrive, ordered by your predecessor.

Figure 3.5: Experimental instructions: order decision screen.

Examples

Distribution

If something is uniformly distributed every value has the same chance of appearing. It can be imagined as rolling a dice. In the case of the demand distribution you can imagine it as rolling a 10-sided dice with every number having the same chance to appear.

Calculation inventory cost

In the following, you will find a short example of how your costs will be calculated:

Exemplary inventories:

- Starting on-hand inventory: 7 pieces
- Incoming orders: 3 pieces.

Exemplary Demand:

- Demand realization : 6 pieces
- Inventory at the end of the week: Starting inventory + incoming orders – demand realization = $7 + 3 - 6 = 4$

Cost:

- Inventory cost: $4 * 0.5 = 2$
- Backlog cost: $0 * 1 = 0$
- Total cost = Inventory cost + Backlog cost = 2

Calculation backlog cost

In the following, you will find a short example of how your costs will be calculated:

Exemplary inventories:

- Starting on-hand inventory: 2 pieces
- Incoming orders: 3 pieces.

Exemplary Demand:

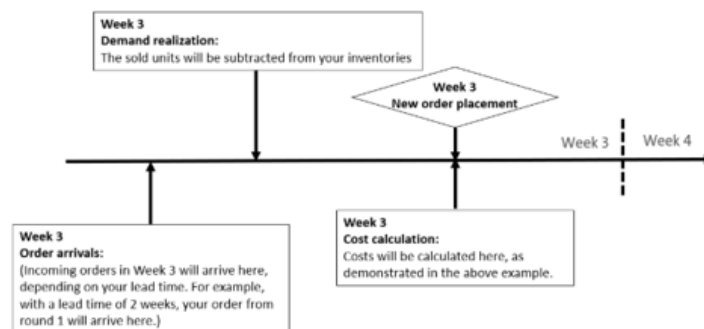
- Demand realization : 7 pieces
- Inventory at the end of the week: Starting inventory + incoming orders – demand realization = $2 + 3 - 7 = -2$
- This implies that the on-hand inventory is 0 pieces and the backlog is 2 pieces.

Cost:

- Inventory cost: $0 * 0.5 = 0$
- Backlog cost: $2 * 1 = 2$
- Total cost = Inventory cost + Backlog cost = 2

Figure 3.6: Experimental instructions: feedback screen.

Below, you will find a timeline visualizing the order in which the events occur.



Please note that if the lead time is 1 week, the order will arrive before the demand realization of the next week occurs. This means you will not see it under "Outstanding orders" but only under "Order arrivals this week".

Figure 3.7: Experimental instructions: forecast information.

Payoff

You have a budget for every week. Your costs get subtracted from this budget to calculate your earnings. The costs subtracted from your budget are your profit for that week. The sum of your profits over all weeks played is the basis for the bonus payment. The conversion rate will be 55 ECU to 1 Euro. Your base payment is €6.00 Euro. You will have a budget of 15 ECU for each week. In the following, you will find a short example of the calculation of your earnings:

Profits and payoff conversion:

- Let your total cost of the week be 3 ECU.
- $(15 - 3) / 55 = 0.22$. This amount of earnings would convert to 22 Cents.

Figure 3.8: Experimental instructions: summary screen.

Inventory data type	Explanation	Example value
On hand inventory	Your on hand inventory is calculated by last week's on hand inventory minus backlogs plus order arrivals minus demand. If this total becomes negative, your on-hand inventory is set to 0, and you generate backlogs.	E.g. 2
Outstanding orders	These are the outstanding orders that have not yet arrived and will arrive in a later week.	E.g. 5
Backlogs	This is your backlog of customer orders. Backlogs are created if the customer demand is larger than last week's on hand inventory minus backlogs plus order arrivals. Backlogs carry over to the next week and do not disappear unless satisfied.	E.g. 0
Order arrivals this week	This is the total number of pieces in the orders that arrived this week.	E.g. 3
Demand in this week	This is the customer demand you have to satisfy this week.	E.g. 9
Inventory cost	This is your inventory multiplied by your cost per piece of inventory at the end of the week.	E.g. 1
Total cost in week	This is your backlog cost plus your Inventory cost.	E.g. 1
Total profit over all weeks	This is calculated by calculating Total budget over all weeks - Total cost over all weeks.	E.g. 9

Figure 3.9: Experimental instructions: final screen.

3.B Outliers and generated costs

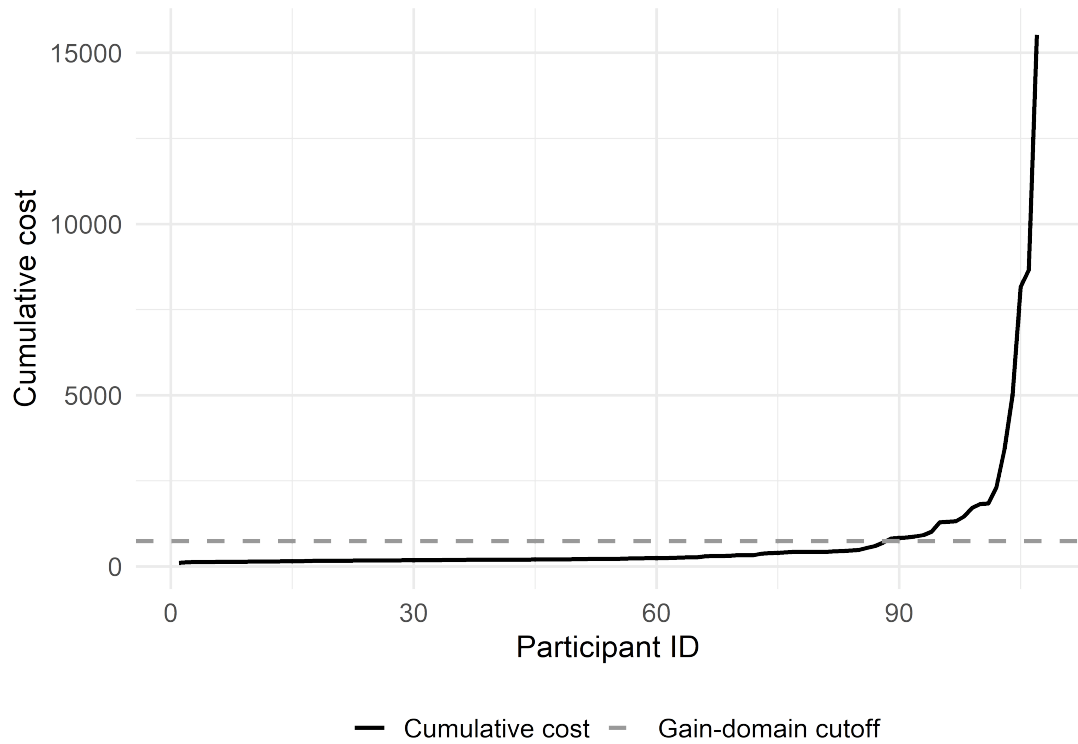


Figure 3.10: Cumulative costs by participant with gain-dDomain exclusion criterion

3.C Benchmark Results

Table 3.7: Benchmark result for the best order-up-to level, average inventory, backlogs and costs

	Constant lead times (1 period)	Uniformly distributed lead times (0–2 periods)
order-up-to-level	12	12
Inventory	2.95	3.37
Backlogs	0.95	1.43
Cost	2.43	3.11

3.D Orders, inventory, and demand for selected participants under stochastic and deterministic lead times

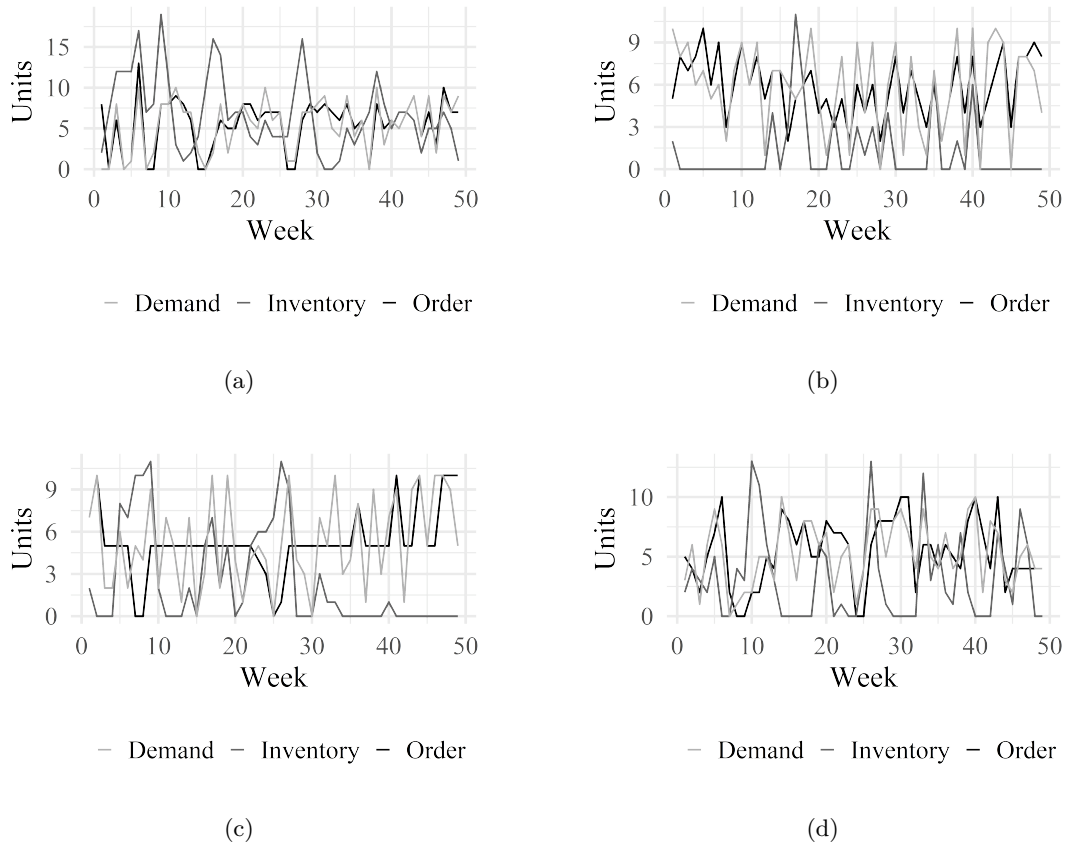


Figure 3.11: Orders, inventory, and demand for selected participants under constant (left) and stochastic (right) lead times. Negative inventory values represent backlogs.

3.E Comparison of Benchmark Gaps and Cost Premium between Treatments

Table 3.8: Comparison of benchmark gaps and cost premium between treatments

		Constant lead time		Dynamic lead time		Stochastic lead time	
		treatment		treatment		treatment	
		Benchmark gap	SE	Benchmark gap	SE	Benchmark gap	SE
Mean	Inventory	0.94	2.18	3.45	5.22	2.75	4.81
	Backlogs	0.90	1.85	0.29	1.61	1.01	2.12
	Cost	1.36	1.88	2.02	2.39	2.39	2.32
Median	Inventory	0.32		1.83		0.94	
	Backlogs	0.42		-0.29		0.96	
	Cost	0.93		1.00		1.34	

3.F Orders, inventory, and demand for selected participants under dynamic lead times

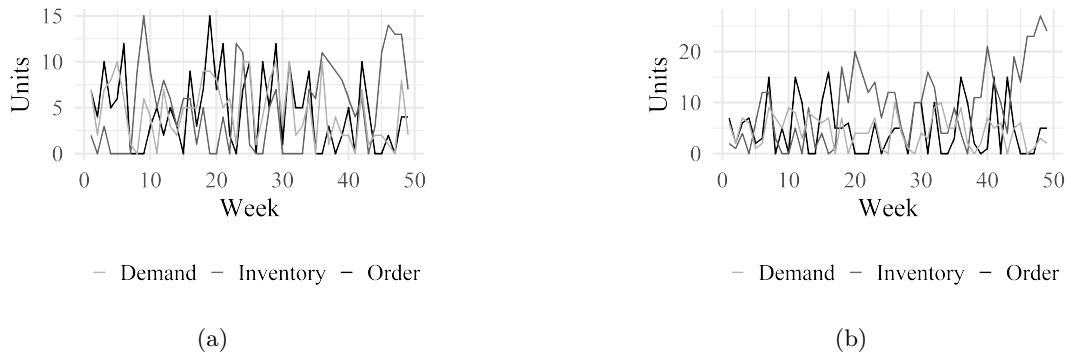


Figure 3.12: Orders, inventory, and demand for selected participants under dynamic lead times. Negative inventory values represent backlogs.

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4 Chapter 4

Revisiting Consumer Responses to Stockouts in Fast Moving Consumer Goods

Alexander Daniels

Abstract

This paper studies consumer responses to out-of-stock situations in the U.S. fast moving consumer goods market using new survey data. It revisits key findings from studies conducted in the early 2000s and shows that several broad response patterns remain stable over time. At the same time, the results indicate meaningful changes for specific product categories. The analysis further shows that planned purchases continue to affect stockout responses in a manner broadly consistent with earlier findings, while the role of hedonic products differs more substantially from prior evidence. Overall, the results suggest that stockout response patterns remain partly stable, but not unchanged. Substitution within the store remains the dominant response, postponement accounts for only a small share of cases, and a substantial proportion of stockouts lead either to no purchase or to store switching. These findings have implications for retail operations and suggest that accounting for lost sales may be important in inventory policies for fast moving consumer goods.

Keywords: Stockouts, Lost sales, Backlogging, Inventory management, Fast moving consumer goods, Hedonic products

4.1 Introduction

In the early and mid 2000s, several survey-based studies examine stockout responses for fast moving consumer goods and document how consumers distribute their responses across the main stockout options (Zinn and Liu, 2001; Corsten and Gruen, 2003; Sloat et al., 2005; van Woensel et al., 2007; Miranda and Jegasothy, 2007; Miranda, 2008; Campo et al., 2000). This paper revisits these findings and examines whether these response distributions remain stable over time.

A substantial body of literature examines lost sales (Bijvank and Vis, 2011; Gijsbrechts et al., 2022) and substitution behavior (Netessine and Rudi, 2003) in inventory systems. Behavioral operations research often relies on backlogging assumptions as a benchmark (Croson et al., 2014; Cui et al., 2015; Haeussler et al., 2021), primarily as a simplifying assumption, despite empirical evidence that lost sales are frequently the dominant outcome. This study revisits this claim using contemporary data.

The managerial relevance of this question is also substantial. In the United States, restaurants, grocery stores, and food service companies together account for about 40% of food waste (Recycle Track Systems, 2026). At the same time, Purdue's Consumer

Food Insights Report shows that the average reported out of stock rate for foods in 2024 is 9.5% (Koppes, 2025). These patterns indicate that product availability and consumer stockout responses remain important for both retail operations and waste related decisions. This study therefore provides updated evidence on how consumers distribute their responses across stockout options and on whether backlogging systems adequately reflect actual customer behavior.

Revisiting this topic may shed light on changes in consumer behavior, as several structural and contextual factors have evolved over the past two decades. First, shopper demographics have changed. Earlier work emerges in a context in which women were more dominant in grocery shopping, whereas evidence from the late 2010s suggests that men and women now shop for groceries at nearly equal rates (Macdonald, 2017). A generational shift may also be relevant. Sloot et al. (2005) treat age largely as a proxy for factors such as available time, while still showing that age significantly correlates with stockout responses. Given that two decades represent a meaningful generational change, it is important to examine whether these age-related differences persist (Strauss and Howe, 1991; Costanza et al., 2012). This issue is particularly relevant in light of population aging in many countries, which may further shift the distribution of stockout responses. In addition, more recent developments may have influenced both consumer perceptions and behavior in stockout situations. The growth of online grocery shopping, post-pandemic inflation in grocery prices, trade policy changes such as tariffs, geopolitical conflicts, and the global egg shortage may all have affected how consumers respond to stockouts (Tyrväinen and Karjalainen, 2022; Giannone and Primiceri, 2024; Bandyopadhyay et al., 2025; Rose et al., 2023; Gunjan et al., 2026). Together, these developments suggest that earlier benchmark results should be reassessed using contemporary data.

The analysis focuses in particular on comparisons with Corsten and Gruen (2003) and Sloot et al. (2005), which approach stockout behavior from different perspectives. While Corsten and Gruen (2003) synthesize evidence from multiple studies to provide an international overview of stockout responses, Sloot et al. (2005) use hypothetical scenarios to analyze the underlying drivers of these decisions. Both papers continue to be widely cited. For example, Sloot et al. (2005) was cited 66 times between 2020 and 2025 according to the Web of Science database, indicating its continued relevance. Although the journal in which Corsten and Gruen (2003) was originally published is not indexed in the Web of Science, the study remains frequently cited in recent research (Kalantary et al., 2023; Menezes and Pinto, 2022; Best et al., 2022). To examine current stockout responses and compare them with earlier findings, this study conducts an online survey with 300 participants. The survey records both experienced stockouts and stated choices in hypothetical stockout situations. Most products for the hypothetical stockout scenarios are based on Corsten and Gruen (2003) to ensure comparability. In addition, the survey includes an extra hedonic product and measures whether purchases are planned in order to connect the analysis to Sloot et al. (2005).

Comparing experienced and hypothetical stockout situations, we find a high degree of

consistency in response patterns, suggesting that hypothetical scenarios can provide meaningful insights. Comparing our findings with Corsten and Gruen (2003), important differences emerge across product categories, indicating that stockout responses have changed over time for some products but remain stable for others.

A similar pattern is observed for the determinants of stockout decisions. While some factors, such as age, remain consistent with earlier findings, others, such as the role of hedonic goods, differ substantially. Overall, the evidence suggests that stockout response patterns remain broadly stable, although several meaningful differences emerge that warrant further investigation.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the survey design. Section 4 reports the results. Section 5 concludes with a discussion and implications.

4.2 Literature review

4.2.1 Out-of-stock literature

A large body of literature has examined consumer responses to retail stockouts. Table 4.1 summarizes key findings from prior empirical studies. Across these studies, substitution within the same store consistently emerges as the dominant response, followed by store switching and postponement, while complete purchase abandonment is relatively rare. Peckham (1963) provides one of the earliest empirical studies of stockouts and consumer decisions under stockout using supermarket exit interviews. Emmelhainz et al. (1991) extend this line of research using in-store interviews in a grocery discounter setting in the Netherlands. Verbeke et al. (1998) conduct a field experiment combined with telephone surveys to analyze how store-related and situational characteristics affect consumer responses to stockouts. Zinn and Liu (2001) further examine the role of situational factors and consumer characteristics such as brand loyalty and perceived time pressure, finding that situational factors dominate demographic characteristics in explaining behavior.

Corsten and Gruen (2003) provide one of the most widely cited syntheses of stockout research, combining evidence from multiple studies and a large international sample of over 70,000 consumers. Their results confirm that most consumers either substitute within the store or switch stores, while postponement and purchase cancellation are less frequent. Sloot et al. (2005) show that stockout reactions depend on both brand equity and the hedonic nature of the product category. This research is extended to perishable products by van Woensel et al. (2007), who find substantially higher substitution rates in bakery categories. Miranda and Jegasothy (2007); Miranda (2008) demonstrate that consumer responses vary across countries, with consumers in emerging markets being more likely to adjust purchases within the store rather than switch stores.

More recent research extends stockout reactions to online retail settings. Gruen and Corsten (2021) examine non-availability in online retail across multiple countries and show that consumers respond through a range of switching behaviors, including switching stores, brands, channels, or purchase intentions. Their findings suggest that responses

vary more strongly across countries than across product categories and depend on how non-availability is communicated.

Overall, while substitution emerges as the dominant response across studies, substantial variation exists across product categories, retail formats, and geographic contexts.

Table 4.1: Consumer Responses to Retail Stockouts in Prior Literature

Study	Context	Subst.	Switch	Postp.	No purch.
Peckham (1963)	US stores	58%	–	–	42%
Emmelhainz et al. (1991)	Disc. NL	73%	14%	13%	–
Zinn et al. (2001)	US survey	62%	23%	15%	–
Gruen et al. (2003)	Multi-country	45%	31%	15%	9%
Sloot et al. (2005)	NL stores	54%	19%	23%	3%
van Woensel et al. (2007)	Bakery	84%	6%	10%	–
Miranda & Jegasothy (2007)	Malaysia	62.2%	18.6%	19.2%	–

4.2.2 Customer Satisfaction

Many works focus on the impact of stockouts on customers rather than on the immediate choices they make. Fitzsimons (2000) show that stockouts decrease consumers’ satisfaction with the decision process and increase the likelihood of switching stores on subsequent shopping trips. Hoang and Breugelmans (2023) examine consumer reactions to retailer-suggested substitutions in online grocery shopping. Using scenario-based experiments, they show that substitution acceptance depends on the retailer’s substitution policy and consumers’ perceptions of fairness and control. Anderson et al. (2006) examine stockouts in a catalog retailing environment. Using field data, they show that orders containing out-of-stock items have significantly higher cancellation rates and that retailer responses to stockouts influence customer satisfaction. Their results highlight that stockouts can have broader order-level consequences beyond the unavailable item itself.

Kök and Fisher (2007) develop a methodology to jointly estimate consumer substitution behavior and optimize assortment and inventory decisions in retail settings. Using store-level data, they show that incorporating substitution into assortment planning significantly improves profitability. Ge et al. (2009) complement the stockout literature by showing that sold-out cues affect the evaluation of remaining options, often increasing their perceived attractiveness and reducing choice deferral. Similarly, Parker and Lehmann (2011) demonstrate that shelf-based scarcity leads consumers to infer that scarcer available options are more popular and of higher quality, which increases their likelihood of being chosen. These findings provide a behavioral explanation for why consumers are more likely to substitute rather than postpone or cancel purchases in the presence of stockouts.

Taken together, these studies highlight that stockout responses are not only immediate behavioral reactions but also influence future shopping behavior and customer satisfaction.

4.2.3 Operational Implications of Stockouts and Substitution

In addition to consumer behavior research on stockouts, operations management studies examine the implications of substitution for inventory performance. For example, Pritchard et al. (2023) analyze how stockout-driven customer switching affects item and category fill rates using simulation modeling. Their results show that substitution can substantially alter realized service levels and create risk pooling effects across products. Smith and Agrawal (2000) analyze multi-item retail inventory systems with demand substitution and show that optimal assortment and inventory decisions depend strongly on the structure of substitution behavior, highlighting that ignoring substitution can lead to suboptimal stocking policies. Mahajan and van Ryzin (2001) examine assortment planning under substitution using choice models and demonstrate that accounting for consumer substitution behavior is critical for optimal assortment decisions.

Disney et al. (2021) analyze the dynamics of inventory systems with lost sales and show that lost sales reduce the bullwhip effect compared to backlogging systems. They further demonstrate that approximating lost sales through backlogging leads to significant errors unless safety stock levels are sufficiently high. Hübner and Kuhn (2012) develop an integrated model for assortment planning, shelf space allocation, and replenishment in fast-moving consumer goods retail. They show that accounting for substitution effects and replenishment constraints jointly leads to significant profit improvements.

Taken together, these studies demonstrate that consumer substitution behavior is a critical input for inventory and assortment decisions. Ignoring substitution can lead to biased estimates of service levels and suboptimal stocking policies, while properly accounting for substitution enables improved demand estimation, better assortment design, and more accurate evaluation of stockout costs. Despite the extensive literature on stockout responses and their operational implications, most empirical evidence on consumer reactions is based on data collected in the 1990s and early 2000s or in specific regional contexts. This raises the question of whether these response patterns remain stable in modern retail environments, particularly given changes in consumer behavior and retail formats. The present study addresses this gap by providing an updated empirical assessment of consumer responses to in-store stockouts in a contemporary U.S. sample.

4.3 Survey design

4.3.1 Survey protocol

The experiment is programmed in the Python-based software oTree (Chen et al., 2016). A total of 300 participants are recruited via Prolific using filters to obtain a sample representative of the United States by age, sex, and race from a pool of 93,087 eligible subjects. The sample distribution is reported in Appendix 4.A. The survey is conducted online in March 2026.

The first part of the survey asks whether participants experienced any stockouts while shopping for groceries within the previous 12 months. If participants select “yes”, they

provide additional information about the product name, the store in which it was purchased, whether the purchase was planned, and the action taken. This part of the survey is repeated up to three times, allowing each participant to report a maximum of three experienced stockouts. Previous work, such as (Corsten and Gruen, 2003), uses responses to actual stockouts. To replicate this approach, the present study includes this first part and uses it to assess how hypothetical responses compare with experienced stockouts.

The second part consists of a hypothetical study that asks participants how they would react if their preferred item in a specific product category were out of stock. Participants indicate whether the purchase is usually planned and which action they would take in the event of a stockout. The hypothetical study includes five core product categories that every participant evaluates. In addition, up to three extra questions are shown, depending on how many experienced stockouts participants report in the first part of the survey. In total, each participant answers eight stockout questions across both parts of the survey. Previous studies, such as Sloot et al. (2005), employ hypothetical stockout scenarios because they allow for the examination of specific product categories and improve comparability across respondents.

At the end of the survey, participants answer demographic questions and provide information about their shopping behavior. Screenshots of representative questions from each part of the survey, including the demographic questionnaire, are provided in Appendix 4.B.

The median completion time is three minutes and one second, and participants receive £0.47 per submission. Responses are screened for unusually short completion times. No responses are excluded, with completion times ranging from 57 seconds to twelve minutes and one second.

4.3.2 Product choices for hypothetical questions

The products in the hypothetical questions are largely based on the categories reported in Corsten and Gruen (2003). The five core products and three additional products are shown in Table 4.2. The core products are presented first in randomized order, followed by the additional products, which are also randomized.

Corsten and Gruen (2003) also include diapers and feminine hygiene products. These categories are excluded because a substantial share of participants may not be able to provide meaningful responses. In addition, toilet tissue is excluded due to its close similarity to paper towels, to avoid redundancy in the product set.

Following Sloot et al. (2005), this study examines whether differences between hedonic and utilitarian goods persist. Sloot et al. (2005) show that store switching is significantly more likely for hedonic goods. Therefore, cola is added to the core items to ensure sufficient representation of hedonic products. For the additional set, one more hedonic item and one utilitarian food item are included. The classification of goods as hedonic or utilitarian is based on prior studies and is implemented as a binary variable in this study (Sloot et al., 2005; Galan-Ladero et al., 2013; Wang et al., 2025).

Table 4.2: Product characteristics and sample sizes

Product	Set	Gruen et al. (2003)	Hedonic	n
Paper towel	core	X		300
Salted snacks	core	X	X	300
Toothpaste	core	X		300
Shampoo	core	X		300
Cola	core		X	300
Cookies	extra		X	143
Laundry detergent	extra	X		137
Oatmeal	extra		X	132

4.3.3 Choices

Previous studies typically distinguish between five possible responses to a stockout situation: switching the intended purchase, postponing the purchase, substituting with the same brand, substituting with a different brand, and switching stores (Zinn and Liu, 2001; Corsten and Gruen, 2003; Sloot et al., 2005; van Woensel et al., 2007; Miranda and Jegasothy, 2007).

In this study, these categories are adapted with one modification. Substitutions with the same brand and with a different brand are aggregated into a single substitution category. This reflects the operations management perspective of the study, where the focus is on stock keeping units rather than brand equity. It also allows the analysis to focus on general purchase patterns rather than differences in brand dominance.

4.3.4 Planned purchases and questionnaire

This study measures several factors identified by Sloot et al. (2005) as influencing consumer responses to stockouts. The first factor is whether a purchase is planned. This variable is recorded for each experienced stockout question and for each hypothetical stockout question. It is defined as a binary variable equal to one if the purchase was planned in the experienced case and if it is usually planned in the hypothetical case, and zero otherwise.

Additionally, a control variable is introduced for participants who report at least one stockout in the first part of the survey. This variable, labeled experienced, equals one if one or more stockout questions are answered and zero otherwise.

The questionnaire includes demographic questions on age and sex, followed by questions on shopping behavior. Age is recorded in years and scaled by a factor of 1/100 in the analysis, following Sloot et al. (2005). Sex is coded as a binary variable equal to one for female and zero otherwise. The shopping behavior questions cover the preferred type of grocery store, with response options comprising supermarkets, discounters, corner stores, and other formats. Further questions measure price consciousness, quality consciousness, stockpiling behavior, and shopping attitude. All items are measured on a Likert scale from 0 to 4, labeled from strongly disagree to strongly agree. A screenshot of the questionnaire is provided in Appendix 4.B.

4.4 Results

4.4.1 Descriptive results

A total of 205 out of 300 participants answer at least one experienced stockout question. In total, 488 experienced stockouts are recorded. The reported stockouts are grouped into 18 categories, with each stockout treated as one observation. Seven of these categories contain 30 or more observations. All categories are reported in Table 4.3. The distribution of responses for categories with at least 30 observations is shown in Figure 4.1. Additional descriptive results for categories with fewer than 30 observations are provided in Appendix 4.C.

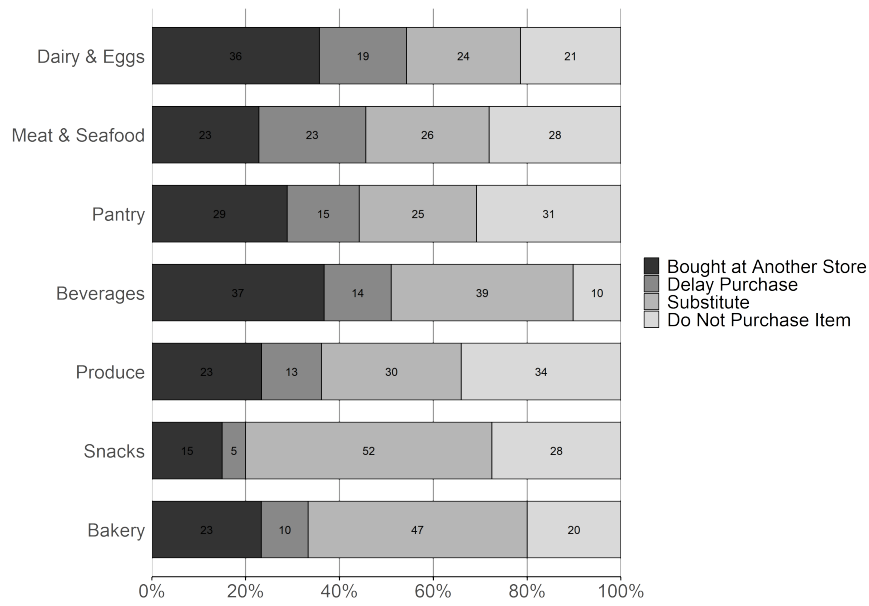


Figure 4.1: Consumer responses by category (categories with at least 30 observations)

The five hypothetical stockout questions for the core products are answered by all 300 participants, while the additional products receive between 132 and 143 responses, as shown in Table 4.2. The corresponding results are presented in Figure 4.2.

The majority of participants report that they usually shop for groceries in supermarkets, accounting for 92.3% of responses, followed by discounters at 4.7%, corner stores at 1.7%, and other store types at 1.3%. A similar pattern is observed for experienced stockouts, with 85% occurring in supermarkets, 5.5% in discounters, 2.3% in corner stores, and 7.2% in other store types.

Regarding planned purchases, participants report in the hypothetical questions that 81.2% of purchases are usually planned, while 18.8% are unplanned. In contrast, 99.6% of experienced stockouts are associated with planned purchases, with only 0.4% classified as unplanned.

Participants are also more likely to make unplanned purchases for hedonic goods than for utilitarian goods (Fisher exact test, $p < 0.001$).

A direct comparison between experienced and hypothetical stockouts is challenging due to differences in product composition. Experienced stockouts consist predominantly of

Category	Frequency
automotive	2
baby food	1
bakery	30
beverages	49
condiments	25
dairy & eggs	70
frozen foods	20
gaming	1
general merchandise	25
household	12
meat & seafood	57
misc	3
pantry	52
personal care & health	27
pet	9
produce	47
snacks	40
vegan alternatives	18

Table 4.3: Frequency of consumer responses by category

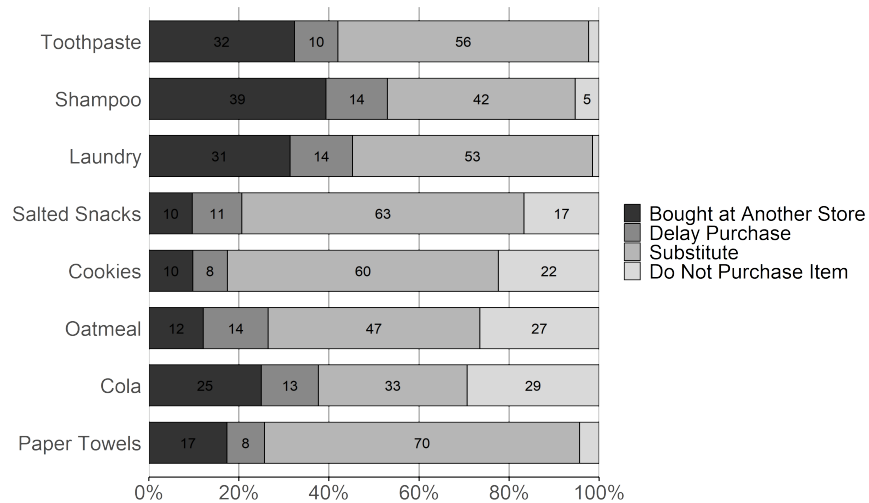


Figure 4.2: Consumer responses for hypothetical stockout questions

food items, accounting for 83.8%, while the hypothetical questions include 40% food items in the core set and 67% in the extra set. Moreover, certain products, such as eggs, may lack close substitutes within a store, which can affect response behavior.

A comparison is most feasible for snacks, which include both salty snacks and sweets. Comparing experienced stockouts in snacks to hypothetical responses for salted snacks shows that 15% of experienced stockouts lead to store switching, compared to 10% in the hypothetical setting. Postponement occurs in 5% of experienced cases and in 11% of hypothetical responses. Substitution is observed in 52% of experienced stockouts, compared to 63% in the hypothetical setting. Finally, 28% of experienced stockouts result in no purchase, compared to 17% in the hypothetical responses.

A Stuart–Maxwell test is conducted for the 31 paired observations of participants who answer both experienced and hypothetical stockout questions for snacks ($\chi^2(3) = 4.96, p = 0.175$). The results indicate no significant difference in response behavior between the two conditions. These findings should be interpreted with caution because the comparison is based on a limited sample and a single product category.

Overall, substitution is more common in hypothetical stockout responses, while the other response categories are less frequent compared to experienced stockouts. This pattern may be driven by differences in product composition. Another explanation is that participants report realized actions rather than initial intentions in experienced stockouts, particularly if acceptable substitutes are also unavailable. This suggests a direction for future research.

4.4.2 Effect of hedonic goods and planned purchases

Sloot et al. (2005) show that whether a product is hedonic and whether purchases are planned can have substantial effects on consumer responses. This section examines whether these effects persist.

As participants provide multiple responses, a random effects multinomial logit model with robust standard errors is used. The model accounts for the panel structure of the data by including an individual-specific effect. The probability $P_{j,i,t}$ that participant i chooses option j in question t is given by Equation (19). The denominator sums over all J available alternatives, where m is an index over the choice set.

$$P_{j,i,t} = \frac{\exp(V_{j,i,t})}{\sum_{m=1}^J \exp(V_{m,i,t})} \quad (19)$$

The utility $V_{j,i,t}$ is defined in Equation (20). The coefficients β_{kj} capture the effects of the corresponding explanatory variables on utility, while $u_{j,i}$ represents the individual-specific effect.

$$\begin{aligned} V_{j,i,t} = & \beta_{1j} \text{hedonic}_{i,t} + \beta_{2j} \text{Planned purchase}_{i,t} + \beta_{3j} \text{Age}/100_i \\ & + \beta_{4j} \text{Female}_i + \beta_{5j} \text{Price consciousness}_i \\ & + \beta_{6j} \text{Quality consciousness}_i + \beta_{7j} \text{Stockpiling}_{i,t} \\ & + \beta_{8j} \text{Shopping attitude}_i + \beta_{9j} \text{Experienced}_i + u_{j,i}. \end{aligned} \quad (20)$$

The estimation uses only observations from the core set of hypothetical stockout questions, as the additional questions are answered by a subset of participants, which may introduce bias. Average marginal effects for all four choices are reported in Table 4.4. Hedonic products are associated with a significantly higher probability of no purchase and a lower probability of substitution and store switching. Planned purchases show a strong and significant negative effect on no purchase and a positive effect on store switching.

Table 4.4: Average Marginal Effects of the Multinomial Logit Model

	No Purchase	Substitute in Store	Switch Store	Postpone
Hedonic	0.109*** (0.017)	-0.045* (0.026)	-0.088*** (0.022)	0.024 (0.017)
Planned purchase	-0.184*** (0.015)	0.016 (0.046)	0.143*** (0.043)	0.025 (0.028)
Age/100	0.049 (0.053)	-0.172* (0.101)	0.144* (0.086)	-0.021 (0.067)
Female	0.014 (0.017)	-0.048 (0.033)	0.017 (0.029)	0.017 (0.020)
Price consciousness	0.000 (0.008)	-0.010 (0.017)	0.005 (0.016)	0.005 (0.011)
Quality consciousness	0.016 (0.012)	-0.032* (0.019)	0.032 (0.020)	-0.017 (0.013)
Stockpiling	0.014* (0.008)	-0.004 (0.014)	-0.001 (0.014)	-0.009 (0.009)
Shopping attitude	-0.014** (0.007)	-0.012 (0.013)	0.021 (0.013)	0.005 (0.008)
Experienced	-0.037** (0.017)	0.064** (0.033)	-0.031 (0.028)	0.004 (0.020)
Observations	1,500			

Notes: Entries are average marginal effects. Robust standard errors are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Sex does not have a significant effect on the observed choices. Age is negatively associated with substitution within the store and positively associated with store switching. As noted by Sloot et al. (2005), age may act as a proxy for time constraints, as older consumers may be more willing to switch stores rather than substitute.

Price consciousness does not show significant effects. Quality consciousness reduces the likelihood of substitution, which is consistent with the idea that consumers with strong quality preferences are less willing to accept alternatives. Stockpiling shows a significant effect only for the no purchase option, which may reflect that consumers with existing inventory are less likely to purchase when a product is unavailable. Shopping attitude has a negative effect on no purchase, indicating that consumers with a stronger preference for shopping are less likely to forgo the purchase.

Participants who report experienced stockouts are less likely to choose no purchase and more likely to substitute within the store. This contrasts with the descriptive results, where experienced stockouts show higher rates of no purchase and lower substitution compared to hypothetical responses.

4.4.3 Comparison to Corsten and Gruen (2003)

The results of Corsten and Gruen (2003) are compared to the findings of this study using the core product set. The differences are summarized in Table 4.5. To ensure comparability, only core items are used in this analysis. Overall, the results indicate

Table 4.5: Change in consumer responses compared to Corsten and Gruen (2003) (percentage points)

	No Purchase	Substitute	Switch Store	Postpone	<i>p</i> -value*
Salted Snacks	+0.7	+3.7	-5.3	+1.0	0.264
Toothpaste	-4.7	+15.7	-4.7	-6.3	< 0.001
Shampoo	-1.7	-3.3	+7.3	-2.3	0.276
Paper Towels	-7.7	+14.0	+4.3	-10.7	< 0.001
All (core products)	-3.3	+7.5	+0.4	-4.6	—

Positive values indicate an increase relative to the original study.

**p*-values are based on Pearson chi-square goodness-of-fit tests comparing the distribution of responses in Corsten and Gruen (2003) with the current study.

a decrease in no purchase and postponement, while substitution increases and store switching remains relatively stable. Chi-square tests are used to assess whether the distributions differ significantly from those reported by Corsten and Gruen (2003). The results show that shampoo and salted snacks do not differ significantly from the original findings, while paper towels and toothpaste exhibit significant differences, even after applying the Bonferroni correction. This suggests that responses to some product categories remain stable.

The experienced stockouts also indicate the emergence of product categories not considered in earlier studies. For example, vegan alternatives account for 18 observations and show a relatively high rate of store switching (39%). While these findings should be interpreted with caution due to the limited sample size, they suggest that changes in product assortments may influence stockout responses.

4.4.4 Comparison to Sloot et al. (2005)

When comparing our results to those of Sloot et al. (2005), substitution and store switching remain relatively similar, with substitution decreasing slightly from 54% to 52% and store switching increasing from 19% to 25%. Larger differences are observed for no purchase and postponement. The share of no purchase responses increases from 3% reported by Sloot et al. (2005) to 12% in the current study, whereas postponement decreases from 23% to 11%.

The multinomial logit results are also compared with those reported by Sloot et al. (2005). Several differences in study design should be noted. The present study uses a subset of the control variables employed by Sloot et al. (2005), while additionally including controls for experienced stockouts and gender. The product set also differs, as it is primarily based on Corsten and Gruen (2003), with the exception of cola, which is included as a hedonic product following Sloot et al. (2005). Furthermore, Sloot et al. (2005) collect one observation per participant, whereas the present study uses multiple observations per participant and accounts for individual-specific effects.

Brand-level distinctions are not considered, as substitutions within and across brands are aggregated into a single category. In addition, unlike Sloot et al. (2005), no purchase and postponement are analyzed separately, as both response categories are sufficiently large in the present survey.

Table 4.6 provides a detailed comparison of the estimated marginal effects and significance levels between the present study and Sloot et al. (2005).

For hedonic products, Sloot et al. (2005) report a positive effect on store switching. In contrast, the present analysis finds a significant negative effect on store switching and substitution, alongside a positive effect on no purchase. This indicates a shift in the role of hedonic products in stockout situations.

For planned purchases, the results are consistent with Sloot et al. (2005), showing a decrease in no purchase and an increase in store switching. As Sloot et al. (2005) aggregate no purchase and postponement, the present results provide additional detail by showing that the effect is primarily driven by no purchase.

Table 4.6: Comparison of Marginal Effects with Sloot (2005)

Variable	Substitute in Store			Store switch		No purch. / postpone		
	2026	2005		2026	2005	2026		2005
		Brand	Item			No purch.	Postp.	
Hedonic	-0.045*	0.10	-0.30	-0.088***	0.50**	0.109***	0.024	-0.30
Planned purchase	0.016	0.30	0.00	0.143***	0.17***	-0.184***	0.025	-0.20***
Age/100	-0.172*	-0.29**	-0.05	0.144*	0.25**	0.049	-0.021	0.09
Price consciousness	-0.010	0.20	-0.01	0.005	-0.03**	0.000	0.005	0.02
Quality consciousness	-0.032*	-0.04*	0.00	0.032	0.01	0.016	-0.017	0.03
Stockpiling	-0.004	0.03	-0.17***	-0.001	-0.10**	0.014*	-0.009	0.24***
Shopping attitude	-0.012	-0.03	0.03	0.021	0.01	-0.014**	0.005	-0.01

Notes: Entries are average marginal effects.

Sloot (2005) separates substitution into brand and item substitution.

The final column reports the aggregated no-purchase/postponement outcome from Sloot (2005).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Shopping attitude does not show significant effects in Sloot et al. (2005), while Campo et al. (2000) suggest a positive relationship with store switching. The present results indicate a significant effect on no purchase, with a positive but not statistically significant effect on store switching. Stockpiling shows directionally similar effects to Sloot et al. (2005), but differs substantially in statistical significance. While Sloot et al. (2005) report significant effects across multiple outcomes, the present analysis finds a significant effect only for the no purchase option.

The results for age and quality consciousness are consistent with those reported by Sloot et al. (2005).

Overall, the results indicate that while several patterns remain consistent with earlier findings, notable differences emerge across product categories and behavioral factors.

4.5 Discussion

No significant difference is observed between experienced and hypothetical stockouts for salted snacks. The underlying data, however, indicate lower substitution rates and higher shares for all other response options in experienced stockouts. This may be driven by differences in product composition or by participants reporting realized behavior

rather than initial intentions, particularly if acceptable substitutes were also unavailable. As the comparison is limited to a single product category, this warrants further research. The results also suggest that changes in product assortments may affect stockout responses over time. For example, vegan alternatives appear as a distinct category in the experienced stockouts.

The comparison between experienced and hypothetical stockouts further suggests that participants are more likely to recognize stockouts for planned purchases than for impulse purchases, which may introduce a bias in reported experienced stockouts.

4.5.1 Comparison to Corsten and Gruen (2003) and Sloot et al. (2005)

We summarize the findings of our comparison with Corsten and Gruen (2003) and Sloot et al. (2005) in Table 4.7.

Overall, the findings indicate that stockout responses in fast moving consumer goods remain partly stable, while significant changes occur for specific product categories. The results from the multinomial logit model support this conclusion, as some effects remain consistent with earlier findings, while others differ in significance or direction. This highlights the relevance of continued research on stockout behavior.

More broadly, the findings are consistent with Corsten and Gruen (2003) in showing that postponement remains the least frequent response, while substitution represents the largest share and lost sales, through no purchase or store switching, account for a substantial portion of stockout outcomes. At the same time, some differences in response patterns emerge, which may be related to product characteristics, particularly the distinction between hedonic and utilitarian goods. A clear causal relationship between product characteristics and these shifts cannot be established within the scope of this study and could be examined in future research. This suggests that stockout responses have evolved over time and highlights the importance of revisiting this area to better understand contemporary consumer behavior as a basis for inventory management.

Table 4.7: Summary of Consistency with Corsten and Gruen (2003) and Sloot et al. (2005)

Comparison	Consistent	Differences	
		Variable	Type
Corsten and Gruen (2003)			
<i>Response distribution</i>	Salted snacks Shampoo	Toothpaste Paper towels	Different category pattern Different category pattern
Sloot et al. (2005)			
<i>Coefficient estimates</i>	Planned purchase Age Quality consciousness	Hedonic Price consciousness Stockpiling Shopping attitude	Opposite sign Significance change Significance change Significance change

Notes: Consistent findings align with the respective benchmark study.

4.5.2 Managerial implications

An increasingly aging population is observed in many countries. As previous research shows, age significantly influences stockout responses, potentially acting as a proxy for

time availability (Sloot et al., 2005). The present results confirm that this relationship persists, with older consumers being more likely to switch stores and less likely to substitute within a store. This implies higher costs of stockouts, as lost sales are more likely to shift to competitors rather than being captured through substitution.

In contrast, the shift toward a more balanced gender distribution in grocery shopping does not appear to significantly affect stockout responses. The effects of hedonic goods differ from those reported by Sloot et al. (2005), leading to lower substitution and store switching rates and higher rates of no purchase. Planned purchases significantly reduce the likelihood of no purchase, primarily through increased store switching.

The results further indicate that 11% of hypothetical stockout responses and 15% of experienced stockouts lead to postponement. These values are consistent with the existing literature, as shown in Table 4.1. This is particularly relevant given that many models in operations management assume backlogging, while the data suggest that the majority of stockouts result in lost sales. The findings therefore highlight the importance of incorporating lost sales and partial substitution into inventory models.

From an operations perspective, these findings suggest that inventory models based on full backlogging may not accurately represent actual consumer responses to stockouts in fast moving consumer goods settings, where postponement represents only a small share of outcomes and substitution and lost sales play a central role.

4.5.3 Limitations

This study has several limitations that provide opportunities for future research.

First, the study relies on an online survey, whereas earlier studies often use in-store or telephone data collection. This difference in methodology may affect the comparability of results.

Second, several control variables used in prior research, such as store- and situation-specific factors, are not included. While this results in a more streamlined survey design, it may affect the estimated relationships.

Finally, the analysis is conducted from an operations perspective, leading to the aggregation of within-brand and between-brand substitution into a single category. This simplifies the analysis but excludes brand-related effects that may influence consumer behavior.

Investigating these aspects in future research may help to better understand changes in consumer behavior over the last two decades. In particular, the role of brand-related factors, which are not considered in this study, may provide an important avenue for further research.

Declaration of Generative AI and AI-Assisted Technologies in the Manuscript Preparation Process

During the preparation of this work, the author used ChatGPT to assist with sentence formulation and bug fixing in R code and LaTeX. After using this tool, the author

reviewed and edited the content as needed and take full responsibility for the content of the published article.

Appendix

4.A Survey demographics

Table 4.8: Demographic characteristics of the sample

Demographic variable	(%)
<i>Sex</i>	
Male	49
Female	51
<i>Age</i>	
18–24	12
25–34	17
35–44	17
45–54	16
55–100	38
<i>Race</i>	
White	63
Black	12
Asian	6
Mixed	11
Other	8

Notes: Age brackets, race, and sex classifications follow the categories provided by Prolific. The survey questionnaire does not collect information on race and allows for a non-binary gender option. All analyses in this study are based solely on the data collected within the survey questionnaire.

4.B Survey

Survey

Have you experienced a stockout in the last 12 months?

☒ Yes

☐ No (adds 3 hypothetical shopping situations)

Product type

Before entering the store, had you planned to buy this item?

Yes No

Store type

Supermarket Discounter Corner store

Other

What did you do?

Buy a substitute product in this store Go to another store to buy this item Buy this item later in this store

Do not buy this item or a substitute

Next

Figure 4.3: Example of an experienced stockout question

Shopping Scenario

Scenario 1 of 8

Item: cola

Imagine you are shopping in a grocery store. You want to buy your usual **cola**. When you get to the shelf, it is out of stock. What would you be most likely to do?

Do you usually plan to buy this item before entering the store?

Yes No

What would you be most likely to do?

Buy a substitute product in this store Go to another store to buy this item Buy this item later in this store Do not buy this item or a substitute

Next

Figure 4.4: Example of a hypothetical stockout question

Survey

Please answer the following questions.

What is your age?

What is your gender?

☐ Male ☐ Female ☐ Diverse

What type of store do you usually frequent?

☐ Supermarket ☐ Discounter ☐ Corner store ☐ Other

I always focus on the price when I am shopping for groceries.

☐ Strongly disagree ☐ Disagree ☐ Neither agree nor disagree ☐ Agree ☐ Strongly agree

I always focus on the quality of products when I am shopping for groceries.

☐ Strongly disagree ☐ Disagree ☐ Neither agree nor disagree ☐ Agree ☐ Strongly agree

I tend to buy extra groceries to keep at home for future use.

☐ Strongly disagree ☐ Disagree ☐ Neither agree nor disagree ☐ Agree ☐ Strongly agree

I generally enjoy grocery shopping.

☐ Strongly disagree ☐ Disagree ☐ Neither agree nor disagree ☐ Agree ☐ Strongly agree

Next

Figure 4.5: Example of the demographic questionnaire

4.C Additional descriptive results

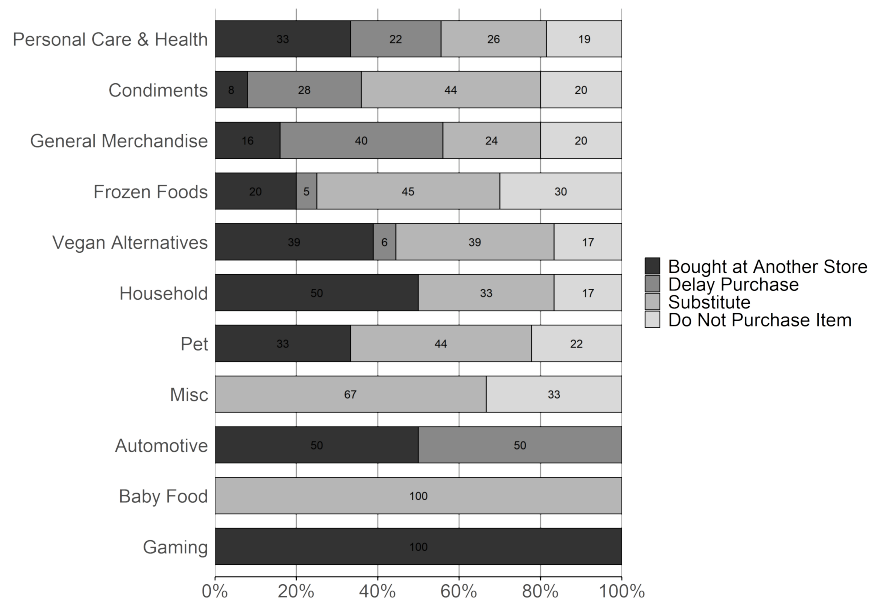


Figure 4.6: Consumer responses by category for categories with fewer than 30 observations

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A Summary

This dissertation combines three papers that examine behavioral factors influencing inventory decisions. Chapter 2 shows that two nearly equivalent inventory policies, a reorder point policy and a Kanban policy, can lead to different decision behavior due to differences in framing and decision space. A laboratory experiment compares performance under the two policies in a repeated decision environment with feedback. The results show statistically significant profit differences in the first decisions, before learning effects reduce the performance gap. A second study uses a survey to examine whether the observed decision patterns also occur under different demand settings. The main findings suggest that participants interpret the two policy parameters differently across policies. Under the reorder point policy, the parameters appear to be interpreted additively, while under the Kanban policy they appear to be interpreted multiplicatively. In addition, the restricted decision space under Kanban excludes several poorly performing parameter combinations that remain possible under the reorder point policy. These findings are relevant for the selection and implementation of inventory policies, as initial performance differences may justify investment in a Kanban setup. However, because these differences diminish quickly, such investment appears relevant primarily for high-value goods.

Chapter 3 examines how exogenous stochastic lead times influence ordering decisions in the downstream firm. A laboratory experiment compares ordering behavior under constant lead times and stochastic lead times. The results show that stochastic lead times reduce the aggressiveness of inventory corrections compared to constant lead times. This weaker adjustment behavior contributes to higher inventories, backlogs, or both. In addition, participants report higher stress under stochastic lead times than under constant lead times. A further comparison examines deterministic but dynamic lead times against stochastic lead times. Providing information about future lead times reduces uncertainty and lowers reported stress, but does not significantly reduce total costs. Participants use the additional information to anticipate longer lead times, which reduces backlogs but increases inventory holdings. The results therefore indicate that stochastic lead times lead to higher costs and that lead time information alone may reduce stress without necessarily improving cost performance.

Chapter 4 addresses how consumers respond to stockouts in fast moving consumer goods. This is relevant because inventory models often assume pure backlogging, whereas empirical evidence from the early 2000s on consumer responses to stockouts challenges this assumption. Given the age of this evidence, this chapter reinvestigates whether this claim still holds. Chapter 4 uses contemporary survey data and compares the results with selected earlier studies. The findings show that stockout response distributions remain stable for some product categories but differ significantly for others. The results also indicate that the effect of certain product characteristics, such as whether a good is hedonic, differs from earlier evidence. In line with prior studies, substitution within the same store remains the dominant response. Postponement, which is most closely related to backlogging assumptions, is the smallest response category. By contrast, store

switching and no purchase account for a sizable share of responses and point to the importance of lost sales in inventory model specification.

B Zusammenfassung

Diese Dissertation umfasst drei Beiträge, die verhaltensbezogene Faktoren in Bestandsentscheidungen untersuchen. Kapitel 2 zeigt, dass zwei nahezu äquivalente Bestandspolitiken, eine Bestellpunktpolitik und eine Kanban Politik, aufgrund von Unterschieden im Framing und im Entscheidungsraum zu unterschiedlichem Entscheidungsverhalten führen können. Ein Laborexperiment vergleicht die Leistung unter beiden Politiken in einem mehrperiodischen Experiment mit Feedback. Die Ergebnisse zeigen statistisch signifikante Gewinnunterschiede in den frühen Entscheidungen, bevor Lerneffekte die Leistungsunterschiede verringern. Eine zweite Studie verwendet eine Umfrage, um zu untersuchen, ob die beobachteten Entscheidungsmuster auch unter unterschiedlichen Nachfrageparametern auftreten. Die zentralen Ergebnisse deuten darauf hin, dass Teilnehmende die beiden Politikparameter je nach Bestandspolitik unterschiedlich interpretieren. Unter der Bestellpunktpolitik scheinen die Parameter additiv interpretiert zu werden, während sie unter der Kanban Politik multiplikativ interpretiert werden. Zusätzlich schließt der eingeschränkte Entscheidungsraum unter Kanban einen großen Teil von Entscheidungen aus, die niedrigen Profite haben. Diese Ergebnisse sind relevant für die Auswahl und Implementierung von Bestandspolitiken, da anfängliche Leistungsunterschiede eine Investition in ein Kanban-System rechtfertigen können. Da diese Unterschiede jedoch schnell abnehmen, scheint eine solche Investition vor allem für hochwertige Güter relevant zu sein.

Kapitel 3 untersucht, wie exogene stochastische Lieferzeiten Bestellentscheidungen im nachgelagerten Unternehmen beeinflussen. Ein Laborexperiment vergleicht das Bestellverhalten unter konstanten Lieferzeiten mit stochastischen Lieferzeiten. Die Ergebnisse zeigen, dass stochastische Lieferzeiten die Aggressivität von Bestandskorrekturen im Vergleich zu konstanten Lieferzeiten verringern. Dieses schwächere Anpassungsverhalten trägt zu höheren Beständen, Backlogs oder beidem bei. Zusätzlich berichten Teilnehmende unter stochastischen Lieferzeiten ein höheres Stressniveau als unter konstanten Lieferzeiten. Ein weiterer Vergleich untersucht deterministische, aber dynamische Lieferzeiten im Vergleich zu stochastischen Lieferzeiten. Die Bereitstellung von Informationen über zukünftige Lieferzeiten reduziert Unsicherheit und senkt das berichtete Stressniveau, führt jedoch nicht zu einer signifikanten Verringerung der Kosten. Die Teilnehmenden nutzen die zusätzlichen Informationen, um längere Lieferzeiten zu antizipieren, wodurch Rückstände reduziert, aber Lagerbestände erhöht werden. Die Ergebnisse deuten daher darauf hin, dass stochastische Lieferzeiten zu höheren Kosten führen und dass Informationen über Lieferzeiten zwar Stress reduzieren können, ohne jedoch zwangsläufig die Kosten zu verringern.

Kapitel 4 untersucht, wie Konsumentinnen und Konsumenten auf Stockouts bei Fast Moving Consumer Goods reagieren. Dies ist relevant, da Bestandsmodelle häufig auf der Annahme von Backlogging basieren, während empirische Evidenz aus den frühen 2000er-Jahren zu Konsumentenreaktionen auf Out-of-Stock-Situationen diese Annahme infrage stellt. Aufgrund des Alters dieser Evidenz untersucht dieses Kapitel erneut, ob diese Aussage weiterhin Bestand hat. Kapitel 4 verwendet aktuelle Umfragedaten

zu erlebten und hypothetischen Stockout Situationen und vergleicht die Ergebnisse mit ausgewählten früheren Studien. Die Ergebnisse zeigen, dass die Verteilungen der Stockout Reaktionen für einige Produktkategorien stabil bleiben, sich für andere jedoch signifikant unterscheiden. Darüber hinaus weisen die Ergebnisse darauf hin, dass sich der Einfluss bestimmter Produkteigenschaften, etwa ob ein Gut hedonisch ist, von früherer Evidenz unterscheidet. In Übereinstimmung mit früheren Studien bleibt die Substitution innerhalb desselben Geschäfts die dominante Reaktion. Die Produkte später zu kaufen, was am engsten mit Backlogging Annahmen verbunden ist, stellt die kleinste Kategorie in den möglichen Kategorien dar. Im Gegensatz dazu machen den Wechsel des Ladens und das Produkt nicht kaufen einen erheblichen Anteil der Reaktionen aus und verdeutlichen die Bedeutung von Lost Sales für die Spezifikation von Bestandsmodellen.

C List of articles

None of the articles are currently published.

Table C.1: List of articles

Title	Authors	Status
Points and Cards – A behavioral view of decision making under equivalent order policies	Alexander Daniels, Guido Voigt	Submitted to Decision Sciences
Behavioral Aspects of Uncertain Arrival Times in Inventory Decisions	Alexander Daniels, Guido Voigt, Florian E. Sachs	Submitted to the International Journal of Production Economics
Revisiting Consumer Responses to Stock-outs in Fast Moving Consumer Goods	Alexander Daniels	Not submitted

D Authors' Contribution

This section shows the authors' contribution to the different papers.

Table D.1: Points and Cards – A behavioral view of decision making under equivalent order policies

Task	Involved authors
Concept Development	Alexander Daniels, Guido Voigt
Manuscript Preparation	Alexander Daniels, Guido Voigt
Experimental Design	Alexander Daniels, Guido Voigt
Coding of Experiment	Alexander Daniels
Survey Design	Alexander Daniels, Guido Voigt
Coding of Survey	Alexander Daniels
Statistical Analysis	Alexander Daniels

Table D.2: Behavioral Aspects of Uncertain Arrival Times in Inventory Decisions

Task	Involved authors
Concept Development	Alexander Daniels, Guido Voigt, Florian E. Sachs
Manuscript Preparation	Alexander Daniels, Guido Voigt, Florian E. Sachs
Experimental Design	Alexander Daniels, Guido Voigt, Florian E. Sachs
Coding of Experiment	Alexander Daniels
Statistical Analysis	Alexander Daniels

Table D.3: Revisiting Consumer Responses to Stockouts in Fast Moving Consumer Goods

Task	Involved authors
Concept Development	Alexander Daniels
Manuscript Preparation	Alexander Daniels
Survey Design	Alexander Daniels
Coding of Survey	Alexander Daniels
Statistical Analysis	Alexander Daniels

E Use of Auxiliary Tools

The following software tools were used to support the preparation of this dissertation.

Table E.1: Software used in the preparation of the dissertation

Software	Use
Microsoft Office	Initial data cleaning and formatting
LaTeX, Overleaf	Preparation and formatting of the manuscript
R	Statistical calculations and creation of figures
Stata	Statistical calculations and creation of figures
Python, oTree, PyCharm	Creation of surveys and experiments
MATLAB	Creation of simulations for benchmark calculations

Declaration of Generative AI and AI Assisted Technologies in the Manuscript Preparation Process

During the preparation of this dissertation, including its individual chapters, ChatGPT was used to support language editing, sentence formulation, coding support and bug fixing in R, MATLAB, and LaTeX code. In all cases, the initial manuscript of each part of the dissertation was written without the use of generative AI. Generative AI was used only after initial drafting for language refinement and technical support. The same applies to statistical calculations. The initial code for statistical analyses was written without the help of generative AI. Generative AI was later used for bug fixing, code refinement, and the implementation of additional code functionality where the analytical objective had been specified by the author. Only in the case of figures created in R was the initial code created directly with the support of generative AI and then adjusted by the author. All AI assisted output was reviewed, critically assessed, and edited where necessary.

The author takes full responsibility for the content of this dissertation.

The following tables specify the use of generative AI in the various parts of this dissertation.

Table E.2: Use of generative AI in dissertation sections outside the individual papers

Task	Use of generative AI
Manuscript preparation	LaTeX code debugging, including support for table creation
Synopsis	Language editing and phrasing support
Summary	Language editing and phrasing support
Kurzfassung	Language editing and phrasing support
List of articles	Language editing and phrasing support
Authors' contribution	Language editing and phrasing support
Use of auxiliary tools	Language editing and phrasing support

Table E.3: Use of generative AI in Chapter 2

Task	Use of generative AI
Concept Development	No use
Manuscript Preparation	Conversion of a Word file to LaTeX and LaTeX code debugging, including support for table creation. Language editing and phrasing support
Experimental Design	No use
Coding of Experiment	Bug fixing
Survey Design	No use
Coding of Survey	Bug fixing, Coding support
Statistical Analysis	Bug fixing, Coding support

Table E.4: Use of generative AI in Chapter 3

Task	Use of generative AI
Concept Development	No use
Manuscript Preparation	LaTeX code debugging, including support for table creation. Language editing and phrasing support
Experimental Design	No use
Coding of Experiment	Bug fixing, Coding support
Statistical Analysis	Bug fixing, Coding support

Table E.5: Use of generative AI in Chapter 4

Task	Use of generative AI
Concept Development	No use
Manuscript Preparation	LaTeX code debugging, including support for table creation. Language editing and phrasing support
Survey Design	Used for Feedback to my idea
Coding of Survey	Bug fixing, Coding support
Statistical Analysis	Bug fixing, Coding support

F Eidesstattliche Erklärung

Hiermit erkläre ich, Alexander Daniels, an Eides statt, dass ich die

Dissertation mit dem Titel "Behavioral Inventory Management: Supply Uncertainty, Policy Choice, and Stockout Responses"

selbstständig – und bei einer Zusammenarbeit mit anderen Wissenschaftler:innen – gemäß der beigefügten Darlegung nach § 6 Abs. 4, 5, 7 der geltenden Promotionsordnung der Fakultät für Betriebswirtschaft (University of Hamburg Business School) verfasst und keine anderen als die von mir angegebenen Hilfsmittel benutzt habe. Die den herangezogenen Werken wörtlich oder sinngemäß entnommenen Stellen sind als solche gekennzeichnet.

Ich versichere, dass auch im Anwendungsfall von generativer Künstlicher Intelligenz (genKI) meine eigene schöpferische Leistung der erhebliche Anteil in dieser Dissertation ist. Ich bin für ggf. durch genKI generierte Inhalte, die Einhaltung urheberrechtlicher Bestimmungen, meine eigenständige Erstellung sowie für die wissenschaftliche Integrität meiner Dissertation selbst verantwortlich.

Ich versichere, dass ich keine kommerzielle Promotionsberatung in Anspruch genommen habe und die Arbeit nicht schon in einem früheren Promotionsverfahren im In- oder Ausland angenommen oder als ungenügend beurteilt worden ist.

Ich versichere, dass diese Druckausführung mit meiner Originalunterschrift zu 100 % der PDF-Datei entspricht, die ich zur Begutachtung eingereicht habe, und dass alle möglichen später erforderlichen Drucke dieser Dissertation ebenfalls zu 100 % diesem Druckexemplar und der eingereichten PDF-Datei entsprechen.

Ort, Datum

Unterschrift