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DECISION MAKING IN SUPPLY CHAINS WITH WASTE CONSIDERATIONS

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Abstract

As global population and income levels have increased, so has the waste generated as a byproduct of our production and consumption processes. Approximately two billion tons of municipal solid waste are generated globally every year – that is, more than half a kilogram per person each day. This waste, which is generated at various stages of the supply chain, has negative environmental effects and often represents an inefficient use or allocation of limited resources.

With the growing concern about waste, many governments are implementing regulations to reduce waste. Waste is a often consequence of the inventory decisions of different players in a supply chain. As such, these regulations aim to reduce waste by influencing inventory decisions. However, determining the inventory decisions of players in a supply chain is not trivial. Modern supply chains often consist of numerous players, who may each differ in their objectives and in the factors they consider when making decisions such as how much product to buy and when. While each player makes unilateral inventory decisions, these decisions may also affect the decisions of other players. This complexity makes it difficult to predict how a policy will affect profit and waste outcomes for individual players and the supply chain as a whole.

This dissertation studies the inventory decisions of players in a supply chain when faced with policy interventions to reduce waste. In particular, the focus is on food supply chains, where food waste and packaging waste are the largest waste components.

Chapter 2 studies a two-period inventory game between a seller (e.g., a wholesaler) and a buyer (e.g., a retailer) in a supply chain for a perishable food product with uncertain demand from a downstream market. The buyer can differ in whether he considers factors affecting future periods or the seller's supply availability in his period purchase decisions – that is, in his degree of strategic behavior. The focus is on understanding how the buyer's degree of strategic behavior affects inventory outcomes. Chapter 3 builds on this understanding by investigating waste outcomes and how policies that penalize waste affect individual and supply chain profits and waste.

Chapter 4 studies the setting of a restaurant that uses reusable containers instead of single-use ones to serve its delivery and take-away orders. With policy-makers discouraging the use of single-use containers through surcharges or bans, reusable containers have emerged as an alternative. Managing inventories of reusable containers is challenging for a restaurant as both demand and returns of containers are uncertain and the restaurant faces various customers types. This chapter investigates how the proportion of each customer type affects the restaurant's inventory decisions and costs.

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Chapter 1

Introduction

Approximately two billion tons of municipal solid waste[1] are generated globally every year (Kaza et al. 2018). The amount of waste generated as a byproduct of our production, consumption, and disposal decisions has increased substantially over the past century due to factors that include population growth and rising incomes (Hoornweg & Bhada-Tata 2012, Kaza et al. 2018).

Waste is problematic for various reasons. First, depending on how waste is disposed of, it can lead to negative externalities in the form of pollutants and toxins that affect both human and animal life. Globally, approximately 33% of waste is openly dumped and 40% is landfilled, making these the two most prevalent disposal methods (Kaza et al. 2018). While waste in landfills can be handled in a more controlled manner to diminish the effects of toxins and pollutants compared to waste that is openly dumped, landfilling does not come without its own share of negative environmental effects. For instance, organic material, which forms a substantial proportion of landfilled waste and consists mostly of food waste[2], produces greenhouse gases as it decays. These gases include carbon dioxide and the more potent methane. To put these effects in context, landfills generate about 16% of all human-related methane emissions in the U.S., making it

[1]Municipal solid waste refers to waste from residential or commercial sources that includes commonly used items such as packaging, paper, glass, organic material (i.e., food residuals or grass trimmings), electronics, batteries, and clothing (US Environmental Protection Agency 2021).

[2]In the U.S., for example, approximately 31% of landfilled waste consists of organic material, with about 24% of landfilled waste consisting of food waste alone and the remainder of yard trimmings (US Environmental Protection Agency 2022).

the third-largest source of such emissions (US Environmental Protection Agency 2020). Aside from organic waste, containers and packaging waste also constitute a substantial proportion of landfilled waste[3]. Many of these containers and packaging items are made out of plastic. Not only are many plastics not easily recycled, but plastic can also take up to hundreds of years to degrade and releases toxins in the degradation process.

Second, waste often represents an inefficient use or allocation of resources. The inefficient use and allocation of resources is perhaps most obvious in the context of food waste. While approximately a third of food produced worldwide for human consumption is lost or wasted (United Nations Food and Agriculture Organization 2011), hunger continues to be a reality for the nearly 800 million people in the world who are undernourished (FAO et al. 2021). This situation suggests that food that may still be suitable for consumption is not able to reach people in other tiers of the supply chain who could consume this food and, as a result, is discarded as waste.

Third, in many supply chains such as in food supply chains, players that generate waste often do not directly incur a cost for it or, if they do, the cost is usually low enough to be negligible. As such, waste is often little but an inconvenience or an afterthought. Even for players that are more environmentally-conscious, the processes and the infrastructure that enable the diversion or appropriate disposal of waste may not be available.

Given growing concerns about waste, policy-makers are taking a greater interest in designing and implementing policies to reduce waste. Environmental policy-making has traditionally been focused on controlling the use of common natural resources to avoid outcomes such as the 'tragedy of the commons'[4] or controlling emissions from transportation, energy generation, and other production processes. Environmental policies consist of two broad categories of policies: command-and-control policies and market-based policies (Callan & Thomas 2013). *Command-and-control policies* establish laws or standards to control activities that have environmental consequences. Examples include limiting or banning activities that have a negative environmental

[3]In the U.S., for example, containers and packaging waste account for more than 23% of landfilled waste (US Environmental Protection Agency 2015).

[4]The 'tragedy of the commons' refers to a situation in which a good or resource that is available for shared use by multiple agents ends up being depleted or otherwise unusable due to the uncoordinated and unilateral use decisions of agents only seeking to maximize their individual benefit (Hardin 1968).

impact, setting reduction targets, or mandating the adoption of a technology or product that is less detrimental to the environment. *Market-based policies* establish economic incentives to encourage players in a supply chain to reduce the negative environmental consequences of their activities. Examples include taxing products that generate pollutants (the proverbial 'stick') or providing tax incentives or subsidies for the adoption of practices that mitigate negative environmental effects (the proverbial 'carrot'). Policy-makers may also implement a blend of both types of policies.

Many jurisdictions are setting targets and implementing regulations to reduce different types of waste, including food waste, electronic waste, textile waste, and packaging waste. The effectiveness of these policy interventions, however, ultimately depends on the decisions that the players in a supply chain make to manage their operations given these interventions. Modern supply chains are often complex and decentralized, consisting of numerous players at various tiers. These players may be heterogeneous in their objectives, in their costs, or in the factors they consider in optimizing decisions such as how much product to buy and when. While each player in the supply chain makes unilateral decisions in optimizing one or more objectives (e.g., maximizing profit, minimizing waste), these decisions frequently affect the decisions of the other players as well. This complexity makes it difficult for policy-makers to predict the effect that a policy intervention may have on individual players and across the supply chain as a whole.

In this dissertation, we study the inventory decisions of different players in a decentralized supply chain when faced with policy interventions to reduce waste. In particular we look at waste reduction policy interventions in food supply chains. We focus on the two most predominant types of waste in these supply chains: food waste and packaging waste (US Environmental Protection Agency 2015). An understanding of how policies affect inventory decisions and associated profit and waste outcomes, both for individual players and for the entire supply chain, is crucial for policy-makers to set reasonable targets and design effective policies that adequately consider the trade-offs involved. If a policy intervention is not designed with these considerations in mind, it can create significant friction for players who attempt to reduce their waste while still remaining profitable and achieving service level targets. The policy intervention may also be simply ineffective an incentive may develop for players to find ways to push waste to other players.

An increasing awareness about waste has led to a burgeoning literature in the Operations Research (OR) / Operations Management (OM) community that deals with waste. A substantial amount of literature exists on closed-loop supply chains. These supply chains are characterized by a reverse flow of products from customers to the manufacturer in addition to the traditional forward flow of product from the manufacturer to customers. Remanufacturing systems (e.g., Fleischmann et al. 1997) and repairable item systems (e.g., Guide Jr & Srivastava 1997) are some of the systems studied in this literature. The closed-loop supply chain literature deals primarily with products such as industrial machines or electrical equipment, which are characterized by relatively high recyclability and high-value components.

More recently, there is a growing interest in lower-value or lower recyclability waste streams such as food waste. Akkaş & Gaur (2021) define an agenda for research on food waste. Current studies focus on different aspects of the food waste problem. Akkaş & Honhon (2022) evaluate the effect of a retailer's inventory issuing policy (i.e., FIFO vs. LIFO) on waste. Kirci et al. (2018) consider the effect on waste of offering products in predefined package sizes as opposed to offering them in bulk, which gives the consumer the freedom to choose the exact purchase quantity. Ketzenberg et al. (2018) look at optimizing expiration dates. In this stream of literature, however, there has been little focus on how policy interventions to reduce waste affect the inventory decisions and waste of players in supply chain individually or as a whole. This dissertation presents a first step to fill this research gap.

The core of this dissertation comprises three chapters. In Chapter 2, we study a two-period inventory game between a buyer and a seller in a supply chain for a limited lifetime product, such as a perishable food product. The type of buyer that the seller faces can differ in his degree of strategic behavior – that is, in the degree to which he considers factors affecting future periods or the seller's stocking decision in his purchase quantity decision for each period. Our main interest in this chapter is to build the analytical machinery to model the interaction between the buyer and the seller and to understand how the buyer's degree of strategic behavior drives his purchase quantity and timing decisions and the seller's stocking decisions. In Chapter 3, we then build on this understanding of the inventory decisions of buyers with varying degrees of strategic behavior to investigate associated waste outcomes and we extend our model to consider policy interventions that penalize waste for the buyer and/or the seller. In Chapter 4, we take a different perspective altogether by looking at the inventory decisions of a restaurant that uses reusable containers in response to a policy intervention aimed at reducing the use of single-use containers. While we do not explicitly model the policy-maker in this dissertation, we investigate the inventory decisions of players in a supply chain for any given level of the parameters that the policy-maker can influence. We now discuss the research setting and contributions of these chapters in further detail.

In Chapter 2, entitled *Strategic Behavior in a Serial Newsvendor Setting*, we consider a supply chain consisting of a seller (e.g., a wholesaler) and a buyer (e.g., a retailer) for a perishable food product. The buyer serves a population of consumers with uncertain aggregate demand in each of the two periods of the horizon, which coincides with the product's lifetime. The buyer can buy product from the seller at the beginning of both periods and, depending on how much of his stock is demanded in the first period, he may have leftover inventory that can be sold in the second period. The seller purchases inventory to serve the buyer only once at the beginning of the horizon, before observing the buyer's demand. Because both the buyer and the seller make quantity decisions before demand is realized, thereby solving a newsvendor problem, we call this supply chain a *serial newsvendor supply chain*. Such a setting can be observed in practice, for example, in the retail and hospitality industries.

In this serial newsvendor supply chain, a buyer may be strategic in two ways: (*i*) in the degree to which he considers the remainder of the horizon and intertemporal effects in his period optimization problem and (*ii*) in the degree to which he considers the decision of other agents, namely the seller, in his period optimization problem. To model the buyer's degree of strategic behavior, we define three buyer types: a myopic buyer, a forward-looking buyer, and a sophisticated buyer. A myopic buyer, who is not strategic at all, does not consider intertemporal effects or the seller's quantity decision. A forward-looking buyer is strategic only in that he considers intertemporal effects but does not consider the seller's stocking decision. A sophisticated buyer is the most strategic buyer who considers both intertemporal effects and the seller's stocking decision.

Using a game-theoretical framework with the seller as the first-mover, we characterize the purchase decisions of each buyer type and the stocking decision of the seller facing each buyer type in a constant pricing setting. We find that a seller facing a forward-looking buyer is better off than one facing a myopic buyer as the forward-looking buyer demands more over the horizon. However, a seller facing a sophisticated buyer is worse off than a seller facing a forward-looking buyer because the sophisticated buyer's cautious purchasing behavior induces the seller to take more risk in his stocking decision. The seller is hence manipulated by the buyer to stock more and the buyer benefits from the additional supply availability. To this end, the seller is better off avoiding inventory level information sharing or making it harder for the buyer to predict inventory levels. The content of Chapter 2 is based on Perez Becker et al. (2021).

In Chapter 3, entitled *Who Should Pay for Waste? Buyer Foresight and Policy Implications in a Serial Newsvendor Setting with Waste Costs*, we build on the serial newsvendor model developed in Chapter 2. More specifically, we extend this model to study how policies that impose a cost on waste at either or both tiers of the supply chain affect overall supply chain waste given buyers with different degrees of strategic behavior. We focus on two of the buyer types examined in Chapter 2: the myopic buyer and the forward-looking buyer.

Given that the buyer and seller's equilibrium inventory decisions are sensitive to the buyer's degree of strategic behavior, our first objective is to understand whether different types of buyers imply different waste levels for a supply chain. Our second objective is to understand whether it is more beneficial to tax the upstream or the downstream agent in a supply chain and whether the effectiveness of a policy intervention to tax waste is sensitive to the buyer type.

We find that buyers that consider factors that affect future periods in their period quantity decisions are better for a supply chain, not only in terms of profit but also in terms of waste. Imposing a waste cost at either echelon of the supply chain is effective in reducing total waste, for a small decrease in profit for each agent. However, imposing a tax on the seller is more effective in reducing total waste. We provide guidance to support the decision-making process of a policy-maker in setting waste-reduction targets to balance the trade-off between waste reduction and profit loss along the supply chain. The content of Chapter 3 is based on Perez Becker et al. (2022b).

In Chapter 4, entitled *Managing Inventories of Reusable Containers for Food Take-Away at a Restaurant*, we shift our attention from food waste to packaging waste. Packaging waste from the food sector accounts for a substantial amount of waste. Given increased regulatory pressure to reduce single-use packaging waste, some restaurants are now using reusable containers for take-away and delivery orders. A third-party supplier typically provides the reusable containers and visits the restaurant regularly to deliver additional containers or collect excess containers for a fee.

While the use of reusable containers instead of disposable containers is an innovative way to reduce packaging waste, it also comes with significant operational challenges. With reusable containers, the restaurant has to manage a resource with both uncertain demand and uncertain returns. It also faces customers with different effects on the restaurant's inventory levels. Customers may simply order a meal in a clean reusable container, return a used reusable container, or do both. This last type of customers generate a *coupled demand and return*.

The restaurant decides on the number of containers that are collected/delivered when the supplier visits and the supplier visit frequency. We formulate this problem as a continuous time Markov Decision Process. Through a numerical study, we study the effect that different balances of demand and return intensities and their coupling have on the average total cost of the restaurant. We find that greater demand-to-return coupling reduces average costs, but the effects are most beneficial when the overall demand and returns of the restaurant are balanced. The restaurant can reduce costs by optimizing the supplier visit frequency in addition to the inventory level of clean containers after the supplier visit. The choice of the level of the supplier visit cost is important as smaller scale restaurants may be penalized by a larger supplier visit cost, dissuading them from participating in reusable container systems. The content of Chapter 4 is based on Perez Becker et al. (2022a).

The main findings and contributions of the three core chapters of this dissertation are summarized below:

1. We study the interaction between a seller and a buyer in a serial newsvendor supply chain to understand how the degree of strategic behavior of a buyer affects the buyer's multi-unit purchase decisions and the seller's multi-unit stocking decision. We find that:

   (a) The seller earns more profit when he faces a buyer that considers factors affecting future periods in his period purchase decisions (i.e., a forward-looking buyer) but less profit when he faces a buyer that additionally considers the seller's supply in his period purchase decisions. The latter buyer is strategically cautious in his period purchase decisions. This strategic caution manipulates the seller into taking more risk in his stocking decision over the horizon by stocking more.

   (b) The buyer benefits from considering the seller's supply availability in addition to factors affecting future periods when making period purchase decisions. Because he manipulates the seller into stocking more, the buyer is able to obtain more of the supply he seeks.

2. We extend the serial newsvendor supply chain model to investigate waste in supply chains with buyer's exhibiting different degrees of strategic behavior and to understand the effect of a policy that penalizes the buyer and/or the seller for waste in terms of profit and waste outcomes. We find that:

   (a) Both in terms of profit and waste, forward-looking buyers who consider factors affecting future periods in their period purchase decisions are better for supply chains than myopic buyers who only consider factors affecting the current period.

   (b) Imposing a waste cost on either the seller (upstream agent) or the buyer (downstream agent) are both effective interventions to reduce waste, although imposing the waste cost on the seller is slightly more effective as it limits the supply of the system and hence the possibility of waste. A policy-maker may, however, be able to achieve better outcomes in terms of both profit and waste by taxing both the buyer and the seller at possibly different rates.

3. We study the inventory decisions of a restaurant manager that uses reusable containers instead of disposable containers. We find that:

    (a) When the supplier visits, the restaurant's optimal inventory rebalancing policy is a state-dependent policy in which the optimal inventory rebalancing level depends on the number of dirty containers at the restaurant. The restaurant minimizes costs by optimizing both the supplier visit frequency and the inventory rebalancing policy.

    (b) A larger proportion of customers with coupled demand and returns is always beneficial to a restaurant. However, it is most beneficial when the restaurant's overall demand to returns ratio is balanced. It is more important for the restaurant's demand and returns to be balanced than for it to have a large proportion of customers with coupled demand and returns.

The remainder of the dissertation is structured as follows. Chapter 2 studies the inventory decisions in a serial newsvendor supply chain with multiple buyer types but without policy interventions to reduce waste. Chapter 3 studies the effect of a policy intervention that penalizes waste on waste and profit outcomes in this serial newsvendor supply chain. Chapter 4 studies the inventory decisions of a restaurant that participates in a reusable containers system in response to an effort by policy-makers to reduce packaging waste. Chapter 5 concludes with a summary of the main results.

Chapter 2

Strategic Behavior in a Serial Newsvendor Setting

2.1 Introduction

Increasing evidence suggests that economic agents exhibit varying degrees of strategic behavior in multi-period environments (e.g., Li et al. 2014, Mak et al. 2014, Osadchiy & Bendoly 2015, Soysal & Krishnamurthi 2012, Yılmaz et al. 2022). In such settings, strategic behavior is manifested in the degree to which agents account for future realizations of prices or inventory availability to guide their current decision-making when facing wait-or-buy decisions. The study of strategic behavior, which started with the seminal paper on durable goods monopolies by Coase (1972), led to a proliferating literature on the interactions between sellers and buyers endowed with varying degrees of strategic behavior. Many studies show that forward-looking buyers, who consider future price realizations over a finite horizon when deciding on when to make their purchases, strategically wait until prices are sufficiently low to purchase, thereby decreasing the seller's profit (e.g., Coase 1972, Bulow 1982, Aviv & Pazgal 2008). As a result, much of the literature has focused on how sellers can mitigate the negative effects of strategic behavior through pricing (e.g., dynamic pricing vs. price commitment) or inventory (e.g., rationing, display format) as tactical levers.

The literature to date has almost exclusively focused on the inter-temporal game between a seller and one or more buyers when buyers purchase *at most one* unit of a good. The single unit assumption is a reasonable assumption for goods that may be bought by a potentially strategic end consumer, such as consumer electronics or fast fashion items, but not as applicable for other types of settings where multi-unit purchases typically occur. Multi-unit purchases are prevalent in practice in industries such as grocery retail and hospitality. They are also prevalent at various tiers of a supply chain – that is, not only do end consumers make multi-unit purchases but so do retailers, wholesalers, and manufacturers. Consider a grocery store, for example, that decides on how many units of each of its products to purchase from a wholesaler to satisfy end consumer demand before this demand realizes. The wholesaler, in turn, also decides on how many units of product to purchase from its upstream supplier so that it can supply the grocery store. In such a situation, both the seller and the buyer make quantity decisions under demand uncertainty of varying magnitudes, which exposes them to demand mismatch risk. Since they each bear risk in their inventory decisions, both agents may have an incentive to limit their risk through inventory tactics such as rationing or changing the timing and quantities of their purchases. The seller also may seek to limit risk through pricing tactics, such as markdowns or price commitments.

Despite the prevalence of multi-unit purchases in practice, only a handful of works study the effect of strategic buyer behavior when multi-unit purchases are involved. These works focus primarily on the seller's pricing decisions. Elmaghraby et al. (2008) characterize the optimal timing of markdowns in a multi-period horizon in an auction setting when multi-unit purchases are possible. In a two-period setting with a monopolist seller and a population of buyers, Jin et al. (2021) study the optimal period prices when a buyer can purchase up to two units of a good. The authors find that the equilibrium outcomes in multi-unit purchase settings differ from those in a single-unit setting (e.g., unlike in single-unit purchase settings, the optimal first period price increases with strategic behavior).

Unlike Elmaghraby et al. (2008) and Jin et al. (2021), we abstract away from the pricing game and focus on the inventory game with multi-unit purchases. Specifically, we examine a supply chain with an upstream seller and an intermediate buyer who faces aggregate uncertain demand from downstream agents. To serve these downstream agents, the buyer purchases product from the seller before downstream demand realizes. Similarly, to serve the buyer, the seller purchases product from her supply source both before downstream demand realizes and before the buyer purchases. Since both the buyer and the seller make quantity decisions before their respective demands realize, they each may seek to limit their demand mismatch risk. The buyer's perception of this risk can be informed by the degree to which the buyer considers factors affecting future periods or the seller's supply availability in his purchase quantity decisions – that is, by his degree of strategic behavior. Accordingly, we pose two main research questions: *(i)* how do the inventory decisions of a buyer and seller differ when the buyer makes multi-unit purchase decisions and how does the buyer's degree of strategic behavior affect these inventory decisions?, and *(ii)* how is the seller's profitability affected by the buyer's degree of strategic behavior given multi-unit buyer purchases?

To study these questions, we model a supply chain consisting of an intermediate buyer and an upstream seller over a two-period horizon. Both of these agents are newsvendors. In each period, the buyer faces independent aggregate uncertain demand from a population of downstream consumers. The buyer purchases product from the seller at the beginning of each period before downstream demand realizes and may carry excess inventory over from the first to the second period. The seller purchases product from an upstream supply source at the beginning of the selling horizon. Like the buyer, the seller can carry inventory over from the first to the second period, but cannot replenish. Hence, in deciding on a stocking quantity for the horizon, the seller needs to consider the buyer's second period purchase decision. In turn, the buyer's second period decision depends on the realization of demand the buyer observes in the first period, which is unobserved by the seller. At the end of the selling horizon both agents salvage excess product.

To model the effect of strategic buyer behavior, we define three buyer types: a myopic buyer, a forward-looking buyer, and a sophisticated buyer. In defining these buyer types, our view of strategic behavior focuses on two components: *(i)* whether the buyer accounts for the entire horizon, and *(ii)* whether the buyer accounts for the seller's actions. The *myopic* buyer is our most basic buyer who exhibits no strategic behavior. He completely ignores the second period when buying in the first period.

The *forward-looking* buyer accounts for the second period and optimizes his purchase decisions over the horizon. Specifically, he considers the inter-temporal effects induced by linking the two periods. The *sophisticated* buyer goes one step further than the forward-looking buyer and additionally considers the seller's stocking decision, and hence potential inventory rationing, in his period purchase decisions.

Using backward induction to find the subgame perfect Nash equilibrium, we characterize the buyer's purchase decisions and the seller's stocking quantity for a supply chain with each buyer type. We first consider a setting in which prices are constant across periods. This abstraction enables us to focus on the inventory game as pricing no longer affects the buyer's purchase timing. As an extension, we relax this constant pricing assumption to test the robustness of our findings in a setting where the period prices can be different but are still pre-announced. We then also investigate optimal pricing policies if the seller is additionally able to set the first or second period prices.

In the constant pricing setting, we find that the forward-looking buyer buys more than the myopic buyer in the first period (as he accounts for the possibility to use leftover inventory in the second period) and less than the myopic buyer in the second period (as he has more leftover inventory). Over the horizon, though, forward-looking behavior has a demand-enhancing effect and the forward-looking buyer demands as much as or more than the myopic buyer. Due to this larger demand over the horizon, the seller facing a forward-looking buyer stocks more than one facing a myopic buyer and makes more profit. However, because the forward-looking buyer demands less in the second period than the myopic buyer, a seller facing a forward-looking buyer may also be more inclined to reduce second period overage risk by stocking less product relative to the forward-looking buyer's demand, resulting in stock-outs. For this reason, one might expect the sophisticated buyer to buy *more* in the first period to encourage the seller to stock more for the horizon. Our results show the opposite however: the sophisticated buyer buys *less* than the forward-looking buyer in the first period. The sophisticated buyer exhibits a strategic caution in his first period purchase decision, which manipulates the seller into taking a greater risk with his supply decision and stocking more over the horizon. Consequently, the seller makes less profit facing a sophisticated buyer compared to a forward-looking buyer. Therefore, the seller is better-off facing buyers with some degree of sophistication but not the full degree of sophistication. Importantly, these results persist when we relax the constant pricing assumption.

This rest of the chapter is structured as follows. Section 2.2 briefly reviews the literature. Section 2.3 describes the modeling approach. Section 2.4 formulates and solves the decision problem for the myopic and forward-looking buyers and for the seller facing these buyer types in a constant pricing setting. Section 2.5 carries out the same analysis for the sophisticated buyer and for the seller facing this buyer in a constant pricing setting. Section 2.6 extends the analysis to a setting in which the seller can markup or markdown product in the second period and examines implications for optimal markup and markdown policies. Section 2.7 concludes with our main findings and future research directions. The proofs for all our results are relegated to Appendix 2.A.

2.2 Literature Review

This research most closely relates to the expansive literature on strategic consumer behavior. Wei & Zhang (2018), Shen & Su (2007), and Elmaghraby & Keskinocak (2003) provide comprehensive reviews of strategic consumer behavior, which include, among others, specific aspects associated with strategic consumer behavior, such as consumer behavior modeling and dynamic pricing.

The majority of the strategic behavior literature focuses on the interaction between a seller and multiple atomistic buyers for a limited-lifetime product in a two-period horizon (e.g., Aviv & Pazgal 2008, Cachon & Swinney 2009). The prices set by the seller may follow either a pre-announced price path or may be dynamically set. In these studies, buyers can be heterogeneous in terms of their valuation of the product, which is modeled as a random variable, or willingness to wait, which is modeled by a discount factor. It is usually assumed that the buyer buys at most one unit of the product. The focus is then on *when* the buyer buys this *one* unit.

When strategic buyers are present, they may wait to buy the product in a lower-price period at the risk of facing a stock-out and potentially a discount to their profit. As such, they engage in inter-temporal substitution. It is generally demonstrated that forward-looking buyers hurt the seller as their expectations about future actions prove to be detrimental to the optimal choices. When the seller prices the goods over time, buyers expect the price to drop over time. Given their willingness to wait, these buyers induce the seller to drop the price. As a result, much of the literature seeks to understand the degree to which strategic consumer behavior affects seller profit and how to mitigate the negative effects of this behavior. One tactic studied to counteract strategic behavior has been price commitment by a seller (Aviv & Pazgal 2008) to discourage strategic waiting. Other tactics are inventory rationing (Liu & Van Ryzin 2008, Zhang & Cooper 2008) and dynamic pricing (Levin et al. 2010) as a function of the amount of seller inventory remaining.

Some studies have extended the number of tiers considered in their analysis to three tiers and demonstrated that strategic consumer behavior may have positive effects for sellers. Lin et al. (2018) study a model with a manufacturer, retailer, and end consumers. They find that forward-looking behavior by end consumers always benefits the manufacturer as the retailer reduces his price to discourage strategic waiting and, as a result, sells more. The retailer may also benefit from forward-looking behavior when end consumers are sufficiently patient and the manufacturer lowers his wholesale price.

With the exception of a few works, multi-unit purchases have not been treated in the literature. In an auction setting, Elmaghraby et al. (2008) study the optimal pre-announced markdown mechanism when any number of markdown steps can be implemented during the sales period and the seller has fixed capacity from the beginning. Jin et al. (2021) revisit the setting of a monopolist seller and a mass of buyers and allow the buyers to buy a second unit. They note that the marginal valuation of the second unit is less than the first and find that, unlike in single-unit purchase settings, a higher first period price is optimal when more strategic buyers are present.

Despite the lack of treatment in the literature, buyers do face multi-unit purchase decisions in practice. When the buyer is able to buy multiple units, several features of the traditional strategic consumer behavior problem change. First, if the buyer has leftover inventory after the first period, he can carry over this inventory for use in the second period, reducing his second period purchase quantity. The seller then needs to consider the uncertainty of this carry-over into his stocking decision. This notion of inventory carry-over relates to the research stream on consumer stockpiling, which often assumes a durable good, as is the case, e. g., in Su (2007). Second, the buyer can purchase the seller's entire stock upfront in the first period (assuming sufficient seller inventory). This upfront full quantity purchase can hurt the seller's profitability, especially if the seller cannot re-stock inventory during the horizon. Our main contribution is to characterize the stocking decisions in the resulting inventory game between a seller and a buyer in a supply chain when both face uncertain multi-unit demands for a limited-lifetime product. Whereas much of the strategic behavior literature focuses on pricing, our primary focus is on the inventory game between the seller and the buyer. Similar to Zhang et al. (2019), we assume that the pricing of the product follows an exogenously determined pre-announced price path.

Several studies have examined the effect of a seller revealing inventory information and of a buyer taking into consideration the seller's stocking decision when making purchase decisions. The results of these studies give mixed directional insights as to whether a seller should disclose inventory information. In a one-period model, Su & Zhang (2009) show that a seller benefits from truthfully announcing his supply. Such a quantity commitment has a demand-boosting effect as it enables consumers to better assess supply availability, encourages them to buy from the seller, and increases their willingness to pay. As a result, the seller can benefit from higher prices and increased sales. Yin et al. (2009) compare two inventory display formats: one in which the seller discloses inventory information by display his supply and another in which the seller does not reveal inventory information and displays only one unit. They find that displaying one unit creates a sense of scarcity and increases seller profits. Our results are consistent with the view that the seller benefits from not revealing inventory information. We find that a buyer who is able to accurately know the seller's stocking quantity and takes this quantity into consideration when making purchase decisions (i.e., a sophisticated buyer) manipulates the seller into stocking more. The seller is thus better off facing a buyer with some degree of strategic behavior (i.e., forward-looking buyer) but not the full degree of strategic behavior (i.e., sophisticated buyer).

2.3 Model

A seller (hereafter referred to as "she") sells a product with a limited lifetime over a two-period horizon. At the beginning of the horizon, she purchases Q units of product from an upstream agent at a unit production cost of $c > 0$. In each period, the seller sells this product at a unit sales price of $p_{U,t}$, $t \in \{1, 2\}$, with $p_{U,1}, p_{U,2} > c$ (to ensure her participation in the market). These unit sales prices are exogenous and pre-announced at the beginning of the horizon.

At the beginning of each period, the buyer (hereafter referred to as "he") seeks to purchase quantities $q_t, t \in \{1, 2\}$ from the seller. The buyer's higher order frequency compared to the seller's reflects the fact that in multi-echelon settings it is common for downstream agents to have higher order frequencies than their upstream counterparts and that these order frequencies are nested within those of the upstream's agent (e.g., Roundy 1985). The buyer faces uncertain demand in each period, denoted by the random variables D_t, $t \in \{1, 2\}$, which each have a distribution F and density f. The buyer's purchase quantity decisions are made before demand in period t is realized. If the demand realization in a period exceeds the amount of product the buyer has on-hand, he purchases additional units exactly up to his demand realization from an alternative source, albeit at a higher unit price of r. The buyer sells product to the downstream market at a unit price of $p_D > 0$, which is constant across both periods. We assume that $p_D > r > p_U$ to ensure that the buyer participates in both the regular market and the runout market. In the first period, if the demand realization is less than the quantity of product on-hand, the buyer carries over leftover inventory $y \equiv (q_1 - D_1)^+$ into the second period at zero holding cost. In the second period, if the demand realization is less than the quantity of product on-hand, because the horizon is ending, any leftover inventory is discarded at zero salvage value. Similarly, for the seller, any product not bought by the buyer during the horizon is discarded at zero salvage value.

The sequence of events is summarized as follows:

1. The seller stocks Q units for the entire horizon, which she buys at a unit cost of c.

2. At the beginning of period 1, the buyer purchases q_1 units at a unit price of $p_{U,1}$.

3. Period 1 demand, D_1, realizes. If $D_1 > q_1$, the buyer buys $D_1 - q_1$ units to satisfy his remaining demand from the alternative source at a unit runout cost of r. If $D_1 < q_1$, the buyer has leftover inventory of $q_1 - D_1$ that he carries over to period 2.

4. At the beginning of period 2, the buyer buys q_2 units at a unit price of $p_{U,2}$.

5. Period 2 demand, D_2, realizes. Once again, if demand exceeds on-hand inventory, the buyer buys $(D_2 - ((q_1 - D_1)^+ + q_2)^+$ units from the alternative source at unit runout cost of r. If demand is less than on-hand inventory, the buyer discards any remaining units at a zero salvage value.

6. The seller discards any inventory not purchased by the buyer at zero salvage value.

This sequence of events is illustrated in Figure 2.1.

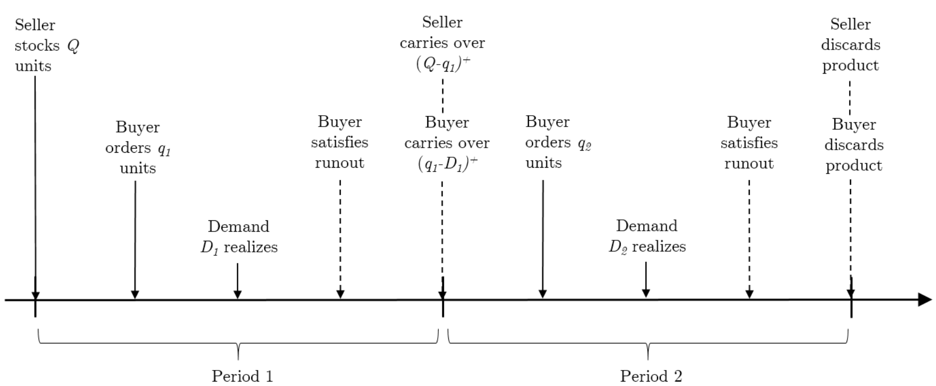


Figure 2.1: Sequence of events

In line with the sequence of events, the decision-making problem is modeled as a three-stage game. The seller is the first-mover and optimizes her stocking quantity Q over the horizon. The buyer optimizes his period purchase quantities of q_1 and q_2. The buyer's demand distribution and cost parameters are common knowledge. For each of the buyer types, we first solve for the buyer's period 2 optimal purchase quantity, q_2^*. Then, we solve for the buyer's period 1 optimal purchase quantity, q_1^*. Finally, we solve for the seller's best response in terms of a horizon stocking decision Q given the buyer's optimal purchase quantity decisions q_1^* and q_2^*.

To study the effect of different degrees of strategic behavior on inventory decisions, we define three buyer types: a myopic buyer, a forward-looking buyer, and a sophisticated buyer. We use the subscript $i \in \{M, F, S\}$ to denote the decisions associated with each buyer type, where M denotes the myopic buyer, F denotes the forward-looking buyer, and S denotes the sophisticated buyer. All three buyer types decide on their period purchase quantities based on their *perceptions* of the trade-offs. The myopic buyer optimizes each period individually and ignores inter-temporal implications. In each period, he simply observes the period price and decides on a purchase quantity for that period based on the amount of product he has on-hand and knowledge of the distribution of downstream demand. The forward-looking buyer takes into account inter-temporality by considering prices across periods, the ability to use leftover inventory from period 1 in period 2, and the upcoming discarding of leftover product at the end of the horizon at zero salvage value. He observes the pre-announced prices for period 1 and period 2 and, using knowledge of his demand distribution and other cost parameters, decides on a purchase quantity for each period.

Neither the myopic buyer nor the forward-looking buyer take into account the seller's optimal stocking decision in their optimization problems. Both buyer types assume that the seller will have sufficient stock to satisfy their calculated optimal purchase quantities in both periods. However, the seller may choose to stock a limited amount of product, which may result in stock-out instances. In such cases, the buyer will buy more units from the alternative supply source at a higher cost. Had the buyer known the seller's stocking quantity, he might have chosen different purchase quantities to induce a different stocking behavior from the seller. The sophisticated buyer, in addition to having the inter-temporal features of the forward-looking buyer, also considers upfront how much stock the seller has for the horizon. It is as if the buyer is able to see the seller's supply at the beginning of the horizon.

In Sections 2.4 and 2.5, we carry out the analysis of this model for each of the buyer types in the constant prices setting in which the seller sets the same unit price for the product in both periods, i.e., $p_{U,1} = p_{U,2} = p_U$. We build on these results in an extension in Section 2.6 in which we allow the prices in periods 1 and 2 to differ. For the derivation of our analytical results, we assume that D_1 and D_2 are uniformly distributed over the interval $[0, B]$, where $B > 0$, and that they are independent.

2.4 Myopic and Forward-Looking Buyers under Constant Prices

2.4.1 Buyer's Problem

Both the myopic and forward-looking buyers face the same problem in period 2. That is, for any given leftover inventory realization $y_i \equiv (q_{1,i} - D_1)^+$ from period 1, a buyer of type $i = \{M, F\}$ chooses purchase quantity $q_{2,i} \geq 0$ to maximize his period perceived profit function, given by:

$$\mathbb{E}[\pi_{D,i,2}(y_i)] = p_D \mathbb{E}[\min(D_2, q_{2,i} + y)] - p_U q_{2,i} + (p_D - r)\mathbb{E}[(D_2 - (q_{2,i} + y_i))^+]. \quad (2.1)$$

The first term captures the revenues from sales to the downstream market. The second term captures the cost of product purchased from the seller. The third term captures the net profit from sales of product purchased from the runout option. This problem is a newsvendor problem with the following solution:

Proposition 2.1. In the constant pricing setting, in period 2, a buyer of type $i = \{M, F\}$ purchases $q^*_{2,i} = (\bar{q}_2 - y_i)^+$ where $y_i \equiv (q^*_{1,i} - D_1)^+$ and $\bar{q}_2 = B\left(\frac{r - p_U}{r}\right)$.

The optimal period 2 purchase decision follows a base-stock policy, where $\bar{q}_2$ is the order-up-to level. This order-up-to level is the same regardless of the buyer type. The differences between the myopic and forward-looking buyers emerge in their optimal period 1 purchase decisions.

Myopic Buyer

The myopic buyer maximizes his perceived profit for each period individually. That is, he decides on a period 1 purchase quantity without considering the possibility of using any leftover inventory from period 1 in period 2 and, more generally, the impact that this decision will bear on his future decisions. In period 1, the myopic buyer's problem is to choose purchase quantity $q_{1,M} \geq 0$ to maximize his period perceived profit function, given by:

$$\mathbb{E}[\pi_{D,M,1}] = p_D \mathbb{E}[\min(D_1, q_{1.M})] - p_U q_{1,M} + (p_D - r)\mathbb{E}[(D_1 - q_{1,M})^+]. \tag{2.2}$$

The maximizer of (2.2) is easily found:

Proposition 2.2. In the constant pricing setting, the myopic buyer purchases $q^*_{1,M} = B\left(\frac{r-p_U}{r}\right)$ in period 1.

The optimal period 1 decision also follows a base-stock policy, where $q^*_{1,M}$ is effectively the period 1 order-up-to level. Since the trade-offs he considers are the same in both periods, his order-up-to levels are the same. We summarize this result in the following corollary:

Corollary 2.1. In the constant pricing setting, $q^*_{1,M} = \bar{q}_2$.

Forward-Looking Buyer

In period 1, the forward-looking buyer maximizes his perceived profit across the entire horizon. His problem is to choose a purchase quantity $q_{1,F} \geq 0$ to maximize his horizon perceived profit function, given by:

$$\begin{aligned}\mathbb{E}[\pi_{D,F,1}] = & p_D \mathbb{E}[\min(D_1, q_{1,F})] - p_U q_{1,F} + (p_D - r)\mathbb{E}[(D_1 - q_{1,F})^+] \\ & + \mathbb{E}[\pi_{D,F,2}((q_{1,F} - D_1)^+)].\end{aligned} \tag{2.3}$$

Compared to the myopic buyer's period 1 problem, the forward-looking buyer's profit function incorporates an extra term to link the outcomes in both periods. Solving for the first order conditions with respect to $q_{1,F}$, we obtain the following result:

Proposition 2.3. In the constant pricing setting, the forward-looking buyer's purchase quantity in period 1 is given by $q^*_{1,F} = B\left(\frac{\sqrt{r^2-p_U^2}}{r}\right)$.

2.4.2 Comparison of Myopic Buyer and Forward-Looking Buyer

Comparing Propositions 2.2 and 2.3, we see that the forward-looking buyer buys more than the myopic buyer in period 1, since $\sqrt{r^2 - p_U^2} = \sqrt{(r - p_U)(r + p_U)}$. This leads us to the following corollary:

Corollary 2.2. In the constant pricing setting, the forward-looking buyer buys more than the myopic buyer in period 1 – that is, $q^*_{1,F} > q^*_{1,M}$.

This result reflects the different trade-offs that each buyer type considers. The forward-looking buyer knows that he can use leftover inventory from period 1 to satisfy demand in period 2. Since $p_{U,1} = p_{U,2}$, he has an incentive to buy more than the myopic buyer in period 1 to hedge himself against paying the higher runout cost in case of high period 1 demand. In effect, the forward-looking buyer shifts some of the quantity he purchases in the second period to the first period:

Corollary 2.3. In the constant pricing setting, $q^*_{1,F} > \bar{q}_2$.

Since $q^*_{1,F} > \bar{q}_2$, any leftover inventory from period 1 would only reduce his purchase quantity in period 2 further. Because the forward-looking buyer buys more than the myopic buyer in period 1, he carries over at least as much or more leftover inventory than the myopic buyer into period 2 for any realization of D_1. The forward-looking buyer also buys at most as much as the myopic buyer in period 2.

A compelling question emerges: is the difference in the purchasing behavior of the forward-looking and myopic buyers merely a shift in the timing of the purchases and does the overall quantity purchased over the horizon remain the same across these buyers? Or does one buyer type actually seek to purchase more than the other? Let $N_i = q^*_{1,i} + (\bar{q}_2 - (q^*_{1,i} - D_1)^+)^+$ denote the demand that the seller faces from each buyer type $i \in \{M, F\}$ over the horizon. The total demand generated by the forward-looking buyer exceeds the total demand generated by the myopic buyer for any given D_1, i.e. demand generated by forward-looking buyers stochastically dominates demand generated by myopic customers. We have the following Lemma:

Lemma 2.1. In the constant pricing setting, for any given realization of D_1, the total demand over the horizon for the seller facing a forward-looking buyer, N_F, is greater than or equal to the total demand over the horizon for the seller facing a myopic buyer. That is, $N_F \geq N_M$.

So the higher period 1 purchase quantity that we observe from the forward-looking buyer in comparison to the myopic buyer is not only a shift in demand from the second period to the first period, but in fact the forward-looking actually seeks to purchase as much as or more than the myopic buyer.

2.4.3 Seller's Problem

The seller's problem is structurally the same regardless of the buyer type she faces. At the beginning of the horizon, given the respective $q^*_{1,i}$ and $q^*_{2,i}$ for buyer type $i \in \{M, F\}$, the seller chooses order quantity $Q_i \geq 0$ to maximize her horizon profit, given by:

$$\mathbb{E}[\pi_{U,i}(Q_i)] = p_U \min(q^*_{1,i}, Q_i) + p_U \mathbb{E}[\min(q^*_{2,i}, Q_i - q^*_{1,i})] - cQ_i. \tag{2.4}$$

The first and second terms of this profit function capture the revenue from sales in each period to a buyer of type i. The third term captures the product wholesale costs incurred by the seller. Note that, because the period prices are equal, equation (2.4) can be written as $\mathbb{E}[\pi_i(Q_i)] = p_U \min(N_i, Q_i) - cQ_i$.

Observe that the seller faces no uncertainty in the buyer's period 1 purchase decision as $q^*_{1,i}$ does not depend on any random variables. Therefore, at optimality, the seller stocks at least $q^*_{1,i}$. In fact, all the uncertainty the seller faces relates to the buyer's period 2 purchase decision. While the seller knows the distribution of downstream demand in each period, the buyer's purchase quantity in period 2 is a random variable that depends on the period 1 demand realization through the buyer's leftover inventory. At optimality, since the buyer never buys more than his order-up-to quantity $\bar{q}_2$ in period 2, the seller would never stock more than $\bar{q}_2$ for this period. Thus, $q^*_{1,i} \leq Q^*_i \leq q^*_{1,i} + \bar{q}_2$. Solving for this constrained optimization problem, we obtain our next result:

Proposition 2.4. In the constant pricing setting, when facing a buyer of type $i \in \{M, F\}$, the seller's stocking quantity over the entire two-period horizon is given by:

$$Q_i^* = \begin{cases} q_{1,i}^*, & \text{if } B\left(\frac{p_U - c}{p_U}\right) + \bar{q}_2 < q_{1,i}^* \\ B\left(\frac{p_U - c}{p_U}\right) + \bar{q}_2, & \text{if } q_{1,i}^* \leq B\left(\frac{p_U - c}{p_U}\right) + \bar{q}_2 < q_{1,i}^* + \bar{q}_2 \\ q_{1,i}^* + \bar{q}_2, & \text{if } B\left(\frac{p_U - c}{p_U}\right) + \bar{q}_2 \geq q_{1,i}^* + \bar{q}_2 \end{cases} \tag{2.5}$$

Proposition 2.4 shows that the seller may ration her supply according to how the risk she faces for the buyer's purchase quantity in period 2 compares to the margin she makes. The seller critical ratio $\frac{p_U - c}{p_U}$ captures the seller's relative margin. The first subcase of Q_i^* corresponds to a low margin setting. In this setting, the seller does not take any risk on the buyer's second period purchase quantity and stocks only enough product to fulfill the buyer's first period purchase quantity. The third subcase of Q_i^* corresponds to a high margin setting. In this setting, the seller stocks the maximum quantity that the buyer could purchase over the horizon of $q_{1,i}^* + \bar{q}_2$. The second subcase of Q_i^* corresponds to a medium margin setting, in which the seller is willing to take some risk on the buyer's period 2 purchase quantity and buys a quantity between the buyer's minimum and maximum demand.

The seller solves a newsvendor problem using the distribution of the demand the seller faces from the buyer, N_i, to determine Q_i^*. Because the forward-looking buyer generates stochastically larger demand than the myopic buyer (Lemma 2.1), the seller facing a forward-looking buyer stocks as much as or more in equilibrium than a seller facing a myopic buyer:

Lemma 2.2. In the constant pricing setting, in equilibrium, the quantity the seller facing a forward-looking buyer stocks is greater than or equal to the quantity the seller facing a myopic buyer stocks – that is, $Q_F^* \geq Q_M^*$.

This result differs from the common notion about sellers facing forward-looking buyers. In the traditional literature, where forward-looking behavior induces the seller to drop prices, the seller can counteract such behavior, which bears negative consequences, by rationing supply (Liu & Van Ryzin 2008). By contrast, in our setting, the seller facing the forward-looking buyer not only brings more supply but also makes as much as or more profit than when she faces a myopic buyer:

Proposition 2.5. In the constant pricing setting, in equilibrium, the seller's profit when facing a forward-looking buyer is greater than or equal to the seller's profit when facing a myopic buyer – that is, $\pi_{U,F}(Q_F^*) \geq \pi_{U,M}(Q_M^*)$.

2.5 Sophisticated Buyer under Constant Prices

In the first two subcases for the optimal seller stocking quantity in Proposition 2.4, the seller stocks less than the buyer's maximum purchase quantity over the horizon of $q_{1,M}^* + \bar{q}_2$. Hence, the buyer may face a stockout at the seller, requiring him to satisfy his demand at the higher priced runout option. In such a scenario, the buyer's perceived profit from his optimization problem will be greater than the actual profit he derives. Such stockout scenarios form the motivation for studying the sophisticated buyer, who does consider the seller's optimal stocking decision.

2.5.1 Buyer's Problem

In addition to considering the possibility of leftover inventory from period 1, the sophisticated buyer also considers the possibility of stock-outs at the seller. That is, recognizing the possibility of stock-outs, the buyer may shift demand to period 1, possibly signaling to the seller to stock more. A dependence is then created between the seller's stocking decision Q and the buyer's purchase quantities q_1 and q_2. To formulate this problem, we need to expand our state space to include one more dimension for the leftover supply at the seller after period 1. Let $s \equiv Q - q_1$ denote the seller's leftover supply after the buyer's period 1 purchase. The starting state in period 2 can then be described in terms of the buyer's leftover inventory and the seller's leftover supply after period 1 by the tuple (s, y). In period 2, with buyer leftover inventory realization y and seller leftover supply s from period 1, the buyer chooses $0 \leq q_2(s, y) \leq s$ to maximize his profit:

$$\begin{aligned}\mathbb{E}[\pi_{D,S,2}(s,y)] =& p_D\mathbb{E}\big[\min\big(D_2, \min\big(q_2(s,y), Q-q_1(Q)\big)+y\big)\big] \\ &- p_U \min\big(q_2(s,y), Q-q_1(Q)\big) \\ &+ (p_D - r)\mathbb{E}\Big[\big(D_2 - (\min\big(q_2(s,y), Q-q_1(Q)\big)+y)\big)^+\Big]. \end{aligned} \tag{2.6}$$

In period 1, the buyer chooses $0 \leq q_1(Q) \leq Q$ to maximize his profit function for the entire horizon:

$$\begin{aligned}\mathbb{E}\big[\pi_{D,S,1}(Q)\big] =& p_D\mathbb{E}\big[\min\big(D_1, q_1(Q)\big)\big] - p_U q_1(Q) + (p_D - r)\mathbb{E}\Big[\big(D_1 - q_1(Q)\big)^+\Big] \\ &+ \mathbb{E}\big[V_{2,S}\big((Q-q_1(Q))^+, (q_1(Q)-D_1)^+\big)\big]. \end{aligned} \tag{2.7}$$

where $V_{2,S}(s,y)$ is the period 2 value function as given by $V_{2,S}(s,y) = \max_{0\leq q_2 \leq s} \mathbb{E}[\pi_{D,S,2}(s,y)]$.

While both of these objective functions are similar to those of the forward-looking buyer, the additional constraints requiring $q_2 \leq s$ in period 2 and $q_1 \leq Q$ in period 1 and the dependence between the seller's stocking decision and the buyer's purchase decisions make this problem more challenging to solve. Not only do the buyer's purchase decisions affect the seller's stocking decision, but now the seller's stocking decision also affects the buyer's purchase decisions, creating a feedback loop. The results of these derivations to determine the sophisticated buyer's optimal purchase quantities are summarized below:

Proposition 2.6. The sophisticated buyer's purchase quantities in period 1 and period 2 are given by:

$$q^*_{1,S}(Q) = \begin{cases} Q, & \text{if } Q < \bar{q}_2 \\ Q + B\left(\frac{p_U}{r}\right) - \frac{1}{r}\sqrt{\Big(Bp_U + Qr\Big)^2 + B\Big(B(r-p_U)^2 - 2Qr^2\Big)}, & \text{if } \bar{q}_2 \leq Q < q^*_{1,F} + \bar{q}_2 \\ B\left(\frac{\sqrt{r^2 - p_U^2}}{r}\right), & \text{if } Q \geq q^*_{1,F} + \bar{q}_2 \end{cases}$$

$$q^*_{2,S}(s,y) = \begin{cases} 0, & \text{if } y \geq \bar{q}_2 \\ \bar{q}_2 - y, & \text{if } y < \bar{q}_2 \leq y + s \\ s, & \text{if } y + s < \bar{q}_2 \end{cases}$$

where $\bar{q}_{2,S} = B\left(\frac{r-p_U}{r}\right)$, $y \equiv (q_{1,S}(Q)^* - D_1)^+$, and $s \equiv Q - q_{1,S}(Q)$.

We illustrate the result for $q^*_{1,S}(Q)$ in Figure 2.2. There are three subcases for $q^*_{1,S}(Q)$, which we discuss in decreasing magnitude of the seller's Q. In the third subcase, when Q is sufficiently large (i.e., above $q^*_{1,F} + \bar{q}_2$), the buyer does not face a risk of seller stock-out over the horizon. For any Q greater than $q^*_{1,F} + \bar{q}_2$, the sophisticated buyer would never buy more in period 1, meaning that his period 1 purchase decision is independent of Q in this range. In fact, in this range, the sophisticated buyer buys exactly as much as the forward-looking buyer in period 1. As the seller reduces Q below $q^*_{1,F} + \bar{q}_2$, a risk of seller stock-out emerges and the buyer now needs to trade-off units purchased in the first period and in the second period. This trade-off results in the sophisticated buyer decreasing the amount he buys in the first period sooner and more sharply than the forward-looking buyer does as Q decreases. Once Q reaches the second period order-up-to level $\bar{q}_2$, the buyer purchases the entire stock in the first period – since he would have bought this amount anyway in the second period, he buys it upfront.

To better understand why the sophisticated buyer buys as much as or less in period 1 than the forward-looking buyer, even when the price is constant across periods, we turn our attention to the marginal analysis of the sophisticated buyer as compared to that of the forward-looking buyer. In Figure 2.3, we depict each buyer type's perceived marginal benefit of increasing his period 1 purchase decision by one unit, for any given period 1 purchase decision and for any given demand realizations of D_1 and D_2. Mathematically, the perceived marginal profit depicted in the figure is $\frac{\partial \pi_D(q_1,D_1,D_2)}{\partial q_1}$ for the forward-looking buyer and $\frac{\partial \pi_D(q_1,D_1,D_2)}{\partial q_1(Q)}$ for the sophisticated buyer. While the forward-looking buyer does not consider Q in deciding on q_1, the sophisticated buyer does, hence the figure illustrates the trade-offs considered by the sophisticated buyer for any given Q such that $q_1(Q) \leq Q \leq q_1(Q) + \bar{q}_2$.

Regions C, D, and E in Figure 2.3 are exactly the same for both buyer types.

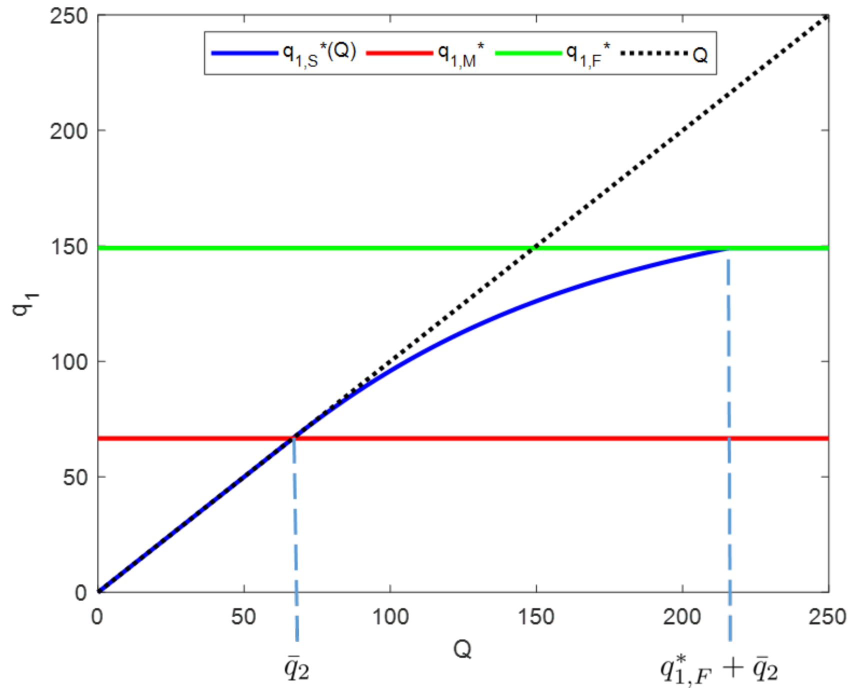


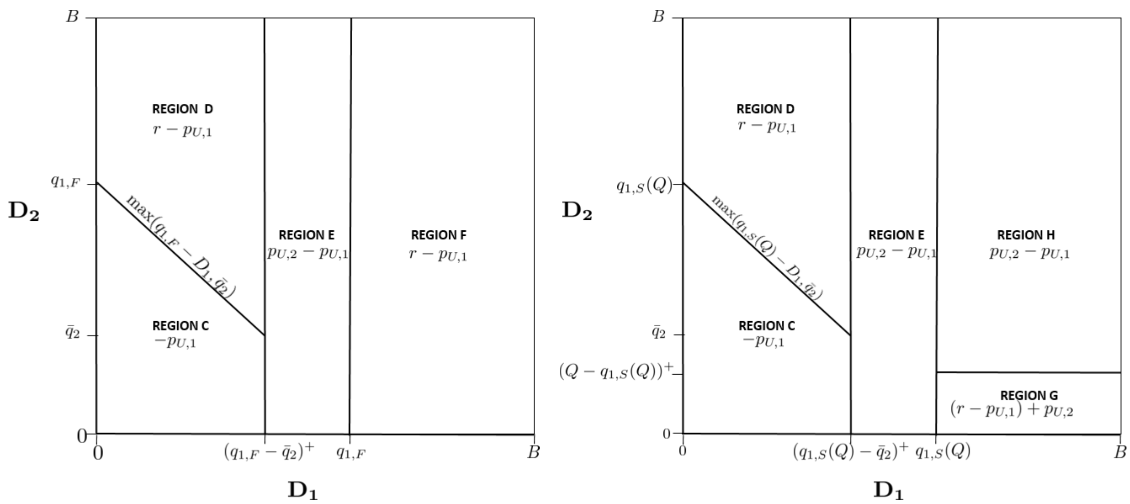
Figure 2.2: $q^*_{1,S}(Q)$ for $B = 200, p_D = 10, r = 9, p_{U,1} = p_{U,2} = 6, c = 3$

Suppose that the forward-looking buyer chooses any given $q_{1,F} \in [0, B]$. If the realization of D_1 turns out to be sufficiently low (i.e. $0 \leq D_1 \leq (q_{1,F} - \bar{q}_2)^+$), the buyer will have enough leftover inventory after period 1 that he does not need to purchase any units in period 2. Then, depending on the realization of D_2, there are two possibilities. If D_2 is low enough that it can be satisfied with this leftover inventory (i.e. less than $\max(q_{1,F} - D_1, \bar{q}_2)$), buying an additional unit of product in period 1 leads to a perceived marginal loss of p_U (region C). But if D_2 is higher than this leftover inventory, buying an additional unit of product in period 1 results in a perceived marginal saving of $r - p_U$ (region D). Note that this marginal saving occurs in period 2 through the leftover inventory effects. Finally, if the realization of D_1 is in an intermediate range (i.e. $q_{1,F}$ is sufficient to cover D_1 but his leftover inventory is less than or equal to $\bar{q}_2$), if he were to buy one more unit in period 1, this unit would be carried over into the next period and deducted from the buyer's order-up-to quantity in period 2. It does not make a difference whether the unit is bought in the first or in the second period as the marginal profit is zero (region E).

The main difference in the marginal analysis for the sophisticated buyer compared to that of the forward-looking buyer is that Region F is replaced by two different regions: Region G and Region H. Both of these regions are regions of high demand realizations. In region G, the realization of D_1 is so high that the buyer does not have leftover and seeks to buy the full $\bar{q}_2$ from the seller. Given the seller's supply, he may or may not be able to buy what he wants from the seller, but given the low realization of D_2 he is able to cover his needs in period 2 without incurring runout costs. If the buyer buys one more unit in first period, he spends $p_{U,1}$ but saves the runout cost of r in that period. The purchase of one more unit in period 1 reduces the seller's supply and takes away the opportunity to buy the unit from the seller in second period so the buyer saves $p_{U,2}$. This means that in this region, the buyer ends up with a gain of $r - p_{U,1}$ in the first period and $p_{U,2}$ in the second period, resulting in a marginal benefit of $(r - p_{U,1}) + p_{U,2}$ (equal to r in the constant pricing setting).

In region H, the realization of D_1 is so high that regardless of whether the buyer buys an additional unit in period 1 or not, he does not have any leftover at the end of period 1. Accordingly, he seeks to buy $\bar{q}_2$ units in period 2, but he may be limited by the seller's leftover supply, $Q - q_1$. Thus, if he buys one more unit in period 1, he pays for one less unit of runout in that period, but then in period 2 he can buy one less unit at $p_{U,2}$ due to the seller's supply constraint and instead incurs one more unit of runout cost. This means that in this region, the buyer ends up with a gain of $r - p_{U,1}$ in the first period but gives up $r - p_{U,2}$ in the second period, resulting in a marginal benefit of $p_{U,2} - p_{U,1}$ (equal to zero in the constant pricing setting).

For the forward-looking buyer, for high realizations of D_1 regardless of the realization of D_2, we had Region F with a marginal saving of $r - p_U$. The attainment of this marginal saving assumed infinite supply at the seller. Now, for the sophisticated buyer, we have for the same high realizations of D_1, Region G with a marginal benefit of r and Region H with a marginal benefit of 0. The lower marginal savings for the sophisticated incentivize the buyer to buy less in period 1 compared to the forward-looking buyer. In a sense, the forward-looking buyer is overly optimistic in high ability to buy product



(a) Forward-looking buyer (b) Sophisticated buyer

Figure 2.3: Marginal profit of the forward-looking q_1 and sophisticated buyer's $q_1(Q)$ decision in the constant pricing setting

from the seller. We can summarize the comparison of $q^*_{1,S}(Q)$ and $q^*_{1,F}(Q)$ for any given Q in the following corollary:

Corollary 2.4. For any given Q, the sophisticated buyer buys as much as or less than the forward-looking buyer in period 1 – that is, $q^*_{1,S}(Q) \leq q^*_{1,F}(Q)$.

When we compared the forward-looking buyer to the myopic buyer, the proof to demonstrate that the demand faced by the seller from a myopic buyer is greater than or equal to that faced by the seller from a forward-looking buyer, i.e. $N_F \geq N_M$ (Lemma 2.1). This proof relied on the fact that $q^*_{1,F}$ is strictly greater than $q^*_{1,M}$ (Corollary 2.2). In comparing $q^*_{1,S}(Q)$ and $q^*_{1,F}(Q)$ for any given Q we do not have this strict inequality, which means we cannot analytically prove that $N_F(Q) \geq N_S(Q)$.

The seller's choice of Q induces certain behaviors in the sophisticated buyer, but the buyer's choice of $q_1(Q)$ also induces certain behavior by the seller. We further explore the delicate interplay between the buyer's decisions and the seller's order quantity in the next subsection.

2.5.2 Seller's Problem

At the beginning of the horizon, given $q^*_{1,S}(Q)$ and $q^*_2(s,y)$, the seller chooses order quantity $Q \geq 0$ to maximize her profit function:

$$\mathbb{E}[\pi_{U,S}(Q)] = p_U q^*_{1,S}(Q) + p_U \mathbb{E}[\min(q^*_{2,S}, Q - q^*_{1,S}(Q))] - cQ \tag{2.8}$$

The first order optimality condition with respect to Q is not a polynomial. While a closed-form expression for the roots exists, the expression does not lend itself to interpretation. Nonetheless, we can obtain the following result:

Proposition 2.7. When facing a sophisticated buyer, there exists a Q^*_S that maximizes the seller's profit function, such that $\bar{q}_2 \leq Q^*_S \leq q^*_{1,F} + \bar{q}_2$.

Not only do we narrow down the domain of Q where Q^*_S exists, but after numerically evaluating numerous instances, we observe that the seller facing a sophisticated buyer stocks as much as or more than a seller facing a forward-looking buyer despite the lower first period purchase quantity of the sophisticated buyer. We summarize this observation in the following conjecture:

Conjecture 2.1. $Q^*_S \geq Q^*_F$

Why is it that, even though the sophisticated buyer buys weakly less than the forward-looking buyer for any given Q in period 1, the seller facing the sophisticated buyer stocks at least as much as or more than the seller facing a forward-looking buyer over the horizon? The reason is that the seller knows that the sophisticated buyer's decision is influenced by her stocking quantity. The seller takes into account the buyer's best response function, which is non-decreasing in Q. Specifically, we have that $0 < \frac{d}{dQ} q^*_{1,S}(Q) < 1$.[1] The seller therefore stocks more to induce the sophisticated buyer, who buys at least as much or less than the forward-looking buyer, to overcome his strategic caution and buy more in the first period. In other words, the sophisticated buyer's strategic caution manipulates the seller into taking a greater risk in her stocking decision by stocking more over the horizon. As a result, the sophisticated buyer benefits

[1] This is provided in the proof of Proposition 2.7.

from the seller's larger stocking quantity and is better off profit-wise as he is able to buy more of the product he wants from the seller.

Numerically, we also observe that in the range where Q^* exists – that is, between $\bar{q}_2$ and $q^*_{1,F} + \bar{q}_2$ – the seller makes as much as or more profit facing a forward-looking buyer than facing a sophisticated buyer. This ordering is illustrated in Figure 2.4.

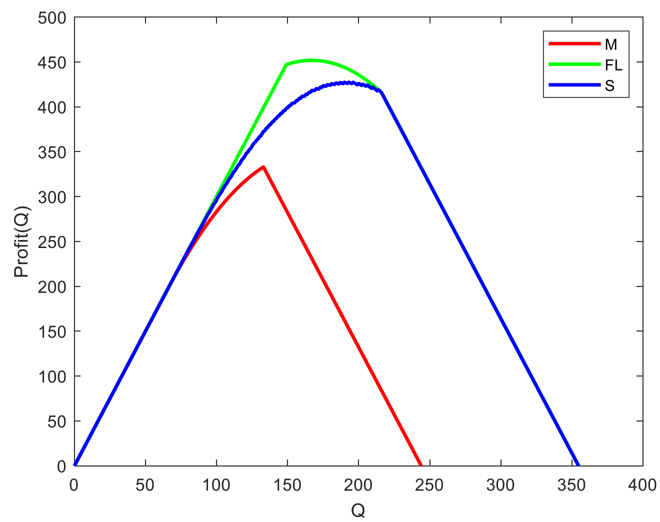


Figure 2.4: Numerical results for seller's expected profit when facing each buyer type: $B = 200, p_D = 10, r = 9, p_{U,1} = p_{U,2} = 6, c = 3$

We formalize this numerical observation in the following conjecture:

Conjecture 2.2. $\mathbb{E}[\pi_{U,M}(Q^*_M)] \leq \mathbb{E}[\pi_{U,S}(Q^*_S)] \leq \mathbb{E}[\pi_{U,F}(Q^*_F)]$

2.6 Extension: Allowing for Different Prices

Suppose that the second period price is lower than the first period price. To take advantage of the lower price in the second period, the forward-looking buyer may shift some of his first period purchase quantity to the second period. Would the magnitude of this shift be large enough that the forward-looking buyer buys less than the myopic buyer, both in the first period and throughout the horizon? Would the seller no longer be better-off facing a forward-looking buyer? In this section, to investigate the effect of price differences between the two periods, we distinguish between the unit sales price in period 1 and in period 2, $p_{U,1}$ and $p_{U,2}$ respectively, and consider both the markdown and markup cases.

2.6.1 Buyer's Problem

For any given leftover inventory realization $y_i \equiv (q_{1,i} - D_1)^+$ from period 1, a buyer of type $i = \{M, F\}$ chooses purchase quantity $q_{2,i} \geq 0$ to maximize his period perceived profit function, given by:

$$\mathbb{E}[\pi_{D,i,2}(y_i)] = p_D \mathbb{E}[\min(D_2, q_{2,i} + y_i)] - p_{U,2} q_{2,i} + (p_D - r)\mathbb{E}[(D_2 - (q_{2,i} + y_i))^+]. \quad (2.9)$$

Proposition 2.8 is the extension of Proposition 2.1 when $p_{U,1} \neq p_{U,2}$:

Proposition 2.8. In the seller markdown/markup setting, in period 2, a buyer of type $i = \{M, F\}$ purchases $q^*_{2,i} = (\bar{q}_2 - y_i)^+$ where $y_i \equiv (q^*_{1,i} - D_1)^+$ and $\bar{q}_2 = B\Big(\frac{r - p_{U,2}}{r}\Big)$.

Myopic Buyer

In period 1, the myopic buyer chooses purchase quantity $q_1 \geq 0$ to maximize his perceived period profit function, given by:

$$\mathbb{E}[\pi_{D,M,1}] = p_D \mathbb{E}[\min(D_1, q_1)] - p_{U,1} q_1 + (p_D - r)\mathbb{E}[(D_1 - q_1)^+]. \quad (2.10)$$

Proposition 2.9 generalizes Proposition 2.2 when $p_{U,1} \neq p_{U,2}$:

Proposition 2.9. In the seller markdown/markup setting, the myopic buyer's purchases $q^*_{1,M} = B\Big(\frac{r - p_{U,1}}{r}\Big)$.

Recall that, in the constant pricing setting, the myopic buyer considers faces the same trade-offs in both periods, resulting in identical order-up-to levels (Corollary 2.1). Now, given price difference between periods, the trade-offs for each period are different, shifting the purchase quantities to one period or another. In the case of a markdown, the relative underage cost for the second period, $\frac{r - p_{U,2}}{r}$, is greater than that for the first period, $\frac{r-p_{U,1}}{r}$, incentivizing the buyer to buy more in the second period. We summarize this result, and its converse in case of a markup, in the following corollary:

Corollary 2.5. When $p_{U,2} < p_{U,1}$, $q^*_{1,M} < \bar{q}_2$. When $p_{U,2} > p_{U,1}$, $q^*_{1,M} > \bar{q}_2$.

Forward-Looking Buyer

In period 1, the forward-looking buyer chooses a purchase quantity $q_1 \geq 0$ to maximize his horizon profit function, given by:

$$\mathbb{E}[\pi_{D,F,1}] = p_D\mathbb{E}[\min(D_1, q_1)] - p_{U,1}q_1 + (p_D - r)\mathbb{E}[(D_1 - q_1)^+] + \mathbb{E}[\pi_{D,F,2}(q_1 - D_1)^+]. \tag{2.11}$$

Following an analysis similar to that in the constant pricing setting, we obtain the next result:

Proposition 2.10. The forward-looking buyer's purchase quantity in period 1 is given by:

$$q^*_{1,F} = \begin{cases} B\left(\frac{r-p_{U,1}}{r-p_{U,2}}\right), & \text{if } \frac{r-p_{U,2}}{r} \geq \frac{r-p_{U,1}}{r-p_{U,2}} \\ B\left(\frac{\sqrt{r^2-p_{U,2}^2-2r(p_{U,1}-p_{U,2})}}{r}\right), & \text{if } \frac{r-p_{U,2}}{r} < \frac{r-p_{U,1}}{r-p_{U,2}} \end{cases}$$

Proposition 2.10 uncovers a difference in behaviors that emerges due to price differences across periods. The ratios that define each subcase of $q^*_{1,F}$, i.e. $\frac{r-p_{U,1}}{r-p_{U,2}}$ and $\frac{r-p_{U,2}}{r}$, capture the trade-offs of buying in the first period versus the second period. These ratios are the relative underage costs out of the total mismatch costs for buying in each period. These two subcases of $q^*_{1,F}$ are illustrated in Figure 2.5.

The first subcase corresponds to a deep markdown scenario. When $p_{U,2}$ is significantly lower than $p_{U,1}$, i.e., $p_{U,2} \leq r - \sqrt{r(r - p_{U,1})}$, the underage cost in period 2 is higher than that in period 1. Despite the lower period 2 price, the buyer benefits from stocking slightly more already in period 1 to avoid runout in period 2. The idea is that, if the buyer has to pay the runout cost, he prefers to do so period 1 instead of in period 2. The second subcase of $q^*_{1,F}$ corresponds to a shallow markdown/markup scenario, which includes the constant pricing setting. As $p_{U,2}$ increases beyond the threshold, i.e., $p_{U,2} > r - \sqrt{r(r - p_{U,1})})$, the underage cost in period 2 forms a smaller proportion of period 2 mismatch costs than the underage cost in period 1 does out of the period 1 mismatch costs, so there is a dampening effect on the amount of product the buyer buys in period 1.

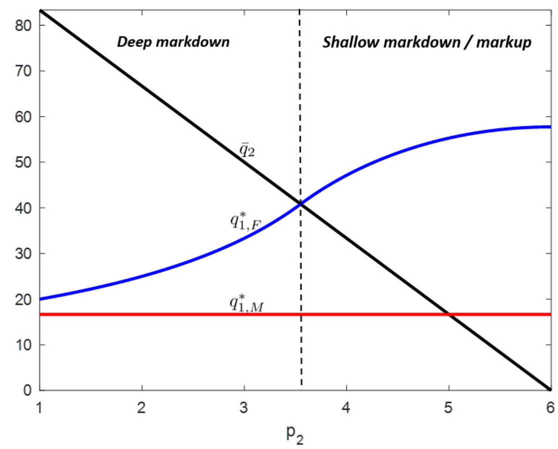


Figure 2.5: Comparison of $\bar{q}_2$, $q^*_{1,F}$, and $q^*_{1,M}$ when varying $p_{U,2}$ for $B = 100, p_D = 10, r = 8, p_{U,1} = 5, c = 1$

In the constant pricing setting, the order-up-to level in the first period was strictly greater than that in the second period for the forward-looking buyer. Because the seller's prices were the same in both periods and lower than the runout option, the forward-looking buyer was inclined to buy more product in period 1 in case demand is high to avoid having to buy from the runout option. In the markdown/markup setting, the relationship between the order-up-to levels in period 1 and period 2 depends on the magnitude of the difference between the period prices. If the markdown is sufficiently deep, the forward-looking buyer's incentive to buy product in the first period is diminished. Otherwise, the forward-looking buyer will buy more in period 1 than in period 2. That is, the buyer's first period decision depends on a threshold $p_{U,2}$:

Corollary 2.6. If $p_{U,2} \leq r - \sqrt{r(r - p_{U,1})}$ (deep markdown), $q^*_{1,F} \leq \bar{q}_2$. If $p_{U,2} > r - \sqrt{r(r - p_{U,1})}$ (shallow markdown), $q^*_{1,F} > \bar{q}_2$. In case of a markup, $q^*_{1,F} > \bar{q}_2$.

Comparison of Myopic Buyer and Forward-Looking Buyer

Regardless of the specific markdown/markup scenario, the forward-looking buyer still buys more in period 1 than the myopic buyer:

Corollary 2.7. In the markdown/markup setting, the forward-looking buyer buys more than the myopic buyer in period 1 – that is, $q^*_{1,F} > q^*_{1,M}$.

This result may seem somewhat counter-intuitive: given the reduced price in the second period, one might expect the forward-looking buyer to buy less in the first period than the myopic buyer who does not consider the price drop. However, as the forward-looking buyer can use any leftover inventory in the second period, the risk of buying more stock in the first period is mitigated. Using Corollary 2.7, we can show that the demand-enhancing effect of the forward-looking buyer persists in the markdown/markup setting. We can generalize Lemma 2.1 to the markdown/markup setting:

Lemma 2.3. The demand for the seller facing a forward-looking buyer, denoted by N_F, is greater than or equal to the demand for the seller facing a myopic buyer – that is, $N_F \geq N_M$.

2.6.2 Seller's Problem

The seller's profit function when she faces a buyer of type $i = \{M, F\}$ is:

$$\mathbb{E}[\pi_{U,i}(Q_i)] = p_{U,1}q^*_{1,i} + p_{U,2}\mathbb{E}[\min(q^*_{2,i}, Q_i - q^*_{1,i})] - cQ_i. \tag{2.12}$$

We derive a similar result for the seller's stocking decision as before:

Proposition 2.11. In the markdown/markup setting, when facing a buyer of type $i \in \{M, F\}$, the seller's stocking quantity over the entire two-period horizon is given by:

$$Q_i^* = \begin{cases} q_{1,i}^*, & B\left(\frac{p_{U,2}-c}{p_{U,2}}\right) + \bar{q}_2 < q_{1,i}^* \\ B\left(\frac{p_{U,2}-c}{p_{U,2}}\right) + \bar{q}_2, & q_{1,i}^* \leq B\left(\frac{p_{U,2}-c}{p_{U,2}}\right) + \bar{q}_2 < q_{1,i}^* + \bar{q}_2 \\ q_{1,i}^* + \bar{q}_2, & B\left(\frac{p_{U,2}-c}{p_{U,2}}\right) + \bar{q}_2 \geq q_{1,i}^* + \bar{q}_2 \end{cases} \tag{2.13}$$

In a supply chain with a myopic buyer, because there is only one subcase for the myopic buyer's $q_{1,M}^*$ (Proposition 2.9), there are three possible situations: low seller margin (L), medium seller margin (M), and high seller margin (H). In a supply chain with a forward-looking buyer, because there are two possible subcases for the forward-looking buyer's $q_{1,F}^*$ (Proposition 2.10), there are six possible situations. We combine the two subcases of Proposition 2.10 for the buyer's $q_{1,F}^*$ (deep markdown and shallow markdown/markup) with the three subcases of Proposition 2.11 for the seller's Q_F^* (low margin, a medium margin, and high margin scenario). One of the resulting situations (deep markdown, low seller margin) is ruled out as it requires the seller to earn negative margin, negating his participation in the market. In summary, we have five situations depending on the relationship between the relevant ratios of the buyer and seller: *(i)* Deep markdown, medium seller margin (DM), *(ii)* Deep markdown, high seller margin (DH), *(iii)* Shallow markdown/markup, low seller margin (SL), *(iv)* Shallow markdown/markup, medium seller margin (SM), and *(v)* Shallow markdown/markup, high seller margin (SH).

The differences in thresholds and in situations for a supply chain with a myopic buyer and one with a forward-looking buyer make it challenging to compare how the quantities purchased and stocked vary with $p_{U,2}$. As $p_{U,2}$ increases for a given $p_{U,1}, r$, and c, the situation in each supply change changes. We illustrate these changes for a specific instance in Figure 2.6 for a supply chain with both buyer types.

In a supply chain with a myopic buyer, the top panel of Figure 2.6 illustrates the effect of increasing $p_{U,2}$ on Q_M^* and $q_{1,M}^*$. Since the buyer is myopic, his incentive to buy in period 1 does not change as $p_{U,2}$ increases so $q_{1,M}^*$ is constant. However, the second period order-up-to quantity $\bar{q}_2$ decreases as it becomes less favorable for the buyer to buy in period 2. For the seller, at the lower values of $p_{U,2}$, the seller is in the

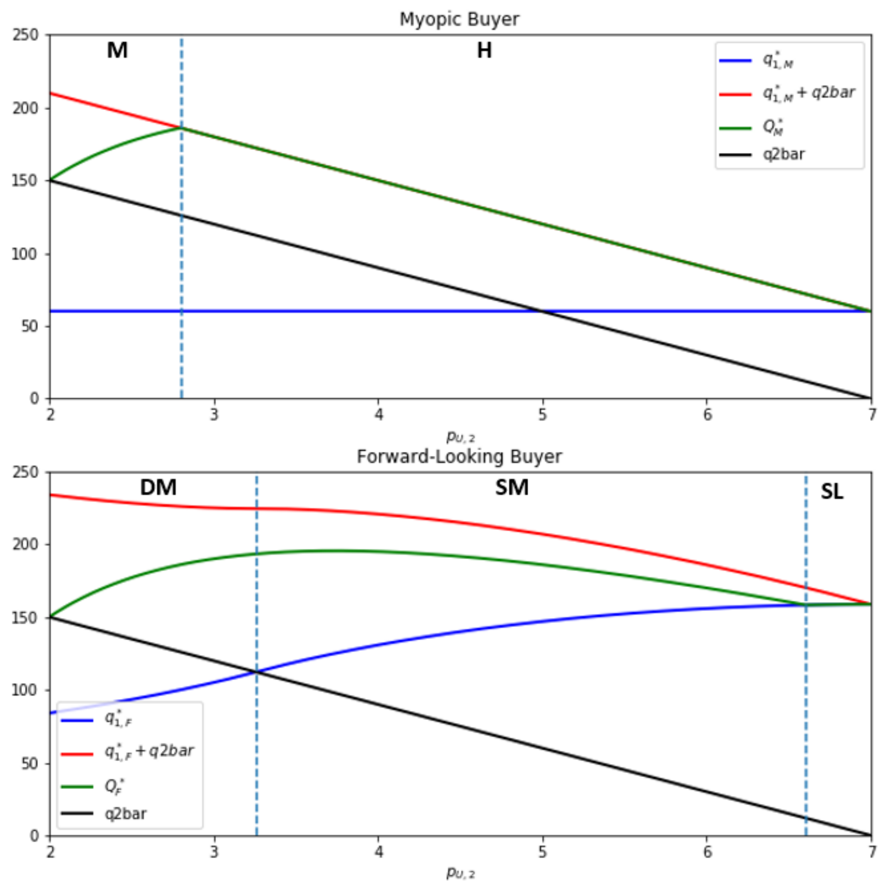


Figure 2.6: Varying $p_{U,2}$ for $B = 210, p_D = 10, r = 7, p_{U,1} = 5, c = 2$

medium margin range (situation M) and brings an intermediate amount of product. As $p_{U,2}$ increases sufficiently above c (threshold shown), the seller enters the high margin range (situation H) and stocks the maximum possible buyer demand over the horizon of $q^*_{1,M} + \bar{q}_2$. For the rest of the range where $p_{U,2} < r$, despite the diminishing incentive for the buyer to buy in period 2, the seller's margin is still high enough that she continues to stock the maximum buyer demand.

For the same instance, in a supply chain with a forward-looking buyer, the lower panel of Figure 2.6 illustrates the effect of increasing $p_{U,2}$ on Q_F^* and $q_{1,F}^*$. At lower values of $p_{U,2}$, the seller is in the medium margin range and the buyer is in the deep markdown range (situation DM). The buyer's $q_{1,F}^*$ increases in $p_{U,2}$ but is below $\bar{q}_2$ because he has an incentive to wait until period 2 to buy at a significantly lower price. The first threshold occurs when $p_{U,2}$ becomes high enough that the buyer's incentive to buy in period 2 equals the buyer's incentive to buy in period 1. At this point, while there is a still a markdown in the second period, $p_{U,2}$ is not low enough to discourage the buyer from buying more in period 1. The buyer has switched to being in a shallow markdown/markup scenario, but the seller is still in the medium margin scenario (situation SM). As $p_{U,2}$ increases above $p_{U,1}$ and further, a second threshold is reached, where the $p_{U,2}$ is so high that the quantities the seller expects the buyer to purchase are not significant enough to induce the seller to bring more than the known period 1 purchase quantity (situation SL). In this instance, for all $c < p_{U,2} < r$, the seller always stocks less than the maximum quantity the forward-looking buyer would buy over the horizon, which means that the buyer may face seller stock-outs as he may not be able to buy the quantities that he seeks to buy from the seller.

For the instance illustrated in Figure 2.6, $Q_F^* = Q_M^*$ for $p_{U,2} \leq \frac{cr}{p_{U,1}}$, otherwise $Q_F^* > Q_M^*$. In fact, despite the price differences, we generalize Lemma 2.2 to the markup/markdown setting:

Lemma 2.4. In the markdown/markup setting, in equilibrium, the quantity the seller facing a forward-looking buyer stocks is greater than or equal to the quantity the seller facing a myopic buyer stocks – that is, $Q_F^* \geq Q_M^*$.

We can also generalize Proposition 2.5 to the markup/markdown setting:

Proposition 2.12. In the markdown/markup setting, in equilibrium, the seller's profit when facing a forward-looking buyer is greater than or equal to the seller's profit when facing a myopic buyer – that is, $\pi_{U,F}(Q_F^*) \geq \pi_{U,M}(Q_M^*)$.

2.6.3 Optimal Seller Markdown / Markup Mechanism

What if the seller, in addition to choosing her stocking quantity for the horizon, could set prices in period 2 or in both periods? Recall that the main competition for the seller is the runout option. For this reason, one might expect that it is optimal for the seller to keep the price just below the runout option in one or even both periods. However, marking up product increases the buyer's overage cost in the second period, possibly resulting in a lower purchase quantity that period and a gravitation of demand to the first period, when the price is lower. While it is true that the buyer's optimal period 2 price is below the runout cost, the degree to which it is below the runout cost varies significantly.

Numerically, we investigate the seller's optimal period 2 price, $p^*_{U,2}$, for a fixed unit production cost c while varying the unit runout cost r and the seller's unit period 1 price $p_{U,1}$. Our results indicate that there is a region where it is optimal to set $p_{U,2} \geq p_{U,1}$ for any given r and $p_{U,1}$ and another region where it is optimal to set $p_{U,2} \leq p_{U,1}$. We illustrate these results for an instance with a forward-looking buyer in Figure 2.7.

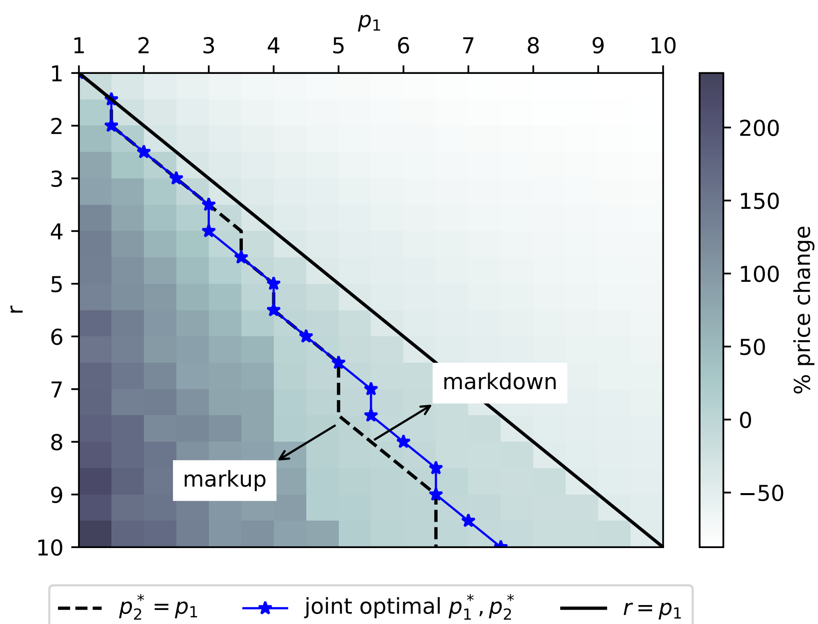


Figure 2.7: Optimal pricing for $B = 100, p_D = 10, c = 1$

In Figure 2.7, for a given c, we vary r along the y-axis and $p_{U,1}$ along the x-axis. The values in the interior of the plot are the percentage change between $p_{U,1}$ and $p^*_{U,2}$, computed for each level of r and $p_{U,1}$. Darker shades represent a higher optimal period 2 price for the seller compared to the period 1 price (deeper markup) and lighter shades represent a lower optimal period 2 price compared to the period 1 price (deeper markdown).

Along the diagonal, the runout cost r is equal to the first period price $p_{U,1}$. When $r < p_{U,1}$ (above the diagonal), the buyer only buys from the runout option in the first period so the seller brings no supply for this period. Since the buyer buys exactly up to his demand realization in period 1 from the the runout option, he has no leftover from period 1 and seeks to purchase $\bar{q}_2$ in period 2. As long as the seller prices $p_{U,2} < r$, the seller can sell $\bar{q}_2$ in period 2 and stocks $Q_F^* = \bar{q}_2$. In this region, the seller sets $p_{U,2}^* = \frac{(c+r)}{2}$. Although $p_{U,2}^* < p_{U,1}$ in this region, it is only trivially a "markdown" as the seller does not participate in the market in the first period.

When $r > p_{U,1}$ (below the diagonal), the buyer prefers to buy from the seller instead of the runout option in period 1. In this region, either a markdown or a markup in period 2 may be optimal for the seller depending on r and $p_{U,1}$. The dashed line is the threshold where it is optimal to set the period prices equal. Below the dashed line, it is optimal for the seller to set a higher price in the second period than in the first period. Above the dashed line, the seller is better off setting a lower price in the second period than in the first period. The optimality of markups is most apparent for higher values of r and lower values of $p_{U,1}$. Hence, the darker shade at the bottom left corner of the figure.

So far in this section we looked at a situation in which the seller's first period price is set exogeneously and the seller is able to set the second period price optimally. How would the seller's optimal price path for a given c and r differ if she were able to set both $p_{U,1}$ and $p_{U,2}$ optimally from the beginning of the horizon? The starred blue line illustrates the jointly optimal $p_{U,1}^*$ and $p_{U,2}^*$ for any given level of r and c. For lower values of r (i.e., in this instance, up to around $r = 4$), it is jointly optimal to markup in period 2 or keep the prices constant. As r increases, however, it becomes jointly optimal to markdown in period 2 (i.e., in this instance, up to around $r = 4$). We summarize this observation formally as follows:

Observation 2.1. There exists a threshold value of r below which it is jointly optimal to set prices such that $p_{U,1} \geq p_{U,2}$. Above this threshold, it is jointly optimal to set prices such that $p_{U,1} \leq p_{U,2}$.

2.7 Conclusion

In this chapter, we characterized the stocking decisions of a seller and an intermediate buyer in a serial newsvendor supply chain when the buyer exhibits varying degrees of strategic behavior. The degree of a buyer's strategic behavior refers to the degree to which the buyer considers *(i)* factors affecting future periods and/or *(ii)* the seller's optimal stocking decision in making his period purchase decisions. We modeled the degree of a buyer's strategic behavior by defining three buyer types: a myopic buyer who considers neither of these factors, a forward-looking buyer who considers only the first factor, and a sophisticated buyer who considers both factors. In the absence of price differences between periods, we showed that, in comparison to the myopic buyer, the forward-looking buyer shifts some of the quantity he would buy in the second period to the first period as he knows he will be able to carry over any excess inventory. In addition to this shift in the first period purchase quantity, however, the forward-looking buyer also seeks to buy more units than the myopic buyer over the horizon. For this reason, a seller facing a forward-looking buyer will stock as much as or more than the seller facing the myopic buyer and will make a greater than or equal profit from the forward-looking buyer than the myopic buyer. A buyer's forward-looking behavior, thus, can benefit a seller in such a supply chain.

Motivated by the observation that in some cases the seller does not stock the maximum quantity that the buyer demands over the horizon, we introduced a third buyer type called the sophisticated buyer. The sophisticated buyer additionally considers both intertemporality and the seller's stocking decision in his purchase decisions. We find that in equilibrium the sophisticated buyer buys less than the forward-looking buyer in the first period for any given seller stocking quantity Q. The sophisticated buyer's strategic caution in his first period purchase decision effectively induces the seller to take on a greater risk with her inventory stocking quantity and bring more supply. As a result, the sophisticated buyer is better off profit-wise being sophisticated instead of forward-looking. But the seller is better off profit-wise facing a forward-looking buyer over a sophisticated buyer. If possible, the seller should encourage a buyer to adopt some degree of strategic behavior and consider inter-temporality (i.e., be forward-looking) but not to adopt the full degree of strategic behavior and consider the seller's stocking decision (i.e., be sophisticated). To this end, the seller should avoid inventory information sharing.

We then extended our study to allow for different prices across the periods, and more specifically, to allow the seller to markdown or markup product from the first period to the second period. Unlike in the constant pricing setting, the first period purchase quantity of the forward-looking buyer follows a threshold policy depending on the price difference. Despite the different prices, however, the results related to the profit generated when facing a forward-looking buyer versus a myopic buyer from the constant pricing setting persist. The forward-looking buyer still buys more than the myopic buyer in the first period. He also still demands as much as or more product from the seller over the horizon, which again results in a profit that is greater than or equal to that generated by the myopic buyer. We then investigated the optimal price in the second period assuming the seller can set this price upfront. Numerically we found that, for a given runout cost, production cost, and first period price, it may be optimal to markup or markdown product in the second period.

One interesting avenue for future research relates to coordination mechanisms. In our present work, we examined the supply chain outcomes in a setting where no coordination can occur. The outcomes under coordination and the optimal coordination mechanism are a promising direction for a follow-up study.

To the best of our knowledge, our work is the first to consider buyer strategic behavior in a serial newsvendor setting. Such serial settings are prevalent in supply chains, and while ample evidence supports the notion that varying degrees of strategic behavior are exhibited by human decision makers, such behaviors have received limited attention in supply chain contexts. As such, this chapter paves the way for a potentially rich research avenue that can build on our modeling framework. For example, another possible extension includes the study of multiple buyers or multiple sellers, thereby incorporating competition.

Appendix 2.A Proofs

Proof of Proposition 2.1. $\mathbb{E}[\pi_{D,i,2}(y_i)]$ can be rewritten as $\mathbb{E}[\pi_{D,i,2}(y_i)] = p_D\mathbb{E}[D_2] - p_U q_{2,i} - r\mathbb{E}[(D_2 - (q_{2,i} + y_i))^+]$. The first term is independent of $q_{2,i}$. The second term is linearly decreasing in $q_{2,i}$. For any realization of D_2, and for any given y_i, both $\mathbb{E}[(D_2 - (q_{2,i} + y_i))^+]$ and $\mathbb{E}[((q_{2,i} + y_i) - D_2)^+]$ are convex in $q_{2,i}$. As these expectations are multiplied by negative coefficients, the third and fourth terms are concave. Therefore, the critical point determined through the first order condition $\frac{d}{dq_{2,i}}\mathbb{E}[\pi_{D,i,2}(y_i)] = \frac{-r}{B}(q_{2,i} + y_i) + r - p_U = 0$ is the unique maximizer. □

Proof of Proposition 2.2. Similarly, $\mathbb{E}[\pi_{D,M,1}]$ can be written as $\mathbb{E}[\pi_{D,M,1}] = p_D\mathbb{E}[D_1] - p_U q_{1,M} - r\mathbb{E}[(D_1 - q_{1,M})^+]$. The first term is constant and does not depend on decision variable $q_{1,M}$. The second term is linearly decreasing in $q_{1,M}$. For any given realization of D_1, $\mathbb{E}[(D_1 - q_{1,M})^+]$ is convex in $q_{1,M}$. As this expectation is multiplied by a negative coefficient, the third term is concave. Therefore, $\mathbb{E}[\pi_{D,M,1}]$ is concave in $q_{1,M}$ and the critical point determined through the first order condition $\frac{d}{dq_{1,M}}\mathbb{E}[\pi_{D,M,1}] = (r - p_U) - r\frac{q_{1,M}}{B} = 0$ is the unique maximizer. □

Proof of Corollary 2.1. $q^*_{1,M} = B\left(\frac{r-p_U}{r}\right) = \bar{q}_2$. □

Proof of Proposition 2.3. Evaluating $\mathbb{E}[\pi_{D,F,2}(y)]$ for $D_2 \sim U[0, B]$, we have that $\mathbb{E}[\pi_{D,F,2}(y)] = (p_D - r)\left(\frac{B}{2}\right) - p_U q_2 + r(q_2 + y) - \frac{r}{2B}(q_2 + y)^2$. Plugging in this expression for $\mathbb{E}[\pi_{D,F,2}((q_{1,F} - D_1)^+)]$ in $\mathbb{E}[\pi_{D,F,1}(q_{1,F} - D_1)^+]$, we obtain $\mathbb{E}[\pi_{D,F,1}(q_{1,F} - D_1)^+] = (p_D - r)B + (r - p_U)q_1 + (r - p_U)\mathbb{E}[(\bar{q}_2 - (q_1 - D_1)^+)^+] - \frac{r}{2B}\mathbb{E}[((\bar{q}_2 - (q_1 - D_1)^+)^+ + (q_1 - D_1)^+)^2]$. To explicitly evaluate these expectation terms, we need to consider two cases: *(i)* $\bar{q}_2 \geq q_1$ and *(ii)* $\bar{q}_2 < q_1$. In case *(i)*, $\mathbb{E}[(\bar{q}_2 - (q_1 - D_1)^+)^+] = \int_0^{q_1}[\bar{q}_2 - q_1 + x_1]f(x_1)\,dx_1 + \int_{q_1}^{B}\bar{q}_2 f(x_1)\,dx_1$ and $\mathbb{E}[((\bar{q}_2 - (q_1 - D_1)^+)^+ + (q_1 - D_1)^+)^2] = \int_0^{q_1}\bar{q}_2^2 f(x_1)\,dx_1 + \int_{q_1}^{B}\bar{q}_2^2 f(x_1)\,dx_1$. Therefore, evaluating for $D_1 \sim U[0, B]$, $\mathbb{E}[\pi_{D,F,1}(q_{1,F} - D_1)^+] = (p_D - r)B + (r - p_U)\left(q_1 + \bar{q}_2 - \frac{q_1^2}{2B}\right) - \frac{r}{2B}\bar{q}_2^2$. The first order optimality condition for q_1 is $\frac{d}{dq_1}\mathbb{E}[\pi_{D,F,1}(q_{1,F} - D_1)^+] = (r - p_U) - \frac{(r-p_U)}{B}q_1 = 0$.

In case *(ii)*, $\mathbb{E}[(\bar{q}_2 - (q_1 - D_1)^+)^+] = \int_{q_1-\bar{q}_2}^{q_1}[\bar{q}_2 - q_1 + x_1]f(x_1)\,dx_1 + \int_{q_1}^{B}\bar{q}_2 f(x_1)\,dx_1$ and

$\mathbb{E}[((\bar{q}_2 - (q_1 - D_1)^+)^+ + (q_1 - D_1)^+)^2] = \int\limits_{0}^{q_1-\bar{q}_2} (q_1 - x_1)^2 f(x_1)\, dx_1 + \int\limits_{q_1-\bar{q}_2}^{q_1} \bar{q}_2^2 f(x_1)\, dx_1 + \int\limits_{q_1}^{B} \bar{q}_2^2 f(x_1)\, dx_1$. Evaluating for $D_1 \sim U[0, B]$, $\mathbb{E}[U_1(q_1 - D_1)^+] = (p_D - r)B + (r - p_U)\left(q_1 + \frac{\bar{q}_2^2}{2B} + \bar{q}_2 - \frac{q_1\bar{q}_2}{B}\right) - \frac{r}{2B}\left(\frac{q_1^3}{3B} - \frac{q_1\bar{q}_2^2}{B} + \bar{q}_2^2\right)$. The first order optimality condition with respect to q_1 is $\frac{d}{dq_1}\mathbb{E}[\pi_{D,F,1}(q_{1,F} - D_1)^+] = (r - p_U)(1 - \frac{\bar{q}_2}{B}) - \frac{r}{2B^2}(q_1^2 - \bar{q}_2^2) = 0$. Substituting $\bar{q}_2 = B\left(\frac{r-p_U}{r}\right)$ and simplifying, $q_1^2 = 2B^2\frac{(r-p_U)}{r} - B^2\frac{(r-p_U)^2}{r^2}$. Clearly, as $q_1 \geq 0$, we are interested in the non-negative root of this quadratic, $q_1^* = B\left(\frac{\sqrt{r^2-p_U^2}}{r}\right)$. Note, however, that there is a contradiction in the first case in which $\bar{q}_2 \geq q_1$ as $q_1^* = B > \bar{q}_2 = B\left(\frac{r-p_U}{r}\right)$. Therefore, only case *(ii)* holds. □

Proof of Corollary 2.2. Observe that $q_{1,M}^* = B\left(\frac{r-p_U}{r}\right) = B\left(\frac{\sqrt{r-p_U}\sqrt{r-p_U}}{r}\right) < B\left(\frac{\sqrt{r-p_U}\sqrt{r+p_U}}{r}\right) = B\left(\frac{\sqrt{r^2-p_U^2}}{r}\right) = q_{1,F}^*$, where the inequality follows because $r > p_U > 0$. □

Proof of Corollary 2.3. Since $\bar{q}_2 = q_{1,M}^* = B\left(\frac{r-p_U}{r}\right)$, the proof follows the same logical steps as for Corollary 2.2. □

Proof of Lemma 2.1. By definition, a random variable X is stochastically greater than or equal to another random variable Y – that is, $X \geq_{st} Y$ – if, and only if, $\mathbb{P}(X \leq x) \geq \mathbb{P}(Y \leq x) \forall x \in (-\infty, \infty)$ This form of stochastic dominance is called stochastic dominance in the usual order or alternatively first-order stochastic dominance (Shaked & Shanthikumar 2007). Observe that N_F and N_M are non-decreasing in $q_{1,F}$ and $q_{1,M}$ respectively, hence $N_F \geq N_M$ for any realization of D_1 because $q_{1,F}^* > q_{1,M}^*$ by Corollary 2.2. □

Proof of Proposition 2.4. The seller's profit function can be written as $\mathbb{E}[\pi_{U,i}(Q)] = (p_{U,1} - p_{U,2})q_{1,i}^* + (p_{U,2} - c)Q - w_U\mathbb{E}[(Q - q_{1,M}^* - (\bar{q}_2 - (q_{1,M}^* - D_1)^+)^+)^+]$. To evaluate the last expectation term in $\mathbb{E}[\pi(Q)]$, we need to consider two cases for the relationship between $q_{1,M}^*$ and $\bar{q}_2$: *(i)* $\bar{q}_2 \geq q_{1,M}^*$ and *(ii)* $\bar{q}_2 < q_{1,M}^*$.

In case *(i)*, since $\bar{q}_2 \geq q_{1,M}^*$, $\bar{q}_2 \geq (q_{1,M}^* - D_1)^+$ and the second inner truncation can be eliminated as this term is always positive. We have $\mathbb{E}[(Q - q_{1,M}^* - (\bar{q}_2 - (q_{1,M}^* -$

$D_1)^+))^+] = \int_0^{\min(q^*_{1,M}, Q-\bar{q}_2)} (Q - \bar{q}_2 - x_1) f(x_1) dx_1 = \int_0^{Q-\bar{q}_2} (Q - \bar{q}_2 - x_1) f(x_1) dx_1$ as at optimality $q^*_{1,M} \leq Q^*_M \leq q^*_{1,M} + \bar{q}_2$. Evaluating for $D_1 \sim U[0, B]$, $\mathbb{E}[\pi(Q)] = (p_{U,1} - p_{U,2}) q^*_{1,M} + (p_{U,2} - c)Q - \frac{p_{U,2}}{2B}(Q - \bar{q}_2)^2$.

In case *(ii)*, since $\bar{q}_2 < q^*_{1,M}$, the second inner truncation cannot be eliminated. We have $\mathbb{E}[(Q - q^*_{1,M} - (\bar{q}_2 - (q^*_{1,M} - D_1)^+)^+)^+] = \int_0^{q^*_{1,M}-\bar{q}_2} (Q - q^*_{1,M}) f(x_1) dx_1 + \int_{q^*_{1,M}-\bar{q}_2}^{Q-\bar{q}_2} (Q - \bar{q}_2 - x_1) f(x_1) dx_1$. Evaluating for the uniform distribution of D_1, $\mathbb{E}[\pi(Q)] = (p_{U,1} - p_{U,2}) q^*_{1,M} + (p_{U,2} - c)Q - \frac{p_{U,2}}{B}\left(\frac{Q^2}{2} - \frac{q^{*2}_{1,M}}{2} - Q\bar{q}_2 + q^*_{1,M}\bar{q}_2\right)$.

In both cases, the first order optimality condition for Q is the same: $\frac{d}{dQ}\mathbb{E}[\pi(Q)] = (p_{U,2} - c) - \frac{p_{U,2}}{B}(Q - \bar{q}_2) = 0$. The concavity of the objective function in both cases can also be easily verified as $\frac{d^2}{dQ^2}\mathbb{E}[\pi(Q)] = \frac{-p_{U,2}}{B} Q < 0$ since $p_{U,2}, B$ and Q are strictly positive.

Finally, as we are dealing with a constrained optimization problem, we account for the requirement that the unique maximizer $B\left(\frac{p_{U,2}-c}{p_{U,2}}\right) + \bar{q}_2$ is indeed such that $q^*_{1,M} \leq Q^*_M \leq q^*_{1,M} + \bar{q}_2$. Note that the first of the three subcases of Q^*_M does not happen in case *(i)* as $\bar{q}_2 \geq q^*_{1,M}$ and $B\left(\frac{p_{U,2}-c}{p_{U,2}}\right) > 0$ therefore $q^*_{1,M}$ is definitely less than or equal to a quantity greater than $\bar{q}_2$.

For the seller facing the forward-looking buyer, the same reasoning as with the seller facing the myopic buyer applies, only with the relevant $q^*_{1,F}$ instead of $q^*_{1,M}$. □

Proof of Lemma 2.2. Since the seller determines Q^* by solving a newsvendor problem with demand N_F or N_M when facing a forward-looking or myopic buyer respectively, $Q^*_M = F^{-1}_{N_M}\left(\frac{p_U - c}{p_U}\right)$ and $Q^*_F = F^{-1}_{N_F}\left(\frac{p_U - c}{p_U}\right)$. By Lemma 2.1, $Q^*_F \geq Q^*_M$. □

Proof of Proposition 2.5. Observe that the seller solves a newsvendor problem with the demand given by N_M or N_F depending on the buyer type she faces. Therefore, $\pi_{U,M}(Q) = p_U \mathbb{E}[\min(Q, N_M)] - cQ$ and $\pi_{U,F}(Q) = p_U \mathbb{E}[\min(Q, N_F)] - cQ$. By Lemma 2.1, $\mathbb{E}[\min(Q, N_M)] \leq \mathbb{E}[\min(Q, N_F)]$ for any $Q \in \mathbb{R}^+$. Therefore, $\pi_{U,M}(Q^*_M) \leq \pi_{U,F}(Q^*_M) \leq \pi_{U,F}(Q^*_F)$, where the second inequality holds due to the optimality of Q^*_F for $\pi_{U,F}$. □

Proof of Proposition 2.6. To evaluate $\mathbb{E}[\pi_{D,S,1}((q_1(Q) - D_1)^+, Q)]$, observe that

$\mathbb{E}[V_2((Q - q_1(Q))^+, (q_1(Q) - D_1)^+)] = \int_0^{q_1(Q)} V_2(Q - q_1(Q), q_1(Q) - x_1) f(x_1) dx_1 + \int_{q_1(Q)}^{B} V_2(Q - q_1(Q), 0) f(x_1) dx_1$. We first evaluate these two integrals for $D_2 \sim U[0, B]$:

$$V_2(s, y) = \begin{cases} (p_D - r)\frac{B}{2} + ry - \frac{r}{2B}y^2, & y \geq \bar{q}_2 \\ (p_D - r)\frac{B}{2} + py + \frac{B}{2}\frac{(r-p_U)^2}{r}, & \bar{q}_2 - s \leq y < \bar{q}_2 \\ (p_D - r)\frac{B}{2} + (r - p_U)s + ry - \frac{r}{2B}(y + s)^2, & y < \bar{q}_2 - s \end{cases}$$

$$V_2(s, 0) = \begin{cases} (p_D - r)\frac{B}{2} + \frac{B}{2}\frac{(r-p_U)^2}{r}, & s \geq \bar{q}_2 \\ (p_D - r)\frac{B}{2} + (r - p_U)s - \frac{r}{2B}s^2, & s < \bar{q}_2 \end{cases}$$

For $V_2(s, 0)$, only two subcases remain as one of the subcases was eliminated since $\bar{q}_2$ cannot be negative. In both of these subcases, the buyer has no leftover inventory and seeks to buy the full $\bar{q}_2$. In the first subcase, the seller's leftover supply is sufficient to cover the buyer's needs for period 2. In the second subcase, the seller's leftover supply is not sufficient.

Based on the relationships between $q_1(Q)$ and $\bar{q}_2$ and $\bar{q}_2$ and $Q - q_1(Q)$, we consider four cases: *(i)* $q_1(Q) > \bar{q}_2$, $\bar{q}_2 > Q - q_1(Q)$, *(ii)* $q_1(Q) \leq \bar{q}_2$, $\bar{q}_2 > Q - q_1(Q)$, *(iii)* $q_1(Q) > \bar{q}_2$, $\bar{q}_2 \leq Q - q_1(Q)$, *(iv)* $q_1(Q) \leq \bar{q}_2$, $\bar{q}_2 \leq Q - q_1(Q)$. Cases *(i)* and *(ii)* are cases in which supply is limited as the seller's remaining supply after the first period is less than the order-up-to quantity in period 2.

In case *(i)*, $\mathbb{E}[\pi_{D,S,1}((q_1(Q) - D_1)^+, Q)] = (p_D - r)B + (r - p_U)Q - \frac{r}{2B}(Q - q_1(Q))^2 + \frac{1}{2}\frac{(r-p_U)^2}{r}(Q - q_1(Q)) + \frac{r}{6B^2}\left[Q^3 - 3q_1(Q)^2 Q + q_1(Q)^3\right] + \frac{(r-p_U)}{B}\left[\frac{q_1(Q)^2}{2} - \frac{Q^2}{2}\right]$. The first order optimality condition with respect to $q_1(Q)$ is $\frac{d}{dq_1(Q)}\mathbb{E}[U_1((q_1(Q) - D_1)^+, Q)] = \frac{r}{2B^2}q_1(Q)^2 - \frac{p_U}{B}q_1(Q) - \frac{r}{B^2}q_1(Q)Q + \frac{r}{B}Q - \frac{1}{2}\frac{(r-p_U)^2}{r} = 0$. The solution to this quadratic is the root with the plus sign that does not violate $q_1(Q) \leq B$.

In case *(ii)*, $\mathbb{E}[\pi_{D,S,1}((q_1(Q) - D_1)^+, Q)] = (p_D - r)B + (r - p_U)Q - \frac{r}{2B}(Q - q_1(Q))^2 + \frac{1}{2}\frac{(r-p_U)^2}{r}Q + \frac{r}{2B^2}\left[\frac{Q^3}{3} - q_1(Q)^2 Q + \frac{2}{3}q_1(Q)^3\right] - \frac{B}{6}\frac{(r-p_U)^3}{r^2} - \frac{(r-p_U)}{2B}Q^2$. Solving for the first order optimality condition with respect to $q_1(Q)$, $q_1(Q)^* = \frac{B+Q}{2} \pm \frac{(B-Q)}{2}$. Using the plus sign for this expression, $q_1(Q)^* = B > \bar{q}_2 = B\left(\frac{r-p_U}{r}\right)$ yields a contradiction as we are in the case where $q_1(Q) < \bar{q}_2$. Therefore, only the result using the minus sign remains.

In case *(iii)*, $\mathbb{E}[\pi_{D,S,1}((q_1(Q) - D_1)^+, Q)] = (p_D - r)B + (r - p_U)q_1(Q) + \frac{B}{2}\frac{(r-p_U)^2}{r} + \frac{B}{6}\frac{(r-p_U)^3}{r^2} - \frac{1}{2}\frac{(r-p_U)^2}{r}q_1(Q) - \frac{r}{6B^2}q_1(Q)^3$. Solving for the first order optimality condition yields the same result that we obtained for the forward-looking buyer when $q_1(Q) > \bar{q}_2$.

In case *(iv)*, $\mathbb{E}\pi_{D,S,1}((q_1(Q) - D_1)^+, Q)] = (p_D - r)B + (r - p_U)q_1(Q) - \frac{(r-p_U)}{2B}q_1^2 + \frac{B}{2}\frac{(r-p_U)^2}{r}$. Solving for the first order optimality condition, $q_1(Q)^* = B\left(\frac{r-p_U}{r-p_U}\right) = B$. However, since we are in the case in which $\bar{q}_2 \geq q_1(Q)$, this result yields a contradiction as $q_1(Q)^* = B > \bar{q}_2 = B\left(\frac{r-p_U}{r}\right)$. This case is eliminated. □

Proof of Proposition 2.7. In optimality, the seller would never stock more than $q_{1,F}^* + \bar{q}_2$ units since any additional units beyond this amount will not be purchased. At the same time, the seller would never order a Q less than $\bar{q}_2$ as she could earn more profit by increasing Q.

Note that $\mathbb{E}[\pi_{U,S}(Q)] = (p_U - c)\mathbb{E}[q_{1,S}^*(Q) + (\bar{q}_2 - (q_{1,S}^*(Q) - D_1)^+)^+)] - (p_U - c)\mathbb{E}[\big((q_{1,S}^*(Q) + (\bar{q}_2 - (q_{1,S}^*(Q) - D_1)^+)^+) - Q\big)^+] - c\mathbb{E}[\big(Q - (q_{1,S}^*(Q) + (\bar{q}_2 - (q_{1,S}^*(Q) - D_1)^+)^+)\big)^+]$. Recall that $\mathbb{E}[q_{1,S}^*(Q) + q_{2,S}^*(Q)] = q_{1,S}^*(Q) + \mathbb{E}[(\bar{q}_2 - (q_{1,S}^*(Q) - D_1)^+)^+)]$. The first component is deterministic and concave in Q in the range of interest. The second component is also concave. For the remainder of the terms we verify that there is a single crossing point. If Q increases, as long as $\mathbb{E}[q_{1,S}^*(Q) + q_{2,S}^*(Q)])$ does not increase faster than the underage cost is decreasing, then a single crossing point exists.

For $\frac{d}{dQ}q_{1,S}^*(Q) = 1 - \frac{Qr - B(r-p_U)}{\sqrt{\left(Bp_U + Qr\right)^2 + B\left(B(r-p_U)^2 - 2Qr^2\right)}}$, we show that $0 < \frac{d}{dQ}q_{1,S}^*(Q) < 1$. Let $\theta = \frac{Qr - B(r-p_U)}{\sqrt{\left(Bp + Qr\right)^2 + B\left(B(r-p_U)^2 - 2Qr^2\right)}}$. Suppose $\theta > 1$. Then, expanding and rearranging, $0 > B^2p^2$. However, by construction, $B^2p^2 > 0$ (contradiction). Therefore, $\theta < 1$ and $\frac{d}{dQ}q_{1,S}^*(Q) > 0$. Furthermore, since $\theta > 0$, $\frac{d}{dQ}q_{1,S}^*(Q) < 1$. Further note that $\frac{d}{dQ}\mathbb{E}[q_{2,S}^*(Q)] = \frac{(r-p_U)}{r}\left(\theta - 1\right) < 0$. By construction, $\frac{(r-p_U)}{r} < 1$. Since $\theta < 1$, $\theta - 1 < 0$ and $\frac{d}{dQ}\mathbb{E}[q_{2,S}^*(Q)] < 0$. Hence, $\frac{d}{dQ}\mathbb{E}[q_{1,S}^* + q_{2,S}^*] = \frac{p_U}{r}(1 - \theta) < 1$. □

Proof of Proposition 2.8. The same logic outlined in the proof for Proposition 2.1

applies to the period 2 objective function modified for the respective period price: $\mathbb{E}[\pi_{D,i,2}(y)] = p_D\mathbb{E}[\min(D_2, q_2 + y)] - p_{U,2}q_2 + (p_D - r)\mathbb{E}[(D_2 - (q_2 + y))^+]$. □

Proof of Proposition 2.9. The same logic outlined in the proof for Proposition 2.2 applies to the period 1 objective functions modified for the respective period price: $\mathbb{E}[\pi_{D,M,1}] = p_D\mathbb{E}[\min(D_1, q_1)] - p_U q_1 + (p_D - r)\mathbb{E}[(D_1 - q_1)^+]$. □

Proof of Proposition 2.10. Evaluating $\mathbb{E}[\pi_{D,F,2}(y)]$ for $D_2 \sim U[0, B]$, we have that $\mathbb{E}[\pi_{D,F,2}(y)] = (p_D - r)\left(\frac{B}{2}\right) - p_2q_2 + r(q_2 + y) - \frac{r}{2B}(q_2 + y)^2$. Plugging in this expression for $\mathbb{E}[\pi_{D,F,2}(q_1 - D_1)^+]$ in $\mathbb{E}[\pi_{D,F,1}(q_1 - D_1)^+]$, we obtain $\mathbb{E}[\pi_{D,F,1}(q_1 - D_1)^+] = (p_D - r)B + (r - p_{U,1})q_1 + (r - p_{U,2})\mathbb{E}[(\bar{q}_2 - (q_1 - D_1)^+)^+] - \frac{r}{2B}\mathbb{E}[((\bar{q}_2 - (q_1 - D_1)^+)^+ + (q_1 - D_1)^+)^2]$. To evaluate these expectations, we need to consider two cases: *(i)* $\bar{q}_2 \geq q_1$ and *(ii)* $\bar{q}_2 < q_1$.

In case *(i)*, $\mathbb{E}[(\bar{q}_2 - (q_1 - D_1)^+)^+] = \int_0^{q_1}[\bar{q}_2 - q_1 + x_1]f(x_1)\,dx_1 + \int_{q_1}^{B}\bar{q}_2 f(x_1)\,dx_1$ and $\mathbb{E}[((\bar{q}_2 - (q_1 - D_1)^+)^+ + (q_1 - D_1)^+)^2] = \int_0^{q_1}\bar{q}_2^2 f(x_1)\,dx_1 + \int_{q_1}^{B}\bar{q}_2^2 f(x_1)\,dx_1$. Therefore, evaluating for $D_1 \sim U[0, B]$, $\mathbb{E}[\pi_{D,F,1}(q_1 - D_1)^+] = (p_D - r)B + (r - p_{U,1})q_1 + (r - p_{U,2})(\bar{q}_2 - \frac{q_1^2}{2B}) - \frac{r}{2B}\bar{q}_2^2$. The first order optimality condition for q_1 is $\frac{d}{dq_1}\mathbb{E}[\pi_{D,F,1}(q_1 - D_1)^+] = r - p_{U,1} - (r - p_{U,2})\frac{q_1}{B} = 0$.

In case *(ii)*, $\mathbb{E}[(\bar{q}_2 - (q_1 - D_1)^+)^+] = \int_{q_1 - \bar{q}_2}^{q_1}[\bar{q}_2 - q_1 + x_1]f(x_1)\,dx_1 + \int_{q_1}^{B}\bar{q}_2 f(x_1)\,dx_1$ and $\mathbb{E}[((\bar{q}_2 - (q_1 - D_1)^+)^+ + (q_1 - D_1)^+)^2] = \int_0^{q_1 - \bar{q}_2}(q_1 - x_1)^2 f(x_1)\,dx_1 + \int_{q_1 - \bar{q}_2}^{q_1}\bar{q}_2^2 f(x_1)\,dx_1 + \int_{q_1}^{B}\bar{q}_2^2 f(x_1)\,dx_1$. Evaluating for $D_1 \sim U[0, B]$, $\mathbb{E}[\pi_{D,F,1}(q_1 - D_1)^+] = (p_D - r)B + (r - p_{U,1})q_1 + (r - p_{U,2})\left(\frac{\bar{q}_2^2}{2B} + \bar{q}_2 - \frac{q_1\bar{q}_2}{B}\right) - \frac{r}{2B}\left(\frac{2\bar{q}_2^3}{3B} + \frac{q_1^3}{3B} - \frac{q_1\bar{q}_2^2}{B} + \bar{q}_2^2\right)$. The first order optimality condition with respect to q_1 is $\frac{d}{dq_1}\mathbb{E}[\pi_{D,F,1}(q_1 - D_1)^+] = (r - p_{U,1}) - \frac{(r - p_{U,2})}{B}\bar{q}_2 - \frac{r}{2B^2}q_1^2 + \frac{r}{2B^2}\bar{q}_2^2 = 0$. Substituting $\bar{q}_2 = B\left(\frac{r - p_{U,2}}{r}\right)$ and simplifying, $q_1^2 = 2B^2\frac{(r - p_{U,1})}{r} - B^2\frac{(r - p_{U,2})^2}{r^2}$. Clearly, as $q_1 \geq 0$, we are interested in the non-negative root of this quadratic, $q_1^* = \frac{B}{r}\sqrt{2(r - p_{U,1})r - (r - p_{U,2})^2}$.

Note that the condition for case *(i)* $\bar{q}_2 \geq q_1 \Leftrightarrow \frac{r - p_{U,2}}{r} \geq \frac{r - p_{U,1}}{r - p_{U,2}}$. Similarly, the condition for case *(ii)* $\bar{q}_2 < q_1 \Leftrightarrow \frac{r - p_{U,2}}{r} < \frac{r - p_{U,1}}{r - p_{U,2}}$. For the equivalence of these conditions in case *(ii)*, note that $\bar{q}_2 < q_1 \Leftrightarrow \bar{q}_2^2 < q_1^2$. Then $2B^2\frac{(r - p_{U,2})^2}{r^2} < 2B^2\frac{(r - p_{U,1})}{r}$. Since

$0 < \frac{r-p_{U,2}}{r} < 1$, $2\frac{(r-p_{U,1})}{(r-p_{U,2})} > \frac{r-p_{U,1}}{r-p_{U,2}} > \frac{r-p_{U,2}}{r} > \frac{(r-p_{U,2})^2}{r^2}$. Further note that the condition for a real root for the quadratic in the optimality condition is that $2\frac{(r-p_{U,1})}{(r-p_{U,2})} \geq \frac{(r-p_{U,2})^2}{r^2}$ and by the reasoning in the last sentence this condition is trivially met. □

Proof of Corollary 2.5. When $p_{U,1} > p_{U,2}$, $q^*_{1,M} = B\left(\frac{r-p_{U,1}}{r}\right) > \bar{q}_2 = B\left(\frac{r-p_{U,2}}{r}\right)$ as the numerator $r - p_{U,1}$ is strictly less than the numerator $r - p_{U,2}$. When $p_{U,1} < p_{U,2}$, the opposite relationship holds. □

Proof of Corollary 2.6. For the first subcase of $q^*_{1,F}$, when $\frac{r-p_{U,2}}{r} \geq \frac{r-p_{U,1}}{r-p_{U,2}}$, it directly follows that $q^*_{1,F} = B\left(\frac{r-p_{U,1}}{r-p_{U,2}}\right) \leq \bar{q}_2 = B\left(\frac{r-p_{U,2}}{r}\right)$. For the second subcase of $q^*_{1,F}$, when $\frac{r-p_{U,2}}{r} < \frac{r-p_{U,1}}{r-p_{U,2}}$, note that after some algebraic steps we can rewrite this condition as $\frac{r-p_{U,2}}{r} < \frac{\sqrt{r^2-p^2_{U,2}-2r(p_{U,1}-p_{U,2})}}{r}$. Then, $q^*_{1,F} = B\left(\frac{\sqrt{r^2-p^2_{U,2}-2r(p_{U,1}-p_{U,2})}}{r}\right) > \bar{q}_2 = B\left(\frac{r-p_{U,2}}{r}\right)$ also directly follows. □

Proof of Corollary 2.7. For the first subcase of $q^*_{1,F}$, when $\frac{r-p_{U,2}}{r} \geq \frac{r-p_{U,1}}{r-p_{U,2}}$, it is easy to verify that $q^*_{1,F} = B\left(\frac{r-p_{U,1}}{r-p_{U,2}}\right) > q^*_{1,M} = B\left(\frac{r-p_{U,1}}{r}\right)$. For the second subcase of $q^*_{1,F}$, when $\frac{r-p_{U,2}}{r} < \frac{r-p_{U,1}}{r-p_{U,2}}$, note that the subcase condition of $\frac{r-p_{U,2}}{r} < \frac{r-p_{U,1}}{r-p_{U,2}} \Leftrightarrow \frac{r-p_{U,2}}{r} < \frac{\sqrt{r^2-p^2_{U,2}-2r(p_{U,1}-p_{U,2})}}{r} \Leftrightarrow 2rp_2 - rp_1 - p^2_{U,2} > 0$. Since $r > p_{U,1}$, $2rp_2 - (p^2_{U,2} + p^2_{U,1}) > 2rp_2 - (rp_1 + p^2_{U,2}) > 0$. Observe that $q^*_{1,F} = \frac{B}{r}\sqrt{r^2 - p^2_{U,2} - 2r(p_{U,1} - p_{U,2})} = B\sqrt{\frac{(r-p_{U,1})^2+2rp_2-p^2_{U,1}-p^2_{U,2}}{r^2}} > B\sqrt{\frac{(r-p_{U,1})^2}{r^2}} = q^*_{1,M}$, where the inequality holds because the second subcase implies $2rp_2 - p^2_{U,1} - p^2_{U,2} > 0$. □

Proof of Lemma 2.3. From Corollary 2.7, the proof follows the same logical steps as the proof for Lemma 2.1. □

Proof of Proposition 2.11. The seller's profit function can be written as $\mathbb{E}[\pi(Q)] = (p_{U,1} - p_{U,2})q^*_{1,M} + (p_{U,2} - c)Q - p_{U,2}\mathbb{E}[(Q - q^*_{1,M} - (\bar{q}_2 - (q^*_{1,M} - D_1)^+)^+)^+]$. To explicitly evaluate the last expectation term in $\mathbb{E}[\pi(Q)]$, we need to consider two cases for the relationship between $q^*_{1,M}$ and $\bar{q}_2$: *(i)* $\bar{q}_2 \geq q^*_{1,M}$ and *(ii)* $\bar{q}_2 < q^*_{1,M}$.

In case *(i)*, since $\bar{q}_2 \geq q^*_{1,M}$, $\bar{q}_2 \geq (q^*_{1,M} - D_1)^+$ and the second inner truncation can be eliminated as this term is always positive. We have $\mathbb{E}[(Q - q^*_{1,M} - (\bar{q}_2 - (q^*_{1,M} -$

$D_1)^+))^+] = \int_0^{\min(q^*_{1,M}, Q-\bar{q}_2)} (Q - \bar{q}_2 - x_1) f(x_1) dx_1 = \int_0^{Q-\bar{q}_2} (Q - \bar{q}_2 - x_1) f(x_1) dx_1$ as in optimality $q^*_{1,M} \leq Q^*_M \leq q^*_{1,M} + \bar{q}_2$. Evaluating for the uniform distribution of D_1, $\mathbb{E}[\pi(Q)] = (p_{U,1} - p_{U,2}) q^*_{1,M} + (p_{U,2} - c)Q - \frac{p_{U,2}}{2B}(Q - \bar{q}_2)^2$.

In case *(ii)*, since $\bar{q}_2 < q^*_{1,M}$, the second inner truncation cannot be eliminated. We have $\mathbb{E}[(Q - q^*_{1,M} - (\bar{q}_2 - (q^*_{1,M} - D_1)^+)^+)^+] = \int_0^{q^*_{1,M}-\bar{q}_2} (Q - q^*_{1,M}) f(x_1) dx_1 + \int_{q^*_{1,M}-\bar{q}_2}^{Q-\bar{q}_2} (Q - \bar{q}_2 - x_1) f(x_1) dx_1$. Evaluating for the uniform distribution of D_1, $\mathbb{E}[\pi(Q)] = (p_{U,1} - p_{U,2}) q^*_{1,M} + (p_{U,2} - c)Q - \frac{p_{U,2}}{B}\left(\frac{Q^2}{2} - \frac{q^{*2}_{1,M}}{2} - Q\bar{q}_2 + q^*_{1,M}\bar{q}_2\right)$.

In both cases, the first order optimality condition for Q is the same: $\frac{d}{dQ}\mathbb{E}[\pi(Q)] = (p_{U,2} - c) - \frac{p_{U,2}}{B}(Q - \bar{q}_2) = 0$. The concavity of the objective function in both cases can also be easily verified as $\frac{d^2}{dQ^2}\mathbb{E}[\pi(Q)] = \frac{-p_{U,2}}{B} Q < 0$ since $p_{U,2}, B$ and Q are strictly positive.

Finally, as we are dealing with a constrained optimization problem, we account for the requirement that the unique maximizer $B\left(\frac{p_{U,2}-c}{p_{U,2}}\right) + \bar{q}_2$ is such that $q^*_{1,M} \leq Q^*_M \leq q^*_{1,M} + \bar{q}_2$. Note that the first of the three subcases of Q^*_M does not happen in case *(i)* as $\bar{q}_2 \geq q^*_{1,M}$ and $B\left(\frac{p_{U,2}-c}{p_{U,2}}\right) > 0$ therefore $q^*_{1,M}$ is definitely less than or equal to a quantity greater than $\bar{q}_2$. □

Proof of Lemma 2.4. Follows same logical steps as in proof of Lemma 2.2. □

Proof of Proposition 2.12. From Corollary 2.7 and Lemma 2.3, the same logic as Proposition 2.5 applies. □

Chapter 3

Who Should Pay for Waste? Buyer Foresight and Policy Implications in a Serial Newsvendor Setting with Waste Costs

In Chapter 2, we studied a supply chain consisting of a buyer and a seller for a product with a limited lifetime. The buyer and the seller both face uncertain demand – the buyer from the downstream market and the seller from the buyer. Whereas the buyer can purchase product to serve the downstream market in each of the periods in a two-period horizon, the seller only has one opportunity to purchase product at the beginning of the horizon. This serial newsvendor supply chain model allowed us to investigate how the multi-unit product purchase decisions of a buyer and a seller vary depending on the degree of strategic behavior of the buyer. We found that different buyer types make different purchasing decisions that induce different stocking decisions in the seller. Moreover, it may be more beneficial for the seller to face certain type of buyers. Specifically, a seller earns more profit when facing buyers that are 'smart' (i.e. forward-looking) but not too 'smart' (i.e. sophisticated). A buyer on the other hand earns more profit the 'smarter' he is. What about waste outcomes?

In this chapter, we push this analysis further by shifting the focus to waste outcomes.

In particular, we build on the serial newsvendor model introduced in the previous chapter and on the insights obtained on the equilibrium inventory decisions associated with the different buyer types, to evaluate the effect that imposing a waste cost on the buyer and/or the seller has on reducing waste. Such a waste cost can be thought of as an increased disposal cost or a Pigouvian tax on units wasted. A waste cost that is applied on the seller leads the seller to stock less over the horizon, de facto reducing the possibility of waste. However, a waste cost applied on the buyer reduces the buyer's purchase quantities, signaling to the seller to stock less product. It is thus not clear a priori where and in what proportion a waste cost is more effectively or to what extent these decisions are sensitive to the buyer type in the supply chain.

We evaluate waste outcomes on both the individual agent level and the supply chain level. To focus the analysis, we restrict our attention to two of the three buyer types defined in the previous chapter: the myopic buyer and the forward-looking buyer.

3.1 Introduction

The United Nations Food and Agricultural Organization estimates that one-third of food produced annually worldwide, approximately 1.3 billion tonnes, is lost or wasted (United Nations Food and Agriculture Organization 2011).[1] In wealthier countries, a substantial proportion of this food waste and loss occurs downstream in the supply chain at the retailer and consumer levels. In the United States, 80% of food loss and waste is generated at the retail and consumer levels (ReFED 2016).

Food waste is problematic from various perspectives. First, food production is a highly resource-intensive process. Worldwide food production in itself uses 70% of freshwater (Molden 2007), occupies 40% of land (Foley et al. 2005), and generates between 19−29% of greenhouse emissions (Vermeulen et al. 2012). When food is wasted, all the resources that went into producing that food are wasted. Second, although food supply is globally sufficient, this supply is unevenly allocated and many people still struggle with food security. Even in the European Union, 33 million cannot afford a

[1] "Food loss" takes place in the upstream food supply chain (production, harvesting, and processing stages) whereas "food waste" takes place in the downstream food supply chain (distribution, retail, and final consumption stages).

quality meal every second day (European Commission 2020). The food lost or wasted worldwide is sufficient to feed 2 billion people, twice the undernourished population (Huber 2017). Third, food waste accounts for 8% of greenhouse gas emissions (Hawken 2017). Food waste discarded in landfills is particularly harmful as it generates methane gas, which is 20 times more powerful than carbon dioxide in terms of the greenhouse effect. Finally, the financial losses that result from not selling or consuming food are significant. In the United States alone, consumer-facing businesses in total and a household of four people lose about \$57B and \$1,600, respectively, due to food waste every year (ReFED 2016).

From a policy perspective, food waste reduction efforts are receiving more attention. Many governments and inter-governmental organizations have set targets for food waste reduction. In 2015, as part of its Sustainable Development Goals, the United Nations set a target to reduce per capita food waste at the retail and consumer levels by 50% by 2030 (United Nations 2015). The European Union is committed to meeting this target. To operationalize its commitment, the EU has implemented a standardized methodology to measure food waste across the EU countries so that national baselines and targets can be defined in 2022 and 2023 (European Commission 2020). Increasingly, we also see examples of policy interventions that effectively impose a waste cost on businesses and consumers. On the business side, for example, in 2016, France imposed a fine on retailers and wholesalers for the disposal of perishables that are still fit for human consumption (LOI 2016-138 du 11 février 2016 relative á la lutte contre le gaspillage alimentaire (1) 2016). On the consumer side, many jurisdictions have dedicated processes for discarding organic waste, including some that operate on a 'pay-as-you-throw' (PAYT) system. For instance, in South Korea in 2013, a process was implemented for households to take their organic waste to weighing stations in large residential areas and be charged accordingly. Alternatively, consumers can buy dedicated bags, which on average cost a family of four \$6 per week, to discard their food waste (Kim 2019). Other municipalities with such PAYT systems include cities in the Netherlands, Seattle, and California. The intent behind such systems is to increase consciousness at the agent-level about how much waste is generated.

Imposing a waste cost on any agent in the supply chain effectively increases the agent's over-stocking cost. An agent may respond with different tactics to an increased over-stocking cost, depending on its position in the supply chain and its degree of foresight. For instance, a seller facing a higher overage cost may stock less from the beginning or may reduce the product price as it approaches its expiration date to incentivize purchases from buyers. Whereas stocking less may reduce waste in the supply chain, marking down product may enhance buyer demand and increase waste at a lower echelon of the supply chain. Similarly, a buyer facing a higher overage cost may buy less product or may change the timing of his purchase if he expects product to be cheaper the next period.

When one agent best responds to another, a feedback loop is created. Take the example of seller markdowns, which are one of the most prevalent mechanisms to reduce excess inventory (Fisher & Raman 2010). If a buyer expects a lower price in later periods, he may decide to limit the amount he buys now to take advantage of the future lower price. If the seller marks down inventory, the buyer may delay his purchase, reducing the seller's incentive to stock inventory, thereby exposing the buyer to the risk of stockout meaning he needs to source from an alternative, potentially more expensive source. This interplay highlights the role of buyer behavior and the degree to which a buyer accounts for future periods or for the seller's decisions.

While a waste cost on either agent, as discussed earlier with the examples of South Korea and France, may be effective in reducing waste for that agent, it is not clear a priori whether such interventions reduce total food waste in the supply chain, and if so, by how much. This leads us to our main research questions: First, should the upstream or the downstream agent be taxed to reduce waste? Second, how is this decision affected by the degree of foresight of the downstream agent? Third, how can a policy-maker set waste reduction targets that trade-off waste reduction with profit loss?

To study these questions, we model a supply chain consisting of two agents – a buyer and a seller – over a two-period horizon. Both of these agents are newsvendors. In each period, the buyer faces independent aggregate uncertain demand from a population of downstream consumers. The buyer purchases product from the seller at the beginning of each period before downstream demand realizes and may carry excess inventory over from the first to the second period. The seller purchases product from an upstream supply source at the beginning of the selling horizon. Like the buyer, the seller can carry inventory over from the first to the second period, but cannot replenish. Hence, in deciding on a stocking quantity for the horizon, the seller needs to consider the buyer's second period purchase decision. In turn, the buyer's second period decision depends on the realization of demand the buyer observes in the first period, which is unobserved by the seller. At the end of the selling horizon both agents discard excess product and pay a penalty for this product. This cost can be thought of as a disposal cost.

In modeling the effect of buyer behavior, we define two buyer types: a myopic buyer and a forward-looking buyer. The *myopic* buyer is our most basic buyer who exhibits no strategic behavior. He completely ignores the second period when buying in the first period. The *forward-looking* buyer accounts for the second period and optimizes his purchase decisions over the horizon.

Using backward induction, we characterize the buyer's purchase decisions and the seller's stocking quantity for a supply chain with each buyer type. We conduct a numerical study to understand to what degree the waste and profit outcomes in a supply chain are influenced by different buyer behavior and whether imposing a waste the buyer and/or the seller actually reduce overall waste in the system. We find that both taxing the buyer and the seller reduces waste without a large decline in profit, but taxing the seller is more effective. We also find that the amount of the tax burden that should be placed on the buyer or the seller to minimize total expected waste is sensitive to different buyer types. When the buyer is forward-looking, it is better to distribute the tax more equally between the buyer and the seller. When the buyer is myopic, it is better to place more of the tax burden on the seller.

Our contribution is two-fold. First, we provide valuable insights into how different degrees of buyer foresight affect waste levels in a supply chain and how policy interventions can be targeted to be more effective given different buyer types. Second, we provide a tool to inform waste reduction targets and understand the degree to which imposing a waste cost can help achieve those targets. As one of the first studies to the best of our knowledge addressing policy interventions to reduce food waste, we pave the way for future research in this area.

This rest of the chapter is structured as follows. Section 3.2 briefly reviews the literature. Section 3.3 describes the modeling approach. Section 3.4 formulates and solves the decision problem for the myopic and forward-looking buyers and for the seller facing these buyer types. Section 3.5 investigates the effect of imposing a waste cost of a buyer or a seller through numerical experiments, with and without seller markdowns. Section 3.6 concludes with our main findings and future research directions.

3.2 Literature Review

This research relates to three main literature streams: food waste, strategic consumer behavior, and perishables inventory management. We briefly review each below.

First and foremost, this research contributes to the nascent but growing literature on food waste. Akkaş & Gaur (2021) review the literature and propose an OM research agenda for food waste, which includes policy interventions to reduce food waste. Other consolidation efforts include the reviews by Do et al. (2021) and He et al. (2018).

Despite the interest in policy interventions in practice, only a handful of works focus on policy interventions to reduce waste. In a one-period model with deterministic demand, Katare et al. (2017) study the interaction between a welfare-maximizing policy-maker and a population of representative end consumers to determine the socially optimal disposal tax. They also look at a substitute policy intervention of providing subsidies for food-preservation capital, such as technology or education to enhance waste consciousness. The authors find that a zero waste target would require an infinitely large disposal tax and, as such, is not realistic. Taking a more supply chain-focused approach in a deterministic demand setting, Beullens & Ghiami (2021) examine an EOQ system with a supplier and retailer in which the retailer can reduce setup costs and/or reduce the product deterioration rate. The authors highlight a conflict of incentives because the supplier can benefit from the retailer ordering larger quantities and producing higher waste as a result of higher deterioration. To address this conflict, they look at the effect of imposing waste targets on the retailer and find they can be useful mechanisms to reduce waste. They comment briefly on the imposition of taxes on retailers to reduce waste by stating that they distort incentives, would have to be very high to have an effect, and would lead to greater losses of supply chain profits. Our results, in contrast, show that taxes in fact do not have to be so high to have a significant waste reduction effect and they do so without large profit losses.

Both Katare et al. (2017) and Beullens & Ghiami (2021) study situations with deterministic demand. However, one of the main causes of food waste in the supply chain is demand uncertainty. Our work contributes to the literature on food waste by incorporating demand uncertainty into the interaction between a seller and a buyer. More specifically, we model the decision-making of both the seller and the buyer using a serial newsvendor framework. We then evaluate the waste and profit outcomes in the supply chain to derive insights on the effect of imposing a waste cost on one or both echelons in the supply chain.

The modeling framework we adopt is inspired by Kirci et al. (2018). In this chapter, the authors study a supply chain with a retailer and end consumer population in which a product can be offered in bulk (meaning that the consumer can purchase exactly as much as he wants) and/or in pre-determined package sizes. The idea is that giving consumers the choice to decide their purchase quantity exactly may reduce waste. In this sense, the waste-reduction intervention is at the retailer level. The consumer's purchase decision is modeled as a one-period newsvendor problem. The authors study the retailer's pricing decision and the impact of the product format offered on waste. While we do not study the format offering, we extend the one-period newsvendor model to a two-period model to study the inter-temporal effects of imposing a tax on the buyer or the seller in a system.

The study of the use of taxation as an instrument to reduce the production or consumption of products with negative externalities is not new. Cachon (2014) looks at the net effect in terms of carbon emissions in a system where retailers locate a large store away from a consumer population (hence requiring driving) and in a system with a small store located more centrally. He finds that the carbon cost would have to be so high that taxing either agent would be impractical. Krass et al. (2013) study how interventions such as taxes, subsidies, and rebates affect the choice between an established technology and a newer greener technology and the effect on emissions reductions. We study the policy intervention of imposing waste cost on agents along the supply case and the effectiveness of such policies in reducing waste in the system.

The second stream of literature that our work builds on is the literature on strategic consumer behavior. Reviews of the strategic consumer behavior literature include Wei & Zhang (2018), Shen & Su (2007), and Elmaghraby & Keskinocak (2003). This literature focuses on the inter-temporal game between a seller and a buyer where buyers can purchase *at most one* unit of a good. Given the negative impact on profitability induced by strategic consumers, the literature is concerned with counteracting such behavior. Liu & Van Ryzin (2008) examine inventory rationing whereas Levin et al. (2010) examine dynamic pricing as strategies to counteract the negative profitability of strategic consumer behavior.

While assuming that buyers purchase at most one unit is reasonable assumption for purchases such as electronics and fast fashion, it is not a reasonable assumption for purchases such as groceries (e.g., fresh produce). Only a handful of studies deal with strategic consumer behavior when making multi-unit purchases. In an auction setting, Elmaghraby et al. (2008) characterize the optimal timing of markdowns in a multi-period horizon when multi-unit purchases are possible. In a two-period setting with a monopolist seller and a population of buyers, Jin et al. (2021) study the optimal period prices when a buyer can purchase up to two units of a good. They find that, unlike in single-unit settings, strategic buyer behavior in multi-unit settings increases the the optimal first period price. Moving away from pricing, Perez Becker et al. (2021) focus on the inventory decisions of a seller and a buyer with varying degrees of foresight. The authors find that, even when pricing is constant, the purchase and stocking decisions are sensitive to buyer foresight. Using a similar model, the present work extends this study to evaluate the impact of buyer behavior on waste and the effectiveness of waste-reduction policies that impose a waste cost on agents at different levels of the supply chain.

Finally, we also build on the literature on perishables inventory management. This literature is rich and well-developed. Reviews of the perishables inventory management literature include Nahmias (1982), Goyal & Giri (2001), Karaesmen et al. (2011), and Bakker et al. (2012). On the OR side, most of this literature is concerned with modeling product deterioration and determining optimal inventory policies that take into account the age of different generations of a product that co-exist with each other. We do not model the deterioration process or account for products of different ages co-existing with each other. Rather, we employ a streamlined inventory model of a perishable good based on a serial newsvendor framework to study the interaction between a seller and a buyer in a decentralized setting under policy interventions.

3.3 Model

A seller sells a perishable product with a fixed deterministic lifetime of two periods. She has a single ordering opportunity at the beginning of the horizon and purchases Q units of product from an upstream agent at a unit production cost of $c > 0$. Each period, the seller sells this product at a unit sales price of $p_{U,t}$, $t \in \{1, 2\}$, with $p_{U,1}, p_{U,2} > c$ (to ensure her participation in the market). The unit sales prices $p_{U,1}$ and $p_{U,2}$ are exogenous and pre-announced at the beginning of the horizon. The seller can carry over unsold product from period 1 into period 2, however, any unsold product at the end of the horizon must be discarded. She incurs a unit waste cost of $w_U \geq 0$ for each discarded product.

At the beginning of each period, the buyer seeks to purchase quantities $q_t, t \in \{1, 2\}$ from the seller. The buyer's higher order frequency compared to the seller's reflects the fact that in multi-echelon settings it is common for downstream agents to have higher order frequencies than their upstream counterparts and that these order frequencies are nested within those of the upstream's agent (e.g., Roundy 1985). The buyer faces uncertain demand in each period, denoted by the random variables D_t, $t \in \{1, 2\}$, which each have a distribution F and density f. The buyer's purchase quantity decisions are made before demand in period t is realized. If the demand realization in a period exceeds the amount of product the buyer has on-hand, he purchases additional units exactly up to his demand realization from an alternative source, albeit at a higher unit price of r. The buyer sells product to the downstream market at a unit price of $p_D > 0$, which is constant across both periods. We assume that $p_D > r > p_{U,t}$ for $t = \{1, 2\}$ to ensure that the buyer participates in both the regular market and the runout market. In the first period, if the demand realization is less than the quantity of product on-hand, the buyer carries over leftover inventory $y \equiv (q_1 - D_1)^+$ into the second period at zero holding cost. In the second period, if the demand realization is less than the quantity of product on-hand, because the horizon is ending, any leftover inventory is discarded. Similar to the seller, the buyer incurs a unit waste cost of $w_U \geq 0$ for product discarded. The sequence of events is illustrated in Figure 3.1.

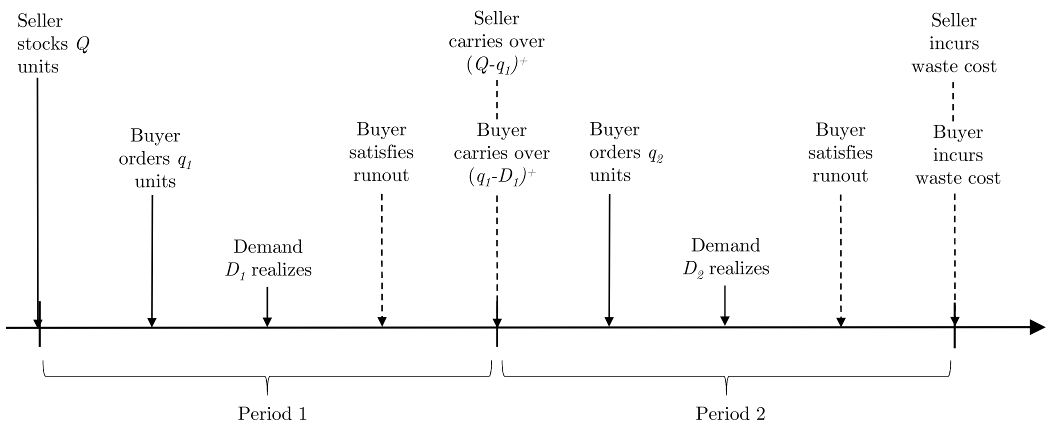


Figure 3.1: Sequence of events with waste costs

In line with this sequence of events, the decision-making problem is modeled as a three-stage game. The seller is the first-mover and optimizes her stocking quantity Q over the horizon. The buyer optimizes his period purchase quantities of q_1 and q_2. The buyer's demand distribution and cost parameters are common knowledge. For each of the buyer types, we first solve for the buyer's period 2 optimal purchase quantity, q_2^*. Then, we solve for the buyer's period 1 optimal purchase quantity, q_1^*. Finally, we solve for the seller's best response in terms of a horizon stocking decision Q given the buyer's optimal purchase quantity decisions q_1^* and q_2^*.

To study the effect of different degrees of buyer foresight on inventory decisions, we define two buyer types: a myopic buyer and a forward-looking buyer. The subscript $i \in \{M, F\}$ denotes the decisions associated with each buyer type, where M denotes the myopic buyer and F denotes the forward-looking buyer. Both buyer types decide on their period purchase quantities based on their *perceptions* of the trade-offs. The myopic buyer optimizes each period individually and ignores inter-temporal implications. In each period, he simply observes the period price and decides on a purchase quantity for that period based on the amount of product he has on-hand and knowledge of the distribution of downstream demand. The forward-looking buyer takes into account inter-temporality by considering prices across periods, the ability to use leftover inventory from period 1 in period 2, and the upcoming discarding of leftover product at the end of the horizon. He observes the pre-announced prices for period 1 and period 2 and, using knowledge of the downstream demand distribution and other cost parameters, decides on a purchase quantity for each period. In Section 3.4, we analyze this model for each of the buyer types.

3.4 Model Analysis

3.4.1 Buyer's Period 2 Problem

The myopic and forward-looking buyers face the same problem in period 2. For any given leftover inventory realization $y_i \equiv (q_{1,i} - D_1)^+$ from period 1, a buyer of type $i = \{M, F\}$ chooses purchase quantity $q_{2,i} \geq 0$ to maximize his perceived period profit function, given by:

$$\begin{aligned}\mathbb{E}[\pi_{D,i,2}(y_i)] =& p_D \mathbb{E}[\min(D_2, q_{2,i} + y)] - p_{U,2} q_{2,i} \\ &+ (p_D - r)\mathbb{E}[(D_2 - (q_{2,i} + y_i))^+] - w_D \mathbb{E}[((q_2 + y) - D_2)^+]. \end{aligned} \tag{3.1}$$

The first term is the revenue from sales of product purchased from the seller to the downstream market. The second term is the cost of product purchased from the seller. The third term is the net profit from sales of product purchased from the runout option. The fourth term is the cost of waste incurred for excess inventory. Solving for this newsvendor problem, in period 2, a buyer of type $i = \{M, F\}$ seeks to purchase:

$$q^*_{2,i} = (\bar{q}_2 - y_i)^+ \text{ where } \bar{q}_2 = F^{-1}\left(\frac{r - p_{U,2}}{r + w_D}\right). \tag{3.2}$$

The optimal period 2 purchase follows a base-stock policy, where $\bar{q}_2$ is the order-up-to level and is the same regardless of the buyer type. The differences between the myopic and forward-looking buyers emerge in their optimal period 1 purchase decisions.

3.4.2 Buyer's Period 1 Problem

In solving the buyer's period 1 problem, we distinguish between the myopic and the forward-looking buyer.

Myopic Buyer

Since the myopic buyer maximizes his perceived profit for each period individually, he does not consider any implications of his period 1 decision on period 2. In period 1, the myopic buyer's problem is to choose purchase quantity $q_{1,M} \geq 0$ to maximize his perceived period profit function, given by:

$$\mathbb{E}[\pi_{D,M,1}] = p_D \mathbb{E}[\min(D_1, q_{1.M})] - p_{U,1} q_{1,M} + (p_D - r)\mathbb{E}\left[(D_1 - q_{1,M})^+\right]. \tag{3.3}$$

Solving for (3.3), in period 1, the myopic buyer seeks to purchase:

$$q^*_{1,M} = F^{-1}\left(\frac{r - p_{U,1}}{r}\right). \tag{3.4}$$

The optimal period 1 decision also follows a base-stock policy, where $q^*_{1,M}$ is effectively the period 1 order-up-to level.

Forward-Looking Buyer

In period 1, the forward-looking buyer maximizes his perceived profit across the entire horizon. His problem is to choose a purchase quantity $q_{1,F} \geq 0$ to maximize his horizon perceived profit function, given by:

$$\mathbb{E}[\pi_{D,F,1}] = p_D \mathbb{E}[\min(D_1, q_{1,F})] - p_{U,1} q_{1,F} + (p_D - r)\mathbb{E}[(D_1 - q_{1,F})^+] + \mathbb{E}[\pi_{D,F,2}(q_{1,F} - D_1)^+)]. \tag{3.5}$$

Compared to the myopic buyer's period 1 problem, the forward-looking buyer's profit function incorporates an extra term to link the outcomes in both periods. In period 1, the forward-looking buyer seeks to purchase:

$$q^*_{1,F} = \text{argmax}_{q_{1,F}} \mathbb{E}[\pi_{D,F,1}]. \tag{3.6}$$

3.4.3 Seller's Problem

The seller's problem is structurally the same regardless of the buyer type she faces. At the beginning of the horizon, given the respective $q^*_{1,i}$ and $q^*_{2,i}$ for buyer type $i \in \{M, F\}$, the seller chooses order quantity $Q_i \geq 0$ to maximize her horizon profit. The seller's horizon profit is given by:

$$\begin{aligned}\mathbb{E}[\pi_{U,i}(Q_i)] =& p_{U,1} \min(q^*_{1,i}, Q_i) + p_{U,2}\mathbb{E}[\min(q^*_{2,i}, Q_i - q^*_{1,i})] - cQ_i \\ &- w_U \mathbb{E}[(Q - (q^*_{1,i} + \min(q^*_{2,i}, Q - q^*_{1,i})))^+].\end{aligned} \tag{3.7}$$

The first and second terms of (3.7) are the revenues from sales in each period to a buyer of type i. The third term is the product cost incurred by the seller. The fourth term is the total waste cost from any product remaining after the second period, which must be discarded.

Observe that the seller faces no uncertainty in the buyer's period 1 purchase decision, since $q^*_{1,i}$ does not depend on any random variables. Therefore, at optimality, the seller stocks at least $q^*_{1,i}$. In fact, the seller only faces uncertainty related to the buyer's period 2 purchase decision. While the seller knows the distribution of downstream demand in each period, the buyer's purchase quantity in period 2 is a random variable that depends on the buyer's leftover inventory, which in turn depends on his realized demand in period 1. At optimality, since the buyer never buys more than his order-up-to quantity $\bar{q}_2$ in period 2, the seller would never stock more than $\bar{q}_2$ for this period. Thus, $q^*_{1,i} \leq Q^*_i \leq q^*_{1,i} + \bar{q}_2$. When facing a buyer of type $i \in \{M, F\}$, the seller's stocking quantity for the horizon is given by:

$$Q^*_i = \operatorname{argmax}_{Q_i} \mathbb{E}[\pi_{U,i}(Q_i)]. \tag{3.8}$$

The seller solves a newsvendor problem using the distribution of the demand the seller faces from the buyer to determine Q^*_i. The demand the seller faces from a buyer of type $i \in \{M, F\}$ over the horizon, denoted by N_i, is:

$$N_i = q^*_{1,i} + (\bar{q}_2 - (q^*_{1,i} - D_1)^+)^+. \tag{3.9}$$

Based on her willingness to take risk on the supply she brings for period 2, however, the seller may not have sufficient inventory to satisfy the buyer's period 1 and period 2 purchase decisions. The buyer's effective purchase quantity for the horizon, denoted by H_i, is:

$$H_i = q^*_{1,i} + \min\left(Q^*_i - q^*_{1,i}, (\bar{q}_2 - (q^*_{1,i} - D_1)^+)^+\right). \tag{3.10}$$

Both waste and profit at the end of the horizon for the buyer and the seller are consequently a function of both how much inventory the seller decides to bring as well as of how much the buyer is actually able to buy. The seller's waste when she faces a buyer of type $i = \{M, F\}$, denoted by SW_i, is given by:

$$SW_i = Q^*_i - H_i. \tag{3.11}$$

The buyer's waste for a buyer of type $i = \{M, F\}$, denoted by BW_i, is given by:

$$BW_i = \left((q^*_{1,i} - D_1)^+ + \min\left(Q^*_i - q^*_{1,i}, (\bar{q}_2 - (q^*_{1,i} - D_1)^+)^+\right) - D_2\right)^+. \tag{3.12}$$

Total waste in a supply chain of buyer type $i = \{M, F\}$, denoted by TW_i, is then:

$$TW_i = SW_i + BW_i. \tag{3.13}$$

Since both agents influence each other's decisions, it is not clear a priori how buyer behavior influences waste and profit outcomes. We explore these outcomes and the effect of imposing a waste cost on either agent numerically in the next section.

3.5 Numerical Study

To ensure that the parameters for our instances are such that both the buyer and the seller participate in the market (i.e., $p_D > r > p_{U,1} \geq p_{U,2} > c > 0$), we set $p_D = 10$ and all other parameters in relation to each other through parameter-specific multipliers, i.e., $r = \alpha p_D$ where $\alpha \in \{0.7, 0.8, 0.9\}$, $p_{U,1} = \beta r$ where $\beta \in \{0.4, 0.5, 0.6\}$, $p_{U,2} = \theta p_{U,1}$ where $\theta \in \{0.8, 0.9, 1\}$, and $c = \gamma p_{U,2}$ where $\gamma \in \{0.4, 0.5, 0.6\}$. The α and γ multipliers are calibrated to ensure that the total amount of waste and the distribution of waste between the buyer and seller are consistent with industry studies (e.g., ReFED 2016, Van Donselaar & Broekmeulen 2012). Under these parameter settings, the seller's profit margin is $40 - 68\%$ in period 1 and $40 - 60\%$ in period 2. While such a profit margin may seem high, it is reasonable in a supply chain with a seller with significant market power. D_1 and D_2 are Gamma distributed with mean $\mu = 50$ and coefficient of variation $CV \in \{0.4, 0.8\}$.[2]

To investigate the levels of waste and the effects of imposing a waste tax on either agent in supply chains with different buyer types, we conduct two types of numerical studies. In the first type of study, we set the values for the waste tax on the buyer and the seller at an absolute level. The purpose of this study is to understand how the level of the waste tax on each agent affects the level of waste in the supply chain under each buyer type. The values for the waste tax on the buyer and the seller are given by $w_D \in \{0, 0.5, 1, 1.5, 2\}$ and $w_U \in \{0, 0.5, 1, 1.5, 2\}$, respectively. Table 3.1 summarizes the parameter settings of this first type of study.

Input parameter	No. of values	Values
Buyer's unit sales price, p_D	1	10
Unit runout cost (r) multiplier, α	3	0.7, 0.8, 0.9
Seller's period 1 price ($p_{U,1}$) multiplier, β	3	0.5, 0.5, 0.6
Seller's period 2 price ($p_{U,2}$) multiplier, θ	3	0.8, 0.9, 1
Seller's product cost (c) multiplier, γ	3	0.4, 0.5, 0.6
Coefficient of variation of demand, CV	2	0.4, 0.8
Seller unit waste cost, w_U	5	0, 0.5, 1, 1.5, 2
Buyer unit waste cost, w_D	5	0, 0.5, 1, 1.5, 2

Table 3.1: Parameter settings for the first numerical study

In the second type of study, we aim to better understand the degree to which taxes should be imposed on each agent. To this end, we consider a situation in which the policy-maker has a maximum absolute amount of tax he is willing to impose on both agents combined. This combined tax is denoted by w_T where $w_T = w_U + w_D$. Let δ denote the proportion of the tax imposed on the buyer, where $\delta \in \{0, 0.25, 0.5, 0.75, 1\}$. The tax imposed on the buyer is then $w_D = \delta w_T$ and the tax imposed on the seller is

[2] We also repeated these experiments with uniformly distributed demands, as a numerical extension of Perez Becker et al. (2021) with waste. The findings are consistent to those with Gamma distributed demands.

$w_U = (1 - \delta)w_T$. We examine values of $w_T \in \{0, 0.5, ..., 4.5, 5\}$ for a supply chain with each buyer type. Table 3.2 summarizes the parameter settings of the second study.

Input parameter	No. of values	Values
Buyer's unit sales price, p_D	1	10
Unit runout cost (r) multiplier, α	3	0.7, 0.8, 0.9
Seller's period 1 price ($p_{U,1}$) multiplier, β	3	0.5, 0.5, 0.6
Seller's period 2 price ($p_{U,2}$) multiplier, θ	3	0.8, 0.9, 1
Seller's product cost (c) multiplier, γ	3	0.4, 0.5, 0.6
Coefficient of variation of demand, CV	2	0.4, 0.8
Combined unit waste cost, w_T	11	0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5
Buyer % of combined unit waste cost, δ	5	0, 0.25, 0.5, 0.75, 1

Table 3.2: Parameter settings for the second numerical study

We first summarize the findings of these studies for the case in which no seller markdowns take place (i.e., $\theta = 1$). Then, to test for the impact of seller markdowns on waste and whether the same findings hold in a scenario where seller markdowns take place, we repeat the studies for the three levels of θ referenced above.

3.5.1 No Seller Markdowns

Absolute Tax Levels

Based on the parameter values, $3 \times 3 \times 1 \times 3 \times 2 \times 5 \times 5 = 1,350$ instances are generated and the model is solved for each buyer type. The results of this experiment for the myopic and forward-looking buyers are displayed in Table 3.3 and Table 3.4, respectively. Specifically, these tables display the average across all instances for each fixed value of the listed parameter.

The first observation is that the amount of waste, both for each agent and overall in the supply chain, is sensitive to the buyer type. As measures of waste, we consider both absolute waste and relative waste. Relative waste is defined as the ratio of expected waste over the seller's stocking decision Q^*, in line with Kirci et al. (2018). On average, the forward-looking buyer wastes more than the myopic buyer in both absolute terms (7.29 vs. 5.09) and relative terms (8.89% vs. 6.63%). The intuition behind this result is that the forward-looking buyer buys more than the myopic buyer from the seller in period 1, knowing that he can still sell this product in period 2 or in case of high downstream demand in period 1. However, he is not actually able to sell as much as he buys to the downstream market. Consequently, the seller facing the forward-looking buyer wastes less than the seller facing the myopic buyer on both absolute terms (1.65 vs. 4.95) and relative terms (2.01 % vs. 6.45 %). Overall, however, the expected total waste in a supply chain with a myopic buyer is greater than the expected total waste in a supply chain with a forward-looking buyer in both absolute terms (10.05 vs. 8.94) and relative terms (13.08% and 10.90%). Even though the myopic buyer wastes less, the seller facing the myopic buyer wastes significantly more.

			Avg Exp Waste			Avg Exp Profit			Avg Quantities		
Parameter	Value	Count	Buyer	Seller	Total	Buyer	Seller	Total	q_1^*	$\bar{q}_2$	Q^*
	0.7	450	4.87	4.78	9.65	513.75	111.85	625.60	43.88	39.92	75.99
α	0.8	450	5.10	4.96	10.07	445.61	129.10	574.72	43.88	40.32	76.87
	0.9	450	5.30	5.12	10.42	377.49	146.43	523.92	43.88	40.65	77.59
	0.4	450	6.42	5.14	11.57	517.11	113.66	630.77	50.89	46.21	83.04
β	0.5	450	5.04	5.23	10.26	443.64	130.53	574.18	43.60	40.12	77.30
	0.6	450	3.81	4.49	8.30	376.11	143.18	519.29	37.14	34.55	70.11
	0.4	450	5.84	6.38	12.22	447.85	159.85	607.70	43.88	40.29	80.34
γ	0.5	450	5.16	5.03	10.19	446.13	128.65	574.79	43.88	40.29	77.21
	0.6	450	4.28	3.45	7.73	442.87	98.88	541.75	43.88	40.29	72.90
	0	270	6.00	6.76	12.76	448.17	134.41	582.57	43.88	40.29	81.11
	0.5	270	5.46	5.61	11.07	447.08	131.34	578.41	43.88	40.29	78.60
w_U	1	270	5.04	4.79	9.83	445.74	128.74	574.48	43.88	40.29	76.59
	1.5	270	4.64	4.08	8.72	444.30	126.53	570.82	43.88	40.29	74.70
	2	270	4.31	3.53	7.84	442.82	124.63	567.45	43.88	40.29	73.08
	0	270	6.52	5.01	11.53	453.21	135.69	588.90	43.88	43.88	80.40
	0.5	270	5.64	5.00	10.64	448.98	131.83	580.80	43.88	41.82	78.34
w_D	1	270	4.95	4.97	9.92	445.23	128.61	573.84	43.88	40.06	76.58
	1.5	270	4.40	4.92	9.32	441.87	125.91	567.77	43.88	38.53	75.06
	2	270	3.96	4.86	8.82	438.81	123.61	562.42	43.88	37.19	73.71
CV	0.4	675	4.30	4.27	8.57	494.96	152.84	647.81	47.47	44.88	86.96
	0.8	675	5.88	5.64	11.52	396.28	105.41	501.69	40.28	35.71	66.68
All		1350	5.09	4.95	10.05	445.62	129.13	574.75	43.88	40.29	76.82

Table 3.3: Numerical results for first experiment – supply chain with myopic buyer (no seller markdowns)

The second observation is that, directionally, the effects of shifting the parameters of study on waste and profit outcomes are similar for both buyer types, suggesting robustness of these effects to different buyer behavior. In terms of the waste-related parameters, as w_U and w_D increase, expected total waste decreases with relatively small losses to expected total profit. These results suggest that both instruments are effective

			Avg Exp Waste			Avg Exp Profit			Avg Quantities		
Parameter	Value	Count	Buyer	Seller	Total	Buyer	Seller	Total	q_1^*	$\bar{q}_2$	Q^*
	0.7	450	7.11	1.56	8.67	526.27	135.09	661.37	77.10	39.92	81.38
α	0.8	450	7.30	1.66	8.96	460.25	155.45	615.70	77.58	40.32	82.09
	0.9	450	7.46	1.74	9.20	394.29	175.86	570.15	77.97	40.65	82.68
	0.4	450	9.88	1.42	11.29	529.83	136.68	666.51	84.46	46.21	88.40
β	0.5	450	7.09	1.64	8.73	458.09	157.08	615.17	77.47	40.12	81.93
	0.6	450	4.90	1.91	6.81	392.89	172.65	565.54	70.74	34.55	75.82
	0.4	450	7.54	2.97	10.50	464.02	188.07	652.09	77.55	40.29	84.88
γ	0.5	450	7.27	1.38	8.65	459.98	155.13	615.10	77.55	40.29	81.64
	0.6	450	7.07	0.61	7.68	456.81	123.21	580.03	77.55	40.29	79.63
	0	270	7.60	3.37	10.97	464.82	157.30	622.12	77.55	40.29	85.61
	0.5	270	7.38	1.99	9.37	461.70	155.99	617.70	77.55	40.29	82.96
w_U	1	270	7.25	1.31	8.56	459.67	155.18	614.85	77.55	40.29	81.45
	1.5	270	7.15	0.92	8.07	458.18	154.64	612.82	77.55	40.29	80.48
	2	270	7.07	0.67	7.74	456.98	154.24	611.22	77.55	40.29	79.76
	0	270	8.91	1.61	10.52	470.86	163.43	634.29	81.71	43.88	86.12
	0.5	270	7.94	1.63	9.57	464.95	158.93	623.88	79.36	41.82	83.80
w_D	1	270	7.15	1.65	8.80	459.71	155.00	614.72	77.31	40.06	81.80
	1.5	270	6.50	1.68	8.18	455.03	151.54	606.57	75.50	38.53	80.04
	2	270	5.95	1.70	7.65	450.80	148.45	599.26	73.89	37.19	78.49
CV	0.4	675	4.21	2.79	6.99	504.92	162.61	667.53	79.82	44.88	87.84
	0.8	675	10.38	0.52	10.90	415.62	148.33	563.96	75.29	35.71	76.26
All		1350	7.29	1.65	8.94	460.27	155.47	615.74	77.55	40.29	82.05

Table 3.4: Numerical results for first experiment – supply chain with forward-looking buyer (no seller markdowns)

for waste reduction. However, taxing the seller results in a sharper reduction in waste for both buyer types. Taxing the seller reduces relative total waste from 12.82% to 9.71% in a supply chain with a forward-looking buyer and from 15.74% to 10.73% in supply chain with a myopic buyer. By comparison, taxing the buyer reduces the percentage of expected total waste from 12.21% to 9.75% in a supply chain with a forward-looking buyer and from 14.35% to 11.96% in a supply chain with a myopic buyer.

The greater effectiveness of taxing the seller can be explained by the mechanism triggered by increases in w_U. As w_U increases, the seller immediately responds by stocking less to limit her overage risk in period 2. The buyer's purchase decisions are unchanged, but his actual purchases may be limited by the seller's supply and he may need to buy more from the runout option, reducing his waste as well as his profit. As w_D increases, the purchase decisions of both buyers decrease, reducing demand for the seller's product and the seller responds by stocking less. However, the seller's response is slower than when she is directly responding to an increase in w_U.

Whereas increasing w_U reduces total waste in similar magnitudes for both the myopic and forward-looking buyer, increasing w_D results in a greater reduction in total waste for the forward-looking buyer. As w_D increases, the myopic buyer buys less in period 2 only, but the forward-looking buyer buys less in both period 1 and period 2, reducing more sharply the demand for the seller's product and the seller's stocking quantity. Increases in w_D, hence, are more effective in reducing waste when the seller faces a forward-looking buyer (i.e., same tax on buyer will have greater waste-reduction effect).

Proportion of Tax Burden

Based on the parameter values, $3 \times 3 \times 1 \times 3 \times 2 \times 11 \times 5 = 2,970$ instances are generated and the model is solved for each buyer type. The results of this experiment are displayed in Table 3.5 for the myopic buyer and Table 3.6 for the forward-looking buyer.

On average, profit for the buyer and seller individually and profit in total decreases in δ, the proportion of the tax imposed on the buyer. As δ increases and more of the tax shifts to the buyer, two competing effects are observed: 1) the buyer's dampening demand for the seller's product as his overage cost increases and 2) the seller's incentivization of supply as her overage cost decreases. When the buyer faces a higher overage cost, his demand for the seller's product decreases, and he buys more instead from the runout option once downstream demand is certain. At the same time, as δ increases, the seller's overage cost decreases and she has an incentive to offer more supply. However, as she best responds to the buyer's dampened demand, the quantity of stock the seller offers is constrained by the buyer's demand. The relative magnitudes of these two effects determine the purchase and stocking decisions and the profit in the system. On average, based on our test bed, it is the demand-dampening effect that dominates. For a policy-maker, this result suggests that, from a profit perspective, it may be better to impose a greater proportion of the tax burden on the seller than on the buyer.

A more intricate story emerges for total waste, which is not monotonic in δ. This

			Avg Exp Waste			Avg Exp Profit			Avg Quantities		
Parameter	Value	Count	Buyer	Seller	Total	Buyer	Seller	Total	q_1^*	$\bar{q}_2$	Q^*
α	0.7	990	4.69	4.65	9.34	512.21	110.92	623.13	43.88	39.51	75.12
	0.8	990	4.91	4.83	9.73	443.97	128.00	571.96	43.88	39.92	76.00
	0.9	990	5.09	4.98	10.07	375.75	145.16	520.91	43.88	40.25	76.73
β	0.4	990	6.25	5.11	11.36	514.74	112.87	627.61	50.89	45.73	82.31
	0.5	990	4.82	5.05	9.88	441.99	129.42	571.42	43.60	39.73	76.36
	0.6	990	3.62	4.29	7.91	375.19	141.79	516.98	37.14	34.22	69.19
γ	0.4	990	5.59	6.18	11.77	446.27	158.37	604.64	43.88	39.89	79.33
	0.5	990	4.96	4.89	9.85	444.48	127.58	572.06	43.88	39.89	76.31
	0.6	990	4.14	3.39	7.53	441.18	98.13	539.31	43.88	39.89	72.21
w_T	0	270	7.59	6.82	14.41	455.34	141.03	596.36	43.88	43.88	84.69
	0.5	270	6.77	6.21	12.98	452.86	137.46	590.32	43.88	42.83	82.34
	1	270	6.10	5.74	11.84	450.44	134.33	584.77	43.88	41.89	80.33
	1.5	270	5.52	5.32	10.84	448.10	131.56	579.66	43.88	41.05	78.49
	2	270	5.02	4.95	9.97	445.83	129.09	574.92	43.88	40.29	76.82
	2.5	270	4.59	4.63	9.23	443.63	126.88	570.51	43.88	39.60	75.30
	3	270	4.22	4.34	8.57	441.51	124.89	566.39	43.88	38.96	73.90
	3.5	270	3.90	4.08	7.98	439.45	123.08	562.53	43.88	38.37	72.61
	4	270	3.62	3.85	7.46	437.45	121.45	558.89	43.88	37.82	71.41
	4.5	270	3.37	3.63	7.00	435.51	119.95	555.46	43.88	37.31	70.31
	5	270	3.15	3.44	6.59	433.63	118.59	552.21	43.88	36.83	69.28
δ	0	594	5.49	3.57	9.06	449.67	130.57	580.23	43.88	43.88	76.09
	0.25	594	4.97	4.02	8.98	445.61	127.87	573.49	43.88	41.44	75.19
	0.5	594	4.71	4.58	9.29	442.97	126.74	569.72	43.88	39.53	75.14
	0.75	594	4.63	5.36	9.99	441.37	126.83	568.20	43.88	37.97	75.87
	1	594	4.69	6.56	11.25	440.26	128.12	568.38	43.88	36.65	77.47
CV	0.4	1485	4.12	4.18	8.31	493.58	151.72	645.31	47.47	44.56	86.24
	0.8	1485	5.67	5.45	11.12	394.37	104.33	498.70	40.28	35.23	65.67
All		2970	4.90	4.82	9.72	443.98	128.03	572.00	43.88	39.89	75.95

Table 3.5: Numerical results for second experiment – supply chain with myopic buyer (no seller markdowns)

non-monotonicity of total waste is related to the non-monotonicity in the seller's stocking decision, Q^*. As δ starts increasing from zero, the buyer's demand-dampening effect dominates over the seller's supply-incentivizing effect and the seller stocks less. This decrease continues until δ reaches a threshold in which the seller's supply-incentivizing effect starts dominating and the seller's stocking decision increases again. Seller's waste always increases in δ, but buyer's waste may decrease or increase depending on how the buyer's demand compares to the seller's supply. The resulting non-monotonicity of total waste in δ, in addition to the previously established monotonicity of total profit in δ, suggests that it may be possible to strike a balance that reduces total waste without reducing profit as heavily by distributing the tax burden

Parameter	Value	Count	Avg Exp Waste			Avg Exp Profit			Avg Quantities		
			Buyer	Seller	Total	Buyer	Seller	Total	q_1^*	$\bar{q}_2$	Q^*
α	0.7	990	6.98	1.70	8.69	525.03	134.28	659.31	76.58	39.51	81.03
	0.8	990	7.16	1.77	8.93	458.81	154.51	613.33	77.07	39.92	81.70
	0.9	990	7.32	1.83	9.15	392.68	174.81	567.49	77.47	40.25	82.27
β	0.4	990	9.70	1.54	11.24	527.94	135.81	663.76	83.87	45.73	87.96
	0.5	990	6.96	1.75	8.71	456.68	156.12	612.80	76.96	39.73	81.53
	0.6	990	4.81	2.02	6.82	391.91	171.67	563.57	70.30	34.22	75.51
γ	0.4	990	7.41	3.24	10.64	462.82	186.98	649.80	77.04	39.89	84.74
	0.5	990	7.12	1.43	8.55	458.40	154.16	612.56	77.04	39.89	81.14
	0.6	990	6.94	0.63	7.57	455.31	122.47	577.77	77.04	39.89	79.13
w_T	0	270	9.27	3.23	12.50	474.97	165.20	640.17	81.71	43.88	89.49
	0.5	270	8.63	2.55	11.18	470.59	162.25	632.84	80.51	42.83	87.00
	1	270	8.10	2.14	10.24	466.81	159.72	626.53	79.43	41.89	85.07
	1.5	270	7.66	1.88	9.54	463.48	157.49	620.97	78.45	41.05	83.49
	2	270	7.27	1.69	8.96	460.44	155.49	615.93	77.55	40.29	82.12
	2.5	270	6.94	1.54	8.48	457.65	153.68	611.33	76.73	39.60	80.91
	3	270	6.64	1.43	8.07	455.09	152.03	607.12	75.96	38.96	79.83
	3.5	270	6.38	1.34	7.72	452.72	150.51	603.23	75.24	38.37	78.86
	4	270	6.14	1.27	7.41	450.51	149.11	599.62	74.57	37.82	77.97
	4.5	270	5.93	1.21	7.14	448.46	147.81	596.27	73.94	37.31	77.17
	5	270	5.74	1.16	6.91	446.55	146.59	593.14	73.35	36.83	76.43
δ	0	594	8.68	0.86	9.53	467.92	162.43	630.35	81.71	43.88	84.17
	0.25	594	7.65	1.05	8.70	461.56	157.33	618.89	78.91	41.44	81.92
	0.5	594	6.93	1.37	8.30	456.93	153.42	610.35	76.65	39.53	80.52
	0.75	594	6.42	1.98	8.39	454.02	150.53	604.54	74.77	37.97	80.07
	1	594	6.10	3.58	9.68	453.79	148.97	602.75	73.16	36.65	81.66
CV	0.4	1485	4.09	2.79	6.88	503.41	161.98	665.39	79.49	44.56	87.33
	0.8	1485	10.22	0.75	10.96	414.28	147.09	561.37	74.60	35.23	76.00
All		2970	7.16	1.77	8.92	458.84	154.53	613.38	77.04	39.89	81.67

Table 3.6: Numerical results for second experiment – supply chain with forward-looking buyer (no seller markdowns)

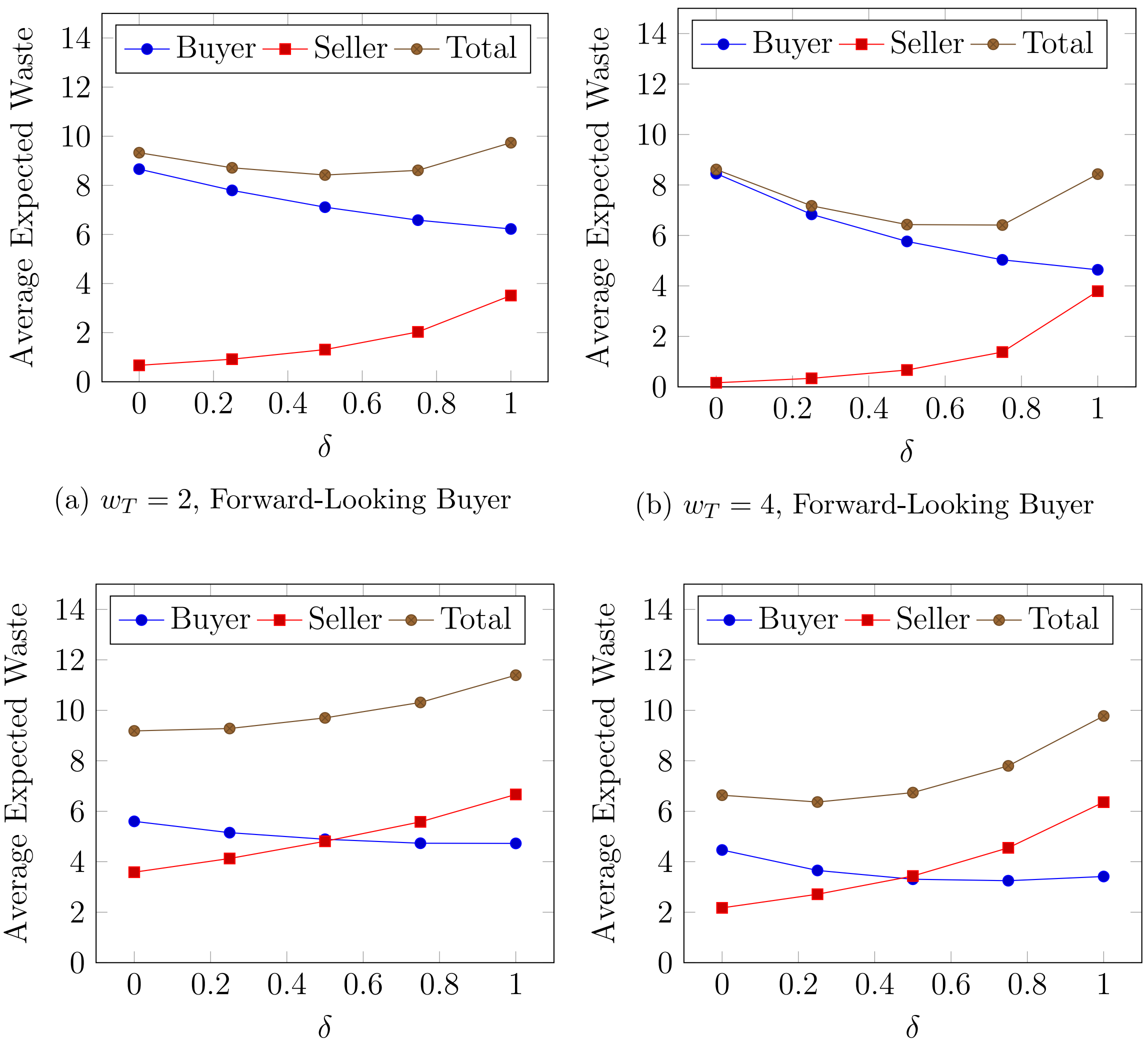
between the buyer and the seller.

How, then, should a policy-maker determine the optimal distribution of the tax burden? We begin this discussion by summarizing a few key observations on the waste-minimizing δ. While the policy-maker may not wish or be able to set δ at the waste-minimizing level, examining this extreme case of the waste-minimizing δ allows us to derive insights about the degree to which it is important to consider different buyer types in making policy decisions. Figure 3.2 shows the effect of changing δ for two levels of w_T (i.e., $w_T = 2$ on the left and $w_T = 4$ on the right) in a supply chain with a forward-looking buyer (top row) and a myopic buyer (lower row) respectively. When $w_T = 2$, the waste-minimizing δ in a supply chain with a forward-looking buyer is one in which the buyer and the seller share the tax burden relatively equally. For a supply chain with a myopic buyer, the waste-minimizing δ is one in which the seller has the entire tax burden. When $w_T = 4$, the waste-minimizing δ is one in which the buyer carries more of the tax burden for a supply chain with a forward-looking buyer and one in which the seller carries more of the tax burden in a supply chain with a myopic buyer. The waste-minimizing δ is therefore not only sensitive to the level of w_T but also to the buyer type in the supply chain.

As the level of w_T increases, the waste-minimizing δ also increases, suggesting that to minimize total waste the policy-maker should place a greater proportion of the waste cost on the buyer. One possible reason for this increase in δ is that, at higher levels of w_T, the seller faces such a high overage cost that she stocks so little compared to the buyer's demand that waste levels at the seller cannot be reduced much further. Any reductions in total waste must then come from targeting the demand-dampening effect by imposing more of the waste tax on the buyer. The buyer's demand dampening has a stronger effect than the seller's supply disincentivization in reducing waste.

The waste-minimizing δ does, however, increase more slowly in a supply chain with a myopic buyer than in one with a forward-looking buyer. For any given level of w_T, a policy-maker seeking to minimize waste should place a greater proportion of the tax burden on the buyer if he is forward-looking. This result is consistent with the observation in the previous section that forward-looking buyers waste more than myopic buyers and hence the policy-maker may need to motivate the forward-looking buyer more to rethink his demand. In this sense, the myopic buyer is "blissfully ignorant" – his lack of foresight actually allows him to benefit from a lower tax burden compared to the forward-looking buyer.

The finding that the waste-minimizing δ depends on the level of w_T highlights the importance of setting δ and w_T jointly. In doing so, the policy-maker needs to balance the waste-minimization objective with the profit-maximization objective, making this decision a bi-objective optimization problem. Figure 3.3 illustrates the Pareto frontier in terms of the profit attained by the profit-maximizing purchase and stocking quantities and the corresponding total waste for each level of w_T for a myopic buyer on the left (Figure 3.3a) and for a forward-looking buyer on the right (Figure 3.3b).



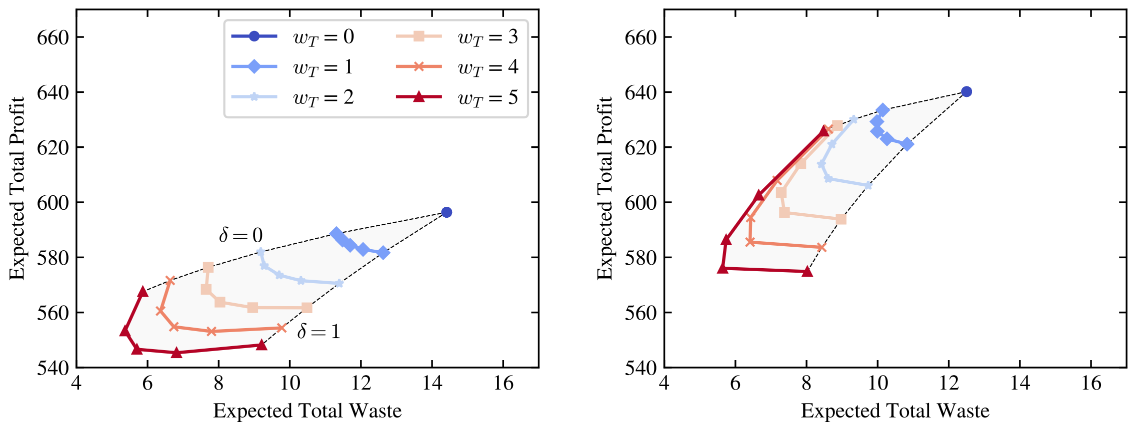
(a) $w_T = 2$, Forward-Looking Buyer

(b) $w_T = 4$, Forward-Looking Buyer

(c) $w_T = 2$, Myopic Buyer

(d) $w_T = 4$, Myopic Buyer

Figure 3.2: Increase in waste-minimizing δ as w_T increases



(a) Myopic Buyer

(b) Forward-Looking Buyer

Figure 3.3: Pareto front for a supply chain with a myopic buyer and a forward-looking buyer

For any given level of w_T, the shape of the Pareto frontiers differs significantly depending on the buyer type. We begin the discussion with the forward-looking buyer. For any value of $w_T > 0$, given the monotonically decreasing nature of total profit in δ, the highest point vertically on the Pareto frontier corresponds to a $\delta = 0$. The second highest point vertically corresponds to a $\delta = 0.25$. The ordering of the points vertically continues in this increasing pattern until the lowest point vertically, which corresponds to $\delta = 1$. The Pareto frontier is characterized by an inflection point, which occurs between $\delta = 0.5$ and $\delta = 0.75$. Above this inflection point, a decrease in δ results in more profit and more waste. Below this inflection point, increasing δ results in less profit and more waste. All values of δ higher than the δ corresponding to the inflection point are thus dominated.

In contrast to the Pareto frontiers for the forward-looking buyer, the Pareto frontiers for the myopic buyer are characterized by an inflection point that corresponds to a significantly lower level of δ. This inflection point occurs between $\delta = 0.25$ and $\delta = 0.5$. Above this inflection point, lower values of δ result in an increase in total profit at the expense of a small increase in total waste. Below this inflection point, increasing δ leads to substantial increases in total waste whereas profit decreases slightly, stays constant, or even increases slightly. In a supply chain with a myopic buyer, for any given level of w_T, a much larger range of values for δ are dominated. This result suggests that a policy-maker may have a narrower range of rational choices for δ for any value of w_T in a supply chain with a myopic buyer.

Looking horizontally, across the Pareto frontiers corresponding to different w_T, we can make several observations. First, it is possible to improve on both the waste-minimization and profit-maximization objectives. Examples of such Pareto optimal pairs of w_T and δ can be found for supply chains with either type of buyer but we illustrate with an example from a supply chain with a forward-looking buyer. The second point from the top in the Pareto frontier of $w_T = 1$ (corresponding to $\delta = 0.25$) yields total profit of 629.29 and total waste of 9.99. The top-most point of the Pareto frontier for $w_T = 2$ (corresponding to $\delta = 0$) yields total profit of 630.07 and total waste of 9.33. Comparing the outcomes for these two points, setting $w_T = 2$ and $\delta = 0$ dominates setting $w_T = 1$ and $\delta = 0.25$. Second, a more aggressive policy with higher values of w_T may actually be inefficient. Compare the (w_T, δ) pairs $(3, 0.25)$ and $(5, 1)$. The latter pair, corresponding to more aggressive policy intervention, results in a total profit of 574.86 and total waste is 8.02. The former pair, a milder policy intervention, results in a total profit of 614.03 and total waste of 7.84, outperforming the latter pair.

As mentioned previously, for any w_T, the policy-maker may not wish to set δ at the waste-minimizing level. One way in which this analysis can be helpful is by informing possible waste reduction targets. Once again, we take the example of a supply chain with a forward-looking buyer (Figure 3.3b). The benchmark total waste and total profit levels without any policy interventions are 12.50 and 640.17, respectively. Suppose the policy-maker is considering to set a target of 30% waste reduction, thereby reducing total waste to at most 8.75. The policy-maker can choose among various alternatives, one of which $w_T = 4$ and $\delta = 0$, which reduces total profit by only 2%. Suppose the policy-maker is instead considering to set a waste reduction target of 50%. Such a waste-reduction target might be achieved by setting $w_T = 5$ and $\delta = 0.5$, but the 8% reduction in total profit may be too much to pass politically. If the policy-maker wishes to reduce waste to this degree, he may need to think of additional interventions that can help to this end. The horn-shaped areas are also useful for a policy-maker to understand the boundaries of his decision. For instance, if a policy-maker would like to set a waste target of 10 units, the boundaries of the horn-shaped area reveal that he cannot promise the seller a profit level of more than approximately 630 but he can ensure at least approximately 605.

3.5.2 Seller Markdowns

Markdowns are a tool for the seller to reduce her overage costs. In choosing a stocking quantity for the horizon, the seller balances the risk of carrying too much stock for the second period (the period driving the seller's uncertainty) with the possible gains from increased buyer demand resulting from lower prices in the second period. When a policy-maker increases the waste cost on the seller thereby increasing overage costs, the seller may respond by marking down product in the second period. How do seller markdowns affect the magnitude and distribution of waste in the supply chain? Does the optimal distribution of the waste cost change when the seller marks down? To study these questions, we repeat the two experiments above with seller markdowns.

Absolute Tax Levels

In this experiment and the next, we include the parameter $\theta \in \{0.8, 0.9, 1\}$ to describe the depth of the seller markdown. Based on all parameter values, $3 \times 3 \times 3 \times 3 \times 5 \times 5 \times 2 = 4,050$ instances are generated and the model is solved for each buyer type. The results of the experiment for the myopic and forward-looking buyers with markdowns are displayed in Table 3.7 and Table 3.8, respectively.

Seller markdowns increase profit both at the individual agent and the supply chain levels. This result may be a consequence of the relatively high margin environment that the seller and buyer operate in. However, seller markdowns are detrimental to waste reduction. Total waste on average is higher in both absolute and relative terms in supply chains where the seller can markdown prices in the second period. In a supply chain with a forward-looking buyer, total waste is 9.55 when seller markdowns take place, compared to 8.94 when no seller markdowns take place. In a supply chain with a myopic buyer, total waste is 11.10 when seller markdowns take place, compared to 10.05 when no seller markdowns take place. The result that seller markdowns are detrimental to waste reduction is consistent with our expectations. When the seller marks down, the buyer buys more in the second period and hence the seller stocks more over the horizon. In this way, the seller not only shifts wastes to the buyer, but she also creates the possibility for more waste in the system by stocking more. However, the mechanism behind the increase in total waste in the case of each buyer type is different and important to understand for deciding which instrument is more suitable for waste reduction.

			Avg Exp Waste			Avg Exp Profit			Avg Quantities		
Parameter	Value	Count	Buyer	Seller	Total	Buyer	Seller	Total	q_1^*	$\bar{q}_2$	Q^*
α	0.7	1350	5.98	4.66	10.64	525.37	119.58	644.94	43.88	42.88	78.53
	0.8	1350	6.28	4.85	11.13	459.11	137.97	597.07	43.88	43.35	79.50
	0.9	1350	6.53	5.01	11.54	392.87	156.43	549.30	43.88	43.72	80.30
β	0.4	1350	7.52	5.01	12.53	528.52	121.65	650.17	50.89	48.92	85.23
	0.5	1350	6.21	5.09	11.30	457.30	139.41	596.71	43.60	43.14	79.87
	0.6	1350	5.05	4.43	9.48	391.52	152.91	544.44	37.14	37.90	73.23
θ	0.8	1350	7.50	4.71	12.21	473.01	146.59	619.60	43.88	46.40	82.09
	0.9	1350	6.20	4.86	11.06	458.71	138.26	596.97	43.88	43.26	79.41
	1	1350	5.09	4.95	10.05	445.62	129.13	574.75	43.88	40.29	76.82
γ	0.4	1350	7.10	6.25	13.35	461.35	166.53	627.89	43.88	43.32	82.97
	0.5	1350	6.34	4.90	11.25	459.61	137.56	597.17	43.88	43.32	79.80
	0.6	1350	5.34	3.38	8.72	456.38	109.88	566.25	43.88	43.32	75.56
w_U	0	810	7.39	6.79	14.18	461.89	143.17	605.06	43.88	43.32	84.13
	0.5	810	6.73	5.54	12.26	460.70	140.12	600.82	43.88	43.32	81.38
	1	810	6.19	4.64	10.83	459.24	137.57	596.81	43.88	43.32	79.15
	1.5	810	5.70	3.90	9.60	457.66	135.45	593.11	43.88	43.32	77.12
	2	810	5.31	3.34	8.65	456.07	133.64	589.71	43.88	43.32	75.43
w_D	0	810	8.15	4.87	13.02	468.35	144.99	613.33	43.88	47.50	83.62
	0.5	810	6.98	4.87	11.84	463.17	140.89	604.06	43.88	45.07	81.20
	1	810	6.07	4.85	10.92	458.61	137.46	596.07	43.88	43.03	79.15
	1.5	810	5.35	4.83	10.18	454.55	134.55	589.10	43.88	41.27	77.39
	2	810	4.77	4.79	9.56	450.89	132.07	582.96	43.88	39.73	75.85
CV	0.4	2025	5.15	4.16	9.30	510.67	159.65	670.32	47.47	47.07	88.83
	0.8	2025	7.38	5.53	12.90	407.56	116.33	523.89	40.28	39.57	70.05
All		4050	6.26	4.84	11.10	459.11	137.99	597.10	43.88	43.32	79.44

Table 3.7: Numerical Results for First Experiment – Supply Chain with Myopic Buyer (Seller Markdowns)

In a supply chain with a myopic buyer, as θ decreases, relative buyer waste increases more substantially (up to 7.88% from 6.63% without markdowns) while relative seller

			Avg Exp Waste			Avg Exp Profit			Avg Quantities		
Parameter	Value	Count	Buyer	Seller	Total	Buyer	Seller	Total	q_1^*	$\bar{q}_2$	Q^*
α	0.7	1350	6.83	2.39	9.22	531.11	144.03	675.14	73.19	42.88	82.07
	0.8	1350	7.04	2.53	9.57	466.04	165.75	631.79	73.58	43.35	82.90
	0.9	1350	7.21	2.66	9.87	401.05	187.52	588.57	73.89	43.72	83.59
β	0.4	1350	9.47	2.11	11.58	533.78	146.08	679.86	80.78	48.92	88.63
	0.5	1350	6.82	2.50	9.32	463.80	167.47	631.27	73.48	43.14	82.66
	0.6	1350	4.78	2.98	7.76	400.64	183.74	584.37	66.41	37.90	77.27
θ	0.8	1350	6.88	3.36	10.24	473.10	175.54	648.64	69.31	46.40	83.86
	0.9	1350	6.91	2.57	9.48	464.84	166.28	631.11	73.80	43.26	82.66
	1	1350	7.29	1.65	8.94	460.27	155.47	615.74	77.55	40.29	82.05
γ	0.4	1350	7.43	4.16	11.59	471.16	195.45	666.61	73.55	43.32	86.47
	0.5	1350	6.99	2.26	9.25	465.86	165.35	631.22	73.55	43.32	82.47
	0.6	1350	6.65	1.17	7.82	461.19	136.49	597.67	73.55	43.32	79.63
w_U	0	810	7.60	4.84	12.43	472.77	168.54	641.31	73.55	43.32	87.79
	0.5	810	7.19	3.05	10.24	468.39	166.62	635.01	73.55	43.32	84.23
	1	810	6.93	2.07	9.01	465.19	165.36	630.56	73.55	43.32	82.03
	1.5	810	6.76	1.51	8.28	462.87	164.48	627.35	73.55	43.32	80.61
	2	810	6.64	1.17	7.81	461.12	163.81	624.93	73.55	43.32	79.62
w_D	0	810	8.60	2.63	11.23	477.32	173.63	650.94	76.80	47.50	87.07
	0.5	810	7.65	2.56	10.21	471.00	169.20	640.19	75.00	45.07	84.65
	1	810	6.89	2.51	9.40	465.44	165.32	630.76	73.39	43.03	82.58
	1.5	810	6.26	2.48	8.74	460.51	161.88	622.39	71.94	41.27	80.78
	2	810	5.73	2.46	8.19	456.08	158.80	614.87	70.63	39.73	79.20
CV	0.4	2025	4.27	3.67	7.94	514.54	173.25	687.80	74.19	47.07	89.65
	0.8	2025	9.78	1.39	11.16	417.60	158.27	575.87	72.92	39.57	76.06
All		4050	7.02	2.53	9.55	466.07	165.76	631.83	73.55	43.32	82.86

Table 3.8: Numerical Results for First Experiment – Supply Chain with Forward-Looking Buyer (Seller Markdowns)

waste decreases slightly (down to 6.10% from 6.45% without markdowns). It is the buyer's waste that drives the increase in total waste in the supply chain. In contrast, in a supply chain with a forward-looking buyer, as θ decreases, relative buyer waste decreases slightly (down to 8.48% from 8.89% without markdowns) but relative seller waste actually increases more substantially (up to 3.05% from 2.01% without markdowns). The increase in the seller's waste drives the increase in total waste in the supply chain. The fact that relative seller waste increases when the seller marks down in a supply chain with a forward-looking buyer suggests that seller markdowns may actually be counter-productive as a seller's strategy to reduce waste. It also suggests that knowing the buyer type is important for a seller when considering whether to mark down as waste reduction strategy.

Seller markdowns have a demand-enhancing effect on both buyer types. In period 1, the myopic buyer buys the same amount of product and has the same amount of leftover inventory, for any given realization of D_1, regardless of whether the seller marks down or not. In period 2, the myopic buyer's higher order-up-to level under seller markdowns results in greater demand for the seller's product in comparison with the no seller markdown setting. The demand-enhancing effect is not as straight-forward to identify for the forward-looking buyer. Under seller markdowns, the forward-looking buyer shifts some of the quantity he would buy in the first period to the second period. For any given realization of D_1, since he buys less in period 1, he has less leftover than a forward-looking buyer under no seller markdowns. In addition to having less leftover inventory from period 1, he also has a higher order-up-to level, resulting in higher demand for the seller's product in period 2. Even though the forward-looking buyer's period 1 demand decreases, the increase in his period 2 demand is just sufficient for the seller to stock slightly more (2.21% more at $\theta = 0.8$). The seller facing the myopic buyer has a stronger response to the enhanced demand and she stocks 6.87% more at $\theta = 0.8$. Despite this stronger response in terms of the stocking quantity, the myopic buyer's demand is high enough that the seller's relative waste decreases.

As in the setting with no seller markdowns, a waste tax on a buyer or a seller are effective instruments in reducing relative total waste in the supply chain. However, when the seller marks down, the same level of w_U or w_D has a slightly greater effect in terms of waste reduction than when the seller does not mark down. In a supply chain with a myopic buyer, as w_U increases, relative total waste decreases from 16.85% to 11.46% (drop of 5.39%) when the seller marks down compared to a decrease from 15.74% to 10.73% (drop of 5.01%) when the seller does not mark down. In a supply chain with a forward-looking buyer, as w_U increases, relative total waste decreases from 14.16% to 9.81% (drop of 4.35%) when the seller marks down compare to a decrease from 12.82% to 9.71% (drop of 3.11%) when the seller does not mark down.

In comparison to taxing the seller, once again, taxing the buyer has a smaller waste reduction effect. In a supply chain with a myopic buyer, as w_D increases, relative total waste decreases from 15.57% to 12.60% (drop of 2.96%) when the seller marks down compared to 14.35% to 11.96% (drop of 2.39%) when the seller does not mark down. In a supply chain with a forward-looking buyer, as w_D increases, relative total waste decreases from 12.89% to 10.34% (drop of 2.56%) when the seller marks down compared to a decrease from 12.21% to 9.75% (drop of 2.46%) when the seller does not mark down.

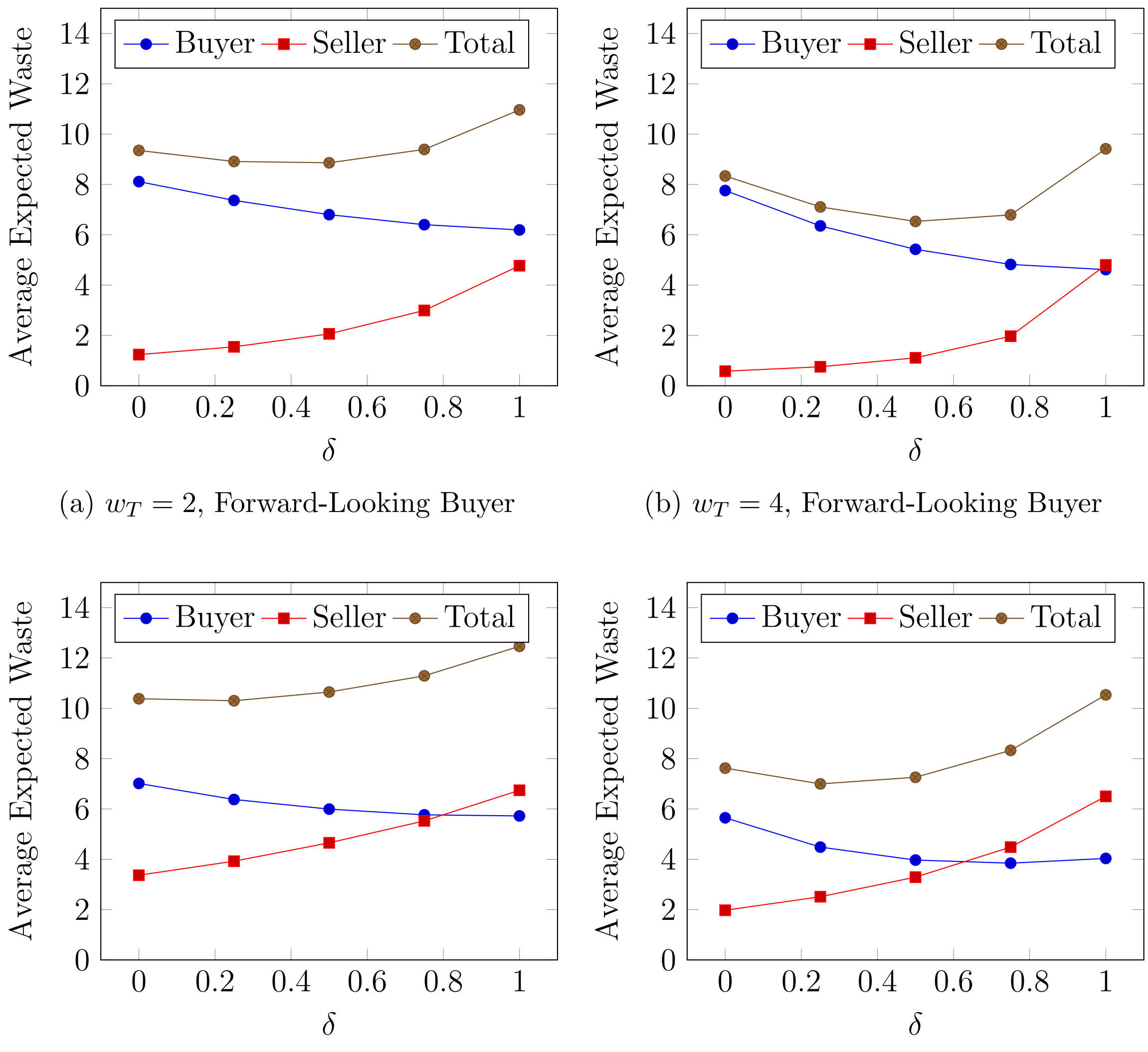
Proportion of tax burden

Given that the myopic buyer's waste increases when the seller marks down, it would make sense for the policy-maker to impose a greater proportion of the cost of waste on the buyer if the buyer in the supply chain is myopic. Conversely, since the seller's waste increases when the seller marks down in a supply chain with a forward-looking buyer, it would make sense to impose a greater proportion of the waste cost on the seller in this case. Our final experiment confirms this hypothesis.

Based on the parameter values, $3 \times 3 \times 3 \times 3 \times 2 \times 11 \times 5 = 8,910$ instances are generated and the model is solved for each buyer type. The results of the experiment for the myopic and forward-looking buyers with markdowns are displayed in Table 3.9 and Table 3.10, respectively.

For any given level of w_T, the waste-minimizing δ for the myopic buyer is equal to or higher with seller markdowns than without seller markdowns. The waste-minimizing δ for the forward-looking buyer is equal to or lower. In fact, the difference between the waste-minimizing δ for the myopic and the forward-looking buyers appears to be shrinking. This shrinking is illustrated in Figure 3.4. From the policy-maker's perspective, this result suggests that knowing the buyer type is less important when the seller marks down.

Figure 3.5 illustrates the Pareto frontier for each level of w_T for a supply chain with a myopic buyer under seller markdowns on the left (Figure 3.5a) and for a supply chain with a forward-looking buyer on the right (Figure 3.5b). The area of the cone outlining the possible outcomes at equilibrium and bounded by the extreme cases in which $\delta = 0$ and $\delta = 1$ expands slightly, most likely as a consequence of the higher waste and profit in the system with seller markdowns. Otherwise, the same insights derived in the case in which the seller does not mark down still hold.



(a) $w_T = 2$, Forward-Looking Buyer

(b) $w_T = 4$, Forward-Looking Buyer

(c) $w_T = 2$, Myopic Buyer

(d) $w_T = 4$, Myopic Buyer

Figure 3.4: Increase in waste-minimizing δ as w_T increases under seller markdowns

			Avg Exp Waste			Avg Exp Profit			Avg Quantities		
Parameter	Value	Count	Buyer	Seller	Total	Buyer	Seller	Total	q_1^*	$\bar{q}_2$	Q^*
α	0.7	2970	5.76	4.57	10.33	523.67	118.68	642.35	43.88	42.45	77.64
	0.8	2970	6.04	4.74	10.78	457.27	136.88	594.15	43.88	42.91	78.60
	0.9	2970	6.28	4.89	11.17	390.92	155.18	546.09	43.88	43.29	79.40
β	0.4	2970	7.32	5.02	12.34	526.01	120.89	646.90	50.89	48.41	84.51
	0.5	2970	5.96	4.95	10.91	455.45	138.32	593.78	43.60	42.70	78.92
	0.6	2970	4.79	4.23	9.02	390.39	151.53	541.92	37.14	37.53	72.21
θ	0.8	2970	7.21	4.63	11.85	470.99	145.54	616.53	43.88	45.92	81.17
	0.9	2970	5.96	4.75	10.71	456.89	137.17	594.06	43.88	42.83	78.51
	1	2970	4.90	4.82	9.72	443.98	128.03	572.00	43.88	39.89	75.95
γ	0.4	2970	6.80	6.06	12.86	459.57	165.10	624.67	43.88	42.88	81.90
	0.5	2970	6.10	4.80	10.90	457.77	136.51	594.29	43.88	42.88	78.89
	0.6	2970	5.17	3.33	8.51	454.51	109.12	563.63	43.88	42.88	74.84
w_T	0	810	9.47	6.82	16.29	470.62	150.19	620.81	43.88	47.50	88.31
	0.5	810	8.42	6.15	14.56	467.65	146.53	614.17	43.88	46.26	85.63
	1	810	7.55	5.65	13.20	464.78	143.32	608.10	43.88	45.17	83.36
	1.5	810	6.81	5.21	12.02	462.02	140.49	602.51	43.88	44.19	81.30
	2	810	6.17	4.84	11.02	459.37	137.97	597.34	43.88	43.32	79.44
	2.5	810	5.63	4.52	10.15	456.82	135.72	592.54	43.88	42.52	77.76
	3	810	5.16	4.23	9.39	454.36	133.70	588.06	43.88	41.79	76.23
	3.5	810	4.75	3.98	8.73	451.99	131.87	583.86	43.88	41.12	74.83
	4	810	4.40	3.75	8.15	449.70	130.22	579.92	43.88	40.50	73.54
	4.5	810	4.09	3.55	7.63	447.49	128.71	576.19	43.88	39.92	72.35
	5	810	3.81	3.36	7.17	445.34	127.33	572.67	43.88	39.38	71.25
δ	0	1782	6.89	3.39	10.28	464.64	140.17	604.81	43.88	47.50	79.09
	0.25	1782	6.15	3.85	10.00	459.42	137.04	596.46	43.88	44.64	77.82
	0.5	1782	5.77	4.46	10.23	456.00	135.52	591.52	43.88	42.44	77.58
	0.75	1782	5.63	5.31	10.94	453.90	135.33	589.24	43.88	40.66	78.26
	1	1782	5.68	6.65	12.33	452.46	136.50	588.96	43.88	39.17	79.99
CV	0.4	4455	4.94	4.08	9.02	509.10	158.61	667.71	47.47	46.72	88.08
	0.8	4455	7.11	5.38	12.49	405.47	115.22	520.69	40.28	39.04	69.01
All		8910	6.02	4.73	10.76	457.29	136.91	594.20	43.88	42.88	78.55

Table 3.9: Numerical Results for Second Experiment – Supply Chain with Myopic Buyer (Seller Markdowns)

3.6 Conclusion

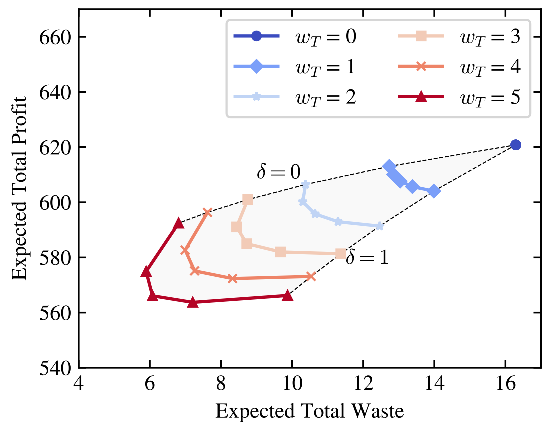
Buyer behavior is an important factor of consideration for a policy-maker when deciding on interventions to reduce waste. In studying the interaction between a seller and a buyer in a supply chain for a perishable food product, we find that different degrees of buyer foresight affect the equilibrium stocking decision of a seller and the purchase decisions of a buyer, which in turn determine the level of profit and waste in a supply chain. ‘Smarter’ buyers (i.e., buyers with more foresight such as the forward-looking

			Avg Exp Waste			Avg Exp Profit			Avg Quantities		
Parameter	Value	Count	Buyer	Seller	Total	Buyer	Seller	Total	q_1^*	$\bar{q}_2$	Q^*
α	0.7	2970	6.71	2.54	9.25	529.78	143.11	672.89	72.72	42.45	81.73
	0.8	2970	6.90	2.65	9.55	464.48	164.70	629.18	73.13	42.91	82.51
	0.9	2970	7.06	2.75	9.82	399.30	186.36	585.65	73.46	43.29	83.16
β	0.4	2970	9.31	2.26	11.57	531.87	145.11	676.98	80.24	48.41	88.24
	0.5	2970	6.69	2.63	9.32	462.31	166.42	628.72	73.03	42.70	82.29
	0.6	2970	4.68	3.06	7.74	399.37	182.65	582.02	66.04	37.53	76.87
θ	0.8	2970	6.75	3.48	10.22	471.38	174.44	645.82	68.93	45.92	83.45
	0.9	2970	6.78	2.70	9.48	463.33	165.20	628.53	73.34	42.83	82.29
	1	2970	7.16	1.77	8.92	458.84	154.53	613.38	77.04	39.89	81.67
γ	0.4	2970	7.30	4.40	11.70	469.67	194.28	663.94	73.10	42.88	86.23
	0.5	2970	6.86	2.36	9.22	464.35	164.30	628.65	73.10	42.88	82.06
	0.6	2970	6.52	1.19	7.71	459.53	135.60	595.14	73.10	42.88	79.11
w_T	0	810	9.31	4.95	14.26	483.71	176.51	660.23	76.80	47.50	92.07
	0.5	810	8.52	3.94	12.46	478.41	173.18	651.59	75.89	46.26	88.90
	1	810	7.90	3.29	11.19	473.81	170.36	644.17	75.05	45.17	86.45
	1.5	810	7.40	2.84	10.24	469.77	167.90	637.67	74.27	44.19	84.48
	2	810	6.97	2.52	9.50	466.17	165.72	631.89	73.55	43.32	82.83
	2.5	810	6.62	2.28	8.90	462.94	163.76	626.69	72.88	42.52	81.42
	3	810	6.31	2.10	8.41	460.00	161.97	621.97	72.25	41.79	80.19
	3.5	810	6.03	1.96	7.99	457.31	160.32	617.63	71.66	41.12	79.09
	4	810	5.79	1.84	7.64	454.81	158.80	613.61	71.10	40.50	78.11
	4.5	810	5.58	1.75	7.33	452.48	157.39	609.86	70.58	39.92	77.21
	5	810	5.38	1.67	7.05	450.30	156.06	606.36	70.07	39.38	76.39
δ	0	1782	8.17	1.56	9.72	472.67	171.71	644.39	76.80	47.50	84.18
	0.25	1782	7.28	1.79	9.07	466.51	167.11	633.63	74.64	44.64	82.25
	0.5	1782	6.67	2.17	8.84	462.27	163.62	625.89	72.84	42.44	81.17
	0.75	1782	6.26	2.92	9.18	460.09	161.12	621.22	71.29	40.66	81.19
	1	1782	6.09	4.82	10.90	461.04	160.06	621.09	69.94	39.17	83.53
CV	0.4	4455	4.15	3.66	7.81	512.74	172.42	685.16	73.94	46.72	89.06
	0.8	4455	9.64	1.64	11.27	416.30	157.03	573.33	72.26	39.04	75.87
All		8910	6.89	2.65	9.54	464.52	164.72	629.24	73.10	42.88	82.47

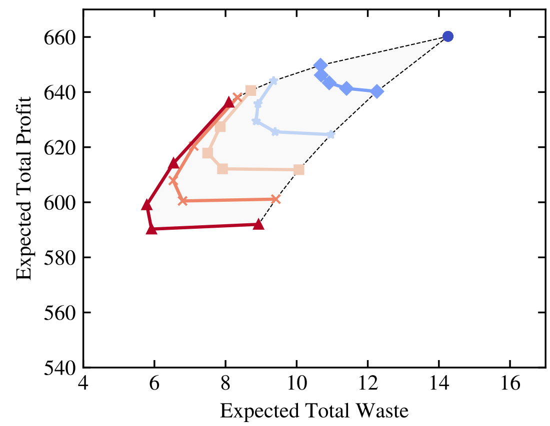
Table 3.10: Numerical Results for Second Experiment – Supply Chain with Forward-Looking Buyer (Seller Markdowns)

buyer) are actually better for a supply chain, not only in terms of profit but also in terms of waste. While a forward-looking buyer demands more and wastes more, the reduction in total waste in the supply chain is driven by the fact that a seller facing a forward-looking buyer sells more of the product she stocks compared to the buyer's demand.

Applying a waste cost at either the higher and lower echelons of a supply chain is an effective policy intervention to reduce waste. Either intervention can result in a substantial reduction in waste at the expense of a small reduction in profit. Taxing



(a) Myopic Buyer



(b) Forward-Looking Buyer

Figure 3.5: Pareto front for different values of w_T with seller markdowns in a supply chains with a myopic and forward-looking buyer

the seller has a more direct and substantial effect on waste reduction, irrespective of buyer type, because the seller immediately reduces the supply to the system, limiting the possibility of waste. Taxing the buyer, however, is more effective when the buyer is a forward-looking buyer. Unlike the myopic buyer who only reduces his second period purchase quantity, the forward-looking buyer also reduces his first period purchase quantity. The resulting stronger reduction in the seller's stocking quantity reduces waste for both agents.

To determine an appropriate waste cost, a policy-maker may perform an analysis to quantify the externalities associated with food wasted (e.g., through techniques such as life-cycle analysis) or may refer to the cost of disposal as a benchmark for the waste cost. After determining the waste cost, the policy-maker may then look to apportion the waste cost appropriately to different agents in the supply chain. The seller's stocking decision and total waste in the supply chain are not monotonic in the proportion to which the buyer is taxed. This result indicates that a stronger intervention targeting the buyer is not necessary, and may even be inefficient, in reducing waste.

The importance of setting both the waste cost and proportion apportioned to each agent jointly as a policy-maker is highlighted by the fact that the waste-minimizing proportion of tax on the buyer increases as the tax level increases. For any given level of taxation, a policy-maker seeking to minimize waste will need to apply a higher proportion of the waste cost on the buyer if he is forward-looking than if he is myopic. However, as the tax level increases, the seller facing either type of buyer reduces her stocking quantity so much that it is more efficient to tax the buyer.

As a seller facing a higher overage cost may have an incentive to mark down product close to expiration, we study the effect of seller markdowns on waste and implications for policy interventions. While seller markdowns are beneficial for profit, they are detrimental for waste.

Several promising avenues for future work can be identified. In this research, we defined two buyer types according to their level of foresight. Neither of these buyer types take into account the seller's optimal stocking decision in their optimization problem. Since both buyer types simply assume that the seller will have sufficient stock to satisfy their calculated optimal purchase quantities in both periods, they can face reduced profits when when this is not the case. Had the buyer known the seller's stocking quantity, he would choose different purchase quantities to induce the seller to stock more. Whether this buyer type is associated with more waste in the supply chain and what type of waste cost interventions are effective in reducing waste are questions we leave for a future study.

Given that the focus of our research is on understanding how the degree of buyer foresight affects equilibrium outcomes and influences the tax policy, we do not focus on actually finding the optimal level of taxation. We leave this question to future studies. Exploring mechanisms to coordinate the supply chain, not only for the profit outcomes but also for the waste outcomes, is also an interesting direction of study.

Another aspect that we do not examine is the effect of competition on waste. Competition is a driver for agents to stock more to ensure high availability levels and hence most likely a driver for increased food waste. Models that incorporate more than one seller or more than one buyer can expand on the degree to which taxing buyers or sellers can reduce waste in a competitive landscape.

Chapter 4

Managing Inventories of Reusable Containers for Food Take-Away at a Restaurant

In addition to food waste, food supply chains also generate a substantial amount of packaging waste. Reducing single-use packaging waste in the food take-away and delivery sectors, in particular, has become an area of focus for policy-makers. Through the application of surcharges on customers for purchasing a meal in a single-use container or through mandates that ban single-use containers, policy-makers effectively impose a penalty on the provision of meals in such containers.

Reusable containers have emerged as an alternative to single-use containers. However, for restaurants, the management of inventory of reusable containers presents numerous operational challenges. Some of these challenges are due to features that are rather unique to this setting. In this chapter, we study how these features and other system parameters (including those that can be influenced by the policy-maker) affect the restaurant's inventory decisions and costs.

4.1 Introduction

Every minute McDonald's uses 2.8 tons of single-use packaging to serve its customers worldwide (Zero Waste France 2017). Every year Starbucks uses approximately seven billion disposable cups worldwide (Lucas 2022). The food services sector generates a substantial amount of single-use packaging waste. In Britain, lunches-to-go are estimated to produce almost 11 billion items of single-use packaging waste annually (Smithers 2019). The rapid growth of take-away and food delivery services over the past years, facilitated by platforms and amplified by the COVID-19 pandemic, has only exacerbated this problem. Since 2017, the food delivery sector alone has more than tripled its revenues and is currently worth $150 billion USD globally (Ahuja et al. 2021).

Most single-use packaging waste cannot be recycled as it consists mainly of plastic products or plastic-coated paper products (used in most disposable coffee cups) that cannot be handled by the regular paper recycling process. As a result, much of this waste landfilled (Schupak 2021). In the United States, single-use containers and packaging in general account for more than 23% of the waste in landfills (US Environmental Protection Agency 2015). This waste accounts for a significant amount of carbon emissions. Single-use packaging waste that is not recycled or landfilled is discarded into the environment, where it is left to degrade and interact with animal life.

Given the detrimental environmental effects of single-use packaging in the food sector, many jurisdictions are passing regulations to reduce its use. One type of regulation is charging customers a fee for purchasing a product in single-use packaging. For example, customers in the cities of Berkeley, California, and Vancouver, Canada incur a surcharge of $0.25 USD ($0.25 CAD, respectively) per beverage purchased in a disposable cup (Peters 2020, City of Vancouver 2022). In The Netherlands, starting in July 2023, a similar measure that extends a surcharge to all single-use plastic food packaging will come into effect (Netherlands Chamber of Commerce 2022). Some countries are going even further in their efforts to limit single-use packaging. For example, from January 2023, restaurants in Germany will be required to provide a reusable packaging alternative at no extra cost to the customer for products currently offered in single-use packaging. In Luxembourg, from January 2025, take-out and delivery meals will only be served in reusable containers (Gouvernement du Grand-Duché de Luxembourg 2022).

The implementation of reusable container systems in the food take-away and delivery sector has become an active area of work for start-ups, public entities, and restaurant chains. While a few restaurant chains run their own reusable container systems, most reusable container systems are operated by a third-party supplier for a network of restaurants. The business models behind these reusable containers systems are rapidly evolving and highly diverse. An important question in the design of a reusable container system is how to ensure that the system is efficient, effective, and economically sustainable. Much of the diversity in business models for reusable containers systems stems from the way different systems aim to address this question. Most third-party suppliers and restaurants, for example, charge a deposit refundable upon return per clean container. This deposit-based approach aims to minimize shrinkage in the inventory of reusable containers by incentivizing returns. Some third-party suppliers operate more technologically integrated systems, deploying an app or QR codes, that enable restaurants and customers to easily track containers and deposits.

Setting system design and incentive questions to the side, however, the introduction of reusable containers at a restaurant brings about multiple operational challenges that may already be enough to dissuade a restaurant from participating in such a system altogether. One of the main decisions for a restaurant using reusable containers is the number of reusable containers to have on-hand. In particular, the restaurant faces a variety of customers that affect the restaurant's reusable container inventory level in different ways and make this inventory level determination non-trivial. Some customers, for example, only demand a clean reusable container with their order, reducing the number of clean containers in the restaurant's inventory. Other customers both demand a clean container with their order and return a dirty container, effectively having a net zero effect on inventory (after a lag time for cleaning the container before it can be used again). To make returns easier for customers, many reusable container systems are designed so that restaurants can also serve as drop-off points, meaning that some customers only return dirty containers to the restaurant, increasing the inventory level of dirty containers. Hence, a restaurant that uses reusable containers faces both uncertain demand and uncertain returns, making it difficult to control inventory levels.

In as much as the restaurant faces uncertain demands and returns, inventory management of a reusable container system resembles a number of well-studied systems in the closed-loop supply chain (e.g., repairable item and remanufacturing inventory systems) or sharing economy (e.g., bike-sharing systems) literature. However, these systems differ from the systems in our setting in two notable ways. First, in the closed-loop supply chain literature, unfulfilled demand is typically backlogged and not lost, unlike in our setting. Second, our setting includes customers that both demand a clean container with their order and return a dirty container, resulting in a *coupled demand and return*. These customers are present in addition to customers that only demand a clean container for their meal (similar to a traditional forward flow supply chain setting) and customers that only return a dirty container (similar to a traditional reverse flow supply chain setting). Having a larger base of customers with coupled demand and returns is likely beneficial to a restaurant as these customers each have a net zero effect on the restaurant's inventory, making the restaurant more internally sustainable in terms of inventory levels and enabling the restaurant to reduce costs. Such high coupling of demand and returns may occur, for instance, in a restaurant with a relatively large loyal base of frequent customers who regularly order a meal in a reusable container and return a previously used container at the same time. In this sense, the existence of customers with coupled demand and returns may give a restaurant using a reusable container system an advantage over other systems with uncertain demands and returns. However, only a few works in the closed-loop supply chain literature (i.e., Van der Laan et al. 1999, Kiesmüller 2003) study systems in which customers with coupled demand and returns co-exist with customers that only demand or only return a product.

Our objective in this paper is to study the inventory decisions of a rational manager of a restaurant that participates in a reusable container system and faces customers that have different effects on reusable container inventory levels, including those that generate a coupled demand and return. In particular, we address the following questions: (*i*) what is the optimal inventory policy for the restaurant?, (*ii*) how does the degree of demand and return coupling affect this policy and the restaurant's costs?, and (*iii*) how do other system characteristics affect the restaurant's inventory decisions and costs?

To answer these questions, we use a continuous-time Markov Decision Process to model the inventory decisions of a restaurant participating in a reusable containers system. In this system, every time the reusable containers supplier visits the restaurant is an opportunity for the restaurant to rebalance its inventory if returns or demands become too high by either giving excess clean containers to the supplier or receiving additional clean containers from the supplier. We determine the restaurant's *optimal rebalancing policy* when the supplier visits and the supplier's optimal visit frequency from the restaurant's perspective if the restaurant is able to decide on this frequency. We model the degree to which customers' demand and returns are coupled by defining three customer streams: a stream of customers that only demand a clean container, a stream of customers that only return a dirty container, and a stream of customers that both demand a clean container and return a dirty container. Through a numerical study, we investigate the sensitivity of the optimal inventory balancing policy, the optimal supplier visit frequency, and the restaurant's costs to changes in parameters including the lost sales penalty (a cost parameter that is highly influenced by government policy for single-use containers), ratio of demand to returns, proportion of demand coupled with returns, scale of the restaurant, supplier visit costs, and dishwasher utilization.

We find that the optimal rebalancing policy is a state-dependent policy in which the optimal rebalancing level depends on number of dirty containers at the restaurant. We also find that the restaurant's costs of operating a reusable container system can decrease by optimizing both the rebalancing policy and the supplier visit frequency. In terms of the effect of customers with coupled demand and returns on the restaurant's performance, our results support the intuition that greater coupling of demand to returns allows the restaurant to decrease its expected total costs. This result holds irrespective of the overall balance of demand and returns at the restaurant. However, the effect of greater coupling of demand to returns is more substantial when overall demand and returns at the restaurant are more balanced. This finding highlights the relatively greater importance of maintaining an overall balance of demands and returns as a restaurant. The third-party supplier visit cost is an important lever in making the system viable for a restaurant. Specifically, if a restaurant is mostly a collector of dirty containers or a dispenser of clean containers, a third-party supplier can make participating in the reusable container system more viable for the restaurant by reducing its visit costs. A higher supplier visit cost may also disproportionately penalize restaurants with lower demand for reusable containers. Through our modeling of this new setting and our findings, we contribute to the literature on sustainable inventory systems by deriving insights into the conditions that make it easier for a restaurant to participate in a reusable container system and factors that policy-makers and reusable container suppliers can influence to make participation more economically sustainable and appealing for a restaurant.

This rest of the chapter is structured as follows. Section 4.2 briefly reviews the literature. Section 4.3 describes the modeling approach. Section 4.4 formulates and solves the restaurant's optimal inventory balancing and optimal balancing frequency decision problems. Section 4.5 describes the performance metrics for the restaurant. Section 4.6 investigates the effect of varying different parameters on these performance metrics through a numerical study. Section 4.7 concludes with our main findings and future research directions.

4.2 Literature Review

The rapid growth in the food take-away and delivery sector has sparked an interest in restaurant operations and take-away / delivery platform operations within the Operations Management (OM)/ Operations Research (OR) community. Mao et al. (2022) focus on the delivery challenges that platforms face, highlight opportunities for future research, and provide a dataset that includes two-months of orders from an online meal delivery platform operating in Hangzhou, China. Although platforms boost the restaurant's visibility and outsource delivery, these benefits also come at the cost of greater congestion in the kitchen and a cut from the restaurant's margins. Feldman et al. (2022) and Chen et al. (2022) model the relationship between platforms and restaurants and identify contract types that can coordinate the supply chain. Unlike these papers, we focus on the sustainability aspect of the rapid growth in food take-away and delivery sector by studying a restaurant's operations vis-à-vis a third-party supplier that provides reusable containers as an alternative to single-use containers.

Reusable containers have been studied in the context of food production and distribution systems in the past. Glock & Kim (2014), Glock (2017), and Accorsi et al. (2022) study systems of reusable containers such as crates for transport of food items between suppliers and retail stores. Taheri et al. (2021) study reusable container systems for consumer goods products and focus on the role of incentives, particularly in terms of the trade-off between durability of the containers and levels of deposit. These studies examine a reusable containers system between a wholesaler and a retailer and these systems are typically governed by contracts.

In terms of modeling, our work relates to the literature on inventory management in closed-loop supply chains and in sharing economy applications. Closed-loop supply chains are characterized by a reverse flow of products from the customer to the manufacturer in addition to the forward flow from the manufacturer to the customer. Reviews of closed-loop supply chain research include Guide Jr & Van Wassenhove (2009), Fleischmann et al. (1997), and Souza (2013). Within the closed-loop supply chain literature, repairable item inventory systems and remanufacturing / hybrid production inventory systems have been extensively studied. In a repairable item inventory system, the breakdown of an item in use by a customer triggers a return of the item to the manufacturer for repair and an immediate demand for a new working item to replace the defective item. If replacement items are not in stock, demand is backordered. Because demand and returns are perfectly correlated, there is no uncertainty about the quantity and timing of returns compared to demand. A review of research on repairable item inventory systems is provided by Guide Jr & Srivastava (1997).

In a remanufacturing / hybrid production inventory system, a manufacturer can produce a new product from scratch or remanufacture the product using recovered materials. Product is recovered from the market once the customer has no further use for the product, upgrades the product, or when the product reaches its end-of-life. A common assumption in this literature is that demand is independent of returns (e.g., Fleischmann et al. 1997, DeCroix 2006, DeCroix et al. 2005). A few works, however, study systems in which uncertain demand and returns are correlated either in the same time period or across time periods. For a periodic review hybrid production system operating on a finite horizon, Kiesmüller & Van der Laan (2001) model the relationship between returns that occur in a current period and demands that occurred in a previous period. They find that ignoring this time-dependence of demand and returns can result in higher costs. For a continuous review hybrid production system, Van der Laan et al. (1999) model a correlation between demand and returns in the same period as the probability that a return will trigger an immediate demand. They evaluate the system under two types of control policies and find that increased correlation between demand and returns results in lower costs under either policy, but is especially beneficial when the return rate is high.

While the literature on these closed-loop supply chain inventory systems provides a background for our study, these systems are fundamentally different from the system we study in several ways. First, demand that is not fulfilled is backordered. This assumption is reasonable for specialized or expensive products such as equipment or in a business-to-business context, but not for consumer products that can easily be substituted by another product. Second, either customers generate perfectly coupled demand and returns (as in the repairable item literature) or customers generate demand and returns that are not explicitly related (as in the remanufacturing literature excluding the above-mentioned exceptions). As such, it is not necessary to consider the arrival of customers that are more diverse in terms of their impact on inventory levels (namely the co-existence of customers that only demand a product or return a product with customers that demand and return a product at the same time) and how the balance of each of those customer types affects the overall system.

Sharing economy inventory systems – and in particular bike-sharing systems (see Kabra et al. 2016, for an overview) – do resemble our problem setting more in that demand can be lost. In a bike-sharing system, customers collect a bike at one station and return it to the same or another station after a period of time, resulting in uncertainty in both the timing and location of returns. If a bike is not available at a station, the user may decide to take a bike from another station (resulting in a spillover of demand to another location) or substitute biking altogether with another mode of transport (resulting in a lost sale). However, bike-sharing systems have other features that do not translate well into our setting. First, demand and returns are never coupled (i.e., a return of a bike does not trigger demand for a bike). Second, bike-sharing system operators, in addition to managing the inventory of bikes at each station, also must manage the inventory of available docks for bikes to be returned. The number of docks available limits the number of returns that can be accepted at each station. To deal with imbalances between demand and availability for bikes and docks at individual stations throughout the day, bike-sharing system operators reposition the bikes. The inventory repositioning decisions in addition to the inventory placement decisions have been the focus of many studies, especially as for realistically-sized applications solving for these decisions can be computationally challenging, under different types of objectives or focusing on different problem features (e.g., Raviv & Kolka 2013, Datner et al. 2019, Shu et al. 2013). In summary, while bike-sharing inventory systems provide insights into how to manage loss inventory systems with uncertain demand and returns, the literature on this area is also limited in terms of its applicability to our setting.

Given that related inventory systems are different in several key ways from the inventory system in our problem setting, our contribution is to model the unique aspects of a restaurant that uses reusable containers instead of single-use containers to serve its take-away and delivery orders. Specifically, we model a lost sales system with uncertain demand and returns. In this system, customers that generate coupled demand for a new product and returns of a used product co-exist with customers that only demand a new product or customers that only return a used product. By studying the restaurant's inventory problem, we develop an understanding of how the level of the cost parameters and the degree of demand and return coupling affect the overall costs of operating such a system. Aside from assisting the restaurant, this understanding can help policy-makers in assessing to what degree they should encourage the use of reusable containers or third-party suppliers in designing systems with the operational challenges of different types of restaurants in mind.

4.3 Model Description

We consider a restaurant that stocks reusable containers for take-away and delivery food products. The restaurant manages two types of inventory: inventory of clean containers (denoted by x_C) and inventory of dirty containers (denoted by x_D). Three different types of customers visit the restaurant. Type 1 customers only demand a meal in a reusable container. Type 2 customers both demand a meal in a reusable container and return a dirty container, hence demands and returns are coupled. If no clean containers are available, the type 2 customer still returns the dirty container. Type 3 customers only return a dirty container. Customers of type $i \in \{1, 2, 3\}$ arrive to the restaurant according to a Poisson Process with rate λ_i.

All returns of dirty containers are accepted and processed by the restaurant's dishwasher. The time to wash one container has an exponential distribution with mean μ_I^{-1}. For stability we require $\lambda_2 + \lambda_3 < \mu_I$. A third-party supplier of clean containers operates the system. When the supplier visits, it can either provide more clean containers or collect excess clean containers from the restaurant, thereby helping the restaurant control the inventory of clean containers. The supplier visits the restaurant according a Poisson process with rate μ_E. The visit frequency μ_E will be a decision variable for the restaurant. Figure 4.1 illustrates the dynamics of the system.

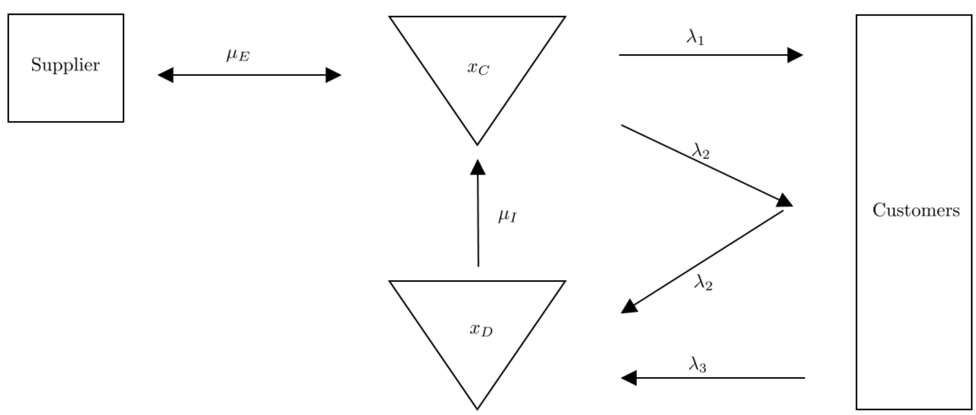


Figure 4.1: Dynamics of the reusable container system at the restaurant

The restaurant incurs a fixed cost k per supplier visit and a holding cost h per container held per time unit. If the restaurant does not have any clean containers on hand when a customer demands a container, the restaurant incurs a penalty p for not being able to satisfy the demand for a reusable container. This penalty represents the negative consequences of a stock-out of clean reusable containers at the moment of demand (i.e., a "lost sale"). In practice, this penalty could be as little as the cost of the single-use container to pack the order instead the reusable one, the cost of decreased customer trust in the restaurant's commitment to sustainability, or the cost of customer dissatisfaction in having to pay a surcharge for a disposable container. Or, it could be as much as the cost of losing the sale of the food product altogether in jurisdictions where single-use packaging is banned. In fact, the level of this penalty is the main parameter that the policy-maker can influence in this model through regulations. The system operates in continuous time over an infinite time horizon. The restaurant's objective is to minimize the long-run average cost rate by deciding on (i) the number of clean containers that it should have in inventory after the supplier visits and (ii) the supplier visit frequency.

4.4 Optimal Inventory Balancing Policy and Balancing Frequency

4.4.1 Optimal Inventory Balancing Policy

The decision of how much inventory of clean containers to take from or give to the supplier can be modeled as a Markov Decision Process (MDP) for any given supplier visit frequency μ_E. The state of this MDP is the tuple $(x_C, x_D) \in \mathbb{N}_0^2$ where x_C and x_D denote the inventory level of clean and dirty containers at the restaurant. The decision in this MDP is the number of clean containers to have in inventory at the restaurant after a visit from the supplier, where the action space is $\mathbb{N}_0$. Note that, if we let y denote the number of clean containers at the restaurant after a visit from the supplier and if the restaurant is in state (x_C, x_D) before the visit, then $y - x_C$ is the number of clean containers taken from the supplier. A negative value of $y - x_C$ indicates that clean containers were returned to the supplier.

To transform this continuous time MDP to a discrete time MDP, we use uniformization with $\gamma = \sum_{i=1}^{3} \lambda_i + \mu_I + \mu_E$ as the uniform transition rate and scale time such that $\gamma = 1$. The probability of transitioning from state (x_C, x_D) to state (x'_C, x'_D) under decision $y \in \mathbb{N}_0$ is given by:

$$p((x_C, x_D), y, (x'_C, x'_D)) = \begin{cases} \lambda_1, & \text{if } x'_C = (x_C - 1)^+ \text{ and } x'_D = x_D \\ \lambda_2, & \text{if } x'_C = (x_C - 1)^+ \text{ and } x'_D = x_D + 1 \\ \lambda_3, & \text{if } x'_C = x_C \text{ and } x'_D = x_D + 1 \\ \mu_I, & \text{if } x'_C = x_C + 1,\ x'_D = x_D - 1, \text{ and } x_D > 0 \\ \mu_I, & \text{if } x'_C = x_C,\ x'_D = x_D, \text{ and } x_D = 0 \\ \mu_E, & \text{if } x'_C = y \text{ and } x'_D = x_D \\ 0, & \text{otherwise} \end{cases}$$

The direct cost of being in state (x_C, x_D) is given by $h(x_C + x_D) + p(\lambda_1 + \lambda_2)\mathbb{I}(x_C = 0)$, where $\mathbb{I}(x)$ is the indicator function of x. Observe that the number of dirty containers at the restaurant x_D is not affected by the choice of y but only by the rate of returns $\lambda_2 + \lambda_3$ and dishwasher capacity μ_I. As such, the holding costs associated with dirty containers are sunk costs and the relevant direct cost function can be written as $h(x_C) + p(\lambda_1 + \lambda_2)\mathbb{I}(x_C = 0)$.

A policy $\pi : \mathbb{N}_0^2 \to \mathbb{N}_0$ is a decision rule that prescribes an action y to every possible system state (x_C, x_D). Policy π induces a stochastic process $(X_C^\pi(t), X_D^\pi(t))$ where $t \in \mathbb{N}_0$ is the indexed time unit in the horizon. Let Π be the set of Markovian policies. The average cost rate of a given rebalancing policy π is given by

$$g(\pi) = \limsup_{T \to \infty} \frac{1}{T} \mathbb{E}\left[\int_0^T hX_C^\pi(t) + p(\lambda_1 + \lambda_2)\mathbf{1}(X_C^\pi(t) = 0) dt \right].$$

We seek to minimize this average cost rate. We let $g^* = \inf_{\pi \in \Pi} g(\pi)$ denote the optimal average cost rate and π^* denote the optimal policy (i.e., $g(\pi^*) = g^*$) that achieves this average cost rate.

For g^* to exist and be finite, the Markov Chain induced by a Markovian policy must have a stationary distribution. Different conditions to establish the existence of a stationary distribution are outlined in Puterman (2014). This MDP is unichain and aperiodic because state $(0,0)$ can be reached from any other state under any policy and because it has a self-transition. Furthermore, observe that the number of dirty containers in the restaurant (X_D) behaves as the number of customers in an M/M/1 queue with arrival rate $\lambda_2+\lambda_3$ and service rate μ_I, regardless of any inventory balancing policy, because returns are always processed. The stability condition $\lambda_2+\lambda_3<\mu_I$ ensures that X_D has a stationary geometric distribution with dishwasher utilization $\rho_I := (\lambda_2+\lambda_3)/\mu_I$ as the parameter for any policy π (see Gross et al. 2008, for general results on M/M/1 queues). When demand exceed returns, X_C will have a stationary distribution under any Markovian policy. When returns exceed demand, a Markovian policy needs to return clean containers to the supplier at a rate of at least $\lambda_3-\lambda_1$. Otherwise, X_C will have positive drift and build up. A policy that reduces clean container inventory to any finite number during supplier visits will avoid this drift and so an optimal policy will too. Thus, there is a large class of Markovian policies that includes an optimal Markovian policy such that X_C will have a stationary distribution. For the remainder of this study we will only look at such policies. Given this discussion, there exists an optimal Markovian policy π^* and optimal cost rate g^* that satisfy the Bellman optimality equations:

$$\begin{aligned} V(x_C,x_D)+g^* = {} & h(x_C+x_D)+p(\lambda_1+\lambda_2)\mathbb{I}(x_C=0)+\lambda_1 V((x_C-1)^+,x_D) \\ & +\lambda_2 V((x_C-1)^+,x_D+1)+\lambda_3 V(x_C,x_D+1) \\ & +\mu_I\mathbb{I}(x_D=0)V(x_C,x_D)+\mu_I\mathbb{I}(x_D>0)V(x_C+1,x_D-1) \\ & +\mu_E \min_y V(y,x_D) \qquad \forall (x_C,x_D)\in\mathbb{N}_0^2 \end{aligned} \tag{4.1}$$

where $V(x_C,x_D)$ is the relative value function.

Inspection of the last term on the right hand side of the Bellman equations (4.1) reveals that for each possible number of dirty containers at the restaurant (x_D), there is an optimal number of clean containers that the restaurant wishes to have when the supplier visits the restaurant. This observation is important and stated in the following proposition.

Proposition 4.1. There exist state-dependent rebalancing levels $y^*(x_D)$ for each number of dirty containers in the restaurant (x_D) such that it is average optimal to increase (decrease) the number of clean containers to $y^*(x_D)$ when the supplier visits the restaurant and the number of clean containers at this time is reset to $x_C \leq y^*(x_D)$ ($x_C > y^*(x_D)$).

We solve this MDP numerically using the value iteration algorithm. The numerical evaluation requires us to set bounds for the state space variables x_C and x_D. Using the fact that the dishwasher is an $M/M/1$ queue and the number of dirty containers in the restaurant X_D is a geometrically distributed random variable with parameter ρ_I, the upper bound for X_D is set at the value on the support of X_D that corresponds to the 99th-percentile of this distribution. We need a different approach to bound X_C since there can be a positive or negative flow of containers between the supplier and the restaurant and unfulfilled demand is lost. As a proxy, we use the demand between supplier visits, D_S, to compute an upper bound on the number of clean containers. The distribution of D_S is a geometric distribution with parameter $\frac{\lambda_1+\lambda_2}{\lambda_1+\lambda_2+\mu_E}$. The derivation of this distribution is in the Appendix. Similar to the upper bound for X_D, we set the upper bound for X_C at the 99th-percentile of D_S.

4.4.2 Optimal Inventory Balancing Frequency

For a supplier visit frequency μ_E, $g^*(\mu_E)$ is the average lost sales penalty and holding cost rate under an optimal balancing policy π^*. Given supplier visit cost k, the restaurant incurs a total cost of $k\mu_E$ for the supplier visits, meaning that the restaurant's relevant costs are

$$C(\mu_E) = k\mu_E + g^*(\mu_E).$$

Whereas $g^*(\mu_E)$ decreases in μ_E, the supplier visit cost term increases in μ_E, creating a trade-off for the restaurant. The restaurant's optimal supplier visit frequency is $\mu_E^* = \operatorname{argmin}_{\mu_E} C(\mu_E)$. We compute μ_E^* using a golden section search.

4.5 Performance Metrics

In addition to the expected total cost rate g^*, several other metrics are used to assess the system's performance. Because unfulfilled demand is lost, the expected lost sales rate and the fill rate are important metrics to track. To clarify, we broadly use the term lost sale to refer to a demand that cannot be met by providing a meal in a clean reusable container, regardless of whether the meal itself can be sold in a disposable container or not. We use that Poisson Arrivals See Time Averages (PASTA) (Wolff 1982) to evaluate the following performance metrics. The expected *lost sales rate* is given by:

$$\mathbb{E}[\text{Loss}] = \mathbb{P}(X_C = 0)(\lambda_1 + \lambda_2).$$

We compute this rate recursively. Details are provided in the Appendix. The *fill rate*, denoted by β, is the ratio of the fulfilled demand to total demand in steady state and is given by:

$$\beta = \frac{\lambda_1 + \lambda_2 - \mathbb{P}(X_C = 0)(\lambda_1 + \lambda_2)}{\lambda_1 + \lambda_2} = 1 - \mathbb{P}(X_C = 0).$$

The restaurant can be a net receiver or giver of clean containers when the supplier visits. We define the *flow* as the long term demand for clean containers from the supplier. A negative flow indicates a net outflow of clean containers from the restaurant to the supplier whereas a positive flow indicated a net inflow of clean containers from the supplier to the restaurant. The expected flow is given by:

$$\mathbb{E}[\text{Flow}] = \lambda_1 + \lambda_2 - \mathbb{P}(X_C = 0)(\lambda_1 + \lambda_2) - (\lambda_2 - \lambda_3) = \lambda_1 - \mathbb{P}(X_C = 0)(\lambda_1 + \lambda_2) + \lambda_3.$$

The final two performance metrics we track are the expected number of clean and dirty containers at the restaurant. The expected number of clean containers at the restaurant can be derived from the fact that in steady state the average total cost $g^* = h\mathbb{E}[X_C] + p(\lambda_1 + \lambda_2)\mathbb{P}(X_C = 0)$. The expected *number of clean containers* at the restaurant is then:

$$\mathbb{E}[X_C] = \frac{g^* - p(\lambda_1 + \lambda_2)\mathbb{P}(X_C = 0)}{h} = \frac{g^* - p\mathbb{E}[\text{Loss}]}{h}.$$

Using general results on the number of items in a $M/M/1$ queueing system, the expected *number of dirty containers* at the restaurant is:

$$\mathbb{E}[X_D] = \frac{\rho_I}{1-\rho_I} = \frac{\lambda_2 + \lambda_3}{\mu_I - \lambda_2 - \lambda_3}.$$

4.6 Numerical Study

As mentioned in Section 4.1, the uncertainty in both the demand for and returns of reusable containers makes it more difficult for the restaurant to control inventory levels than if it were just facing uncertainty in demand (i.e., as in the single-use containers case). If the restaurant has too much demand relative to returns on average, it mostly uses the supplier's visit to obtain additional clean containers. If the restaurant has too many returns relative to demand, it mostly uses the supplier's visit to offload excess containers. The overall balance of demand to returns at the restaurant is a key characteristic of the restaurant's reusable containers operations and it affects the restaurant's inventory decisions and costs. To control for possible differences in inventory decisions and costs driven by differences in the balance of demand to returns, we define the average demand to returns ratio τ as a parameter that we vary systematically in our numerical study, where

$$\tau = \frac{\lambda_1 + \lambda_2}{\lambda_2 + \lambda_3}. \tag{4.2}$$

A restaurant's demand and returns are *balanced* when $\tau = 1$. When $\tau > 1$ (respectively $\tau < 1$), the restaurant has on average more (respectively less) demand for containers than returns.

Since the restaurant faces customers that are heterogeneous in terms of their effects on the inventory levels of reusable containers and one of the customer types it faces generates coupled demand and returns, one question we set out to investigate is how the proportion of coupled demand and returns out of total demand affects the restaurant's inventory decisions and costs. To do so, we define the average proportion of demand that is coupled with returns η as a second control parameter in our numerical study, where

$$\eta = \frac{\lambda_2}{\lambda_1 + \lambda_2}. \tag{4.3}$$

Scaling effects, such as economies of scale or congestion effects, may result in inappropriate comparisons as they may drive differences in inventory decisions and costs across systems. To control for such effects, we define a third control parameter for the scale of the average demand for reusable containers at the restaurant, denoted by κ, where

$$\kappa = \lambda_1 + \lambda_2. \tag{4.4}$$

To generate the instances in our numerical study, we calculate $\lambda_i, i \in \{1,2,3\}$ for fixed levels of τ, η, κ. Solving for the system of equations consisting of equations (4.2), (4.3), and (4.4) we calculate $\lambda_i, i \in \{1,2,3\}$ as $\lambda_1 = (1-\kappa)\eta$, $\lambda_2 = \kappa\eta$, and $\lambda_3 = \frac{\kappa}{\tau} - \lambda_2$.

Note that the proportion of coupled demand and returns η is in fact limited by the demand to returns ratio τ. That is, the greater the demand for reusable containers relative to returns (the higher $\tau > 1$), the more that customers that only demand a container but not return one (type 1 customers) dominate the overall demand relative to customers that have coupled demand and returns (type 2 customers). Type 2 customers help balance the restaurant's inventory whereas type 1 customers reduce inventory, tipping the overall demand and returns ratio so that demand outstrips returns. As a result, for a given demand to returns ratio $\tau > 1$, some levels of η may not be feasible. Mathematically, for such inconsistent τ and η values, λ_3 becomes negative. For example, for a restaurant with a $\tau = 1.5$, type 1 customers dominate to the extent that the highest proportion of coupled demand and returns possible is 0.67. Otherwise, $\lambda_3 < 0$. Therefore, in our selection of parameters, we restrict our settings for η and τ to values that are feasible and consistent for all τ.

The last control parameter we define is the utilization of the dishwasher, ρ_I. Using the fact that the dishwasher behaves like an $M/M/1$ queue with utilization $\rho_I = \frac{\lambda_2+\lambda_3}{\mu_I}$, we calculate μ_I for fixed levels of ρ_I from $\mu_I = \frac{\lambda_2+\lambda_3}{\rho_I}$. Setting values for $\rho_I < 1$ trivially ensures that the stability condition $\lambda_2 + \lambda_3 < \mu_I$ is met. Table 4.1 summarizes the parameters for the numerical study.

Generating instances in this way yields a full factorial test bed of $1 \times 4 \times 4 \times 5 \times$

Input parameter	No. of values	Values
Holding cost (per time unit per unit), h	1	1
Underage penalty (per unit underage), p	4	50, 100, 150, 200
Supplier visit cost, k	4	100, 200, 300, 400
Ratio of demand to returns, τ	5	0.8, 0.9, 1.0, 1.1, 1.2
Proportion of demand that is coupled with returns, η	5	0, 0.2, 0.4, 0.6, 0.8
Scale of demand, κ	3	50, 75, 100
Dishwasher utilization, ρ_I	4	0.6, 0.7, 0.8, 0.9
Total number of instances	4,800	

Table 4.1: Input parameter values for test bed

$5 \times 3 \times 4 = 4,800$ instances. Table 4.2 summarizes the results of the numerical study.

Parameter	Value	Count	μ_E^*	g^*	g_L	g_H	$\mathbb{E}$[Loss]	$\mathbb{E}[X_C]$	$\mathbb{E}[X_D]$	$\mathbb{E}[Flow]$	β
τ	0.8	960	0.293	145.631	2.851	78.033	0.029	78.033	4.208	-18.779	1.000
	0.9	960	0.193	110.895	5.075	63.241	0.052	63.241	4.208	-8.385	0.999
	1.0	960	0.122	98.158	17.093	52.844	0.176	52.844	4.208	-0.176	0.998
	1.1	960	0.283	170.035	30.145	79.556	0.332	79.556	4.208	6.486	0.995
	1.2	960	0.408	223.511	35.082	100.730	0.385	100.730	4.208	12.115	0.995
η	0	960	0.263	159.757	20.663	82.041	0.222	82.041	4.208	-1.775	0.997
	0.2	960	0.261	154.997	19.474	78.698	0.210	78.698	4.208	-1.763	0.997
	0.4	960	0.260	149.985	18.191	75.132	0.196	75.132	4.208	-1.749	0.997
	0.6	960	0.258	144.653	16.747	71.363	0.181	71.363	4.208	-1.734	0.997
	0.8	960	0.257	138.838	15.172	67.171	0.165	67.171	4.208	-1.718	0.998
κ	50	1600	0.212	124.189	15.825	62.007	0.171	62.007	4.208	-1.206	0.997
	75	1600	0.262	151.017	18.198	75.609	0.196	75.609	4.208	-1.749	0.997
	100	1600	0.306	173.732	20.125	87.027	0.217	87.027	4.208	-2.288	0.998
ρ_I	0.6	1200	0.260	148.798	17.971	74.077	0.194	74.077	1.500	-1.747	0.997
	0.7	1200	0.260	149.119	17.993	74.376	0.194	74.376	2.333	-1.747	0.997
	0.8	1200	0.260	149.678	18.025	74.908	0.195	74.908	4.000	-1.748	0.997
	0.9	1200	0.259	150.989	18.207	76.162	0.196	76.162	9.000	-1.749	0.997
p	50	1200	0.232	134.943	19.901	64.460	0.398	64.460	4.208	-1.951	0.994
	100	1200	0.257	148.112	18.147	73.804	0.181	73.804	4.208	-1.735	0.997
	150	1200	0.271	155.307	17.326	78.898	0.116	78.898	4.208	-1.669	0.998
	200	1200	0.280	160.222	16.822	82.362	0.084	82.362	4.208	-1.637	0.999
All		4800	0.260	149.646	18.049	74.881	0.195	74.881	4.208	-1.748	0.997

Table 4.2: Numerical study results

4.6.1 Ratio of Demand to Returns

The results of the numerical study in terms of how the system metrics change as the demand to returns ratio τ changes are consistent with the intuition that a system in which demands and returns are more balanced has lower costs. Indeed, the restaurant minimizes its total costs when demand and returns are balanced, i.e., when $\tau = 1.0$.

When returns are higher than demand, the restaurant's inventory of containers increases. Although the restaurant has fewer lost sales, the higher holding costs result in an overall increase in total costs. When the supplier visits, the restaurant uses this opportunity to offload clean containers to the supplier as can be seen by the negative expected flow between the restaurant and the supplier.

In the opposite direction, as τ increases further beyond $\tau = 1.0$ and the restaurant faces more demand than returns, the restaurant is penalized from both the underage and holding costs perspective. Not only do lost sales increase because of the additional demand but holding costs also increase as the restaurant stocks more to avoid the high underage penalty. The supplier's visit is an opportunity for the restaurant to receive an inflow of clean containers.

Figure 4.2 illustrates how the average cost rates vary with the demand to returns ratio.

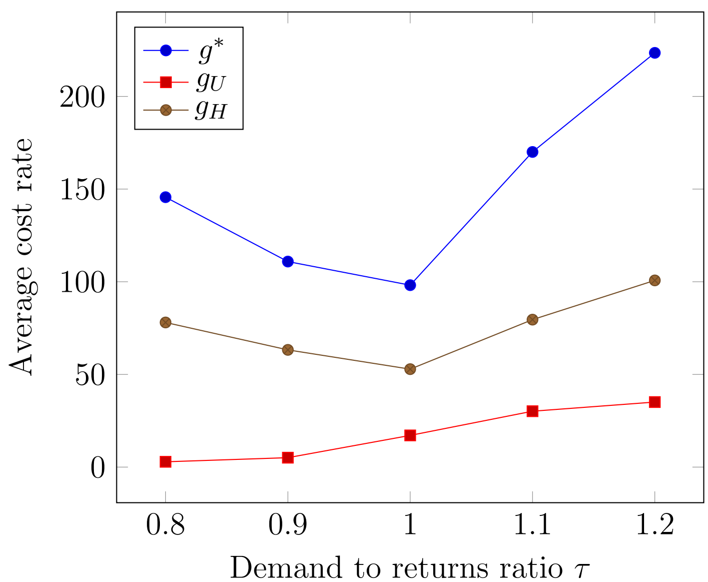


Figure 4.2: Average cost rate as a function of the ratio of demand to returns ratio τ

The restaurant benefits from a more balanced demand to returns ratio in one more way, namely that it allows the restaurant to reduce the fixed costs incurred from the supplier visits. As τ moves away from 1.0 in either direction, the optimal supplier visit frequency μ_E^* increases. The restaurant is less able to manage its inventory in a cost efficient manner internally from its demand and returns and more dependent on the supplier for rebalancing. For the supplier operating the container system, it is crucial to understand that this service must be designed in such a way that restaurants can rely on the rebalancing, especially when demand and returns are not balanced.

In practice, it may be difficult for the restaurant to have balanced demand and returns. However, if there is an imbalance between demand and returns, it is preferable for the restaurant to have more returns than demand instead of more demand than returns. This observation is likely a result of the relatively high underage penalty, which is in line with reality.

Notice that, even in a balanced system, there is an average net outflow of clean containers from the restaurant to the supplier when the supplier visits. This observation is a consequence of the fact that unsatisfied demand is lost. The supplier, despite serving the role of an inventory balancer in the system, is not able to balance demands and returns. All returns are collected but not all demands are fulfilled, so in steady state, fulfilled demand is lower than returns and the restaurant generates a net outflow of containers to the supplier.

4.6.2 Proportion of Demand Coupled to Returns out of Total Demand

The more demand and returns are coupled (i.e., the higher η), the easier it is for the restaurant to balance its inventory levels locally. Both lost sales and holding costs decrease, resulting in an overall decrease in the average total cost rate. The restaurant mostly uses the supplier visits to reduce its inventory of clean containers, but it does not reduce this inventory by much.

The fact that μ_E^* is not more sensitive to changes in the proportion of coupled demand is a more unexpected result. The restaurant's improved ability to sustain its operations internally when more of its demands are coupled with returns would suggest that the restaurant does not need the supplier as much for rebalancing, leading to a lower optimal supplier visit frequency. The results in Table 4.2 support this intuition, but the decrease in μ_E^* as η increases is modest.

One plausible explanation is that the benefit of an increased proportion of coupled demand and returns depends on the overall balance of demand to returns at the restaurant. To investigate this relationship, we examine the restaurant's performance metrics for each level of the demand to returns ratio τ as the proportion of coupled demand η increases. The results are displayed in Table 4.3.

τ	η	Count	μ_E^*	g^*	g_L^*	g_H^*	$\mathbb{E}$[Loss]	$\mathbb{E}[X_C]$	$\mathbb{E}[X_D]$	$\mathbb{E}$[Flow]	β
0.8	0	192	0.292	149.495	3.894	81.102	0.040	81.102	4.208	-18.790	0.999
	0.2	192	0.292	147.308	3.289	79.384	0.034	79.384	4.208	-18.784	1.00
	0.4	192	0.293	145.320	2.735	77.800	0.028	77.800	4.208	-18.778	1.00
	0.6	192	0.294	143.635	2.297	76.447	0.024	76.447	4.208	-18.774	1.00
	0.8	192	0.294	142.397	2.043	75.433	0.021	75.433	4.208	-18.771	1.00
0.9	0	192	0.193	119.274	7.401	69.409	0.076	69.409	4.208	-8.409	0.999
	0.2	192	0.192	114.897	6.195	66.260	0.063	66.260	4.208	-8.397	0.999
	0.4	192	0.192	110.598	4.979	63.089	0.051	63.089	4.208	-8.385	0.999
	0.6	192	0.193	106.555	3.837	60.058	0.039	60.058	4.208	-8.373	0.999
	0.8	192	0.193	103.150	2.961	57.391	0.031	57.391	4.208	-8.364	1.000
1.0	0	192	0.137	117.781	22.086	65.768	0.228	65.768	4.208	-0.228	0.997
	0.2	192	0.130	109.386	20.054	60.305	0.206	60.305	4.208	-0.206	0.997
	0.4	192	0.123	99.907	17.699	54.017	0.182	54.017	4.208	-0.182	0.998
	0.6	192	0.115	88.817	14.757	46.715	0.151	46.715	4.208	-0.152	0.998
	0.8	192	0.108	74.897	10.871	37.417	0.111	37.417	4.208	-0.111	0.999
1.1	0	192	0.287	181.103	32.880	87.440	0.361	87.440	4.208	6.457	0.995
	0.2	192	0.284	175.932	31.698	83.764	0.348	83.764	4.208	6.470	0.995
	0.4	192	0.282	170.436	30.332	79.914	0.334	79.914	4.208	6.484	0.996
	0.6	192	0.281	164.546	28.789	75.679	0.317	75.679	4.208	6.501	0.996
	0.8	192	0.281	158.157	27.025	70.984	0.298	70.984	4.208	6.520	0.996
1.2	0	192	0.409	231.130	37.057	106.486	0.406	106.486	4.208	12.094	0.995
	0.2	192	0.408	227.463	36.134	103.775	0.396	103.775	4.208	12.104	0.995
	0.4	192	0.408	223.663	35.209	100.841	0.386	100.841	4.208	12.114	0.995
	0.6	192	0.408	219.712	34.055	97.916	0.374	97.916	4.208	12.126	0.995
	0.8	192	0.409	215.589	32.958	94.629	0.362	94.629	4.208	12.138	0.995

Table 4.3: Effect of increasing the demand-return coupling η for different levels of the demand to returns ratio τ

The largest benefit of increased coupling of demand and returns is realized when demand and returns are balanced, i.e., $\tau = 1.0$. In this situation, increased coupling of demand and returns enables the restaurant to be more internally sustainable and to reduce the supplier visit frequency significantly. The restaurant needs to hold very little inventory of clean containers when most customers bring the same number of dirty containers as they demand when ordering take-away or delivery meals. In fact, the restaurant only needs to hold enough clean containers to bridge the time required to clean returned containers while serving customers with clean ones on the spot.

The benefit of increased coupling of demand and returns decreases as the ratio of demand to returns becomes more imbalanced in either direction. Because of the imbalance of overall demand to returns, the restaurant hold higher levels of reusable containers. In this case, the benefit of supply and demand being coupled is less pronounced. Figure 4.3 illustrates how the expected total cost rate differs for each level of τ and η.

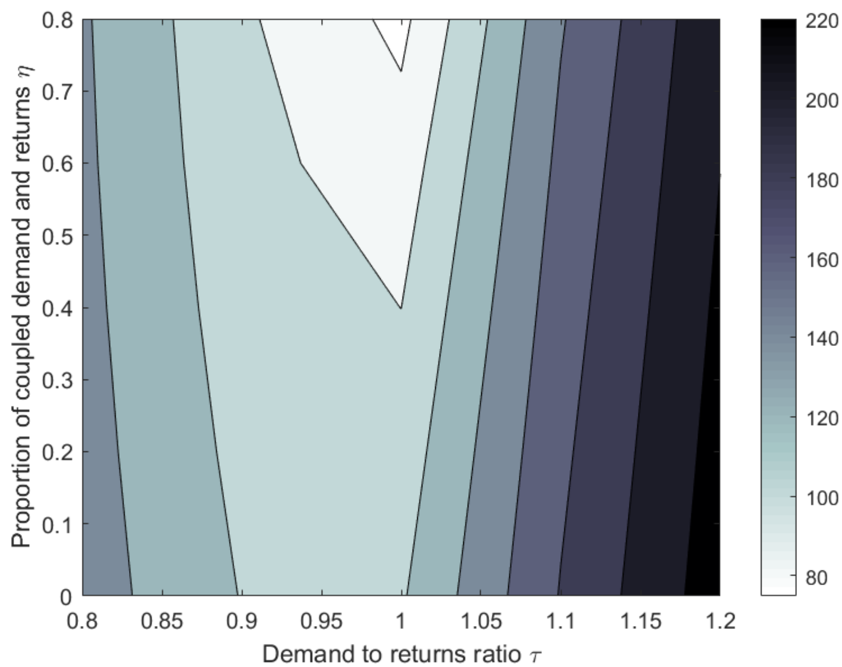


Figure 4.3: Average total cost rate g^* as demand to returns ratio τ and demand-return coupling η vary

Another observation from Table 4.3 is that, even when controlling for differences in the effect of coupled demand and returns at various levels of the demand to return ratios, μ_E^* remains relatively stable, except for when overall demand and returns are balanced. This observation suggests that, for systems that are not balanced, μ_E^* is robust to changes in coupled demand and returns and most of the adjustment occurs in the optimal inventory balancing policy. Therefore, the value of optimizing μ_E as the coupling of demand and returns varies is limited when demand and returns are imbalanced and a one-time optimization of μ_E for a given τ may suffice.

4.6.3 Scale of Demand and Cost of Supplier Visit

More frequent supplier visits are required to rebalance a system with a higher scale of demand. The reason for the more frequent rebalancing is that, as the restaurant's demand increases, the restaurant stocks more containers to meet the additional demand but it also incurs more lost sales, making it harder for the restaurant to balance its inventory through its local demand and returns.

As the scale of demand increases, all costs increase, but they increase by less compared to the increase in scale. This observation suggests that larger restaurants may benefit from economies of scale. One of the key decisions in designing a reusable container system is the cost per supplier visit. A higher supplier visit cost k decreases the optimal supplier visit frequency μ_E^*. With less frequent supplier visits, lost sales increase and the restaurant holds more inventory on average, either because it cannot offload excess inventory as frequently or because it carries more in light of the less frequent visits to satisfy demand.

Does a higher supplier visit cost affect restaurants of different scales equally? The answer to this question is not immediately clear as larger scale restaurants incur higher supplier visit costs from more frequent supplier visits and higher underage and holding costs but also can divide these costs among more customers. To answer this question, we examine the average cost per demand fulfilled (i.e., per meal served in reusable container), which we compute as $C(\mu_E^*)/(\lambda_1 + \lambda_2)(1 - \mathbb{P}(X_C = 0))$. Figure 4.4 shows the average cost/demand fulfilled as a function of scale for every level of supplier visit cost k. The difference between the average cost/demand fulfilled when the supplier visit cost $k = 400$ (green curve) compared to when $k = 100$ (blue curve) is greater for a smaller scale restaurant than for a larger scale restaurant. More specifically, the increase in demand at a larger restaurant is able to offset the increase in the supplier visit cost by more than the increase in demand at a smaller restaurant. This observation suggests that smaller restaurants are penalized more with a higher supplier visit cost and highlights the importance of the choice of the supplier visit k and its potential impact on the decision of smaller restaurants to participate in a reusable containers system.

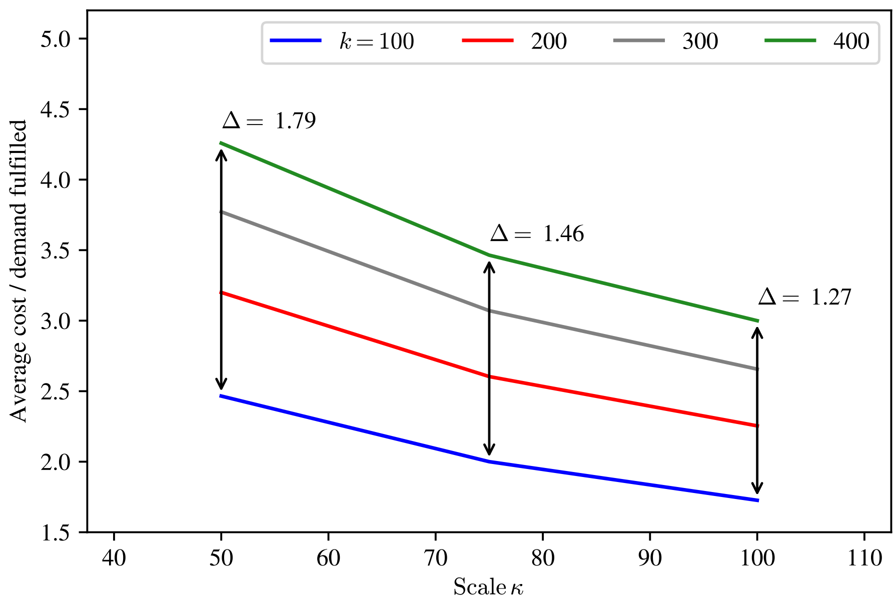


Figure 4.4: Scale effects on average cost/demand fulfilled for a given supplier visit cost k

4.6.4 Utilization of Dishwasher

The dishwasher utilization has a negligible effect on the cost of the system. Recall that, since X_D behaves as the number of customers in an M/M/1 queue regardless of the rebalancing policy, we dropped the holding cost of dirty containers as it is sunk. Note however, that reducing utilization does significantly reduce the holding cost of dirty containers. The number of clean containers is little affected by the utilization of the dishwasher. This result is consistent with Burke's theorem (Burke 1956) which says that the departure process from an M/M/1 queue is a Poisson Process. Hence, the arrival process of clean containers from the dishwasher is a Poisson process with rate $\lambda_2 + \lambda_3$ in steady state regardless of the utilization.

4.6.5 Underage Penalty

A higher underage penalty p results in a higher average total cost rate. To avoid lost sales, both a higher supplier visit frequency and a higher inventory level are optimal. The increase in the average total cost rate is driven by these higher supplier visit costs and holding costs.

Policy-makers can influence the level of the underage penalty p through regulations. For example, in jurisdictions that ban single-use containers altogether (the model that Luxembourg and Germany are moving towards), the underage penalty for stocking-out on a reusable container is high as it means that the restaurant is not able to make the sale of the food item. In jurisdictions that charge a customer a surcharge for the use of a disposable container, the underage penalty for the restaurant is likely much lower. The restaurant's decision to hold higher inventory levels of reusable containers when p increases in response to such regulations shows that these regulations can help promote the availability of reusable containers in restaurants. Our model can be extended to study the sensitivity of the number of single-use containers displaced as a function of the level of the underage penalty. Such an analysis can inform policy-makers in terms of realistic target-setting for reductions of single-packaging waste from the food services sector.

4.7 Conclusion

The increased popularity and availability of food take-away and delivery options has contributed to a growth in single-use packaging waste. Policy-makers, start-ups, and restaurants are introducing reusable container systems to reduce the demand for and production of single-use packaging.

The design of reusable container systems is still evolving and many strategic and operational issues remain to be resolved. At the very core of these systems, individual restaurants need to decide on how many reusable containers to have on-hand and how frequently the supplier should visit to help balance inventory. The uncertainty in both demand and returns of reusable containers makes it difficult for the restaurant to control its inventory levels. Additionally, restaurants cater to multiple customer types that have different effects on the inventory level of reusable containers at the restaurant. Some customers only demand a clean container with their order (forward flow of products), other customers only return used containers (reverse flow of products), and some customers do both at the same time. This last set of customers have coupled demand and returns and, because they have a net zero effect on inventory levels, have the potential to balance the system. Our problem setting differs from related settings previously studied in that it is a lost sales system where traditional forward flow customers and reverse flow customers co-exist with customers with coupled demand and returns.

We find that having a greater proportion of customers with coupled demand and returns is always beneficial to a restaurant in that it allows the restaurant to better control the inventory of containers internally. The restaurant is less dependent on the supplier to balance its inventory and can reduce costs. However, just how beneficial depends on the overall balance of demand and returns at the restaurant. The cost reduction from increased coupling of demand and returns is most substantial when overall demand and returns are balanced. Such a balance is likely to emerge, for example, in a restaurant that has a base of loyal customers that frequently order from the restaurant.

The restaurant can reduce costs by optimizing the supplier visit frequency as well as the inventory balancing policy. From a system-design perspective, one important decision for the supplier is the level of the supplier visit cost. A higher supplier visit cost can disproportionately penalize restaurants with a smaller scale of demand for reusable containers. Although the optimal supplier visit frequency is lower for a restaurant with a smaller scale of demand, restaurants with a larger scale of demand are able to distribute total costs across more demand than smaller restaurants. A high supplier visit cost may thereby make it more difficult financially for smaller restaurants to use reusable containers. Another important design decision for the policy-maker is the level of the underage penalty. A policy-maker, through influencing the level of the underage penalty for not having a clean reusable container available, can play a role in promoting the use of reusable containers. A higher underage penalty encourages the restaurant to stock more reusable containers.

Many questions remain about how to design reusable container systems in the food services sector and how to incentivize customers, restaurants, and the third-party supplier to participate in the system. In this study, we put these questions to the side and focused on a single restaurant's inventory decisions to derive insights on how a restaurant can manage its inventory of reusable containers. A similar analysis of the inventory and visit frequency decisions for the reusable container supplier would highlight the key trade-offs faced by the supplier and how a supplier may operate this system. Another natural extension would be to analyze the operations of a network of restaurants offering reusable containers and the reusable container supplier's inventory decisions.

Appendix 4.A Distribution of Demand Between Supplier Visits

Let S denote the time between supplier visits, then S is exponentially distributed with mean $\frac{1}{\mu_E}$. Let D_S denote the demand between supplier visits. Observe that demand in a fixed interval of length s has a Poisson distribution with mean $(\lambda_1 + \lambda_2)s$. The demand over an interval of random length S can be found by using the law of total probability:

$$
\begin{aligned}
\mathbb{P}(D_S = x) &= \int_0^\infty \mathbb{P}(D_S = x | S = s) f_S(s) ds \\
&= \int_0^\infty e^{-\lambda s} \frac{(\lambda s)^x}{x!} \mu e^{-\mu s} ds \\
&= \frac{\mu}{x!} \int_0^\infty e^{-(\lambda+\mu)s} (\lambda s)^x ds \\
&= \frac{\mu}{x!} \left(\frac{\lambda}{\lambda+\mu}\right)^x \left(\frac{1}{\lambda+\mu}\right) \underbrace{\int_0^\infty z^x e^{-z} dz}_{\Gamma(x+1)=x!} \\
&= \frac{\mu}{\lambda+\mu} \left(\frac{\lambda}{\lambda+\mu}\right)^x \\
&= \left(1 - \frac{\lambda}{\lambda+\mu}\right) \left(\frac{\lambda}{\lambda+\mu}\right)^x
\end{aligned}
$$

In the fourth line, we change the variable of integration to $z = (\lambda + \mu)s$. The integral at the end of this line the Gamma function, $\Gamma(x + 1)$. For integer x, $\Gamma(x + 1) = x!$, so $x!$ cancels out. Observe that D_S has a geometric distribution with parameter $\frac{\lambda_1+\lambda_2}{\lambda_1+\lambda_2+\mu_E}$.

Appendix 4.B Computation of Expected Lost Sales Rate

Let $U_n(x_C, x_D)$ be the expected lost sales rate after n events starting in state (x_C, x_D), where $U_n(x_C, x_D)$ is given by:

$$\begin{aligned}
U_n(x_C, x_D) = \mathbb{I}(x_C = 0)(\lambda_1 + \lambda_2) \\
&+ \lambda_1\big(\mathbb{I}(x_C = 0)U_{n-1}(x_C, x_D) + \mathbb{I}(x_C > 0)\lambda_1 U_{n-1}(x_C - 1, x_D)\big) \\
&+ \lambda_2\big(\mathbb{I}(x_C = 0)U_{n-1}(x_C, x_D + 1) + \mathbb{I}(x_C > 0)U_{n-1}(x_C - 1, x_D + 1)\big) \\
&+ \lambda_3 U_{n-1}(x_C, x_D + 1) \\
&+ \mu_I\big(\mathbb{I}(x_D = 0)U_{n-1}(x_C, x_D) + \mathbb{I}(x_D > 0)U_{n-1}(x_C + 1, x_D - 1)\big) \\
&+ \mu_E U_{n-1}(y_n^*(x_D), x_D),
\end{aligned}$$

where $y_n^*(x_D) \in \operatorname{argmin}_{y \in \mathbb{N}_0} V_n(y, x_D)$ and V_n is defined recursively as

$$\begin{aligned}
V_n(x_C, x_D) &= h(x_C + x_D) + p(\lambda_1 + \lambda_2)\mathbb{I}(x_C = 0) + \lambda_1 V_{n-1}((x_C - 1)^+, x_D) \\
&+ \lambda_2 V_{n-1}((x_C - 1)^+, x_D + 1) + \lambda_3 V_{n-1}(x_C, x_D + 1) \\
&+ \mu_I \mathbb{I}(x_D = 0)V_{n-1}(x_C, x_D) + \mu_I \mathbb{I}(x_D > 0)V_{n-1}(x_C + 1, x_D - 1) \\
&+ \mu_E \min_y V_{n-1}(y, x_D) \qquad \forall (x_C, x_D) \in \mathbb{N}_0^2.
\end{aligned}$$

For an optimal policy, the expected lost sales rate is:

$$\mathbb{E}[\text{Loss}] = \lim_{n \to \infty} U_{n-1}(x_C, x_D) - U_n(x_C, X_D)$$

for any $(x_C, x_D) \in \mathbb{N}_0^2$.

Chapter 5

Conclusion

In this dissertation, we studied the inventory decisions of players in decentralized food supply chains when faced with policy interventions to reduce waste. While we did not explicitly model the decisions of a policy-maker, through policy interventions, the policy-maker influences the parameters that factor into the optimization problems that these players solve in managing their operations. A better understanding of the decisions made by players at different levels of the supply chain and possible frictions they face can inform policy-makers in the design of more effective policy interventions.

In Chapter 2, we introduced a serial newsvendor supply chain as an approach to model the multi-unit inventory decisions of a buyer and a seller when the buyer can exhibit different degrees of strategic behavior. To investigate the effect of a buyer's strategic behavior, we defined three buyer types. The myopic buyer exhibits no strategic behavior in that he does not consider factors that affect other periods or the seller's stocking decisions when making his period inventory decisions. The forward-looking buyer is more strategic in that he considers factors affecting other periods in making period inventory decisions. The sophisticated buyer is the most strategic buyer who considers both factors affecting other periods and the seller's stocking decision in making his period inventory decisions.

We showed that the equilibrium inventory decisions and profit outcomes are sensitive to the degree to which a buyer is strategic. The seller makes the most profit when he faces a forward-looking buyer. The seller benefits from the demand-enhancing effect of a buyer that considers factors affecting other periods in his period inventory decisions. Although sophisticated buyer behavior also has a demand-enhancing effect, the sophisticated buyer's strategic caution in his purchase decisions manipulates the seller into bringing more supply and taking more risk in his stocking decision.

In Chapter 3, we extended the analysis of a serial newsvendor supply chain to investigate waste outcomes when a buyer exhibits varying degrees of strategic behavior. In particular, we focused the analysis to two types of buyers: the myopic buyer and the forward-looking buyer. We then studied the effect of policies that penalize waste by imposing a waste cost on the seller and/or the buyer. We showed that, while applying a waste cost on either the seller or the buyer can both be effective policy instruments to reduce waste, better outcomes in terms of profit and waste may be attainable if a tax is applied on both agents at possibly different rates.

In Chapter 4, we shifted our focus to the effect of policy interventions to reduce single-use packaging waste in the food take-away and delivery sector. Given increasing regulations that effectively penalize the use of single-use packaging in this sector, reusable containers have emerged as an alternative. However, managing inventories of reusable containers comes with numerous operational challenges for a restaurant. Both the demand for and supply (i.e., returns) of reusable containers are uncertain. Forward-flow customers that only demand a clean container and reverse-flow customers that only return a used container co-exist with customers that generate a coupled demand and return by both demanding a clean container and returning a used one at the same time.

We found that having a greater proportion of customers that generate a coupled demand and return is always beneficial to a restaurant in that it allows the restaurant to better control the inventory of containers internally and reduce all types of costs. However, the largest cost reductions from increased coupling of demand and returns is most substantial when the overall demand and returns are more balanced. The restaurant can reduce costs by optimizing both the supplier visit frequency and the inventory rebalancing policy during the supplier visits. From a system-design perspective, one important decision is the level of the supplier visit cost as a higher supplier visit cost can penalize smaller restaurants.

Various promising directions for future work exist. The incorporation of pricing, modeling the decisions of policy-makers, and modeling competition or at least the decisions of multiple players at each tier of a supply chain are a number of ways that our analysis of the settings in this dissertation can be enriched. For example, the study of the interaction between a buyer and a seller in a serial newsvendor supply chain when a policy-maker penalizes waste for the buyer and/or the seller can be enriched by allowing the seller to set prices in either or both periods. It is possible that a seller faced with a waste cost decides to increase the price of the product sold and pass on this waste cost to the buyer. Such a situation is likely to hurt the buyer the most who may respond by reducing his purchase decisions thereby decreasing the product he has available for sale to the downstream market and profits. The effect on the seller and the entire supply chain is not clear a priori. On the one hand, the seller may be relatively unaffected as he passes the burden of the tax to the buyer and the seller's waste may be unaffected as well. On the other hand, the lower purchase quantities of the buyer may be a sufficiently strong signal for the seller to stock less, earning less profit but still decreasing the possibility of waste on the system.

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