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MECHANISMS TO COORDINATE NEW AND USED PRODUCT SALES: AN EMPIRICAL AND ANALYTICAL INVESTIGATION

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Abstract

This dissertation investigates the coordination between new and used product sales using both empirical and analytical approaches.

The first essay studies the potential for cannibalization of new product sales by remanufactured versions of the same product, which is a central issue in managing the secondary market. Practitioners have no fact-based information to guide practice at companies and academics have no studies available to use as the basis for assumptions in models. We address the cannibalization issue by using auctions to determine consumers' willingness-to-pay for both new and remanufactured products. The auctions also allow us to determine the potential impact of offering new and remanufactured products at the same time, which provides us insights into the potential for new product cannibalization. Our results indicate that for the consumer and commercial products auctioned, there is a clear difference in willingness-to-pay for new and remanufactured goods. For the consumer product, there is scant overlap in bidders of the new and the remanufactured product, leading us to conclude that the risk of cannibalization in this case is minimal. For the commercial product, however, there is evidence of overlap in bidding behavior, exposing the potential for cannibalization.

Trade-in programs are designed to promote new product sales and give companies control over the secondary market. Motivated by a real problem facing a high-tech company, in the second essay, we develop methods to analyze data from Return Merchandise Authorization (RMA) forms, which contain information such as product number, quantity, and date. To accurately forecast the returned quantity of a product in an RMA, we treat the booked quantity as a signal and adjust its noise by taking product characteristics and customer heterogeneity into account. For our data set, we

find that the proposed forecasting strategy that captures both product and customer information outperforms the two benchmark strategies that represent the high-tech company's current practice and a widely-adopted method in the literature, respectively. In addition, our analysis can also serve as a tool for companies to uncover the root causes of RMA reporting errors, to provide valuable insights on effective design of trade-in policies, and to monitor and evaluate the performance of trade-in policies on a continuous basis. Our forecasting methods are currently under a trial implementation in the company and can potentially be applied to similar business settings to extract useful information from noisy, yet valuable signals.

In the third essay, we build an analytical model to study the trade-in strategy in the context of a monopolistic manufacturer offering a technology product to a heterogeneous consumer population. We consider an exogenous innovation process that governs the availability of new technology, and therefore a product is subject to two types of value decay: technological obsolescence (due to technology innovation) and functional depreciation (due to wear and tear). The manufacturer chooses the prices for the new products featuring a new and an existing technologies, respectively, and the trade-in credit for the used products featuring a previous-generation technology and an existing technology, respectively, to maximize her long-run average profit. Heterogeneous consumers make their consumption choice accordingly to maximize their utility.

We characterize the optimal stationary pricing strategy for the manufacturer and the corresponding optimal consumption strategies that consumers choose based on their willingness-to-pay. We find that manufacturers with different production cost and resell cost structures should leverage trade-in differently to take the full advantage of it. Low production cost and low resell cost manufacturers should offer trade-in programs regardless of innovation state in order to induce the highest-valuation consumers to purchase a new product in every period. However, when production cost and/or resell cost are higher, trade-in programs should be restrained accordingly. We also evaluate the impact of innovation frequency, technological obsolescence, functional depreciation, and production and resell costs on the manufacturer's maximum long-run average profit. Some of the findings are interesting and not so intuitive. In general, technological obsolescence and functional depreciation reduce consumer valuation of used products, which should in turn lower the manufacturer's profitability. However, we identify scenarios under which they can actually increase a manufacturer's expected profit. Moreover, we characterize situations under which higher innovation frequency helps or hurts the manufacturer's bottom line.

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Chapter 1

Introduction

With the ever-increasing competition in primary markets and environmental concerns, companies pay more attention to secondary markets and product reuse in general. Under such situation, the coordination between new and used product sales is crucial to a company's profitability. In this dissertation, we intend to understand the interaction between new and used product sales using different methodologies and provide managerial insights on the coordination of the two.

In the first essay (Chapter 2), we use an experimental method to learn consumer perception of one important type of secondary-market products, the remanufactured products, and address the potential for market cannibalization of new product sales by remanufactured products. The study is motivated by both the academic literature and the practice. The first motivating factor is the widespread use of assumptions about new product market cannibalization by academics when modeling various scenarios involving the marketing and sales of remanufactured products. Consumers' willingness-to-pay (WTP) for remanufactured products is an inevitable question when studying product acquisition, remanufacturing, and market competition. However, a lack of such knowledge results in researchers using assumptions that best support modeling tractability. In practice, the prevailing view regarding cannibalization among sales and marketing managers is that new products sales are cannibalized by remanufactured products; therefore at many companies managers are reluctant to introduce remanufactured products. In contrast, although representing a small proportion, there are managers who believe selling remanufactured products serves to expand market share. All of these managers' assertions are based on personal experience and hunches; hence, we are interested in investigating the validity of managers' assessment of cannibalization using quantitative analysis.

In the research, we auctioned products donated by Robert Bosch Tools, NA and Cisco Systems, Inc. to determine the difference between consumers' willingness-to-pay for new and remanufactured products, and to help assess the extent to which new product sales is cannibalized by remanufactured products. For the consumer product offered by Bosch, auction results show that consumers' WTP for the remanufactured version is 16.4% lower than that for the new product. In addition, bidders of the new and remanufactured products are segmented, suggesting that the remanufactured product does not cannibalize the sales of the new product. For the commercial product offered by Cisco, auction results show that consumers' WTP for the remanufactured product is 11.4% lower than that for the new product. The bidding history reveals a certain degree of overlapping of consumers of the new and the remanufactured products.

After learning consumer valuation and market potential of remanufactured products, in the second essay (Chapter 3), we focus on the supply side of used products by investigating the forecasting and management issues of trade-in programs in business-to-business (B2B) markets. Trade-in programs are designed to promote new product sales, generate additional revenues by selling remanufactured and used products in secondary markets, and gain control of the entire product life cycle. Our study is motivated by a real problem facing a high-tech manufacturer. When customers of the company trade in their current products, they are required to generate a Return Merchandise Authorization (RMA) containing information such as product number and quantity, and to return the products within a pre-specified time window. However, considerable discrepancies exist between RMA information and actual returns. Therefore, in this essay we propose forecasting models incorporating information of product characteristics, i.e., substitutability and complementariness, and customer heterogeneity to obtain accurate forecast of trade-in product returns based on noisy

RMA information. We develop methods to characterize the data structure of RMAs and adopt two main approaches, *cluster analysis* and *finite mixture regression models* to analyze customer heterogeneity, whereas the former provides information of customer behavior at the individual level, which helps to design segmentation-based enforcement and incentive mechanisms, and the latter is at the customer population level, which may provide better forecast under certain situations. Our results show that capturing product characteristics and customer heterogeneity helps to improve forecasting accuracy of return flow which enables proactive and timely planning and dispatch of used products. In addition to support operational decision-making, our study enables companies to uncover trade-in behavior of customers in different segments and identify the root causes of RMA discrepancies, and thus aids in the design of effective trade-in terms that provide incentives for customers and sales personnel to reduce noises in RMA reporting. Furthermore, our models can be used as a monitoring and evaluation tool to assess the effectiveness of enacted trade-in policies on a continuous basis.

Given the role that trade-ins play in coordinating new and used products sales, in the third essay (Chapter 4), we build an analytical model to study the trade-in strategy in the context of a monopolistic manufacturer offering a technology product to a heterogeneous consumer population. We consider an exogenous innovation process that governs the availability of new technology; therefore a product is subject to two types of value decay: technological obsolescence and functional depreciation. Trade-ins can be offered both when innovation occurs and when it doesn't. Though operated in the same way, they serve different purposes to the manufacturer and consumers. When innovation occurs, the manufacturer uses trade-in programs to buy back technologically obsolete, used products in order to accelerate new technology adoption. When innovation doesn't occur, new and used products use the same technology and co-exist in the marketplace. When offering trade-in programs, the manufacturer buys back used products from some customers and resells them to other customers. As such, during the no innovation periods, the manufacturer essentially serves as an intermediary to facilitate the transaction between consumers who want to replace their one-period-old products by brand-new ones and consumers who demand used products.

The manufacturer chooses the prices for the new products featuring a new and an existing technologies, respectively, and the trade-in credit for the used products featuring a previous-generation technology and an existing technology, respectively, to maximize her long-run average profit. Heterogeneous consumers make their consumption choice based on their willingness-to-pay and the prices charged by the manufacturer. We characterize the optimal stationary pricing strategy of the manufacturer under which heterogenous consumers choose their consumption strategy to maximize their utility. We find that facing the same exogenous innovation process and product wear and tear situation, the manufacturer having the low production cost and low resell cost should take advantage of trade-in programs regardless of innovation state and induce the highest-valuation consumers to purchase a brand-new product in every period. On the other hand, the manufacturer with the low production cost but high resell cost should offer trade-in programs only when innovation occurs because assuming the intermediary role in the secondary market is too expensive. Finally, the manufacturer with high production cost and low resell cost should take the advantage of trade-in programs when innovation doesn't occur and avoid to promote new technology too aggressively.

We also evaluate the impact of innovation frequency, technological obsolescence, functional depreciation, and production and resell costs on the manufacturer's maximum long-run average profit. Some key findings are summarized here. Technological obsolescence and functional depreciation reduce consumer valuation of used products, which in turn should lower the manufacturer's profitability. However, we observe that when innovations do not occur very frequently, manufacturers whose product has a slow functional depreciation rate and whose production cost is low can benefit from a higher degree of technological obsolescence because it makes prompt innovation adoption more attractive to consumers and therefore enables the manufacturers to better take the advantage of trade-in programs to promote early adoption. We also find that when innovations have a moderate frequency and the degree of technological obsolescence is low, manufacturers with low resell cost should make their products less durable physically to increase profit. Lastly, although higher innovation frequency means shorter expected technology lifespan and hence the time to recoup the production cost, manufacturers with high resell cost and severe product wear and tear can benefit from a high innovation frequency because it is more profitable to have the product become technologically obsolete than to let it deteriorate functionally and remain on the market.

Chapter 2

The Potential for Cannibalization of New Products Sales by Remanufactured Products

2.1. Introduction

Closed-loop supply chains (CLSC) are focused on taking back products from customers and creating value by reusing the products, components, parts and materials. CSLCs are composed of traditional forward supply-chain activities and additional activities of the reverse supply chain. The additional activities required for a reverse supply chain may be categorized into three main processes. The first process is the front end of the reverse supply chain that focuses on product returns management. The second process consists of remanufacturing operational issues. The third process is devoted to market development of remanufactured products. These three processes are interrelated and jointly determine the success of reverse supply chains (Guide and Van Wassenhove 2009). Any of these processes can be a bottleneck that prevents companies from exploiting the full value potential of product returns. Extensive research has been done in remanufacturing operational issues (see Dekker et al. 2004 for recent reviews). More recently, research has addressed the problems of product returns management (e.g., Guide et al. 2003, Aras et al. 2004).

We know, based on our interactions with many companies, that the remarketing process is indeed a bottleneck. An extreme example comes from our interactions with a leading networking equipment manufacturer with annual returns in excess of $800 million. The company scraps, due primarily to a fear of new product sales cannibalization, almost all of their product returns instead of engaging in remanufacturing. Recent research in CLSC has started to explore various issues of remanufacturing market development, most of which has been focusing on modeling competition and pricing issues. As observed by Guide and Van Wassenhove (2006), cannibalization and many other basic assumptions made by models studying CLSC require validation and an interdisciplinary approach to explore these assumptions is needed. In this essay, our focus is the market development of remanufactured products; more specifically, we address the potential for market cannibalization of new product sales by remanufactured products.

Our research is motivated by two, interrelated, phenomena. The first is that, the prevailing view regarding cannibalization among practicing sales and marketing managers at OEMs is that new products sales are cannibalized by remanufactured products, though there are managers who disagree. At many companies managers are reluctant to introduce remanufactured products because of the fear of cannibalization. A Hewlett-Packard product returns manager reports that sales personnel firmly believe that one new product sale is cannibalized by the sale of four remanufactured products, despite a lack of data to support this conviction (Rysavy 2002). In contrast, although representing a small proportion, there are companies where managers believe selling remanufactured products serves to expand market share. Randy Valenta, Director of Product Service at Bosch Power Tools NA, believes that, if a company is not the market leader in terms of market share, introducing remanufactured products cannibalizes the sales of new products offered by the market leader more than that of the company itself (Valenta 2004). All of these managers' assertions are based on personal experience and hunches, rather than any formal analysis. Therefore, we are interested in investigating the validity of the managers' assessment of cannibalization using quantitative analysis.

The second motivating factor for this research is the widespread use of assumptions about new product market cannibalization by academics when modeling various facets of closed-loop supply chains. Consumers' perception and willingness-to-pay (WTP) for remanufactured products is an inevitable question when studying product acquisition, remanufacturing, and primary and secondary market coordination. A lack of knowledge about consumers' WTP and cannibalization results in researchers using assumptions that best support modeling tractability. Some researchers assume that consumers do not distinguish between new and remanufactured products, i.e., remanufactured products are perfect substitutes for new products. At the other extreme, some research assumes consumers of new and remanufactured products are completely segmented, and therefore there is no cannibalization at all. Other research assumes that partial cannibalization exists and remanufactured products compete with new products on the basis of price. A detailed review is provided in Table 2.1.

Remanufactured products may pose a cannibalization threat to new product sales when the new product is still in production. Presumably, when a product is no longer being produced, due to technological advances or style changes, direct market cannibalization by remanufactured products is not a risk since the remanufactured version represents an earlier generation. Customers may be willing to adopt earlier technology for a lower price, but the older technology will not directly compete with the newer generations. Therefore, the greatest concern to managers is the case when a remanufactured version of a current-generation product is available. This situation arises most commonly when the commercial return rate is significant or when trade-in programs are aggressively used to promote newer- generation products. Commercial returns, in excess of $100 billion annually, are a result of liberal retail return policies where customers may return products within 30, 60 or even 90 days. Trade-in programs are offered when a new-generation product becomes available, which usually happens long before the current generation reaches its end-of-use stage. Manufacturers are increasingly driven to extract value from these returns, and selling remanufactured products has, in many cases, the greatest financial potential. Our research focuses on product recovery systems that market remanufactured products and have a new product version of the same product available. Product recovery systems that focus on end-of-life products are unlikely to pose a direct cannibalization threat since these products are no longer in production and the technology is most often out of date (e.g., mobile phones based on analog technology). Similarly, a product recovery system that focuses on end-of-use returns is of less concern with respect to market cannibalization since the remanufactured product is still viable technology, but not the latest generation (e.g., mobile phones without a camera or mp3 player).

In this research, we auctioned products donated by Robert Bosch Tools, NA and Cisco Systems, Inc. to determine the difference between consumers' willingness-to-pay for new and remanufactured products, and to help assess the extent to which new product sales is cannibalized by remanufactured product sales. The auctions were conducted on eBay for a consumer product (a Bosch Skil brand jigsaw) and eBay Business for a commercial product (a Cisco network security system). For the consumer product, auction results show that consumers' WTP for the remanufactured version is 16.4% lower than that for the new product. In addition, bidders of the new and the remanufactured products are segmented, implying that the remanufactured product does not cannibalize the sales of the new product. For the commercial product, auction results show that consumers' WTP for the remanufactured product is 11.4% lower than that for the new product. The bidding history reveals a certain degree of overlapping between bidders of the new and the remanufactured products. However, because of the significant presence of third-party resellers, it is difficult to infer end users' WTP and behavior from the commercial product auctions.

The rest of the essay is organized as follows. Section 2.2 reviews three streams of literature that are related to our research. Section 2.3 presents the auction design and discusses our research hypotheses. Sections 2.4 and 2.5 discuss the auction results and managerial insights, respectively. Finally, we conclude in 2.6.

2.2. Literature Review

There are three streams of literature relevant to our research. First, there is a stream of marketing research on cannibalization of competing new products. Second, there are a limited number of studies on various marketing related activities in closed-loop supply chains. Further, there is a large body of closed-loop supply chain research that is built on various assumptions about the extent of cannibalization of new product sales by remanufactured products. Finally, there are extensive studies that explore the use of auctions to reveal consumers' true willingness-to-pay.

2.2.1 Cannibalization

Cannibalization is defined as the extent to which one product's customers are at the expense of customers of other products offered by the same firm (Copulsky 1976). The theoretical roots of product cannibalization can be traced to the cross-elasticity of demand theory (Kerin et al. 1978). Product line extensions, with the possible resulting market cannibalization, have been studied extensively in the marketing literature. Two forms of product line extensions are distinguished in the literature: brand extension and line extension. A brand extension refers to the case where a current brand name is used to enter a completely different product class, e.g., HP expanding into the photocopier market. A line extension is where a current brand name is used to enter a new market segment in its product class, e.g., HP inkjet and laserjet printers (Aaker and Keller 1990). Remanufactured products may be considered as a line extension to their new counterparts since both belong to the same product class.

One research stream is devoted to building conceptual frameworks to define and explain cannibalization. Harvey and Kerin (1979) and Buday (1989) suggest that as the similarity between the attributes of products increases, the probability of the new product cannibalizing the existing products in the portfolio increases. Thus, cannibalization is more of a concern to line extensions than brand extensions. Line extensions of mature products gain revenue from two major sources: customers of competing brands and customers of existing products of its own firm. The ideal situation is where a line extension draws all its customers from products offered by competing firms. The other extreme is that all its customers are customers of existing products of the firm, where 100% (complete) cannibalization occurs. In practice, most cannibalization falls somewhere in between (Mason and Milne 1994). Remanufactured products have the same functionality as new products. Therefore, as suggested by this stream of literature, they should incur a significant risk of cannibalization of new products sales. The prevailing view among sales and marketing practitioners regarding the potential for cannibalization of new product sales by remanufactured products is consistent with the marketing literature.

The other research stream focuses on developing measures of cannibalization and empirically applying them. Conjoint analysis and a number of pre-test market new product forecasting models, such as ASSESSOR and BASES Source of Volume Analysis (SOVA), have been widely used to estimate cannibalization (Silk and Urban 1978). Mason and Milne (1994) propose an approach for measuring cannibalization based on the concept of "niche" in ecology. The niche of each brand describes the customers the brand is competing for and cannibalization may occur when two or more brands have overlapping niches. The authors apply this approach to the cigarette market to identify cannibalization between variants within a brand or between the brands of a common manufacturer. Speed (1998) tests hypotheses regarding cannibalization by a line extension and a second brand using data from producers in the Australian wine industry. The input of all the models mentioned above is consumer survey data. To avoid the potential drawbacks from using consumer surveys, Kerin et al. (1978), posits that the most accurate method to assess the actual degree of cannibalization is via a market test, where goods or services are exposed to a small, representative sample of consumers to test various marketing strategies. There are a limited number of studies that use real market data to measure cannibalization. Reddy et al.

(1994) set up an econometric model to capture the extent of cannibalization using data on 75 line extensions of 34 cigarette brands over a 20-year period. Lomax et al. (1997) examine three methods, gains loss analysis, duplication of purchase tables and a method based on deviations from the expected share movements, for measuring cannibalization based on actual consumer purchase data of three detergent line extensions in the UK and Germany. In order to take advantage of using real market data instead of consumer survey data, in this study, we use auctions, which will be elaborated later, as a price discovery tool to measure the extent of cannibalization of new product sales by remanufactured products.

A final stream of literature in marketing related to this study investigates the impact of grey market goods. Grey market goods are the unauthorized flows of products across countries competing with authorized distribution channels. These grey market goods may not be entirely harmful to a firm in terms of profit maximization. The customers of products from authorized distribution channels may stay with the authorized version even when grey market goods are available, as they place more value on the warranty and services that come with the authorized version. In addition, if the grey market goods generate a new segment of customers who would not buy the product at the higher price, grey market can result in higher profits for a firm (Assmus and Wiese 1995). Based on this observation, Ahmadi and Yang (2000) propose a two-country, three-stage model to quantitatively study the effects and strategies of parallel importation. Through a Stackelberg game, the authors give the conditions of demand and cost parameters under which allowing parallel importation will result in the increase of global profit and solve for optimal jointly pricing of the product offered by authorized and unauthorized channels. Grey markets goods can be considered as a counterexample of the line extension cannibalization literature. They have exactly the same functionality as their counterparts from authorized distribution channels. However, the value placed on warranty and services segments the consumer bases. Remanufactured products may behave in a similar way as grey market goods, since some customers may value the newness of products as some do for warranty and services.

2.2.2 Closed-Loop Supply Chains

Academic research in closed-loop supply chains has noted the lack of research into marketing related issues and discussed the need for research exploring issues in market creation for remanufactured products and the potential for cannibalization of new product sales (Guide and Van Wassenhove 2009). This call for research is motivated by the large body of closed-loop supply chain research that relies on strong assumptions about market cannibalization. Table 2.1 provides an overview of selected research on various aspects of CLSC processes and how the potential for market cannibalization is viewed. These assumptions about cannibalization, whether explicit or implicit, are a pervasive factor in CLSC research.

2.2.3 Auction and Willingness-to-Pay

Willingness-to-pay (WTP) is the maximum amount of money a consumer is willing to pay for a given quantity of a product (Kalish and Nelson 1991). Existing methods of estimating WTP differ in whether they require real economic commitments from respondents. If actual payments are required, the estimated WTP is real WTP. Common methods for estimating real WTP are auctions, lotteries and revealed preference data. In contrast, if no real economic commitments are required, the revealed WTP is hypothetical WTP. Hypothetical WTP is often measured using contingent valuation and conjoint analysis (Volckner 2005). Studies have shown that WTP elicited under such environments suffers from hypothetical bias and may differ substantial from real WTP (Harrison and Rutstrolm 1999). Therefore, in this study, we use real auctions on eBay and eBay Business that require real economic commitments to elicit consumers' real WTP.

Table 2.1: Cannibalization Assumptions

Area	Authors	Cannibalization	Product
Product returns management	Guide et al. 2003	None	Mobile phones
	Aras et al. 2004	None	Hypothetical
Remanufacturing			
Forecasting	Kelle, Silver 1989	Complete	Refillable containers
	Toktay et al. 2000	Complete	Single-use cameras
PP&C	Ferrer, Whybark 2001	None	Vehicle components
	Golany et al. 2001	Complete	Hypothetical
	Souza et al. 2002	None	Mobile phones
	Ketzenberg et al. 2003	Complete	Hypothetical
	Ferrer, Ketzenberg 2004	Complete	Copiers, engines, and medical equipments
Inventory	Fleischmann et al. 1997	Complete	Copier modules
	van der Laan, Salomon 1997	Complete	Copier modules and vehicle components
	van der Laan et al. 1999	Complete	Copiers
	Mahadevan et al. 2003	Complete	Rescue hoists and cargo hooks
	Bayindir et al. 2003	Complete	Hypothetical
	Van der Laan, Teunter 2006	Complete	Vehicle components
Competition and remanufacturing market development	Majumder, Groenevelt 2001	Complete	Single-use cameras and toner cartridges
	Debo et al. 2005	Partial	Hypothetical
	Robotis et al. 2005	None	Mobile phones
	Ferguson, Toktay 2006	Partial	Hypothetical
	Atasu et al. 2006	Partial	Hypothetical
	Ferrer, Swaminathan 2006	Complete	Single-use cameras
	Vorasayan, Ryan 2006	Partial	PCs
	Debo et al. 2006	Partial	Hypothetical
	Geyer et al. 2006	Complete	Hypothetical

2.3. Auction Design and Research Hypotheses

The purpose of this study is to explore the possible cannibalization of new product sales by remanufactured products using auctions as a price discovery tool. We chose to use one product representative of consumer purchases and one product representative of commercial business-to-business purchases. In part, our final choice of products was limited by the offering of companies who agreed to participate. We recognize that our study is the starting point in this stream of research, but not the final answer about cannibalization in this setting. We do believe this research provides an insightful set of initial findings and a solid foundation for further studies.

We solicited the support of companies to provide new and remanufactured products that would be sold via Internet auction sites. Two companies, Robert Bosch Tools, NA and Cisco Systems, Inc., agreed to provide multiple units of new and remanufactured products. Robert Bosch Tools, NA has several brand lines, including Bosch, Skil, and Dremel, and is a major supplier in the power tool business. Products are primarily returned from retailers as a result of generous return policies. Bosch sees return numbers in the order of 310,000 units annually, or about 1.5-2.5% of sales revenue. The returns are sent to a consolidated return center and remanufactured. Remanufactured products are then sold on secondary markets at a 30-35% discount off the price of their new counterparts. Bosch sales managers, who hold a different view than Randy Valenta, fear the potential cannibalization of new product sales by remanufactured products. In order to minimize the possibility of cannibalization, Bosch policy calls for limits on the amount of remanufactured tools that are allowed into the market and care is taken to make certain the remanufactured tools are sold in secondary markets (e.g., through liquidators).

Cisco Systems, Inc. offers trade-in credits for customers who upgrade their current equipment. Promotional trade-in programs are offered when a newer generation product becomes available, which usually happens long before the current generation product reaches its end-of-use or end-of-life stage. Therefore, the majority of trade-in returns are products still in production. A third-party vendor tests, sorts, stores, and remanufactures the returned equipment. Annual trade-in returns are 2-4% of Cisco's annual net sales and almost all of these returns are scrapped. The number of remanufactured units sold by Cisco is very small since marketing and sales strongly believe that significant market cannibalization exists.

Bosch donated a representative product from their consumer product line, a Skil brand jigsaw aimed at the home do-it-yourself market. Cisco donated a network security device commonly used in small- and medium-sized business computer networks. The products were auctioned by us and shipped directly to the winning bidders by either Bosch or Cisco. We compared the highest bid submitted by each bidder of new and/or remanufactured products to measure the difference in consumer' WTP. We also compared the winning bids and the number of bids received by the new products, with and without the presence of the remanufactured products, to provide insights as to the extent of cannibalization. In addition, we examined the bidding histories of the auctions to provide more evidence of whether cannibalization exists. In order to control for competition from other similar items being auctioned, after each of our auctions began, data of other auctions selling products with comparable features and within the same price range were collected for the entire length of the auction. The total number of comparable auctions remained stable throughout our experiment period. Moreover, our supply, two units of products each week, contributed to less than 1% of the total supply. Presumably, our entry into the eBay market did not affect the market structure, and given the stable nature of the market for our products, comparable listings would not have significant impact on our auction results.

2.3.1 Auction Design and Mechanics

The Bosch Skil jigsaws were listed on eBay (www.ebay.com) and the Cisco security systems were listed on eBay Business (www.ebaybusiness.com). eBay Business was launched in 2003, focusing heavily on office technology products and targeting at small- and medium-sized company buyers. The chosen Cisco security system fits the product category and customer base of eBay Business well.

Both eBay and eBay Business use ascending price auctions where, depending on bidders' behavior, the auctions can be either first-price or second-price auctions. If bidders bid manually by themselves, when they win, they pay the price they bid. This is a first-price auction. Bidders can also use proxy bid, which adopts a software system that can operate as a proxy to place bids on behalf of buyers. In such proxy bidding, a bidder places the first bid manually by entering her maximum bid, then the proxy will execute the bidder's bids, trying to keep the bids as low as possible while ensuring winning. When another bidder enters a new bid, the proxy will automatically raise the bid to the next level until it reaches the predetermined maximum bid. In this case, a winning bidder pays the minimum increment above the second-highest bid. This is a second-price auction. Regardless of whether the auctions are first-price or second-price auctions, ascending auctions provide a process of price discovery. Price is determined through the escalation of bids. The iterative price discovery in an ascending auction allows the learning needed to identify the intersection of supply and demand, and hence the market price (Crampton 1998).

Inferring consumers' WTP from bidding data is challenging. The ascending bidding process reveals only that the winner is willing to pay at least the bid amount, but the upper portion of the demand curve and the maximum willingness-to-pay are never expressed (Crampton 1998). However, even though an auction stops with the maximum bid rather than being to successfully extract all WTP from consumers, the bid amount can be viewed as indicating a lower bound of WTP (Bajari and Hortacsu 2004). The highest bid submitted by each bidder during our eBay auctions provide lower bounds of the bidders' WTP of the new and/or the remanufactured products, which serve as basis for our analysis.

We used a single, established, eBay ID with 78 positive feedbacks (100%) to list all the auctions in order to avoid any possible bias against sellers with no reputation (Katok et al. 2004). A seven-day auction was used in all cases to give the auction listing the maximum exposure to potential buyers. Seltzer (2002) established that weekdays may be better than weekends for selling new and remanufactured electrical and electronic merchandise. Therefore, we used a starting and ending time of 10:00PM EST on Tuesdays for our auctions. There was a starting bid for each product. We chose to use public starting bids instead of undisclosed reserve prices because starting bids could serve the purpose of reserve prices without incurring the negative effects associated with them. Empirical research (e.g., Bajari and Hortacsu 2003, Katkar and Reiley 2005) has shown that undisclosed reserve prices reduce the probability of auctions resulting in a sale, deter serious bidders from entering auctions, and lower the expected transaction price of auctions. The starting bid was \$29.99 for the Skil jigsaw and \$1,167 for the Cisco security system. Starting bids were suggested by managers at Bosch and Cisco reflecting the minimal acceptable price for selling the products. We realize that by setting a nontrivial starting bid, the resulting demand curve is truncated and we cannot obtain information of consumers who have WTP lower than the starting bid. However, we believe that this does not pose serious problems for two reasons. First, the starting bids we use are well below the retail price of the new and the remanufactured products. Therefore, the auctions should be able to attract a significant portion of consumers with lower evaluation of the products or lower purchasing power, compared to existing customers who pay the full retail price. Second, because the starting bids are the minimal amount that the manufacturers would sell the products for, consumers who have lower WTP are not potential customers and therefore are not of immediate interest to the manufacturers.

The auction listing of the new products included a product description and the starting bid of the product. The auction listing of the remanufactured products included the same product description, a brief overview of remanufactured products offered by the corresponding company, and the same starting bid as the new products. The remanufactured products offered the same term of warranty as their brand-new counterparts, and this was stated explicitly on the auction listings. Table 2.2 provides an overview of other aspects of the auctions.

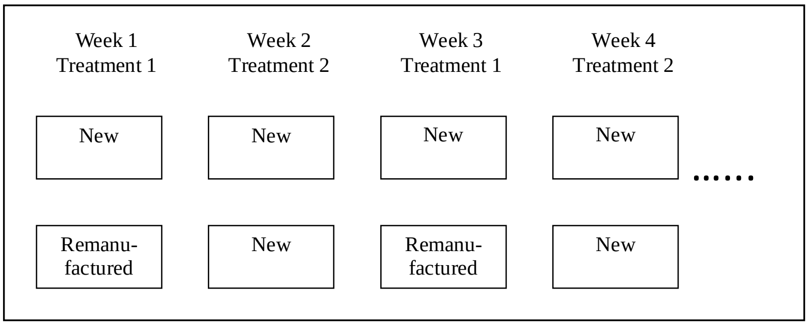
Price, in our case the ending bid, is determined by the supply and demand of a product. Therefore, in order to control for the supply of the products, we limited the total quantity available of each product to two for each week. Thus, two auctions

Table 2.2: Overview of Auctions

Product	Auction Site	Auction Length	Weekend Included?	# of New Auctioned	# of Reman. Auctioned	Staring Bid
Skil Jigsaw	eBay	7 days	Yes	20	10	$29.99
Cisco Security	eBay	7 days	Yes	20	10	$1,167

for either one new product and one remanufactured product (Treatment 1) or two new products (Treatment 2) were listed on the auction site each week alternately, as illustrated in Figure 2.1. The duration of the experiment for each product was 15 weeks. During this 15-week interval, 5 weeks contained two new products each, and 10 weeks contained one new product and one remanufactured product each, which resulted in a total number of 20 new products and 10 remanufactured products.

Figure 2.1: Auction Design



2.3.2 Research Hypotheses

Remanufactured products are often claimed to have the same functionality and quality as new products (Lund 1983). However, consumers may have different WTP for a remanufactured product compared to its brand-new counterpart. This difference in WTP may be resulted from a variety of reasons. Consumers may lack knowledge about remanufacturing or confuse remanufactured products with pre-owned/used products. In addition, since remanufacturing represents cost-savings for companies, consumers may expect companies to transfer at least part of the cost-savings to them.

Therefore, our Hypothesis 1 is stated as follows.

H1: *Consumers' WTP for a remanufactured product is lower than that of its new counterpart.*

Given the similarity between a new product and its remanufactured counterpart, marketing literature suggests that the risk of cannibalization of new product sales by remanufactured products is significant. The prevailing view regarding cannibalization among practicing managers concurs with the marketing literature. We are interested in testing whether the cannibalization literature about line extension can indeed be applied to remanufactured products, and whether the prevailing view based on practitioners' experience and hunches is correct. Cannibalization is defined at the aggregate level, i.e., the total customer base or the market share of a product. Therefore, our auction setting, which is designed to auction individual units of products, cannot measure cannibalization directly. However, we can use two measurements to infer the existence of cannibalization. One is the number of bids received by new product auctions with (Treatment 2) and without (Treatment 1) the presence of the remanufactured products. The number of bids received by an auction indicates the number of bidders participated in the auction and the intensity of competition. If the number of bids received by a new product auction is fewer when the remanufactured product is available than when it is not available, it indicates that cannibalization exists. The other measurement is the ending (winning) bid of new product auctions with and without the presence of remanufactured products. In reality, when companies are price makers, cannibalization usually does not affect selling prices directly. However, in auction settings, ending bids are affected in a similar way as numbers of bids received are. Therefore, it can also be leveraged to infer cannibalization. Specifically, we test the following hypotheses.

H2a: *H2a: The presence of remanufactured products decreases the ending bid of new products.*

H2b: *H2b: The presence of remanufactured products decreases the number of bids* *received by new products.*

Furthermore, we examine the bidding history of each auction in order to uncover additional evidence to investigate our hypothesis that new product sales is cannibalized by remanufactured products. The ending bid and the number of bids received are collected for all auctions. The bidding history of each auction is also maintained to extract the highest bid submitted by each bidder during the auctions and to examine bidders' behavior in detail.

2.4. Results

Given the small sample sizes we have for this study, the NPAR1WAY procedure of SAS was used to conduct nonparametric tests for the auction results. Wilcoxon rank-sum test (also known as the Mann-Whitney U test) and Kolmogorov-Smirnov test (K-S test) are suggested to be used to determine whether two underlying one-dimensional probability distributions differ, given two independent unstratified samples. Specifically, Wilcoxon rank-sum test focuses on assessing the medians of two samples, while K-S test is capable of detecting differences in both location and shape of the empirical cumulative distribution functions of two samples (Hollander and Wolfe 1999). Both tests were performed in our analysis. Both tests require that the two samples under consideration are independent of each other, and within each sample, the values are independent and identically distributed. Each auction is conducted independently, so inter-sample independence should not be a concern. However, to be conservative, we did test for independence between samples using Spearman's rank-order correlation coefficient and found no evidence of dependence between data sets. In order to test for intra-sample independence, we used correlation plots and scatter diagrams, as suggested by Law and Kelton (1991). While both these tests are somewhat informal, we found no patterns that suggested non-independence within the data sets.

The auctions show that the average ending bid for the remanufactured Skil jigsaw and the remanufactured Cisco security system are 16.4% and 11.4% lower than that of their new counterparts, respectively. Wilcoxon and K-S exact test statistics indicate that both differences are statistically significant. Therefore, Hypothesis 1 is supported by both products and the results are summarized in Table 2.3. Consumers do have a lower valuation of remanufactured products compared to their new counterparts.

Table 2.3: Consumers' WTP for New and Remanufactured Products

	Skil Jigsaw		Cisco Security System	
	Reman.	New	Reman.	New
Mean	\$30.43	\$36.41	\$1,244.93	\$1,405.00
Std. Dev.	0.81	3.35	79.02	153.94
# of Obs	7†	20	10	20
Wilcoxon p-value	6.42×10^{-5}		1.30×10^{-3}	
K-S p-value	8.11×10^{-5}		1.07×10^{-3}	

†: 7 out of 10 remanufactured Skil jigsaws we auctioned were actually sold.

If the remanufactured products cannibalize the sales of the new products, when the remanufactured products are available (as in Treatment 1), the ending bid and the number of bids received by the new products should decrease. This is intuitive logic since if there is cannibalization, then remanufactured products would attract at least a portion of the bidders who would otherwise bid on new products. Tables 2.4 and 2.5 show the analysis results. Wilcoxon and K-S exact test fail to reject the null hypothesis that the probability distributions of the two samples are the same, i.e., there is no difference in the distribution of the ending bid and the number of bids received by the new product auctions with and without the presence of the remanufactured products. Therefore, the auction results fail to support Hypothesis 2a and 2b. We can then conclude that for both products, the ending bid and the number of bids received by the new products are not affected by the availability of their remanufactured counterparts. The result seems to suggest that consumers of the new and the remanufactured products are segmented and therefore cannibalization should not be a concern. However, we also need to closely examine bidders' behavior during the auctions to search for more evidence regarding cannibalization.

Table 2.4: Price of New Products with and without Remanufactured Products Available

	Skil Jigsaw		Cisco Security System	
	New w/o Reman.	New with Reman.	New w/o Reman.	New with Reman.
Mean	\$36.17	\$36.65	\$1,416.60	\$1,393.40
Std. Dev.	\$2.19	\$4.33	\$170.09	\$142.67
# of Obs	10	10	10	10
Wilcoxon p-value	0.49		0.75	
K-S p-value	0.39		0.99	

Table 2.5: Bids Received by New products with and without Remanufactured Products Available

	Skil Jigsaw		Cisco Security System	
	New w/o Reman.	New with Reman.	New w/o Reman.	New with Reman.
Mean	3.50	3.00	3.60	3.90
Std. Dev.	1.27	1.56	1.51	2.16
# of Obs	10	10	10	10
Wilcoxon p-value	0.43		0.88	
K-S p-value	0.91		0.92	

Another clue as to the potential for cannibalization is to determine whether bidders were interested in both new and remanufactured products. eBay allows a seller to track bidder ID, bid amount, and date of bid for each bid occurred. We collected this information for both products and compared them in order to check how bidders behaved and whether they behaved differently when bidding on the consumer vs. the commercial products. There were a total of 44 and 29 bidders participated in the Bosch jigsaw auctions and Cisco security system auctions, respectively. We can determine, by simply looking at the bidders' ID and by tracking down bidders' websites suggested by their IDs, that at least 6 bidders (20.7% of total) of the Cisco security system auctions are third-party resellers of network equipments. Moreover, these IDs won 9 out of the total of 30 auctions, i.e., 30%. However, there was no such evidence among the bidders of the Bosch jigsaw auctions.

Table 2.6 compares the bidding behavior of participants in the Bosch jigsaw and Cisco security system auctions. After learning the presence of third-party resellers in the Cisco auctions suggested by bidder IDs, we are interested in finding more evidence from the bidding behavior. The majority of Bosch auction bidders, 79.5% of them, participated in only one auction. However that percentage was only 41.4% for Cisco auction bidders. A similar situation held for the winning bidders in the Bosch and Cisco auctions. All Bosch auction winners won only one unit, but 42.9% of the Cisco auction winners won more than one unit. Moreover, in Bosch auctions, there was only 1 bidder (2.3% of total) who bid again after winning one unit. However, in Cisco auctions, there were 6 bidders (20.1% of total) who bid again after winning a unit. The intention of buying multiple units indicates a higher possibility of resale. Therefore, the bidding history gives us a firmer belief that the presence of third-party resellers is significant in the Cisco auctions, which makes it extremely hard to infer end users' WTP and behavior.

Table 2.6: Comparison of Bidding Behavior between Skil Jigsaw and Cisco Security System Auction

Key Bidding Behavior	Skil Jigsaw	Cisco Security System
Total # of IDs bid in all auctions	44	29
# of IDs bid in only one auction	35 (79.5%)	12 (41.4%)
# of winners won more than one unit	0 (0%)	6 (42.9%)
# of IDs continued to bid after winning	1 (2.3%)	6 (20.1%)
# of IDs bid on both new and reman. products	2 (4.5%)	8 (27.6%)
# of IDs bid under both treatments	6 (13.6%)	10 (34.5%)

Two factors of interest related to cannibalization are the number of bidders who bid on both new and remanufactured products, and the number of bidders who bid under both treatments. Only 2 bidders (4.5% of total) bid on both new and remanufactured products in the Bosch auctions. Also, despite the availability of the remanufactured Skil jigsaw, among the 6 bidders who bid under both treatments, 5 of them bid exclusively on the new products. This means that the bidders who didn't win any unit of the new product during a week continued bidding on new products in the coming weeks, even if the remanufactured products were available at a lower price. Both observations indicate a segmentation of consumers of the new and the remanufactured Skil jigsaw, given that the bidders of Bosch auctions are end users. In the auctions for the commercial Cisco security system, 8 bidders (27.6% of total) bid on both new and remanufactured products. Among the 10 bidders who bid under both treatments, only 3 of them bid on the new products exclusively. The ending bid and the number of bids received by the new Cisco products demonstrate no indication of cannibalization; however, the bidding history does show more overlap in terms of auction participation. Because a significant portion of third-party resellers participate in the Cisco auctions, we are unable to determine whether it is the preference and behavior of end users, or resellers, or both that are reflected by the auction results.

2.5. Managerial Implications

Our study yields different results for the consumer product, Bosch jigsaw, and the commercial product, Cisco security system. For the Bosch consumer product, auction results indicate that consumers of new and remanufactured products are segmented and have minimal overlap. The availability of the remanufactured product does not affect the ending bid and the number of bids received by the new product. Additionally, bidders for the new product remain interested only in the new product even when the remanufactured product is available. In this case, cannibalization should not be a concern. When introducing remanufactured products, price sensitive consumers are usually the consumer segment where cannibalization should be an issue since lower priced remanufactured products are more appealing to them than to price insensitive consumers. Online shoppers, especially eBay customers, are known to be price sensitive consumers (McTigue 2000, Bettis 2006). Therefore, since our results indicate that cannibalization is not a concern for this consumer segment, it should not be a concern for other consumer segments. Our results provide support for Randy Valenta's conjecture and our hypothesis that remanufactured products may behave similar to grey market goods. The marketing of remanufactured products, with their lower price points, may be a way to prevent low cost competitors from eroding market share for firms. The remanufactured products may also reach consumers who would prefer the Bosch brand name and image, but cannot, or will not, pay the premium price for new products. Selling remanufactured products may encourage the increased consumption of related new products. For example, HP inkjet printers are sold at, or very near, the margin, but HP makes high profit margins from ink sales needed for the printers to operate. HP, by selling more printers, even remanufactured printers, should lead to higher HP ink sales. Randy Valenta at Bosch relates a similar experience at Bosch where service centers selling remanufactured tools have substantially higher sales of new drill bits and cutting blades. We recognize that our study is limited to consumer power tools and the results may not directly apply to other consumer products. However, the auction method used here can easily be replicated for other consumer products and over time a framework for understanding when a remanufactured product has significant potential for market cannibalization may be developed.

The results for the Cisco commercial product are less conclusive. Because of the significant presence of third-party resellers, it is more difficult to learn end users' behavior from the auctions. The results do clearly show that the availability of the remanufactured product does not affect the ending bid and the number of bids received for the new product. However, there are a larger proportion of bidders who are interested in both new and remanufactured products in the Cisco auctions. This behavior suggests overlap of consumers for new and remanufactured products and, as a result, a certain degree of cannibalization. The heavy involvement of third-party resellers makes it extremely difficult to determine what drives the behavior. Our follow-up investigations with the winning participants give some insights into the possible underlying mechanisms. The buyers were all small, third-party, IT providers who offered turnkey network solutions for small businesses. Since small businesses are unlikely to have a dedicated IT staff, it is logical that these small business customers are extremely price sensitive and rely on IT service providers to provide whole package solutions. This would motivate the third-party to provide packages at certain price points. In fact, many buyers did not source equipment until a price point was established with the customer. At present, Cisco does not cater to these small buyers, preferring larger corporate customers who need cutting edge technology. Selling remanufactured products to this customer segment would not overlap with their traditional market and may represent a way to extend the Cisco brand and provide protection against competitors with lower priced products. A final factor for consideration is an online search reveals that there are numerous unauthorized sellers offering remanufactured Cisco products online. This underground market for recovered Cisco products is making money without Cisco sharing in the profits or, perhaps more importantly, Cisco has no control over the quality of the remanufactured products being sold. Certainly more studies are needed to fully understand the complexities of the commercial markets.

2.6. Concluding Remarks

Our study was motivated by the pervasive belief by practitioners that remanufactured products cannibalizing new product sales and by the lack of information for academics building models for understanding the dynamics of closed-loop supply chain systems. We auctioned products through real online auctions to determine the difference between consumers' willingness-to-pay for new and remanufactured products and to assess the extent of cannibalization. For the consumer product, the Bosch jigsaw, consumers' willingness-to-pay for the remanufactured product is 16.4% lower than that for the new product. The ending bid and the number of bids received by the new product are not affected by the availability of the remanufactured product. The experimental evidence shows that, for this consumer product, consumers of the new and the remanufactured product are segmented, and therefore, cannibalization is not a significant managerial concern. The auction results for the commercial product, a Cisco security system, is more difficult to interpret because of the significant presence of third-party resellers. Consumers' willingness-to-pay for the remanufactured product is 11.4% lower than that for the new product. As in the Bosch auctions, the ending bid and the number of bids received by the new product are statistically the same with and without the presence of the remanufactured product. However, the bidding history shows that a significant portion of the auction participants bid on both the new and the remanufactured product. This suggests a certain degree of cannibalization. However, because of third-party resellers we cannot conclude that cannibalization of new product sales by remanufactured products exists.

We hope to have provided a starting point for the research on the potential for cannibalization of new product sales by remanufactured goods. We have not investigated the underlying behavioral reasons for consumer preferences or attitudes toward remanufactured goods. Our follow-up survey of the Bosch auction winning bidders reveals several factors that may affect consumers' preference and valuation of remanufactured products. These factors include consumers' knowledge about a product class and remanufacturing in general, consumers' past experience of remanufactured products, and the reputation of brands. A thorough exploration of the behavior factors is needed to fully understand consumer behavior in a CLSC setting. Cannibalization is one of the fundamental elements in further research on closed-loop supply chains in areas such as product returns management, remanufacturing and remanufacturing market development. Therefore, exploration in this area will benefit the research of the entire field. This study provides some evidence that the long-held view of significant cannibalization simply isn't true in some settings. We also show that auctions provide a straightforward method for determining consumers' willingness-to-pay and the extent of cannibalization of new product sales by remanufactured goods. Further research should continue to explore the potential for cannibalization for other products in both consumer and commercial settings.

Chapter 3

Managing Trade-In Programs Based on Product Characteristics and Customer Heterogeneity in Business-to-Business Markets

3.1. Introduction

Trade-in programs are offered extensively by the automobile, electronics and technology industries, aiming at promoting newer generations of products by guiding customers through a product migration path, generating additional revenues by selling remanufactured and used products in secondary markets, and taking control of the entire product life cycle. With the ever-increasing competition in primary markets and environmental concerns, companies rely on trade-in programs not only as an effective new product sales mechanism but also as an important strategic leverage to increase profitability through product reuse and to enhance image in sustainability. Motivated by a real problem facing a high-tech manufacturer, in this essay we propose forecasting models incorporating information of product characteristics and customer heterogeneity to obtain accurate forecast of trade-in product returns. We also discuss management issues facing trade-in programs in business-to-business (B2B) markets.

Typical trade-in programs in B2B markets operate as follows: when customers purchase new products from a company, they are offered an allowance for trading in their existing products, known as the *trade-in credit*, which is used toward new purchases. A company usually generates a Return Merchandise Authorization (RMA) form when a customer places a purchase order. An RMA typically contains information of several trade-in products, including product types, model numbers, quantities and conditions. The trade-in products in an RMA are required to be returned within a pre-specified time window. In B2B markets, especially transactions between large companies, trade-in credits are often granted *up front*, that is, customers receive immediate discount for new purchases, while their returns claimed on RMAs take place in the future. For example, Sun Microsystems, IBM, and Nortel provide up-front trade-in credits for their trade-in program of large-scale IT equipment. In contrast, in business-to-consumer (B2C) markets, trade-in credits are often awarded when used products are physically received (e.g., automobiles) or afterwards as rebate checks (e.g., computers).

An important driver of a successful trade-in program is the profitability of secondary uses of returned products. Companies use trade-in returns primarily for remanufacturing final products and dismantling valuable parts for use as spare parts to fulfil warranties and service contracts. Other possible uses include providing to design and testing labs and donating to charitable organizations. Accurate prediction of return flow characteristics is critical to the success of closed-loop supply chains (Toktay et al. 2004). It enables proactive and timely dispatch of used products, which directly impacts revenue-generation and cost-saving from secondary uses. For warranties and service contracts, companies often manage a hybrid inventory pool with both new and used spare parts; thus the procurement decision of new parts depends on the forecasted return quantity and timing of used products (Aronis et al. 2004).

Despite their maturity and popularity, trade-in programs face many challenges. One of such challenges is how to use information given on RMAs to forecast trade-in product returns. A major concern is RMA information accuracy. The *booked quantity* is the quantity of a trade-in product indicated in an RMA, and the *returned quantity* is the quantity actually received in the future. The RMA discrepancy rate, defined as the percentage of products in RMAs whose booked quantity does not match its returned quantity, can be considerable. For example, the RMA discrepancy rate of the high-tech company in our analysis is about 40% (personal communication). Due to the lack of effective forecasting methods, the company is currently using the booked quantity as the forecast of the returned quantity, which, not surprisingly, results in poor forecasts and affects its ability to make sound operational decisions.

There are several factors contributing to RMA information inaccuracy. First, many companies, especially the ones in the electronics and technology industries, offer broad product portfolios that consist of *substitutable* and *complementary* products. Substitutable products normally have similar model names and similar appearances, which makes customers likely mistake one by another in RMA reporting. Complementary products tend to be purchased, used, and returned together. Due to complexities of customers' product portfolios or the lack of dedicated information technology (IT) personnel, it can be difficult for customers to provide exact model names and booked quantities without scrutinizing their equipment lists. A customer may misidentify a product as one of its substitutable products, or report only one product among several complementary products that are intended to be returned together (an example of substitutable and complementary products is provided in Section 3.3.1). Second, the quality of RMA information is highly variable. While some customers always provide accurate RMA information and return trade-in products in a timely manner, other customers are more error-prone, do not return products on time or even fail to return them at all. Third, other unpredictable events when an RMA is generated, such as delayed delivery and installation of new equipment and changes in customers' IT upgrade plans, cited by the company as possible reasons for late-/never-returned products, also contribute to RMA discrepancies. Last but not least, trade-in programs sometimes lack enforcement mechanisms for return policies, which are especially needed when up-front credits are granted. Given that customers in a B2B environment are often large firms with long-term relationships, sales personnel tend to focus on selling new products and fostering good customer relationships, and are reluctant to enforce terms in the trade-in policy. The laissez-faire practice may have contributed to the increased mistakes in RMA reporting and delayed returns.

The purpose of this study is to provide companies in general, and the specific company in our study, with statistical tools for better management of trade-in programs. At the operational level, we propose new forecasting models for trade-in returns to support companies' inventory and remanufacturing/disposal decisions. At the strategic level, our study provides companies with valuable insights on the design and execution of effective trade-in policies. Many high-tech companies in B2B markets have trade-in programs with similar characteristics as the company in our analysis. They also face heterogeneous customers with complex product portfolios and various trade-in behavior. Hence, our methods can find applications in these and other similar trade-in programs, which have become prevalent practice nowadays with growing environmental awareness, social responsibility, and popularity of green initiatives.

To achieve our objectives, we first develop methods to characterize the data structure of RMAs, using a data set from a high-tech company (called *the company* hereafter) who serves the B2B market primarily. We consider a booked quantity as a *signal* of its returned quantity. Because of the aforementioned reasons, this signal contains considerable noise and therefore we develop methods to process the signal by leveraging 1) the source of the signal, i.e., the customer who generates the booked quantity; and 2) the associated signals, i.e., the booked quantities of its substitutable and complementary products reported in the same RMA. The former captures *customer heterogeneity* in RMA reporting, while the latter takes *product characteristics,* namely, substitutability and complementarity, into account. We adopt two main approaches for customer segmentation, *cluster analysis* and *finite mixture regression models* to analyze customer heterogeneity. While both approaches capture customer heterogeneity, the former is at the *individual* customer level and the latter is at the customer *population* level. Since cluster analysis provides information of customer behavior at the individual level, which helps the company to design segmentation-based enforcement and incentive mechanisms at the strategic level, it appears to be more appropriate in our application. To capture product characteristics in RMA reporting, we use count regression models (Cameron and Trivedi 1998), which are appropriate if the data set contains *count data* and may have *excessive zeros* (due to late-/never-returned products), as in our case. For each segment, we select the best-fitting count regression model, among several commonly-used models, to forecast the returned quantity of a customer belonging to that segment. To evaluate the effectiveness of our model constructs, we propose three forecasting strategies to predict returned quantities: Strategy 1 (S1) utilizes product characteristics, Strategy 2 (S2) considers customer heterogeneity, and Strategy 3 (S3) incorporates both. We also compare the proposed strategies against two benchmark strategies, including one adopted by the company currently. The results show that S3, which leverages both product characteristics and customer heterogeneity, is the best strategy against S1 and S2 and the two benchmark strategies. To validate the flexibility, generality and robustness of our results, we perform extensive sensitivity analysis on several key factors under different settings. In particular, our sensitivity study shows that the proposed methods are able to generate forecasts for *early returns*, i.e., products returned before the required time, which is a forecasting capability currently not existing in the company. The ability to forecast early returns helps companies gain competitive advantages. For example, it can shorten the supply lead time, thus offering the opportunities to reduce inventory costs and fasten the delivery time of remanufactured goods to secondary markets. In addition to supporting operational decisions, our study enables the company to uncover trade-in behavior of customers in different segments and identify the root causes of RMA discrepancies and late- and never-returns, and thus aids the company in the design of effective trade-in terms that provide incentives for customers and sales personnel to reduce noises in RMA reporting. Furthermore, our models can also be used as a monitoring and evaluation tool to assess the effectiveness of enacted trade-in policies on a continuous basis. A more detailed discussion in this regard is given in Section 3.7.

We emphasize that maintaining RMA accuracy must be promoted at multiple management levels. At the strategic level, better policy designs and enforcement mechanisms are effective tools to mitigate RMA inaccuracies. However, strategic-level changes in trade-in programs cannot eliminate the needs for accurate return-flow forecasts due to the following several factors. First, policy changes come with significant execution challenges. Given that a company and its customers often have long-term relationships in a B2B environment, there are resistances from both customers and sales personnel to follow stringent enforcement rules. Providing incentives to customers and sales personnel is more practical; however, it still requires executive support and multi-departmental collaboration, which normally entails lengthy negotiation and preparation. Given these challenges, forecasting models provide an immediate cure for the problem which can be adopted readily by the department of a company who is in charge of the trade-in program to facilitate daily operations. Second, even a perfectly designed and executed trade-in policy can only reduce, but not eliminate, RMA discrepancies. As mentioned earlier, the size and complexity of a customers' IT portfolio and the level of IT personnel support directly contribute to the magnitude of the customer's RMA discrepancy. For example, our cluster analysis results show that customers with large RMA errors tend to be large businesses with complex IT portfolios or small businesses lacking dedicated IT personnel. In this case, reporting errors may be due to the sheer difficulty of collecting reliable data within a company (e.g., data may be collected via individual- or departmental-level self-reporting), rather than negligent behavior of its representative. Also, some random events uncontrollable by customers when RMAs are generated, such as delayed delivery and installation of new equipment and changes in customers' upgrade plans, cannot be resolved by enforcement and incentive mechanisms. Finally, our models allow companies to predict returns happened prior to the required return time, which, again, cannot be accomplished by strategic-level decisions.

It is also worth mentioning that our study echoes the literature of inventory inaccuracy in inventory management (DeHoratius and Raman 2007, Kok and Shang 2007, DeHoratius et al. 2008). In this literature, researchers identify several factors that mitigate record inaccuracy and several factors that exacerbate record inaccuracy, and propose inventory planning tools to account for its presence. In the same token, we identify factors that cause supply (return flows) inaccuracy and develop forecasting models to adjust the noise in RMA reporting, which is an essential input for determining optimal inventory and disposal policies in manufacturing/remanufacturing operations (van der Laan et al. 1999).

The rest of the essay is organized as follows. Section 3.2 reviews related literature. Section 3.3 introduces count regression models and segmentation methods, and proposes forecasting and benchmark strategies. Sections 3.4, 3.5, and 3.6 present model selection, forecasting strategy comparison, and sensitivity analysis results, respectively. Section 3.7 offers managerial insights, and Section 3.8 summarizes our contributions and discusses future research directions.

3.2. Literature Review

There are three streams of research closely related to our work: signal-based demand forecast, count regression models, and finite mixture regression models.

Signal-based demand forecast in operations management (OM) considers a setting where updated downstream demand signals, such as promotion plans, competitors' prices, and expert judgment, become available to a supplier periodically. Heath and Jackson (1994) apply the Martingale Model of Forecast Evolution (MMFE) model to update demand forecast accommodating new demand signals. In essence, MMFE captures both time series models of prediction as well as the impact of factors that may affect future demand. MMFE has been applied by a number of researchers under different problem settings (e.g., Aviv 2001, Milner and Kouvelis 2005). An important extension of this stream of research considers the fact that signals may not always be accurate and reliable. This type of signals is termed as Imperfect Advance Demand Information (IADI) and is modeled in different ways with the focus of determining the optimal inventory policy and potential operational benefits. DeCroix and Mookerjee (1997) consider a scenario where IADI can be purchased before production decisions are made. In Treharne and Sox (2002), parameters of the probability distribution representing IADI are determined by a partially observed Markov decision process.

Our study differs and builds upon the signal-based forecast literature from the following perspectives. First, similar to MMFE, our models consider signals that may affect the returned quantity. In addition, we consider signal sources, i.e., customers who generate RMAs, and treat signals generated by different sources separately. Second, in recent years, empirical research has been gaining attention in the OM community (see, e.g., the 2007 special issue of Manufacturing & Service Operations Management on applications of empirical science in OM and references therein). In the area of forecasting, Terwiesch et al. (2005) investigate forecast sharing using data collected in the semiconductor equipment supply chain. Gaur et al. (2007) propose a method of using dispersion among forecasting experts to measure demand uncertainty. We provide an empirical study that explicitly models the noise in signals in order to improve forecast accuracy. Third, we use count regression models to formally capture the discrete nature of booked and returned quantities.

The second stream of related research is the development and application of count regression models. The ordinary least square (OLS) method for count data results in biased, inefficient and inconsistent estimates. Various nonlinear models have been developed to deal explicitly with characteristics of count outcomes. The simplest ones are discrete probability distribution models, such as the Poisson and negative binomial distributions. However, these models rarely fit observed data well because they assume that all observations follow the same distribution with the same parameters, and cannot sufficiently account for heterogeneity across individual observations. This leads to count regression models in which the parameters of a discrete distribution are specified as a function of independent variables. Cameron and Trivedi (1998) is an excellent reference for count data analysis.

The Poisson regression model (PRM) is the most basic form of count regression models. Here, the dependent variable has a Poisson distribution with a *conditional* mean that depends on the values of independent variables. This is referred to as *observed heterogeneity*: different values of independent variables result in different values of a distribution parameter, but all individual observations with the same independent variable values have the same distribution parameter. Despite its simplicity, two major problems limit applications of PRM. First, PRM restricts the mean to equal the variance; second, in many applications, there are more zero counts than what can be modeled by the Poisson distribution. To address these issues, families of mixed Poisson models are developed to deal with overdispersion and excessive zeros. The negative binomial regression model (NBRM) is the most commonly used model to deal with overdispersion. Compared to PRM, NBRM captures not only *observed heterogeneity*, but also *unobserved heterogeneity,* by including a random error to the conditional mean. Unobserved heterogeneity reflects the fact that observations with the same independent variable values may still result in different distribution parameters because of the factors not captured by independent variables. Zero-inflated Poisson regression model (ZIPRM) adopts a *splitting mechanism* to deal with excess zeros and is also commonly applied. The splitting mechanism assumes that zero counts are generated by two different processes: one is a parent probability distribution such as the Poisson or negative binomial distribution, which generates both zero and positive counts; the other is a degenerate distribution whose probability mass is concentrated on zero. In addition, zero-inflated negative binomial regression model (ZINBRM) can capture both unobserved heterogeneity and splitting mechanism. In recent years, there has been considerable interest in using count regression models in the fields of ecology (Royle and Nichols 2003) , sociology (Melkersson and Rooth 2000), and medical study (Lee et al. 2001).

The third stream of literature is finite mixture regression models. Finite mixture models assume that observations arise from two or more segments with unknown probabilities. Building upon finite mixture models, finite mixture regression models predict distribution parameters of each segment by using a set of independent variables. Finite mixture regression models can identify segments and simultaneously estimate regression parameters within each segment. A variety of finite mixture regression models have been developed to capture customer heterogeneity in the marketing literature. They model different distribution types of the dependent variable, such as normal, binomial, multinomial, and count data (see Wedel and Kamakura 2000 and references therein). Despite the popularity in various fields, count regression models and finite mixture regression models have rarely been applied in OM research. Hence, our study serves to introduce these models to our research community and to demonstrate their usefulness in applications.

3.3. Data Structure and Forecasting Models

In this section, we first discuss the distinctive features of our data set. The aforementioned count regression models are formally presented next. We then discuss two main approaches to capture customer heterogeneity. Finally, we present benchmark and forecasting strategies to be evaluated in the remaining sections.

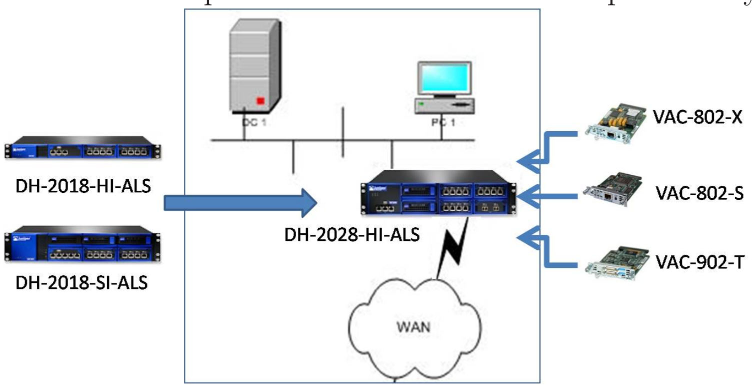
3.3.1 Data Set Overview

The data set contains RMAs generated between January 2006 and September 2007 by the company's trade-in programs. Information that could identify the company or its products has been disguised. The company offers an extensive and complex product portfolio and has a broad customer base, which are reflected by the 364 products belonging to 29 product families and the 515 customers in the data set. The number of RMAs that each product has ranges between 1 and 549. Products with low sales volumes and/or in an early stage of their life cycle tend to have fewer RMAs. For each trade-in product in each RMA, the data set contains its booked and returned dates, booked and returned quantities, and the name of the customer who booked the product.

We work with design engineers and sales personnel of the company to identify 20 *high-value* products belonging to 3 major product families, which the company is most interested in forecasting. We label them as P1 to P20, following the alphabetic order of product family name and random order within a product family. For each of the 20 products, field experts identify 4 to 7 substitutable and complementary products. In the forecasting literature, it is common to include relevant independent variables in a regression model, see, e.g., Heath and Jackson (1994). In our problem context, relevant independent variables are the book quantities of substitutable and complementary products.

The following example of a wide area network (WAN), as shown in Figure 3.1, illustrates the concept of substitutable and complementary products in our research setting. All the products used in the example are manufactured by the company. Although the model names are disguised, they resemble the format and complexity of real product names. Product DH-2028-HI-ALS is a router commonly used in WANs. DH-2018-HI-ALS and DH-2018-SI-ALS are two substitutable routers providing the same core functionalities (represented by “DH” and “ALS” in the product names), but having different non-core features, such as the number of ports and backplane capacity (captured by the middle part of product names). As shown, the product names and appearance of the three routers exhibit a significant degree of similarity. Moreover, a WAN interface card needs to be used together with the router to connect and transmit data over a WAN. VAC-802-X, VAC-802-S, and VAC-902-T are three WAN interface card choices that are compatible to the router, which are considered as its complementary products. A customer of the company with a complex product portfolio typically has multiple units of similar WANs as exhibited in Figure 3.1, featuring various combinations of the routers and interface cards. As a result, an RMA booking and return from the customer contains DH-2028-HI-ALS may also include the other two routers and the three interface cards. Therefore, to forecast the returned quantity of DH-2028-HI-ALS, it may be helpful to include in the forecasting model not only its own booked quantity, but also the booked quantities of these substitutable routers and complementary interface cards.

Figure 3.1: An Example of Substitutable and Complementary Products



The company requires trade-in products to be returned within 90 days from the RMA generation date. Hence, we will focus on 90-day returned quantity forecast in the analysis (in Section 3.6, we perform sensitivity analysis to test the effectiveness of our methods for different time windows). Appendix A provides the relative frequencies and summary statistics of the booked and returned quantities of the 20 products, where B_i and R_i denote booked and returned quantities of Pi, $i = 1, 2, \ldots, 20$, respectively. We observe that both booked and returned quantities have large proportions of small (including zero) counts. The unit of our analysis is an RMA, so if a product is not booked in an RMA but is returned along with other products in the same

RMA, it has a zero booked quantity and a positive returned quantity. Moreover, for all products, the sample mean is much smaller than the sample variance, indicating that overdispersion is a prevailing phenomenon. We also find that only about 64% of booked products are returned within the required 90 days.

Figure 3.2 illustrates the discrepancy between booked and returned quantities using the data of P1. At each level of B_1, circles of different sizes represent the proportions of RMAs with various returned quantities. The circles on the 45-degree line represent the proportions of RMAs with matched booked and returned quantities, as indicated by the numbers inside the circles. The circles lying on the horizonal axis show the proportions of RMAs with returned quantity of zero. If returned quantity signals were perfect, there would only be circles on the 45-degree line with proportion 1. However, this is clearly not what is supported by the data. Figure 3.2 also shows that, in general, returned quantity signals become less reliable at higher levels, as evidenced by the decreasing circle size on the 45-degree line. This is expected, as a customer's RMA accuracy deteriorates when the size of product portfolio increases. Figure 3.3 shows the mean booked and returned quantities of the 20 products. Based on the data presented in Appendix A, the average 90-day returned quantity is 57% of the average booked quantity, i.e., the RMA discrepancy rate is 43%. Considering that the weekly trade-in volume of the company is about 10,000 units, annual discrepancy amounts to around 224,000 units, which inarguably causes significant management challenges.

In summary, our data set exhibits several distinctive features. First, the data are overdispersed and contain a considerable proportion of zero counts. Second, returned quantity signals become noisier when their magnitudes increase. Finally, the returned quantity of a product is affected not only by its own booked quantity, but also likely by the booked quantities of its substitutable and complementary products.

Figure 3.2: Discrepancy in P1

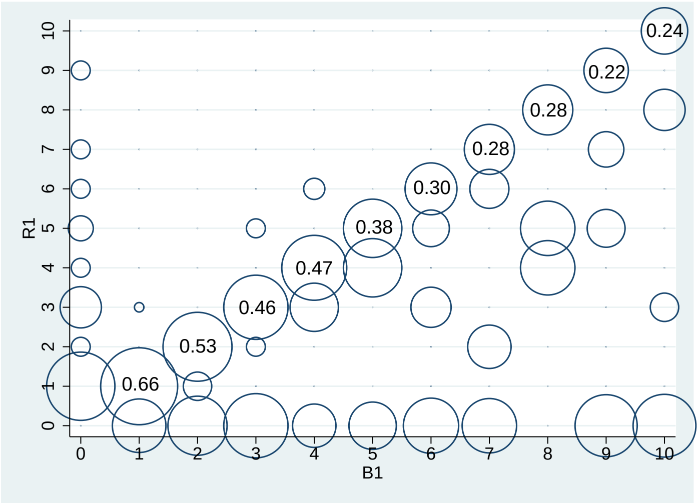
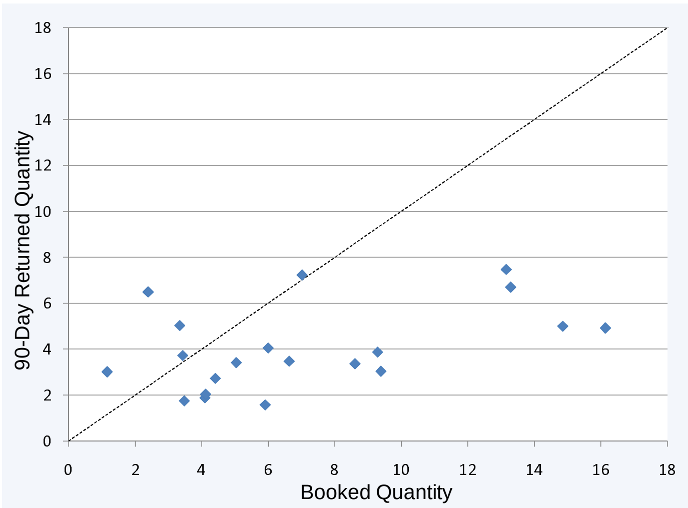


Figure 3.3: Discrepancy in P1-P20



3.3.2 Count Regression Models

In contrast to univariate discrete distributions, count regression models relax the assumption of a homogeneous population by formulating a conditional model in which distribution parameters depend on a vector of covariates. For each product and customer segment, we compare the four commonly-used count regression models discussed in Section 3.2.

We denote booked and returned quantities of product i in RMA j by B_{ij} and R_{ij}, respectively, $i = 1, 2, \ldots, 20$ and $j = 1, 2, \ldots, N_i$, where N_i is the total number of RMAs containing product i. In each model, the returned quantity of a product is the dependent variable and the booked quantities are independent variables. Independent variables and regression coefficients to be estimated in a regression model depend on the forecasting strategy used and take on one of the two forms: when only the booked quantity of product i itself is used as the independent variable, we denote the vector of covariates by $\mathbf{B}_{ij} = (1, B_{ij})$, and its corresponding regression coefficients by $\boldsymbol{\beta}_i = (\beta_{i0}, \beta_{ii})$; when the booked quantities of product i and its substitutable and complementary products are used, we let the vector of covariates be $\mathbf{B}_{ij} = (1, B_{ij}, B_{ij}^1, B_{ij}^2, \ldots, B_{ij}^{M_i})$, and its corresponding regression coefficients be $\boldsymbol{\beta}_i = (\beta_{i0}, \beta_{ii}, \beta_i^1, \beta_i^2, \ldots, \beta_i^{M_i})$, where M_i is the number of identified substitutable and complementary products of product i, and B_{ij}^k is the booked quantity of the kth related product of product i in RMA j, for $k = 1, \ldots, M_i$.

The Poisson regression model (PRM) assumes that the returned quantity of product i, given by $\mathbf{B}_{ij}$, follows a Poisson distribution:

$$\Pr(R_{ij} = r|\mathbf{B}_{ij}) = \frac{\exp(-\mu_{ij})\mu_{ij}^r}{r!}, \quad r = 0, 1, 2, \ldots, \tag{3.1}$$

with a *conditional* mean $\mu_{ij} = \exp(\mathbf{B}_{ij}\boldsymbol{\beta}_i')$. As discussed in Section 3.2, PRM extracts *observed heterogeneity* from the data set, i.e., a different vector of booked quantities, $\mathbf{B}_{ij}$, results in a different point estimate of the mean returned quantity μ_{ij}, and hence a different conditional distribution forecast of returned quantity R_{ij}.

The negative binomial regression model (NBRM) is defined similarly as:

$$\Pr(R_{ij} = r|\mathbf{B}_{ij}) = \frac{\Gamma(r + \alpha_i^{-1})}{r!\Gamma(\alpha_i^{-1})} \left(\frac{\alpha_i^{-1}}{\alpha_i^{-1} + \mu_{ij}}\right)^{\alpha_i^{-1}} \left(\frac{\mu_{ij}}{\alpha_i^{-1} + \mu_{ij}}\right)^r, \quad r = 0, 1, 2, \ldots, \tag{3.2}$$

where $\Gamma(x)$ is the gamma function, $\mu_{ij} = \exp(\mathbf{B}_{ij}\boldsymbol{\beta}_i')$, and $\alpha_i > 0$ is the *dispersion* *parameter*, which needs to be estimated along with the other model parameters $\boldsymbol{\beta}_i$. As such, NBRM cpatures not only observed heterogeneity, as PRM does, but also *unobserved heterogeneity*. In our application, NBRM permits RMAs with the same $\mathbf{B}_{ij}$ to have different forecasts of μ_{ij}. Therefore, unobserved heterogeneity enables us to extract other useful information, such as each customer associated with an RMA, in addition to the booked quantities $\mathbf{B}_{ij}$.

When there are excessive zeros in a data set, zero-inflated Poisson regression model (ZIPRM) can provide a better fit than PRM. ZIPRM is given by

$$\Pr(R_{ij} = 0|\mathbf{B}_{ij}, \mathbf{Z}_{ij}) = \pi_{ij} + (1 - \pi_{ij}) \exp(-\mu_{ij}), \tag{3.3}$$

$$\Pr(R_{ij} = r|\mathbf{B}_{ij}, \mathbf{Z}_{ij}) = (1 - \pi_{ij}) \frac{\exp(-\mu_{ij})\mu_{ij}^r}{r!}, \quad r = 1, 2, 3, ..., \tag{3.4}$$

where $\mathbf{Z}_{ij}$ is a vector of covariates used to estimate the proportion of structural zeros π_{ij}, which may or may not be the same set of covariates used to estimate $\mu_{ij} = \exp(\mathbf{B}_{ij}\boldsymbol{\beta}_i')$. In our model, we assume $\mathbf{Z}_{ij} = \mathbf{B}_{ij}$. As discussed in Section **??**, ZIPRM interprets excessive zeros by *splitting mechanism*. In our study, splitting mechanism attempts to ascertain the sources of structural zeros, that is, separating the returned quantities of zeros of a fixed forecast time window into two sources: (1) the returns that are delayed; and (2) the returns that will not happen at all. In viewing of Eqn.(3.3), the former is represented by the proportion of structural zeros, π_{ij}, and the latter by the proportion of the parent Poisson distribution and its probability mass at point zero, $(1 - \pi_{ij})e^{-\mu_{ij}}$. Finally, the zero-inflated negative binomial regression model (ZINBRM) is obtained by adjusting Eqn.(3.4) according to NBRM, given in Eqn.(3.2). Compared to ZIPRM, which captures overdispersion via splitting mechanism, ZINBRM captures overdispersion from both unobserved heterogeneity and splitting mechanism.

In our analysis, the estimated conditional mean μ_{ij} is used as a point forecast of the returned quantity R_{ij}. The estimated conditional variance is used to perform goodness-of-fit analysis for model selection.

3.3.3 Customer Segmentation

In the presence of customer heterogeneity, a more accurate model is achievable when customers are segmented into groups with similar preferences or behavior (Talluri and van Ryzin 2005). Segmentation is especially useful when the link between observable characteristics of individuals and the desired forecast event differs across segments (Elsner et al. 2004). Behavior-based segmentation proves to have relatively strong predictive power and has been adopted by various authors (e.g., Reutterer et al. 2006). We believe that behavior-based segmentation is an appropriate choice for our analysis because a customer' past RMA reporting behavior is likely to be a good indicator of her future RMA accuracy. This motivates us to segment customers into more homogeneous subgroups, and forecast for each subgroup separately. We adopt two main approaches of customer segmentation, *cluster analysis* and *finite mixture regression models*. After segmentation, we choose the best count regression model for each segment and finally combine subgroup forecasts to provide overall population forecasts.

Cluster Analysis

Our RMA data set contains customer names. For each customer, we measure her historical RMA accuracy by mean squared error (MSE), which is the average squared difference between her booked and returned quantities of all products from all RMAs in the data set except the one to be forecasted. (Mean absolute deviation (MAD) is used as an alternative measure for cluster analysis and the result is presented and briefly discussed in Appendix B.) We do this in order to avoid using the same data to segment customers and to perform forecast. This measure captures the average magnitude of discrepancies that a customer made historically and is used as the distance measure in cluster analysis. We apply *agglomerative hierarchical clustering methods* (Johnson and Wichern 2008). We choose Ward's minimum variance linkage method because it is less susceptible to noise and outliers, and often outperforms other methods over a wide variety of conditions.

An important decision in cluster analysis is to determine the number of clusters. Milligan and Cooper (1985) consider 432 data sets and provide a comparative evaluation of 30 stopping rules for determining the correct number of clusters for hierarchical clustering methods. Calinski & Harabasz's pseudo-F uses the maximum hierarchy level to indicate the correct partitions and is the best-performing stopping rule, measured by the number of times the correct number of clusters is selected for the 432 data sets. Hence, we use pseudo-F to determine the number of customer segments in our cluster analysis. Moreover, as noted by Arabie and Hubert (1994), from a practical point of view, the number of customer segments must be small enough to be managerially relevant and each segment must be large enough to warrant attention. Using these criteria, we find that the most appropriate number of customer segments is either 3 or 4 for each of the 20 products. Our results are summarized in Table 3.1, where a large pseudo-F statistic, labeled in bold, indicates the most appropriate number of clusters. When we refer to cluster analysis results later in the essay, we label customer segments in the ascending order of MSE (indicated by the resulted dendrograms), i.e., Segment 1 has the smallest MSEs, while Segment 4 has the largest MSEs.

Table 3.1: Pseudo-F for Cluster Analysis

# Clusters	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
2	30.85	257.27	6.05	192.43	321.87	300.39	199.69	97.25	96.00	92.84
3	55.80	**582.69**	22.65	250.15	**605.22**	325.86	294.54	**125.49**	**141.66**	**164.07**
4	**106.01**	576.26	**37.10**	**591.05**	581.93	**681.30**	**808.28**	115.71	117.50	162.25
5	91.90	574.07	28.52	369.61	577.59	639.66	540.72	122.26	134.18	157.03

# Clusters	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
2	90.58	257.27	92.84	92.84	92.84	6.05	321.87	130.84	199.69	6.05
3	106.59	463.03	**146.79**	**146.95**	**146.95**	22.65	**550.30**	199.69	**782.32**	**116.82**
4	**130.49**	**750.87**	145.99	105.17	105.35	**93.71**	541.68	771.91	644.16	93.71
5	106.60	730.94	138.04	84.19	84.19	86.20	477.28	602.89	634.26	86.20

To understand the composition of customers in each segment, we use the number of employees in a company as a proxy to the size and complexity of the company's product portfolio, since initial IT capacity planning is usually determined by the number of headcounts (Microsoft Corporation 1999). Consistent with the convention adopted by the U.S. Census Bureau, we categorize companies with fewer than 100 employees, between 100 and 1,000 employees, and more than 1,000 employees as small, medium, and large enterprises, respectively. Out of the 515 customers in our data, 476 customers have employment information available (the rest are privately-held companies that do not disclose the information publicly). The number and percentage of companies in each of the three categories in each segment are shown in Table 3.2. We observe that as the segment number increases, the percentage of large enterprises in each segment also increases. This concurs with one of the inferences we draw from Figure 3.2, i.e., RMA discrepancy is positively correlated with the size and complexity of a company's product portfolio. In contrast, as the segment number increases, the percentage of medium-sized enterprises in each segment decreases. This suggests that medium-sized enterprises, whose equipment portfolios are not exceedingly complex and often have dedicated IT personnel, tend to report more accurate RMA information. Finally, we observe that the percentage of small businesses in each segment is not monotonic as the segment number increases; for example, the two largest percentages, 24.53% and 21.74%, appear in Segments 1 and 3, respectively. A conversation with the company reveals that small businesses can have high RMA accuracy because of the smaller IT equipment size, but can also have low RMA accuracy due to the lack of dedicated IT personnel.

Table 3.2: Customer Composition of Different Segments

Enterprise Size	Seg 1	Seg 2	Seg 3	Seg 4	Total #
Small	39	22	25	0	86
	24.53%	14.86%	21.74%	0.00%	
Medium	82	62	18	6	168
	51.57%	41.90%	15.65%	11.11%	
Large	38	64	72	48	222
	23.90%	43.24%	62.61%	88.89%	

Finite Mixture Regression Models

Customer heterogeneity captured by cluster analysis concerns the average error a customer made in previous RMAs, regardless of products. As argued by Hess and Mayhew (1997), the narrower the scope of products used in customer segmentation, the higher accuracy in representing customer heterogeneity for a particular set of products under consideration. However, a narrower scope of products may result in a limited data set and little predictive power. For a product with relative long life cycle and/or high trade-in volume, we may have enough observations to use an attentive approach for customer segmentation for the product alone. Next, we discuss one such approach, the *finite mixture regression models.*

For the data associated with each product, suppose that there are C customer segments with mixing proportions $\pi_1, \pi_2, \ldots, \pi_C$, $(0 < \pi_k < 1,\ k = 1, 2, \ldots, C$, and $\sum_{k=1}^{C} \pi_k = 1)$, which are unknown parameters to be estimated in a finite mixture regression model. For product i, the finite mixture Poisson regression model (PRM) assumes that its returned quantity follows the mixture Poisson distribution,

$$\Pr(R_{ij} = r | \mathbf{B}_{ij}) = \sum_{k=1}^{C} \pi_k \frac{\exp(-\mu_{ijk})\mu_{ijk}^{r}}{r!}, \quad r = 0, 1, 2, \ldots, \tag{3.5}$$

where, similar to PRM, μ_{ijk} is the conditional mean of RMA j in segment k of product i, and is modeled by $\mu_{ijk} = \exp(\mathbf{B}_{ij}\boldsymbol{\beta}'_{ik})$, and $\boldsymbol{\beta}_{ik}$ is a vector of regression coefficients, with $\boldsymbol{\beta}_{ik} = (\beta_{i0k}, \beta_{iik})$, if only the booked quantity of product i itself is used as an independent variable; or $\boldsymbol{\beta}_{ik} = (\beta_{i0k}, \beta_{iik}, \beta_{ik}^{1}, \ldots, \beta_{ik}^{M_i})$, if the booked quantities of product i and its substitutable and complementary products are used as independent variables. The finite mixture negative binomial regression model (NBRM) is obtained by substituting the Poisson distribution in Eqn. (3.5) by the negative binomial distribution.

Both cluster analysis and finite mixture regression models capture customer heterogeneity: the former is at the *individual* customer level and the latter is at the customer *population* level. Cluster analysis determines the number of customer segments and the partition of customers into different segments. When forecasting the returned quantity of an RMA submitted by a particular customer, we use the best-fitting count regression model estimated for the segment containing that customer. In contrast, finite mixture regression models do not capture each customer's individual behavior; rather, it concerns customer heterogeneity at the population level. Hence, when forecasting the returned quantity of an RMA of a particular customer, we treat this customer as a typical customer drawn from the entire customer population characterized by a finite mixture regression model, i.e., with probability π_k, the customer belongs to segment k, for $k = 1, 2, \ldots, C$, and use the fitted finite mixture regression model to forecast the returned quantity. We discuss how to select the best number of segments, C, in finite mixture regression models in Section 3.4.3.

3.3.4 Forecasting and Benchmark Strategies

In this section, we propose three forecasting strategies and two benchmark forecasts, which differ in the way of using returned quantity signals to predict returned quantities. As discussed earlier, we adjust returned quantity signals based on two pieces of information: product characteristics and customer heterogeneity.

The three forecasting strategies are designed as follows. Strategy 1 (S1) captures product characteristics by using *all* the booked quantities of a product itself and its substitutable and complementary products as independent variables. That is, in a count regression model for product i, S1 uses booked quantity signals $\mathbf{B}_{ij} = (1, B_{ij}, B_{ij}^1, B_{ij}^2, \ldots, B_{ij}^{M_i})$, as defined in Section 3.3.2, to predict the returned quantity R_{ij}. Strategy 2 considers customer heterogeneity by applying count regression models for different customer segments separately, but uses only the booked quantity of a product itself as the independent variable. Customer heterogeneity can be captured by either cluster analysis or finite mixture regression models. Using cluster analysis, for RMAs belonging to segment k, Strategy 2 uses $\mathbf{B}_{ij} = (1, B_{ij})$, $j = 1, 2, \ldots, N_i^k$, to forecast R_{ij}, where N_i^k is the total number of RMAs containing product i in segment k, $i = 1, 2, \ldots, 20$. We label Strategy 2 using cluster analysis as Strategy 2A (S2A). Another option is to apply finite mixture regression models using $\mathbf{B}_{ij} = (1, B_{ij})$ as the only independent variable, which is labeled as Strategy 2B (S2B). Finally, Strategy 3 incorporates both product characteristics and customer heterogeneity. Specifically, Strategies 3A and 3B (S3A and S3B) apply cluster analysis and finite mixture regression models, respectively, to observations $\mathbf{B}_{ijk} = (1, B_{ijk}, B_{ijk}^1, B_{ijk}^2, \ldots, B_{ijk}^{M_i})$, to predict returned quantity R_{ij}.

We also design two benchmark forecasts and compare the three proposed forecasting strategies against them. The first benchmark, termed B-F, directly uses a returned quantity signal at its face value, i.e., it uses B_{ij} as the point forecast of R_{ij}. We note that B-F is currently adopted by the company. The second benchmark, labeled as D-F, relies on a single best-fitting univariate distribution of *historical* returned quantities of a product to predict its future returned quantities. D-F is supported by the literature of using historical sales data to estimate demand distribution (e.g., Agrawal and Smith 1996, and DeHoratius et al. 2008). In essence, for a newly generated RMA, D-F uses the mean of the best-fitting distribution as the point forecast of an RMA's returned quantity, discarding booked quantity information.

3.4. Model Selection

We are interested in explanatory power as well as predictive accuracy of the selected models. Therefore, we divide the data of each product into a calibration set (containing 90% of observations) to estimate model parameters, and a validation set (containing 10% of observations) for model validation and predictive power evaluation (Cabrini et al. 2004). In Sections 3.4.1- 3.4.3, we select the best count regression models and the best finite mixture count regression models for our three strategies, respectively, based on the calibration sets.

3.4.1 Model Fitting Results of Strategy 1

We use Consistent Akaike information criteria (CAIC) to compare models based on likelihood and model parsimony. A smaller value of CAIC indicates a better model (Cameron and Trivedi 1998). Recall that S1 uses the booked quantities of the product itself and its substitutable and complementary products as independent variables in a count regression model and does not segment customers based on historical RMA transactions. Under S1, among the four count regression models discussed in Section 3.3.2, NBRM and ZINBRM are selected as the best models for 75% and 25% of the 20 products, respectively. Because of its restrictive assumption of the equal mean and variance, it is not surprising that PRM is favored for none of the 20 products. Recall that NBRM and ZIPRM adopt two different explanations of overdispersion, unobserved heterogeneity and splitting mechanism, respectively, while ZINBRM incorporates both. The dominant preference of NBRM suggests that when considering all customers together, even after taking into account of product characteristics, unobserved heterogeneity still plays a more important role than splitting mechanism in capturing the differences among RMAs. This makes sense because the unobserved heterogeneity in this case is largely resulted from different customers who generate the RMAs.

Figure 3.4 provides a sample result illustrating the effect of product characteristics using the best count regression model, either NBRM or ZINBRM, identified under S1. (A sample of detailed parameter estimation is provided in Appendix C where numbers in parenthesis are the estimated standard errors.) Experts' product knowledge gives us a starting point for understanding and evaluating common errors in returned quantity signals caused by substitutable or complementary relationship among products. Based on the 4 to 7 identified substitutable and complementary products for each product, our count regression models provide a formal and rigorous examination of their effects. The three blocks in Figure 3.4 indicate the three product families to which the 20 products belong. As seen, each product and its substitutable and complementary products belong to the same product family. A check mark associated with a product indicates that the corresponding booked quantity is statistically significant at the 5% level of explaining the corresponding returned quantity. For example, for P1, although P2 and P3 are identified as its substitutable products, they are found to be statistically insignificant in predicting the returned quantity of P1. In addition, 18 other products, labeled as P21-P38, are also identified as substitutable and complementary products for the 20 products. The column labeled "Other Product(s)" lists products among P21-P38 and the statistically significant ones are presented in bold. For the 20 products, the number of significant independent variables ranges between 2 to 7, with an average of 4.5, indicating the value of considering product characteristics in our forecasting models. As expected, most products have a different set of significant independent variables. The cells in grey indicate *mutual* relationship, for example, the booked quantity of P6, $B6$, affects the returned quantity of P1, $R1$, and at the same time, $R6$ is affected by $B1$. We observe from Figure 3.4 that while the majority of relationships are mutual, one-way relationships also exist, shown by off-diagonal white cells containing a check mark. Among the 13 incidences of one-way relationships, 10 of them are between complementary products. We find that a one-way relationship often exists in the system consisting of a pair of primary and secondary/subordinate products. For example, in Figure 1, a router is a primary product and an interface card is a secondary product in a WAN. While the booked quantity of a primary product may affect the returned quantity of a secondary product, the converse may not be true, i.e., the booked quantity of a secondary product may give no indication about the returned quantity of a primary product.

Figure 3.4: Summary of the Effects of Product Characteristics

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	Other Products
R1	√			√	√	√															**P21**
R2	√	√	√	√	√	√															**P22**
R3		√	√		√																**P22, P23**
R4		√		√	√																P24, **P25**
R5		√	√	√	√																**P22**, P24, P25
R6	√				√	√															
R7							√		√												**P27**, P30
R8								√	√												
R9							√	√	√	√											P26, P28, **P29**
R10							√		√	√	√										P28, P30
R11								√		√	√										P30, **P31**
R12												√	√	√							**P32**, P33, P34
R13												√	√						√	√	**P33**, P37
R14												√		√		√			√	√	**P32**
R15															√	√					P32, **P35**, P28
R16														√	√	√	√	√			P37
R17														√	√	√	√	√			**P37**, **P38**
R18														√	√	√	√	√			P33, **P38**
R19													√						√	√	**P32**, P33
R20													√						√	√	**P31**, P33

3.4.2 Model Fitting Results under Cluster Analysis

We again use CAIC to select the best-fitting count regression models. Table 3.3 reports the percentage of each of the four count regression models being selected as the best model under S2A, which applies cluster analysis to a product's own booked quantity, and S3A, which applies cluster analysis to the booked quantities of the product itself and its substitutable and complementary products. As seen, PRM is preferred only for Segment 4, which, as defined earlier, consists of customers who have the largest MSEs in historical RMA transactions. The relatively large MSEs make the data more likely to satisfy the restriction that the variance equals the mean. The prevailing disfavor of PRM for the other three segments suggests that considering observed heterogeneity, i.e., the difference in booked quantities, alone, is insufficient to accurately predict returned quantities. Hence, we focus on the other three models, NBRM, ZIPRM, and ZINBRM, which take overdispersion into account. Our results show that compared to NBRM, and ZINBRM, ZIPRM is less frequently preferred and, as PRM, is only selected for Segment 4. This means that the effect of unobserved heterogeneity dominates the effect of splitting mechanism in the other three segments. In other words, in those three segments, given booked quantities, the remaining difference among RMAs plays a more important role in determining returned quantities than the effect of late returns, i.e., products returned after 90 days. Recall that the choice between NBRM and ZINBRM indicates whether splitting mechanism still plays a role when both observed and unobserved heterogeneities are taken into account. Our result shows that about 17% of the returns occur between 90 and 180 days, which explains the preference of ZINBRM for the majority of cases.

Table 3.3: Best-Fitting Models for S2A and S3A using Cluster Analysis

Segment	PRM	NBRM	ZIPRM	ZINBRM	Segment	PRM	NBRM	ZIPRM	ZINBRM
S2A					S3A				
Seg 1	0	30.0%	0	70.0%	Seg 1	0	70.0%	0	30.0%
Seg 2	0	45.0%	0	55.0%	Seg 2	0	40.0%	0	60.0%
Seg 3	0	30.0%	0	70.0%	Seg 3	0	25.0%	0	75.0%
Seg 4	11.1%	11.1%	66.7%	11.1%	Seg 4	33.3%	11.1%	33.3%	22.2%

3.4.3 Model Fitting Results of Finite Mixture Regression Models

As in Section 3.4.1, we use CAIC to choose the best-fitting finite mixture regression model for S2B and S3B. “PRM#” and “NBRM#” are used to label the models, for example, PRM2 means that a finite mixture PRM with two underlying customer segments fits the best. For S2B, the percentages of PRM2, PRM3, PRM4, and NBRM2 chosen as the best-fitting model are 0%, 20%, 25%, and 55%, respectively, while the corresponding percentages are 20%, 25%, 0%, and 55%, respectively, for S3B. Overall, 2, 3, and 4 customer segments are identified by finite mixture regression models for the 20 products, with NBRM2 as the most-frequently preferred model. Compared to S2B, S3B captures common features of RMA discrepancy across different customer segments by considering product characteristics and therefore results in fewer segments in general.

3.5. Forecasting Strategy Comparison

In this section, we compare the forecasting strategies against each other and also against the two benchmark forecasts, to provide justification of the usefulness of our model constructs, including product characteristics and customer heterogeneity.

For each product, we use the best-fitting model identified under each forecasting strategy based on the calibration set to predict the returned quantity of RMAs in the validation set. We compare the five strategies (S1, S2A, S2B, S3A, S3B) against the two benchmark forecasts (B-F and D-F) and against each other. Comparisons are based on the mean squared error (MSE). Table 3.4 reports the MSE for each product under each strategy, with the 20 products listed in descending order of sample size. For each product, MSE of the best strategy is shown in bold. In addition, at the bottom of Table 3.4, we show the percentages of MSE reduction of the forecasting strategies compared to the two benchmarks, averaged over the 20 products.

Table 3.4: Validation Set Forecast Comparison by MSE

Product	Total # of RMAs	B-F	D-F	S1	S2A	S2B	S3A	S3B
P5	454	141.98	93.30	67.13	59.57	57.60	50.20	**46.33**
P2	414	133.00	160.68	81.44	77.17	53.06	49.66	**41.59**
P4	410	83.34	37.79	36.41	23.33	14.35	20.04	**14.06**
P11	397	82.39	95.41	76.43	58.10	41.17	32.70	**32.27**
P1	302	66.37	37.19	24.08	22.19	21.07	**17.05**	18.01
P7	297	112.10	111.62	98.98	66.45	68.61	**58.98**	60.30
P9	284	84.44	78.65	65.22	58.48	46.45	37.76	**32.48**
P20	277	128.65	128.78	76.85	54.74	53.97	18.43	**16.41**
P19	265	210.95	110.88	98.42	61.78	71.79	**47.29**	53.06
P8	224	129.41	91.50	78.39	26.98	28.92	**12.58**	16.25
P15	201	64.79	92.37	34.08	19.64	22.23	**17.67**	18.39
P16	180	281.30	190.65	98.71	91.78	90.56	**42.96**	66.56
P13	142	66.81	74.86	58.34	37.97	48.06	**22.89**	23.26
P6	140	54.73	50.09	49.35	46.27	45.53	**32.95**	36.03
P14	138	46.72	39.74	28.06	8.97	13.69	**7.92**	8.18
P18	137	52.43	43.00	24.83	14.14	16.91	**5.48**	5.50
P10	110	107.70	70.04	42.64	27.08	28.62	**19.32**	20.03
P3	103	51.78	85.62	49.56	36.42	37.73	**19.64**	23.55
P12	98	76.43	67.04	44.64	24.40	24.70	**20.06**	22.67
P17	85	138.20	133.68	80.23	71.22	75.13	**45.49**	53.80
Average MSE		105.68	89.64	60.69	44.33	43.01	28.95	30.44
Avg % Reduction								
B-F				38.09%	55.87%	56.84%	70.73%	69.84%
D-F				29.58%	50.27%	51.51%	66.27%	65.50%

Table 3.4 shows that all proposed forecasting strategies outperform the two bench-

mark forecasts, with the percentage MSE reduction ranging between 4.29%-90.28% for individual products and between 38.09%-70.73% overall when compared to B-F, and between 1.48%-87.26% for individual products and between 29.58%-66.27% overall when compared to D-F. The comparison to B-F reflects the existence of substantial amount of noise in RMA booking information; while the comparison to D-F shows that even with the presence of noise, it is not wise to ignore the signals altogether and to rely on a single univariate distribution fitted to historical returned data to generate forecasts. Contrast to the single distribution estimated in D-F, the count regression models estimate a distribution family, within which distribution parameters are determined by the values of independent variables, i.e., for a different set of booked quantities, an estimated model provides a different set of distribution parameter values. The superior of count regression models to D-F concurs with the belief that insights can be gained by moving from a simple average to a regression model that includes factors that may affect the dependent variable (Hess and Mayhew 1997). In summary, the results in Table 3.4 support our belief that returned quantity signals provide valuable information for predicting actual returned quantities; however, they must be adjusted appropriately based on product characteristics and customer heterogeneity.

We now compare the five strategies. First, we note that S2A and S2B perform better than S1, suggesting that, for our data set, segmenting customers is more beneficial than utilizing product information. Next, we compare S2A and S3A to S2B and S3B, respectively, with the former using cluster analysis and the latter using finite mixture regression models. Recall that cluster analysis segments customers using RMA accuracy based on customers' entire RMA transaction history, whereas finite mixture regression models capture customer heterogeneity based on entire customer population's RMA transaction history for a single product. At the first glance, there is no definite preference of one to the other. However, as shown in Table 3.4, when we make the comparison considering the sample size of each product, we find that the larger the sample size, the more likely that finite mixture regression models outperform cluster analysis, i.e., S2B and S3B perform better than S2A and S3A, respectively. Therefore, finite mixture regression models appear to be more appropriate for products with a relatively long life cycle and/or a large trade-in volume, which imply larger sample sizes; whereas cluster analysis may be more suitable for products with a relatively short life cycle and/or a low trade-in volume. Overall, S3A wins the contest in 14 out of 20 products, suggesting that cluster analysis may be a more robust method compared to the finite mixture regression models. In addition, S3A can pinpoint the segment to which each customer belongs. Thus, evaluated by the overall needs of trade-in program management, including supporting both operational and strategic decisions, S3A is more useful than S3B, and is our recommended strategy to the company. As such, we focus on S3A in the sensitivity study provided in Section 3.6.

3.6. Sensitivity Analysis

In this section, we conduct sensitivity analyses to test the robustness of our proposed models. We exam how forecast accuracy will be affected by the number and types (i.e., substitutability and complementarity) of products included as independent variables. We vary the length of forecasting time window to test the robustness of our best performing strategy against the two benchmark forecasts. Finally, we compare the performance of a unified, single count regression model with that of our best-fitting count regression model to examine the tradeoffs between a simple and more sophisticated models. Our analysis is performed on six products, P1, P2, P7, P8, P12, and P13, with two products from each of the three product families.

3.6.1 Sensitivity to Product Characteristics

We examine the sensitivity of forecast accuracy to the number and types of returned quantity signals included in model specification. For each customer segment of a product, we first use the product's own booked quantity as the independent variable for model estimation and selection. We then add its substitutable and complementary products to the count regression models one at a time, following the random order of product index. The results will be compared against (1) Random-F, which uses the booked quantities of M_i randomly-selected products, instead of the M_i identified substitutable and complementary products of product i, as independent variables; (2) All, which includes the booked quantities of all identified substitutable and complementary products as independent variables; (3) Subs, which includes only the booked quantities of all substitutable products as independent variables; and (4) Comps, which includes only the booked quantities of all complementary products as independent variables. The inclusion of Random-F allows us to verify that it is the appropriate choice of substitutable and complementary products, not merely increasing the number of independent variables, that helps to improve forecast accuracy. The purpose of considering the last two scenarios is to gain insights on which product characteristics, substitutability or complementarity, is more effective in helping to forecast.

Table 3.5 first presents MSEs of the validation set forecast with different numbers of substitutable and complementary products included as independent variables. A bold number denotes that the newly-added independent variable is statistically significant. The results of using a product's own booked quantity, in the column labeled as "1(own)", and all identified substitutable and complementary products, in the columns labeled as "5", "6", or "7" depending on the total number of related products identified, are equivalent to the results for S2A and S3A in Table 3.4, respectively.; The only difference is that Table 3.5 reports MSEs at the segment level, while Table 3.4 reports them at the product level. We first observe that as the number of statistically significant independent variables increases, forecasting MSE decreases. This validates our approach that starts with substitutable and complementary products identified by experts, and then uses statistical methods to determine significant ones and verify their effect. Second, it is evident that for all six products, the number of significant independent variables increases with the segment number. To understand the implication of this observation, recall that in cluster analysis we label the segments so that a customer with a larger historical MSE has a higher segment number. It suggests that, for more reliable customers, including a product's own booked qua ntity in forecasting models already provides significant benefit (reflected by fewer significant independent variables associated with more reliable customers). This further indicates that the discrepancy between booked and returned quantities made by these customers is mainly caused by late returns (i.e., returned after 90 days), instead of inaccuracy in RMA reporting. On the other hand, customers with higher segment numbers not only tend to return products late, but also are more likely to misspecify products in RMA reporting.

Table 3.5: Sensitivity to the Number and Types of Products Included

	Seg	MSE with # of Products Included							# of	% MSE Reduction			
		1(own)	2	3	4	5	6	7	Sig.Var.	Random-F	All	Subs	Comps
P1	Seg 1	**14.3**	15.0	14.3	15.0	**13.0**	**12.5**	12.6	3	-28.9%	14.2%	14.2%	-5.1%
	Seg 2	**18.1**	17.9	18.5	18.8	**17.2**	**16.4**	**15.1**	4	-24.0%	19.5%	11.5%	3.3%
	Seg 3	**26.7**	27.3	27.0	**25.6**	**23.6**	**22.4**	**21.0**	5	-24.4%	27.2%	15.0%	10.1%
	Seg 4	**33.9**	33.9	34.5	**31.0**	**28.1**	**25.5**	**24.8**	5	-20.5%	36.4%	18.4%	14.0%
P2	Seg 1	**46.6**	46.9	46.9	47.0	**45.3**	**42.8**	**38.9**	4	-25.8%	19.8%	13.4%	4.7%
	Seg 2	**74.9**	**72.5**	**69.0**	**65.8**	**61.6**	**59.4**	**55.6**	7	-16.9%	34.6%	17.6%	14.9%
	Seg 3	**105.3**	**97.7**	**93.5**	**88.6**	**82.9**	**77.5**	**72.0**	7	-20.0%	46.2%	24.1%	21.6%
P7	Seg 1	**41.3**	41.7	42.7	42.0	42.4	42.3	**38.1**	2	-16.2%	8.5%	8.4%	-0.3%
	Seg 2	**56.9**	57.9	**53.7**	53.9	54.8	54.9	**49.8**	3	-18.8%	14.3%	14.3%	-0.1%
	Seg 3	**85.8**	84.9	**85, .8**	**76.7**	79.8	78.1	**71.7**	4	-19.6%	19.8%	13.9%	4.4%
	Seg 4	**100.1**	101.2	**94.9**	**88.7**	90.8	91.3	**83.7**	4	-20.0%	19.5%	14.2%	4.3%
P8	Seg 1	**10.6**	**9.6**	10.0	9.7	10.0	-	-	2	-43.8%	16.7%	6.1%	0.2%
	Seg 2	**20.9**	22.9	**12.9**	14.2	12.4	-	-	2	-37.1%	68.6%	62.0%	-0.3%
	Seg 3	**39.9**	48.9	**21.4**	26.4	20.4	-	-	2	-31.3%	95.5%	86.3%	-0.3%
P12	Seg 1	**11.3**	**10.8**	**10.3**	12.0	10.4	-	-	3	-30.7%	8.8%	4.6%	3.4%
	Seg 2	**23.9**	**22.5**	**19.2**	19.8	19.6	-	-	3	-33.4%	21.4%	7.9%	7.5%
	Seg 3	**44.7**	**42.3**	**36.4**	**33.2**	33.1	-	-	4	-26.8%	30.5%	20.9%	6.6%
P13	Seg 1	**21.0**	**20.1**	20.9	20.7	**17.6**	17.7	-	3	-20.1%	18.5%	19.3%	-0.5%
	Seg 2	**29.3**	**27.9**	28.6	**27.2**	**26.1**	**23.4**	-	5	-20.5%	25.5%	10.5%	10.7%
	Seg 3	**42.2**	**38.4**	40.4	**34.4**	**33.0**	**31.4**	-	5	-16.2%	34.5%	17.9%	14.7%
	Seg 4	**56.0**	**49.4**	50.4	**42.9**	**36.2**	**32.2**	-	5	-17.1%	73.7%	38.1%	33.0%

The last four columns in Table 3.5 show the percentage reduction of forecasting MSEs from S1 to Random-F, and 1(own) (i.e., S2A) to the other three comparing scenarios, All (i.e., S3A), Subs, and Comps, respectively. Random-F underperforms S1 substantially, which confirms that merely increasing the number of independent variables will not improve forecast accuracy. We observe that S3A significantly reduces the percentage MSEs at each segment level as compared to their counterparts in S2A, and the reduction increases with the segment number, which again validates our choice of using product characteristics to improve forecast accuracy, especially for customers with larege historical MSE. Moreover, we find that using booked quantities of substitutable products tends to be more effective than using booked quantities of complementary products. One plausible explanation is that usually the number of substitutable products is less than that of complementary products. Therefore, it is relatively easy to identify the proper substitutable products to be included in the forecasting models. However, for complementary products, we may need to expand the list of potential products to be tested in order to discover the most appropriate ones.

3.6.2 Sensitivity to the Forecasting Time Window

Although we focus our analysis on 90-day forecasts, our models can be used to provide forecasts for different time windows, including the time windows either shorter or longer than 90 days. Specifically, we conduct analysis for 30-, 60-, 120-, 150-, and 180-day forecasts by defining the dependent variable as the returned quantity within each of the five time windows. Table 3.6 summarizes the percentage reduction in forecasting MSE under S3A compared to the two benchmark forecasts. For the early-return (30- and 60-day) forecasts, we only use D-F as a benchmark forecast since it is not appropriate to compare S3A with B-F, given that the required return time is 90 days. For the late-return (120-, 150-, and 180-day) forecasts, we use both B-F and

D-F as benchmark forecasts.

Table 3.6: Percentage Reduction in MSE under Different Forecasting Time Windows

Product	30-day	60-day	90-day		120-day		150-day		180-day	
	D-F	D-F	B-F	D-F	B-F	D-F	B-F	D-F	B-F	D-F
P1	58.92%	70.99%	74.31%	54.15%	65.96%	79.81%	57.39%	56.11%	58.21%	75.61%
P2	55.70%	58.42%	62.66%	69.09%	63.69%	66.49%	52.42%	57.46%	50.33%	65.57%
P7	59.14%	56.07%	47.39%	47.16%	53.19%	51.35%	52.05%	57.15%	50.54%	57.53%
P8	72.33%	66.39%	90.28%	86.25%	71.11%	58.12%	62.79%	59.00%	62.28%	54.75%
P12	52.80%	67.83%	73.75%	70.08%	61.55%	57.53%	52.47%	61.64%	47.75%	52.21%
P13	54.45%	74.28%	65.74%	69.42%	63.42%	60.32%	59.60%	72.60%	56.29%	75.81%
Average	58.89%	65.66%	69.02%	66.03%	63.15%	62.27%	56.12%	60.66%	54.23%	63.58%

Early-return forecast is a much-desired forecasting capability currently not existing in the company. Time-sensitive products, such as computers and printers, can lose value at the rate greater than 1% per week (Blackburn et al. 2004). Hence, companies may want to expeditiously dispatch early returns, if the product is in high demand or loses value rapidly. Our results, displayed in Table 3.6, show that S3A can reduce the average MSE by 58.89% for the 30-day forecast, and by 65.66% for the 60-day forecast, as compared to that under D-F.

For the late-return forecasts, we observe from Table 3.6 a decreasing trend of percentage MSE reductions compared to B-F, which suggests that B-F's performance improves as the time window extends. This is consistent with the observation that 17% of RMAs were returned between 90 and 180 days. However, even under the 180-day time window, S3A still reduces MSE of B-F by more than 50% on average, suggesting that the effectiveness of S3A does not diminish against B-F as the forecasting time window increases. When comparing S3A and D-F, we do not detect conspicuous trend of MSE deductions for any of the six products as the forecasting time window varies. As seen, for each forecasting time window, S3A reduces MSE of D-F by more than 60% on average. Based on the above observations, we conclude that the performance of S3A is robust against the change of forecasting time window and is significantly better than that of the benchmark forecasts. Therefore, our proposed method can be readily and reliably applied under different forecasting time windows.

3.6.3 Sensitivity to the Choice of Count Regression Models

In Table 3.3, we report the percentage of each of the four count regression models being the best model for each customer segment, and discuss the underlying reasons and implications. However, for implementation, companies may prefer a single, unified model that can be applied to all customer segments and all products. Hence, we examine, for a given time window, which count regression model is the most appropriate model. Because it is already shown that NBRM and ZINBRM outperform PRM and ZIPRM in general (due to the prevailing unobserved heterogeneity), we show in Table 3.7 the percentages of MSE increase when using NBRM and ZINBRM, respectively, for all customer segments and all six products, as compared to using the best-fitting count regression models. From Table 3.7, the average performance of NBRM improves whereas that of ZINBRM deteriorates, as the time window increases. Furthermore, ZINBRM outperforms NBRM for each of 30-, 60-, 90-, and 120-day forecasts on average. We find that the performance of ZINBRM is only slightly worse than that of S3A in the majority of cases, with the largest MSE increase of 15.13% for the 90-day forecast for P13. For 150- and 180-day forecasts, NBRM outperforms ZINBRM on average, and shows only a negligible deteriorating performance compared to S3A, with the largest MSE increase of 5.81% for the 150-day forecast for P7. Our results indicate that when a single, unified model is desired, ZINBRM should be chosen for a short forecasting time window when the percentage of not-yet-returned products is high. For a long forecasting time window, late-returns are of a lesser concern and NBRM becomes more appropriate. Overall, our results suggest that an appropriately-chosen, unified model is effective against S3A. On the other hand, S3A is a valuable method to uncover customer behavior in different segments and identify the root causes of RMA discrepancies at the segment level, and provides insights to guide companies' strategic decisions, which cannot be achieved by a unified model.

Table 3.7: Percentage Increase in MSE under Unified Models

	NBRM						ZINBRM					
	30-d	60-d	90-d	120-d	150-d	180-d	30-d	60-d	90-d	120-d	150-d	180-d
P1	20.85%	13.75%	9.42%	12.41%	3.26%	1.65%	0.00%	1.49%	10.59%	8.20%	6.07%	12.77%
P2	34.08%	23.87%	14.83%	8.18%	3.81%	2.87%	0.00%	0.00%	0.00%	7.27%	13.40%	6.80%
P7	36.72%	30.04%	15.95%	14.48%	5.81%	2.78%	1.67%	1.53%	2.01%	3.63%	10.61%	10.58%
P8	33.94%	29.44%	20.37%	14.95%	3.71%	1.44%	0.00%	0.00%	3.40%	7.00%	8.35%	11.57%
P12	26.50%	19.87%	17.00%	7.12%	2.72%	2.03%	0.00%	0.00%	3.13%	8.47%	6.94%	14.82%
P13	28.28%	21.69%	14.66%	8.51%	2.39%	1.48%	0.00%	4.95%	15.13%	5.24%	6.52%	14.24%
Ave	30.06%	23.11%	15.37%	10.94%	3.62%	2.04%	0.28%	1.33%	5.71%	6.63%	8.65%	11.80%

3.7. Managerial and Operational Implications

We have shown that, with proper use of product and customer information, a company can not only improve forecast accuracy of product returns, but also gain valuable insights on the design and execution of successful trade-in policies. We discuss below several managerial and operational implications of our analysis.

Accurate return flow forecasts can benefit a company at different levels. At the strategic level, a reverse logistics network design needs forecasts of quantity, quality and return timing of used products. Accurate forecasts enable companies to make better decisions of selecting locations for recovery facilities and determining collection methods. In addition, statistical analysis of RMA data can pinpoint the strengths and weaknesses of the existing trade-in policies and guide companies to design new policies that rectify the root causes of problems. At the tactical level, balancing supply and demand in the secondary market is an important task. Different from the primary market, supply in secondary markets is highly volatile. Accurate return flow forecasts give companies visibility into future supply with reduced volatility, and allow sales personnel to engage in proactive selling and collecting efforts to better match supply and demand. For example, sales personnel can provide a supply list of products ahead-of-time to their potential customers to stimulate demand. At the operational level, supply forecast is an essential input for inventory and remanufacturing decisions.

The company in our analysis currently has a centralized facility dedicated to receiving and storing trade-in returns. Secondary market demands come from three large organizations: a remanufacturing and remarketing organization, a warranty and service contract organization, and a product development organization, with each having its own warehouse. Due to the lack of good forecasts, trade-in products are currently first consolidated in the centralized facility and then routed to secondary demand channels after demand is identified, incurring substantial inbound transit and storage costs at the centralized facility. With reliable forecasting methods at its disposal, the company can identify a demand channel after receiving RMA information and require trade-in products to be sent directly to that channel. This will reduce the storage capacity at the centralized facility and save transportation, receiving, and storage costs. Moveover, dispatching time of used products to secondary markets will be shortened, helping the company to improve its financial performance.

In this project, we utilize product characteristics and customer heterogeneity as the basic constructs of our models, and demonstrate that both constructs are valid and indispensable. Specifically, our analysis shows that *multi-signal, segmentation-based forecasts,* S3A and S3B, improve the *single-signal, segmentation-based* forecasts, S2A and S2B, by 32.78% and 29.46%, measured by average MSE reduction, respectively. In addition, S3A and S3B reduce the average MSE of the *multi-signal, non-segmentation-based* forecast, S1, by 52.59% and 50.98%, respectively. The results suggest that management of a successful trade-in program needs to have rich and up-to-date product knowledge, and needs to collect and analyze customer information on a continuous basis, classify return signals from different customers into different segments, and adjust return signal noises accordingly. Via an extensive sensitivity analysis, we validate our models under different settings and demonstrate their effectiveness and robustness. The company has expressed a significant interest in using our models, in particular, S3A, to replace its current method, B-F. They have been building a comprehensive database which maps out the substitutable and complementary relationships between major products and collecting additional data to further validate the effectiveness of our models.

Our analysis also generates insights on the design of effective monitoring and enforcement mechanisms to improve financial performance of trade-in programs. Via cluster analysis, we capture customer heterogeneity by the average error that customers made in their RMA reporting history, and characterize the root causes of such errors. For example, our analysis shows that customers in the segment with small MSEs tend to be small businesses with simple IT portfolios or medium-sized enterprises with more complex IT infrastructures but dedicated IT personnel. For this segment of customers, the primary source of RMA discrepancies is late returns rather than product misspecification. On the other hand, customers in the segment with large MSEs tend to be small businesses without dedicated IT personal or large enterprises with exceedingly complex IT infrastructures. For this segment, both late-/never-returns and product misspecification contribute to large RMA discrepancies. This insight allows the company to design segment-specific, incentive-based trade-in policies. Currently, the company is utilizing our customer segmentation results in their asset recovery practice, including designing segment-based trade-in policies and enforcement mechanisms that encourage early-returns, and instructing their sales personnel to assist and monitor the customers with difficulty to generate accurate RMAs. Furthermore, our cluster analysis can assist companies to evaluate and improve incentive schemes, by measuring customers' MSEs and return timing before and after the implementation of an incentive scheme, and make dynamic adjustments of the scheme when called for. Valuable insights can be gained by analyzing the change of the number of significant independent variables, the change of return timing, the magnitude of regression coefficients, and the choice of best-fitting count regression models to assess the impact of an incentive scheme. Indeed, our methods can be used by trade-in programs as a tool for problem detection, customer behavior monitoring, and policy performance evaluation.

3.8. Concluding Remarks and Future Work

In this essay, we study the issues pertaining to the management of trade-in programs. We propose and compare forecasting strategies that differ in whether and how they use returned quantity signals. We use a real data set from a high-tech company to demonstrate the effectiveness of the proposed methods, and gain managerial insights on improving the performance of trade-in programs. The contributions of our work to the academic literature and to practice can be summarized as follows.

From the academia perspective, in the OM literature, Ray et al. (2005) determine optimal trade-in credits for durable and remanufacturable products. Toktay et al. (2004) point out that forecasting of product returns, if any, is handled by applying time series methods to the historical return stream without exploiting other data sources that may affect returns. Our work complements Ray et al. (2005) and reacts upon Toktay et al. (2004) by developing effective forecasting models for product returns based on RMAs, a *real-time* data source. We also contribute to the signal-based forecasting literature by developing innovative statistical methods that segment signals based on their sources to improve forecast accuracy. Compared to D-F, which uses a single distribution to characterize the returned quantity of a product using historical return data but ignoring booked quantity information, our forecasting strategies use *real-time* signals to fit *a family of count regression models*. In a broader context, our modeling approach demonstrates how a real-time data source can be adjusted to support strategic and operational decisions, even when the source contains significant noises and systematic bias, which, we believe, is a significant contribution of this essay. Our methods can also be adapted to other OM applications that use real-time data sources to support execution decisions. For example, consider a B2B environment where customers provide pre-order information to a company that offers a broad range of products. In a pre-order, a customer provides the company with information regarding the types of products that she is interested in, the desired order quantity of each product, and the intended order confirmation date (Gao et al. 2010). Such a pre-order is often subject to revision or cancellation so that a customer's final order and pre-order often present significant discrepancies in terms of order quantity and confirmation date. Also, we can expect that customer heterogeneity plays a role in explaining these discrepancies. Therefore, our methods can be generalized to provide demand forecast under such scenarios based on pre-order information. Moreover, although count regression models and finite mixture regression models have attracted attention and been applied to various disciplines, they have been rarely applied in the OM literature. Therefore, our study serves to introduce these models to our research community and to demonstrate their usefulness in OM applications.

From practice perspectives, our research is motivated by a real problem facing the trade-in program of a high-tech company. We develop tailored statistical models using real-time RMA data, and demonstrate that they significantly outperform the current method employed by the company. Via an extensive sensitivity analysis, we validate the flexibility, generality, and robustness of our models under different settings. We show that our strategies, in particular S3A, are capable of generating forecasts for early returns, whereby providing the company with a new, much-needed forecasting capability. As mentioned, the company is in an early stage of implementing our methods to support its operational decisions. In addition, our study provides insights on the effective management of trade-in programs, including customer monitoring and segmentation based on historical RMAs, product grouping based on substitutability and complementarity, and designing incentive and enforcement mechanisms to promote responsible and responsive customer behavior and, ultimately, to maximize a company's profitability. The company has begun to use insights gained from our analysis to assist its strategic decisions in terms of asset recovery practice and segmentation-based customer monitoring.

For future research, it is interesting to forecast the exact timing of trade-in returns. Our study can provide forecasts under different time windows; however, we do not leverage information of each RMA's exact return time. A bivariate forecasting model that considers the returned quantity and return time jointly is a useful extension. In our analysis, we use the size of business to characterize customers in different segments. Another possible area for future research is to identify other appropriate features, such as the industry and the duration of customer-company relationship, to gain deeper understanding of different customer segments. This can provide further insights on underlying factors that drive customers' trade-in behavior and forecasting for new customers who have no historical trade-in records.

Chapter 4

Sale and Trade-In of a Durable Product with Technology Innovations

4.1. Introduction

Trade-in is a widely-adopted strategy by companies in a variety of industries serving both business-to-consumer (B2C) and business-to-business (B2B) markets, including products ranging from golf clubs and automobiles to CT scanners and large-scale communication devices. Trade-in enables companies to achieve two basic goals. First, it can be used to incentivize consumers to upgrade to products featuring newly-introduced technology or simply to replace used products with brand-new ones. Second, since traded-in products are returned to companies, they can gain better control over secondary markets in order to achieve higher profits and fight counterfeits. Despite the prevalence and importance of trade-in sales to companies, there has been relatively limited exploration of this phenomenon in the literature (Rao et al. 2009).

In this paper, we study the trade-in strategy in the context of a monopolistic manufacturer offering a technology product to a heterogeneous consumer population. The technology product is designed to last for two periods functionally, i.e., after it is been used for two periods, it fully depreciates physically and has no residual value at all. We assume that there is an exogenous innovation process governing the availability of a next-generation technology. Whenever a new technology becomes available, the manufacturer introduces a new product to the market featuring the latest technology and no longer offers products using the previous-generation technology. After the product is sold and used for one period, one of the two following scenarios will occur. First, if innovation occurs, consumers who have a one-period-old product on hand can still keep the unit for one more period until it fully depreciates functionally. In the meantime, the manufacturer may offer to buy back these used products from the consumers, but she will dispose them by ways that do not compete with new products featuring the new-generation technology, for example, by disassembling and reusing parts or donating to charity. Second, if innovation doesn't occur, apparently, consumers may also keep their on-hand units; but this time after the manufacturer obtains used products from offering trade-in programs, she will resell the used products in the marketplace because they are still technologically current.

The manufacturer determines the prices for the new products featuring a new and an existing technologies, respectively, and the trade-in credit for the used products featuring a previous-generation technology and an existing technology, respectively, in anticipation of consumer choices to maximize her long-run average profit. Trade-ins are offered in each period regardless whether an innovation occurs or not. Though operated in the same way, they serve different purposes to the manufacturer and consumers. When innovation occurs, the manufacturer uses trade-in programs to buy back technologically obsolete, used products in order to accelerate new technology adoption. In this case, traded-in products are disposed by ways that do not interfere with the market where new products featuring the newly-introduced technology are sold. When innovation doesn't occur, new and used products have the same generation of technology and co-exist in the marketplace. When offering trade-in programs, the manufacturer buys back the used products from some customers and resells them to other customers. As such, during the no innovation periods, the manufacturer essentially serves as an intermediary to facilitate the transaction between consumers who want to replace their one-period-old products by brand-new ones and consumers who demand used products. Consumer heterogeneity is captured by a distribution depicting their sensitivity to the technological and functional attributes of the product. Consumers make their consumption choices based on their willingness-to-pay and the prices of different options provided by the manufacturer.

We focus on the class of stationary pricing strategies and characterize the optimal stationary prices that should be offered by the manufacturer under which heterogenous consumers choose their consumption strategies to maximize their own utility. From the manufacturer's perspective, prices are her enabler to induce consumer behaviors that result in her maximum expected profit. We identify different combinations of consumption strategies that should be induced under different parameter value ranges. We find that facing the same exogenous innovation process and product wear and tear situation, the manufacturer having the low production cost and low resell cost should take advantage of trade-in programs regardless of innovation occurrence and induce the highest-valuation consumers to purchase a brand-new product in every period. On the other hand, the manufacturer with the low production cost but high resell cost should offer trade-in programs only when innovation occurs because assuming the intermediary role in the secondary market is too expensive. Finally, the manufacturer with high production cost and low resell cost should take the advantage of trade-in programs when innovation doesn't occur and avoid to promote new technology too aggressively.

We also evaluate the impact of innovation frequency, technological obsolescence, functional depreciation, and production and resell costs on the manufacturer's maximum long-run average profit. Some of the findings are interesting and not so intuitive. Technological obsolescence and functional depreciation reduce consumer valuation of used products, which in turn lowers the manufacturer's profitability. However, we identify scenarios under which technological obsolescence or functional depreciation can actually increase a manufacturer's expected profit. When innovation does not occur very frequently, manufacturers whose product has a slow functional depreciation rate and whose production cost is low can benefit from a higher degree of technological obsolescence because it makes prompt innovation adoption more attractive to consumers and therefore enables the manufacturers to better take the advantage of trade-in programs to promote early adoption. Functional depreciation reduces the value of used products featuring a current technology; however, when innovations have a moderate frequency and technological obsolescence is not very significant, manufacturers with a low resell cost should make their products less durable physically in order to increase the expected profit. This is because when technology innovations fail to boost product upgrade, the manufacturer with cost-efficiency in the secondary market can resort to encouraging consumers to replace used products by brand-new ones with the same technology to improve profitability. Lastly, although higher innovation frequency means shorter expected technology lifespan and hence the time to recoup the production cost, manufacturers with high resell cost and severe product wear and tear can benefit from a high innovation frequency because it is more profitable to have the product become technologically obsolete than to let it deteriorate functionally and remain on the market

The rest of the paper is organized as follows. In Section 4.2, we review the related literature. We provide the model setup in Section 4.3. The consumers' and the manufacturer's optimization problems are presented in Sections 4.4 and 4.5, respectively. We discuss the results and key insights in Section 4.6 and provide concluding remarks and future research opportunities in Section 4.7.

4.2. Literature Review

Our study is primarily related to two streams of literature: durable-goods monopolist offering sequentially improving products, and the optimal assortment problem under vertically differentiated products.

Coase (1972) famously postulates the time inconsistency problem for a durable-goods monopolist where the monopolist might not be able to capture any monopoly profits if she can change the price over time. An extensive body of research has been built upon Coast (1972) and the stream that is most relevant to our study considers monopolists supplying improving durable goods. Moorthy and Png (1992) consider a monopolist who has a high- and low-quality version of a product available and needs to decide how to introduce and price the two versions. They find that if the monopolist decides to introduce the two versions sequentially, the high-quality version should be introduced first. In the two-period model set up by Dhebar (1994) and a followup work by Kornish (2001), they assume that a low-quality version exists in the first period and a high-quality version becomes available in the second period. The monopolist chooses first- and second-period prices and second-period quality level to maximize the discounted profit, while consumers decide whether and when to purchase the product to maximize their utility. No secondhand markets exist in either Dhebar (1994) or Kornish (2001). Fudenberg and Tirole (1998) analyze pricing for sequentially improving products under different market information conditions: anonymous consumers with frictionless secondhand markets (e.g., textbooks), identified consumers with no secondhand markets (supercomputers), and semi-anonymous consumers with no secondhand markets (software). Our study also takes into account the interaction between the primary and secondary markets, but we consider a monopolist-controlled secondary market where the private secondhand market does not exist due to high transaction cost.

This body of literature mainly adopts a two-period model where innovation occurs with certainty in the second period. Moreover, in order to focus on the aspect of product improvement, these papers generally assume that physical wear and tear is minimal. In our study, we use an infinite-horizon model to consider a case where innovation is governed by a stochastic process, i.e., there is no guarantee that an innovation will occur in the next period. Also different from this area of literature, we assume that the product under consideration is subject to both technological obsolescence and functional depreciation and as we will discuss later, the relative degree of the two types of value decay affects consumer choices and the expected profit can be obtained by the manufacturer.

Another paper that is related to ours is Rao et al. (2009) where the role of trade-ins in durable goods markets is examined. Motivated by automobile trade-ins, lemon problems and adverse selection are a major focus of the paper and trade-in is shown to be an intervention by the monopolist to reduce inefficiencies caused by lemon problems. Rao et al. (2009) assume constant technology. In our study, we do not distinguish used products with different qualities, but take into account the interplay between technological obsolescence and functional depreciation. In terms of the role trade-in programs play, we also have a different focus: we regard trade-in as a means of promoting and facilitating innovation adoption and product upgrade, and coordinating the primary and secondary markets.

The second stream of literature concerns the optimal assortment from a set of vertically differentiated products. Berry (1994) analyzes and estimates a consumer choice model with discrete, vertically differentiated products. Bhargava and Choudhary (2001) consider the problem of selecting and pricing of vertically differentiated products, but focus on two special cases: when the optimal assortment contains only the highest quality product and when it contains all the products. Honhon and Pan (2009) solve the general optimal assortment problem where the optimal assortment may contain a subset of products and characterize the properties of the optimal solution. Our study treats consumption strategies as vertically differentiated products that the manufacturer can induce via its pricing scheme. Different from Honhon and Pan (2009), we impose additional constraints on the products. In our model, the secondary market clearance condition dictates that the choice probabilities of certain products have to be equal.

4.3. A Selling with Trade-In Model

4.3.1 The Model Setup

We consider an infinite-horizon, discrete-time model in which a monopolistic manufacturer offers a technology product to heterogenous, utility-maximizing consumers, to maximize her profit. Specifically, our model consists of the following constructs.

Innovation Process and Product Lifetime: The functional life of each new product is designed to last for two periods, after which the product is fully depreciated physically. We assume that there is an exogenous innovation process that governs the introduction of the next-generation technology of the product to the market. The innovation process follows a geometric distribution, with q_0 being the probability that a new technology becomes available in the next period. The state of the innovation process in each period is denoted by a binary variable j, where $j = 0$ means that the next-generation technology just becomes available and state 1 means otherwise.

As soon as a new technology is launched, the previous-generation technology becomes obsolete and is no longer offered in the marketplace. Consumers who have a one-period-old product on hand can still keep the unit for one more period until it fully depreciates functionally. In the meantime, the manufacturer may offer to buy back these used products from the consumers, but she will dispose them by ways that do not compete with new products featuring the new-generation technology, for example, by disassembling and reusing parts or donating to charity; instead of reselling them to the consumers as used products. We refer to product value decay caused by the innovation process as the *technological obsolescence (TO)*. During periods when innovation doesn't occur, the product undergoes wear and tear caused by normal usage while its technology remains the latest. We refer to product value decay caused by usage as the *functional depreciation (FD)*. In essence, after a product is sold and used for one period, if innovation doesn't occur, the value of the product is reduced because of functional depreciation; however, if innovation occurs, the value of the product is decreased due to both functional depreciation and technological obsolescence.

The manufacturer: At any time, the monopolistic manufacturer, who faces no production capacity constraint, sells products featuring the latest technology to consumers. For convenience, we call a product a state-j product if the innovation process is in state j, for $j = 0, 1$. In addition, she offers two trade-in opportunities to customers: one at $j = 0$, when a new technology becomes available, termed as *state-0 trade-in*, and one at $j = 1$, when one-period-old, used products are still technologically up-to-date, termed as *state-1 trade-in*. In either case, a customer uses the given trade-in credit as a partial payment to purchase a new product. Though operated in the same way, state-0 and state-1 trade-in programs serve different purposes to the manufacturer and the consumers. At state 0, the manufacturer buys back technologically obsolete products in order to accelerate new technology adoption; while at state 1, because new and used products have the same technology and co-exist in the marketplace, the manufacturer essentially serves as an intermediary to facilitate the transaction between consumers who want to replace their one-period-old products by brand-new ones and consumers who demand used products.

The manufacturer controls the price of a new product and the trade-in credit given to a used product in each period to maximize her long-run average profit per period. More specifically, if the innovation process is in state 0 at the beginning of period t, the manufacturer immediately stops selling new and used products featuring the previous technology, and starts to offer a new product featuring the new technology. The manufacturer determines the price of the state-0 new product in period t, $p^N_{0,t}$, and the trade-in credit for returning a used product and upgrading to a state-0 new product featuring the newly-introduced technology, $p^T_{0,t}$. If the innovation process is in state 1 in period t, the manufacturer determines the price of the state-1 new product, $p^N_{1,t}$, and the trade-in credit for the state-1 used product, $p^T_{1,t}$. Given that the used products in state 1 are not technologically obsolete, the manufacturer sells and clears them in the secondary market in each period, with the per-unit price, $p^U_{1,t}$, being determined endogenously by the market clearance condition. That is, price $p^U_{1,t}$ is set such that all traded-in products are sold out in the secondary market. Secondary market transactions incur a per-unit resell cost γ, to the manufacturer, which may include costs such as inspection, repair, refurbishing, marketing, and other expenditures related to secondary-market activities. Note that this cost applies only at state 1 when the manufacturer sells used products to the consumers, but doesn't apply at state 0 when she disposes them. The manufacturer also has a marginal production cost, c. We assume that $\gamma < c$.

Consumers: The population of consumers is constant and normalized to 1. A consumer can own at most one unit of the product in any period. Consumers have the universally-agreed, common attribute values θ^N, θ^U_0, and θ^U_1, which represent the one-period utilities of consuming a new product (regardless of innovation state because all new products feature the latest technology), a state-0 used product, and a state-1 used product, respectively. Because of the memoryless property of the innovation process, these attribute values depend only on the innovation state but are independent of the age of the current technology. We assume that $0 < \theta^U_0 < \theta^U_1 < \theta^N = 1$, where, without loss of generality, θ^N is normalized to 1 . Note that the innovation state affects the attribute value of a used product. The difference, $\theta^U_1 - \theta^U_0$, captures the value of technological difference between the latest technology (i.e., a state-1 used product) and the previous-generation technology (i.e., a state-0 used product) of a used product. Therefore, $\theta^U_1 - \theta^U_0$ is a measure of the technological obsolescence. At the same time, product usage, i.e., wear and tear, deteriorates the value of a state-1 used product even though its technology is still current. Therefore, $\theta^N - \theta^U_1 = 1 - \theta^U_1$, the functional difference between a new and a used product using the existing technology, measures the functional depreciation.

Although consumers agree upon these common attribute values, they differ in their sensitivity to them. We use a type parameter, w, to represent consumer heterogeneity, and assume w follows a uniform distribution between $[0,1]$. A w-consumer's valuation for a product is w multiplied by the common attribute value of the product. For example, a w-consumer values a state-1 used product at $w\theta_1^U$.

4.3.2 Rule of the Game and Solution Characterizations

The manufacturer and the consumers are assumed to be rational and to maximize their own expected payoff. We study an infinitely-repeated game with complete information by assuming that all payoff-relevant information is common knowledge. Uncertainty in this repeated game stems from the random innovation process captured by the innovation probability, q_0, and consumer heterogeneity reflected by the distribution of w. At the beginning of each period, the manufacturer announces the new product price and the trade-in credit, and the used product price is then inferred by the market clearance condition in the technology state-1. The utility-maximizing consumers then choose a consumption strategy based on their own type and the prices offered by the manufacturer. In this game, the consumers play strategically against the manufacturer, but not against each other.

In our analysis, we assume that the manufacturer deploys a stationary pricing strategy that depends only on the innovation state, i.e., for a given innovation state, the prices are independent of time period t as well as the market share of the new product sold in the previous period. Let $\boldsymbol{p}_0 = (p_0^N, p_0^T)$, $\boldsymbol{p}_1 = (p_1^N, p_1^T, p_1^U)$, and $\boldsymbol{p} = (\boldsymbol{p}_0, \boldsymbol{p}_1) = (p_0^N, p_0^T, p_1^N, p_1^T, p_1^U)$, which are the stationary prices for state-0 new product, state-0 trade-in, state-1 new product, state-1 trade-in, and state-1 used product, respectively, where p_1^U is endogenously determined by the secondary market clearance condition and is not a decision variable of the manufacturer. On the other hand, a w-consumer's consumption strategy in each period depends on the innovation state, j, the price vector announced by the manufacturer, $\boldsymbol{p}_j$, and his action in the previous period, a' (because the maximum physical life of a product is two periods, we only need to track a consumer's action in the previous period). Therefore, a w-consumer's state, s, can be expressed by $(a', j, \boldsymbol{p}_j)$, for $j = 0, 1$.

4.4. Consumer Behavior - Stationary Consumption Strategies and Long-Run Average Payoffs

We assume that due to high transaction cost, it is not economically plausible for consumers to sell their used products directly in the secondhand market. Therefore, a consumer with a state-j, for $j = 0, 1$, used product can either purchase a new product with a discount price of $p_j^N - p_j^T$ from the manufacturer or keep the used unit for one more period until it fully depreciates physically. We denote a consumer's feasible actions in the current period by a, which depend on his action in the previous period a' and the price vector revealed by the manufacturer $\boldsymbol{p}_j$ in state j, for $j = 0, 1$. When the innovation process is in state 0, if the consumer took the action $a' = N$ in the previous period, he can choose to (i) trade in his used product and buy a new one, denoted by N, or (ii) keep his used product for another period, denoted by K. If he took an action $a' \neq N$ in the previous period, which will be denoted as $a' = \bar{N}$ (i.e., he does not have a useable unit on hand), he can choose to (i) buy a new product, also denoted by N, or (ii) be inactive, denoted by I. When the innovation process is in state 1 and the consumer took the action $a' = N$ in the previous period, he has the same choices, N and K, as in state 0. If he took an action $a' = \bar{N}$, he can choose to (i) take action N, (ii) buy a used product, denoted by U, or (iii) take action I. A w-consumer's payoff in the current period depends on his state $s = (a', j, \boldsymbol{p}_j)$ and his current action a, which is summarized in Table 4.1. We use $r_w(a, s)$ to denote a w-consume's single-period payoff when he chooses action a at state s.

In responding to the manufacturer's stationary pricing vector $\boldsymbol{p}$, a w-consumer

Table 4.1: The Single-Period Payoff Matrix of a w-Consumer

	State			
Action a	$(N, 0, \boldsymbol{p}_0)$	$(\bar{N}, 0, \boldsymbol{p}_0)$	$(N, 1, \boldsymbol{p}_1)$	$(\bar{N}, 1, \boldsymbol{p}_1)$
N	$w - p_0^N + p_0^T$	$w - p_0^N$	$w - p_1^N + p_1^T$	$w - p_1^N$
$K/U^\dagger$	$w\theta_0^U$	$-$	$w\theta_1^U$	$w\theta_1^U - p_1^U$
I	$-$	0	$-$	0

†: K and U are grouped since they result in the same payoff.

chooses a *stationary* consumption strategy that maximizes his long-run average utility per period. A stationary consumption strategy of a consumer is a function that maps each possible state s to a particular feasible action $d(s)$. In our case, we have four distinct states that may induce different actions, labeled as $s_1 = (N, 0, \boldsymbol{p}_0)$, $s_2 = (\bar{N}, 0, \boldsymbol{p}_0)$, $s_3 = (N, 1, \boldsymbol{p}_1)$, and $s_4 = (\bar{N}, 1, \boldsymbol{p}_1)$. From our earlier discussion, $d(N, 0, \boldsymbol{p}_0) \in \{N, K\}$, $d(\bar{N}, 0, \boldsymbol{p}_0) \in \{N, I\}$, $d(N, 1, \boldsymbol{p}_1) \in \{N, K\}$ and $d(\bar{N}, 1, \boldsymbol{p}_1) \in \{N, U, I\}$. Consequently, there are 24 feasible consumption strategies in total. Given that we are interested in analyzing the long-run behavior of the manufacturer and the consumers, we choose long-run average payoff as the optimization criterion. The following proposition shows that there are 15 distinct consumption strategies that a consumer can choose from. We label these strategies as S1-S15.

Proposition 4.4.1. *For a given stationary price vector $\boldsymbol{p}$ offered by the manufacturer, a w-consumer must choose one of the 15 consumption strategies presented in Table 4.3 to maximize his long-run average utility.*

Proof. In order to determine the long-run average payoff of each consumption strategy, we first calculate the limiting probabilities of Strategy i, π_s^i, where $s \in \{s_1, s_2, s_3, s_4\}$ and $i = 1, 2, \ldots, 24$, as shown in Table 4.2. It is obvious to see that since the limiting probabilities of states $(\bar{N}, 0, \boldsymbol{p}_0)$ and $(\bar{N}, 1, \boldsymbol{p}_1)$, i.e., $\pi_{(\bar{N},0,\boldsymbol{p}_0)}$ and $\pi_{(\bar{N},1,\boldsymbol{p}_1)}$ are 0 for both S1 and S16, and they have the same actions at the rest of the two states, they essentially collapse into the same strategy and we use S1 to represent it. Similar argument applies to the elimination of S17-S23. Consequently, by considering the limiting probabilities, the 24 feasible consumption strategies collapse into 15 strategies, i.e., S1-S15. □

Table 4.2: Limiting Probabilities of the 24 Feasible Consumption Strategies

Strategy	State				Limiting Probabilities			
	$(N,0,\boldsymbol{p}_0)$	$(\bar{N},0,\boldsymbol{p}_0)$	$(N,1,\boldsymbol{p}_1)$	$(\bar{N},1,\boldsymbol{p}_1)$	$\pi_{(N,0,\boldsymbol{p}_0)}$	$\pi_{(\bar{N},0,\boldsymbol{p}_0)}$	$\pi_{(N,1,\boldsymbol{p}_1)}$	$\pi_{(\bar{N},1,\boldsymbol{p}_1)}$
S1	N	N	N	N	q_0	0	q_1	0
S2	N	N	K	N	$\frac{q_0}{1+q_1}$	$\frac{q_0q_1}{1+q_1}$	$\frac{q_1}{1+q_1}$	$\frac{q_1^2}{1+q_1}$
S3	N	N	K	U	q_0^2	q_0q_1	q_0q_1	q_1^2
S5	K	N	K	N	$\frac{q_0}{2}$	$\frac{q_0}{2}$	$\frac{q_1}{2}$	$\frac{q_1}{2}$
S6	N	N	K	I	q_0^2	q_0q_1	q_0q_1	q_1^2
S7	K	N	N	N	$\frac{q_0}{1+q_0}$	$\frac{q_0^2}{1+q_0}$	$\frac{q_1}{1+q_0}$	$\frac{q_0q_1}{1+q_0}$
S8	K	I	N	N	q_0q_1	q_0^2	q_1^2	q_0q_1
S9	K	I	K	N	$\frac{q_0q_1}{1+q_1}$	$\frac{q_0}{1+q_1}$	$\frac{q_1^2}{1+q_1}$	$\frac{q_1}{1+q_1}$
S10	K	N	K	I	$\frac{q_0^2}{1+q_0}$	$\frac{q_0}{1+q_0}$	$\frac{q_0q_1}{1+q_0}$	$\frac{q_1}{1+q_0}$
S11	K	I	K	U	0	q_0	0	q_1
S12	I	I	I	I	0	q_0	0	q_1
S13	N	I	K	N	$\frac{q_0}{2}$	$\frac{q_0}{2}$	$\frac{q_1}{2}$	$\frac{q_1}{2}$
S14	K	N	N	U	$\frac{q_0}{2}$	$\frac{q_0}{2}$	$\frac{q_1}{2}$	$\frac{q_1}{2}$
S15	K	N	N	I	$\frac{q_0}{2}$	$\frac{q_0}{2}$	$\frac{q_1}{2}$	$\frac{q_1}{2}$
S16	N	N	N	U	q_0	0	q_1	0
S17	N	N	N	I	q_0	0	q_1	0
S18	N	I	N	N	q_0	0	q_1	0
S19†	N	I	N	U	q_0	0	q_1	0
					0	q_0	0	q_1
S20†	N	I	N	I	q_0	0	q_1	0
					0	q_0	0	q_1
S21	N	I	K	U	0	q_0	0	q_1
S22	N	I	K	I	0	q_0	0	q_1
S23	K	I	N	U	0	q_0	0	q_1
S24	K	I	N	I	0	q_0	0	q_1

†: S19 and S20 result in two disjoint classes of states: $\{(N,0),(N,1)\}$ and $\{(\bar{N},0),(\bar{N},1)\}$.

The long-run average payoff for a w-consumer choosing the 15 consumption strategies are shown in Table 4.3, where $u_w^i(\boldsymbol{p})$ is the w-consumer's average payoff if he adopts consumption strategy i in responding to the manufacturer's pricing scheme $\boldsymbol{p}$,

Table 4.3: A w-Customer's Consumption Strategies, Long-Run Average Rewards, and the Manufacturer's Costs

	State				A w-consumer's long-run average reward	
Strategy	$(N, 0, \boldsymbol{p}_0)$	$(\bar{N}, 0, \boldsymbol{p}_0)$	$(N, 1, \boldsymbol{p}_1)$	$(\bar{N}, 1, \boldsymbol{p}_1)$	$u_w^i(\boldsymbol{p})$	c_i
S1	N	N	N	N	$w - \left(q_0(p_0^N - p_0^T) + q_1(p_1^N - p_1^T)\right)$	c
S2	N	N	K	N	$\frac{1+q_1\theta_1^U}{1+q_1} w - \left(q_0 p_0^N - \frac{q_0}{1+q_1} p_0^T + \frac{q_1^2}{1+q_1} p_1^N\right)$	$\frac{c}{1+q_1}$
S3	N	N	K	U	$(q_0 + q_1\theta_1^U) - (q_0 p_0^N - q_0^2 p_0^T + q_1^2 p_1^U)$	$q_0 c + q_1^2 \gamma$
S4	K	N	K	U	$\left(\frac{q_0(1+q_0\theta_0^U)}{1+q_0} + q_1\theta_1^U\right) - \left(\frac{q_0}{1+q_0} p_0^N + \frac{q_1}{1+q_0} p_1^U\right)$	$\frac{q_0 c + q_1 \gamma}{1+q_0}$
S5	K	N	K	N	$\frac{1+q_0\theta_0^U+q_1\theta_1^U}{2} w - \left(\frac{q_0}{2} p_0^N + \frac{q_1}{2} p_1^N\right)$	$\frac{c}{2}$
S6	N	N	K	I	$q_0(1 + q_1\theta_1^U)w - (q_0 p_0^N - q_0^2 p_0^T)$	$q_0 c$
S7	K	N	N	N	$\frac{1+q_0\theta_0^U}{1+q_0} w - \left(\frac{q_0^2}{1+q_0} p_0^N + q_1 p_1^N - \frac{q_1}{1+q_0} p_1^T\right)$	$\frac{c}{1+q_0}$
S8	K	I	N	N	$q_1(1 + q_0\theta_0^U)w - (q_1 p_1^N - q_1^2 p_1^T)$	$q_1 c$
S9	K	I	K	N	$\frac{q_1}{1+q_1}\left(1 + q_0\theta_0^U + q_1\theta_1^U\right) w - \frac{q_1}{1+q_1} p_1^N$	$\frac{q_1}{1+q_1} c$
S10	K	N	K	I	$\frac{q_0}{1+q_0}\left(1 + q_0\theta_0^U + q_1\theta_1^U\right) w - \left(\frac{q_0}{1+q_0} p_0^N\right)$	$\frac{q_0}{1+q_0} c$
S11	K	I	K	U	$q_1\theta_1^U w - q_1 p_1^U$	$q_1 \gamma$
S12	I	I	I	I	0	0
S13	N	I	K	N	$\frac{1+q_1\theta_1^U}{2} w - \left(\frac{q_0}{2} p_0^N - \frac{q_0}{2} p_0^T + \frac{q_1}{2} p_1^N\right)$	$\frac{c}{2}$
S14	K	N	N	U	$\frac{1+q_0\theta_0^U+q_1\theta_1^U}{2} w - \left(\frac{q_0}{2} p_0^N + \frac{q_1}{2} p_1^N - \frac{q_1}{2} p_1^T + \frac{q_1}{2} q_1^U\right)$	$\frac{c+q_1\gamma}{2}$
S15	K	N	N	I	$\frac{1+q_0\theta_0^U}{2} w - \left(\frac{q_0}{2} p_0^N + \frac{q_1}{2} p_1^N - \frac{q_1}{2} p_1^T\right)$	$\frac{c}{2}$

$i = 1, 2, \ldots, 15$. We explain the computation of $u_w^1(\boldsymbol{p})$ and $u_w^5(\boldsymbol{p})$. The long-run average payoff of a w-consumer who adopts S1 (Strategy-(N, N, N, N)), which stipulates the purchase of a new product in each period regardless of innovation state and on-hand product, is

$$
\begin{aligned}
u_w^1(\boldsymbol{p}) &= \pi^1_{(N,0,\boldsymbol{p}_0)} r_w(N, (N, 0, \boldsymbol{p}_0)) + \pi^1_{(\bar{N},0,\boldsymbol{p}_0)} r_w(N, (\bar{N}, 0, \boldsymbol{p}_0)) + \pi^1_{(N,1,\boldsymbol{p}_1)} r_w(N, (N, 1, \boldsymbol{p}_1)) + \\
&\quad + \pi^1_{(\bar{N},1,\boldsymbol{p}_1)} r_w(N, (\bar{N}, 1, \boldsymbol{p}_1)) \\
&= w - \left(q_0(p_0^N - p_0^T) + q_1(p_1^N - p_1^T)\right).
\end{aligned}
$$

Intuitively, the above expression states that, over the long run, a w-consumer adopting Strategy-(N, N, N, N) earns a payoff of $(w - p_0^N + p_0^T)$ in $q_0 \times 100\%$ of periods and a payoff of $(w - p_1^N + p_1^T)$ in $q_1 \times 100\%$ of periods. Next consider $u_w^5(\boldsymbol{p})$. Under S5

(Strategy (K, N, K, N)), at innovation state j, for $j = 0, 1$, the consumer purchases a new product if his previous action is $\bar{N}$, and keeps his used product if his previous action is N. The long-run average payoff of a w-consumer who adopts S5 is

$$\begin{aligned}
u_w^5(\boldsymbol{p}) &= \pi^5_{(N,0,\boldsymbol{p}_0)} r_w(N, (N, 0, \boldsymbol{p}_0)) + \pi^5_{(\bar{N},0,\boldsymbol{p}_0)} r_w(N, (\bar{N}, 0, \boldsymbol{p}_0)) + \pi^5_{(N,1,\boldsymbol{p}_1)} r_w(N, (N, 1, \boldsymbol{p}_1)) + \\
&\quad + \pi^5_{(\bar{N},1,\boldsymbol{p}_1)} r_w(N, (\bar{N}, 1, \boldsymbol{p}_1)) \\
&= \frac{q_0}{2}(w - p_0^N) + \frac{q_0}{2}(w\theta_0^U) + \frac{q_1}{2}(w - p_1^N) + \frac{q_1}{2}(w\theta_1^U) \\
&= \frac{1 + q_0\theta_0^U + q_1\theta_1^U}{2} w - \left(\frac{q_0}{2} p_0^N + \frac{q_1}{2} p_1^N\right).
\end{aligned}$$

A w-consumer adopting Strategy-(K, N, K, N) alternates between using a new and a used product, where a new product has the same common attribute value regardless of the innovation state, while the attribute value of a used product depends on the innovation state. Hence, at state 0, with probability $\frac{q_0}{2}$, the consumer doesn't have a used unit on hand and therefore buys a new product and earns utility $w - p_0^N$; and with the same probability, he has a used unit on hand, keeps it, and earns $w\theta_0^U$. Similarly, at state 1, with the same probability $\frac{q_1}{2}$, the consumer earns $w - p_1^N$ or $w\theta_1^U$.

The last column of Table 4.3 lists the manufacturer's cost of inducing the consumption strategies, where c_i is the cost of inducing Strategy i. We still use c_1 and c_5 to demonstrate the computation. Following the same logic as calculating $u_w^i(\boldsymbol{p})$, it is easy to see that

$$\begin{aligned}
c_1 &= \pi^1_{(N,0,\boldsymbol{p}_0)} c + \pi^1_{(\bar{N},0,\boldsymbol{p}_0)} c + \pi^1_{(N,1,\boldsymbol{p}_1)} c + \pi^1_{(\bar{N},1,\boldsymbol{p}_1)} c = c, \\
c_5 &= \pi^5_{(\bar{N},0,\boldsymbol{p}_0)} c + \pi^5_{(\bar{N},1,\boldsymbol{p}_1)} c = \frac{c}{2}.
\end{aligned}$$

The payoffs and costs of the other consumption strategies in Table 4.3 can be computed analogously.

For convenience, we call consumers who play Strategy i the Strategy-i consumers or $(d_i(s_1), d_i(s_2), d_i(s_3), d_i(s_4))$-consumers interchangeably. For example, Strategy-1 consumers are also referred to as (N, N, N, N)-consumers. Observe from Table 4.3 that (N, N, N, N)-consumers are consumers with the highest willingness-to-pay. They highly value both new technology and the physical newness of a product, i.e., they not only adopt new technology as soon as it becomes available, but also consume only brand-new products. Strategies 2 (N, N, K, N), 3 (N, N, K, U), and 6 (N, N, K, I) behave the same as Strategy 1 at state 0, which suggests that they are also early adopters of the new technology, but differ in their behaviors when no innovation occurs. Strategy-2 consumers keep a product for two periods as long as its actual lifetime is not ended earlier by a technological innovation; Strategy-3 and Strategy-6 consumers buy used products and stays inactive, respectively, when technology remains the same. In terms of the promptness of technology adoption, the next tier of consumers are later adopters of the new technology and may choose from Strategies 4 (K, N, K, U), 5 (K, N, K, N), 7 (K, N, N, N), 10 (K, N, K, I), 14 (K, N, N, U), and 15 (K, N, N, I). They all behave the same at state 0 when innovation occurs: when they have a used unit on hand, they keep it for one more period even though its technology becomes obsolete; when they do not have a one-period-old product on hand, they purchase the new technological product without delay. At state 1, Strategy 7 behaves the same as Strategy 1, which suggests that Strategy-7 consumers also highly value the physical newness of a product; Strategies 4, 5, and 14 use a combination of new and used products with different frequency; and Strategies 10 and 15 may stay inactive when no new technology is available. Strategy-13 (N, I, K, N) consumers are also not early adopters: they may take advantage of state-0 trade-in, but when they are not eligible, they wait to adopt. Strategies 8 (K, I, N, N), 9 (K, I, K, N), and 11 (K, I, K, U) are truly laggards of technology adoption. They continue using their on-hand used products or remain inactive when innovation occurs; in particular, Strategy-11 consumers only buy used products. Finally, (I, I, I, I)-consumers (who adopt Strategy 12) have the lowest range of willingness-to-pay and always remain inactive. Note that Strategies 1, 2, 3, 6, and 13 (which choose action N at state $(N, 0, \boldsymbol{p}_0)$) take advantage of state-0 trade-in; Strategies 1, 7, 8, 14, and 15 (which choose action N at state $(N, 1, \boldsymbol{p}_1)$) are suppliers to the secondary market at state 1, while Strategies 3, 4, 11, and 14 (which choose action U at state $(\bar{N}, 1, \boldsymbol{p}_1)$) demand used products at state 1.

4.5. The Manufacturer's Optimization Problem

The manufacturer decides the stationary pricing strategy $\boldsymbol{p}$, in anticipation of consumers' reaction, to maximize her expected long-run average profit. By choosing difference pricing strategies, the manufacturer can induce consumers to choose different combinations of consumption strategies. Consumers' choices of strategies determine the aggregate market sizes of new, used, and trade-in products, which in turn affect the manufacturer's profit from the primary and secondary markets. At a stationary equilibrium, the manufacturer may or may not induce all of the 15 consumption strategies listed in Table 4.3. We now argue in Lemma 4.5.1 that a profit-maximizing manufacturer should never induce S13, S14, and S15, as defined in Table 4.3.

Lemma 4.5.1. *In order to maximize long-run average profit, the manufacturer should never offer price vector, $\boldsymbol{p}$, which induces consumers to choose S13, S14, or S15.*

Proof. First we compare S13 and S5. As shown in Table 4.3, $c_5 = c_{13}$, but $\hat{\theta}_5 > \hat{\theta}_{13}$. This suggests that it costs the manufacturer the same to offer S5 and S13, but S5 is valued more by consumers; thus, S13 is dominated by S5 and therefore S13 should be eliminated. Similar argument applies to the comparison of S15 to S5, and consequently S15 is eliminated. Next, we compare S14 to S5. It is easy to show that $\hat{\theta}_5 = \hat{\theta}_{14}$, but $c_5 < c_{14}$. This means that S5 and S14 are valued the same by the consumers, but it costs more to offer S14; therefore S14 is also eliminated. $\square$

4.5.1 Ordering Consumers' Consumption Strategies

In Table 4.3, we express a w-customer's long-run average payoff under Strategy i as the difference between his valuation of the consumption $\hat{\theta}_i w$ and his payment for the consumption $\hat{p}_i(\boldsymbol{p})$. For example, a w-consumer's valuation and payment under Strategy 5 are $\hat{\theta}_5 w = \frac{1+q_0\theta_0^U+q_1\theta_1^U}{2}w$ and $\hat{p}_5(\boldsymbol{p}) = \frac{q_0}{2}p_0^N + \frac{q_1}{2}p_1^N$, respectively. If we treat $\hat{\theta}_i$ as the attribute value and $\hat{p}_i$ as the price of Strategy i, we may view a customer's selection of a consumption strategy as a consumer choice problem of a set of vertically-differentiated variants and an outside option with its payoff normalized to zero (Berry 1994).

Based on Lemma 4.5.1, there are now 12 consumption strategies remaining, S1-S12. In order to apply the vertical differentiation consumer choice model, we need to rank the 12 strategies based on their attribute value. Before we proceed, let us consider the following condition on the values of q_0, θ_0^U, and θ_1^U:

$$q_0(\theta_1^U - \theta_0^U) > 1 - \theta_1^U. \tag{4.1}$$

This condition holds when q_0 is not too small, which implies that technology innovations are relatively frequent, and technological obsolescence is more significant than functional depreciation. This is a reasonable condition for a broad range of technology products studied here. When (4.1) holds, the rank order of the 12 strategies is

$$\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_6 > \hat{\theta}_7 > \hat{\theta}_8 > \hat{\theta}_9 > \hat{\theta}_{10} > \hat{\theta}_{11} > \hat{\theta}_{12}, \tag{4.2}$$

and we label it as RO1. When (4.1) doesn't hold, the following is true

$$\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_7 > \hat{\theta}_8 > \hat{\theta}_9 > \hat{\theta}_{11} > \hat{\theta}_{10} > \hat{\theta}_{12}, \tag{4.3}$$

and we are left to determine only $\hat{\theta}_6$'s position in (4.3). It can be shown that regardless of parameter values, $\hat{\theta}_5 > \hat{\theta}_6 > \hat{\theta}_{10}$, but $\hat{\theta}_6$'s relationships with $\hat{\theta}_7$, $\hat{\theta}_8$, $\hat{\theta}_9$, and $\hat{\theta}_{11}$ depend on the values of q_0, θ_0^U, and θ_1^U. We show in Table 4.4 the five complete possible rank orders of the 12 consumption strategies when (4.1) doesn't hold, labeled as RO2-RO5, and their corresponding conditions.

Table 4.4: Rank Orders and Conditions of the Twelve Consumption Strategies

	Conditions	Resulting Rank Order
RO1	(4.1) holds	$\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_6 > \hat{\theta}_7 > \hat{\theta}_8 > \hat{\theta}_9 > \hat{\theta}_{10} > \hat{\theta}_{11} > \hat{\theta}_{12}$
	(4.1) doesn't hold:	
RO2	$1 - q_1 - q_1^2 \geq 0$ & $\theta_1^U \geq \theta_{1,1}^U$	$\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_6 > \hat{\theta}_7 > \hat{\theta}_8 > \hat{\theta}_9 > \hat{\theta}_{11} > \hat{\theta}_{10} > \hat{\theta}_{12}$
RO3	$1 - q_1 - q_1^2 \geq 0$ & $\theta_{1,2}^U \leq \theta_1^U < \theta_{1,1}^U$	$\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_7 > \hat{\theta}_6 > \hat{\theta}_8 > \hat{\theta}_9 > \hat{\theta}_{11} > \hat{\theta}_{10} > \hat{\theta}_{12}$
RO4	$1 - q_1 - q_1^2 \geq 0$ & $\theta_{1,3}^U \leq \theta_1^U < \theta_{1,2}^U$	$\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_7 > \hat{\theta}_8 > \hat{\theta}_6 > \hat{\theta}_9 > \hat{\theta}_{11} > \hat{\theta}_{10} > \hat{\theta}_{12}$
RO5	$1 - q_1 - q_1^2 < 0$ & $\theta_1^U < \theta_{1,4}^U$	$\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_7 > \hat{\theta}_8 > \hat{\theta}_9 > \hat{\theta}_6 > \hat{\theta}_{11} > \hat{\theta}_{10} > \hat{\theta}_{12}$
RO6	$1 - q_1 - q_1^2 < 0$ & $\theta_1^U \geq \theta_{1,4}^U$, or,	$\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_7 > \hat{\theta}_8 > \hat{\theta}_9 > \hat{\theta}_{11} > \hat{\theta}_6 > \hat{\theta}_{10} > \hat{\theta}_{12}$
	$1 - q_1 - q_1^2 \geq 0$ & $\theta_1^U < \theta_{1,3}^U$	

$\theta_{1,1}^U = \frac{q_0\theta_0^U - q_1^2 + 3q_1 - 1}{q_0 q_1 (1+q_0)}$, $\theta_{1,2}^U = \frac{q_0 q_1 \theta_0^U + 2q_1 - 1}{q_0 q_1}$, $\theta_{1,3}^U = \frac{-q_0 q_1 \theta_0^U - q_1^2 - q_1 + 1}{q_1(q_1^2 + q_1 - 1)}$, $\theta_{1,4}^U = \frac{q_0}{q_1^2}$.

4.5.2 Choice Probabilities of Consumption Strategies

We use the relevant result of a consumer choice model with vertically-differentiated variants (Berry 1994, Akcay et al. 2010). We illustrate this using RO1, as defined in Table 4.4, i.e., $\hat{\theta}_1 > \hat{\theta}_2 > \hat{\theta}_3 > \hat{\theta}_4 > \hat{\theta}_5 > \hat{\theta}_6 > \hat{\theta}_7 > \hat{\theta}_8 > \hat{\theta}_9 > \hat{\theta}_{10} > \hat{\theta}_{11} > \hat{\theta}_{12}$ where Strategy-(I, I, I, I), with the attribute value $\hat{\theta}_{12} = 0$, is treated as an outside option.

A w-consumer's utility, u_w^i, from the consumption of Strategy i with attribute value $\hat{\theta}_i$ at price $\hat{p}_i(\boldsymbol{p})$, is given by $u_w^i = w\hat{\theta}_i - \hat{p}_i(\boldsymbol{p}), \quad i = 1, \ldots, n$, (in our problem context, $n = 11$) where w is a uniform random variable between [0,1], and $\hat{\theta}_i$ is decreasing in i. Here, all consumers agree on the attribute values $\hat{\theta}_i$ and their rank order, and the distribution of w captures the heterogeneity of consumer sensitivity to $\hat{\theta}_i$. To determine consumer choice probabilities, it is sufficient to consider prices such that (Akcay et al. 2010)

$$0 \le \frac{\hat{p}_n(\boldsymbol{p}) - \hat{p}_{n+1}(\boldsymbol{p})}{\hat{\theta}_n - \hat{\theta}_{n+1}} \le \frac{\hat{p}_{n-1}(\boldsymbol{p}) - \hat{p}_n(\boldsymbol{p})}{\hat{\theta}_{n-1} - \hat{\theta}_n} \le \cdots \le \frac{\hat{p}_1(\boldsymbol{p}) - \hat{p}_2(\boldsymbol{p})}{\hat{\theta}_1 - \hat{\theta}_2} \le 1, \tag{4.4}$$

where variant $n+1$ represents the outside option with $\hat{p}_{n+1} = \hat{\theta}_{n+1} = 0$. For prices $\boldsymbol{p}$ satisfying (4.4), the probability that a consumer chooses variant (strategy) i, denoted by $m_i(\hat{\boldsymbol{p}})$, can be expressed as

$$m_i(\boldsymbol{p}) = \begin{cases} 1 - \frac{\hat{p}_1(\boldsymbol{p}) - \hat{p}_2(\boldsymbol{p})}{\hat{\theta}_1 - \hat{\theta}_2}, & i = 1, \\ \frac{\hat{p}_{i-1}(\boldsymbol{p}) - \hat{p}_i(\boldsymbol{p})}{\hat{\theta}_{i-1} - \hat{\theta}_i} - \frac{\hat{p}_i(\boldsymbol{p}) - \hat{p}_{i+1}(\boldsymbol{p})}{\hat{\theta}_i - \hat{\theta}_{i+1}}, & i = 2, \ldots, n, \\ 1 - \sum_{j=1}^{n} m_j(\boldsymbol{p}) = \frac{\hat{p}_n(\boldsymbol{p})}{\hat{\theta}_n}, & i = n+1. \end{cases} \tag{4.5}$$

In our problem context, (4.4) and (4.5) imply that interval [0,1] can be partitioned into $n+1 = 12$ segments by $n = 11$ cutoff points,

$$w_i(\boldsymbol{p}) = 1 - \sum_{j=1}^{i} m_j(\boldsymbol{p}) = \frac{\hat{p}_i(\boldsymbol{p}) - \hat{p}_{i+1}(\boldsymbol{p})}{\hat{\theta}_i - \hat{\theta}_{i+1}} \quad i = 1, 2, \ldots, n, \tag{4.6}$$

such that a w-consumer will choose Strategy 1 if $w \in (w_1(\boldsymbol{p}), 1]$, choose Strategy i, $i = 2, \ldots, n$, if $w \in (w_i(\boldsymbol{p}), w_{i+1}(\boldsymbol{p})]$, and choose the outside option (Strategy-(I, I, I, I)) if $w \in [0, w_n(\boldsymbol{p})]$. The cutoff point $w_i(\boldsymbol{p})$ itself can be understood as the aggregate fraction of consumers who select one of the $(n - i)$ least valuable strategies or the outside option.

4.5.3 The Manufacturer's Problem

From the manufacturer's perspective, the optimal stationary price vector $\boldsymbol{p^*}$ is her enabler to induce consumer behaviors that result in her maximum expected profit. In other words, we can consider each rank order of the twelve consumption strategies as a set of vertically-differentiated products that the manufacturer can offer to the consumers. We now formulate the manufacturer's long-run average profit maximization problem. Given $\boldsymbol{p}$, the manufacturer's long-run average profit, denoted by $u^M(\boldsymbol{p})$, is the sum of the long-run average payments from consumer segments playing different consumption strategies, subtracted by the manufacturer's long-run average cost of inducing such strategies.

The manufacturer's long-run average profit maximization problem depends on the rank order of the twelve strategies. To be consistent with Section 4.5.2, we again use RO1 defined in Table 4.4, as an example. Under RO1, the manufacturer's maximization problem is

$$u^M = \max_{\boldsymbol{p}} \left\{ u^M(\boldsymbol{p}) \right\} = \max_{\boldsymbol{p}} \left\{ \sum_{i=1}^{n} m_i(\boldsymbol{p})(\hat{p}_i(\boldsymbol{p}) - c_i) \right\}, \tag{4.7}$$

$s.t.$

$$0 \le \frac{\hat{p}_n(\boldsymbol{p}) - \hat{p}_{n+1}(\boldsymbol{p})}{\hat{\theta}_n - \hat{\theta}_{n+1}} \le \frac{\hat{p}_{n-1}(\boldsymbol{p}) - \hat{p}_n(\boldsymbol{p})}{\hat{\theta}_{n-1} - \hat{\theta}_n} \le \cdots \le \frac{\hat{p}_1(\boldsymbol{p}) - \hat{p}_2(\boldsymbol{p})}{\hat{\theta}_1 - \hat{\theta}_2} \le 1, \tag{4.8}$$

$$m_1(\boldsymbol{p})\pi^1_{(N,1,\boldsymbol{p}_1)} + m_7(\boldsymbol{p})\pi^7_{(N,1,\boldsymbol{p}_1)} + m_8(\boldsymbol{p})\pi^8_{(N,1,\boldsymbol{p}_1)} =$$
$$m_3(\boldsymbol{p})\pi^3_{(\bar{N},1,\boldsymbol{p}_1)} + m_4(\boldsymbol{p})\pi^4_{(\bar{N},1,\boldsymbol{p}_1)} + m_{10}(\boldsymbol{p})\pi^{10}_{(\bar{N},1,\boldsymbol{p}_1)}, \tag{4.9}$$

where $\hat{p}_i(\boldsymbol{p})$ and c_i are the payment and the cost associated with Strategy i, which can be seen from Table 4.3, (4.9) is due to the secondary market clearance condition, and $n = 11$.

Proposition 4.5.2. *The manufacturer's profit-maximization problem is a quadratic program and has a unique global maximizer $\boldsymbol{p}^*$.*

Proof. Proof. It is easy to show that the Hessian matrix of the objective function (4.7) is negative definite *everywhere* by verifying that the seven leading principal minors alternate in sign and start with a negative first-order leading principal minor. This, along with the linear constraints, guarantees that the quadratic program has a unique global maximizer if there exists at least one $\boldsymbol{p}^*$ vector satisfying (4.8)-(4.9). □

4.6. Results

4.6.1 The Optimal Strategy Sets

A summary of the optimal strategy sets, labeled as $OS_1 - OS_5$, under different parameter value ranges are provided in Table 4.5 and illustrated by Figure 4.1, in which parameter c_1 and the four conditions expressed as functions of $\gamma(c)$, labeled as $\gamma_j(c)$, $j = 1, 2, 3, 4$, are defined as:

$$c_1 = \frac{\theta_1^U(q_1\theta_1^U - (1+q_1)\theta_0^U + 1)}{\theta_1^U - \theta_0^U}, \tag{4.10}$$

$$\begin{aligned}\gamma_1(c) = &\frac{(1-\theta_1^U)(\theta_1^U - q_0\theta_0^U - 1)}{q_1\left((2-q_1^2){\theta_1^U}^2 + (2-q_1-q_1^2)\theta_0^U\theta_1^U - 2\theta_1^U + q_0\theta_0^U + 1\right)}c+ \\ &+ \frac{(1-\theta_1^U)(1 - q_0\theta_0^U\theta_1^U - q_1{\theta_1^U}^2 - q_0\theta_1^U - +q_0\theta_0^U)}{q_1\left((2-q_1^2){\theta_1^U}^2 + (2-q_1-q_1^2)\theta_0^U\theta_1^U - 2\theta_1^U + q_0\theta_0^U + 1\right)},\end{aligned} \tag{4.11}$$

$$\begin{aligned}\gamma_2(c) = &\frac{(\theta_1^U - q_0\theta_0^U - 1)(1-(1+q_0)\theta_1^U + q_0\theta_0^U)}{q_1\left((2-q_1^2){\theta_1^U}^2 + (2-q_1-q_1^2)\theta_0^U\theta_1^U - 2\theta_1^U + q_0\theta_0^U + 1\right)}c+ \\ &+ \frac{(1-(1+q_0)\theta_1^U + q_0\theta_0^U)(1 - q_1^2{\theta_1^U}^2 - q_0\theta_0^U\theta_1^U - q_0\theta_1^U + q_0\theta_0^U)}{q_1\left((2-q_1^2){\theta_1^U}^2 + (2-q_1-q_1^2)\theta_0^U\theta_1^U - 2\theta_1^U + q_0\theta_0^U + 1\right)},\end{aligned} \tag{4.12}$$

$$\begin{aligned}\gamma_3(c) = &\frac{(3q_1^2 - 5q_1){\theta_1^U}^2 + (2q_1^2 - 3q_1 + 1){\theta_0^U}^2 - (5q_1^2 - 8q_1 + 2)\theta_0^U\theta_1^U + (3q_1 - 2)(\theta_1^U - \theta_0^U) + 1}{q_1((1+q_1)\theta_0^U - q_1\theta_1^U - 1)(q_0\theta_0^U + q_1\theta_1^U + 1)}c+ \\ &+ \frac{(3q_1^3 - 5q_1^2){\theta_1^U}^3 - (q_1^3 - q_1^2 - q_1 + 1){\theta_0^U}^3 + (4q_1^3 - 4q_1^2 - 2q_1 + 2){\theta_0^U}^2\theta_1^U - (6q_1^3 - 7q_1^2 - 3q_1)\theta_0^U{\theta_1^U}^2}{q_1((1+q_1)\theta_0^U - q_1\theta_1^U - 1)(q_0\theta_0^U + q_1\theta_1^U + 1)} \\ &+ \frac{(6q_1^2 - 7q_1){\theta_1^U}^2 + (3q_1^2 - 2q_1 - 1){\theta_0^U}^2 - (8q_1^2 + 6q_1)\theta_0^U\theta_1^U + (4q_1 - 2)\theta_1^U - (3q_1 + 1)\theta_0^U + 1}{q_1((1+q_1)\theta_0^U - q_1\theta_1^U - 1)(q_0\theta_0^U + q_1\theta_1^U + 1)},\end{aligned} \tag{4.13}$$

$$\gamma_4(c) = -\frac{1}{q_1}c + \frac{q_1\theta_1^U + q_0\theta_0^U + 1}{q_1}. \tag{4.14}$$

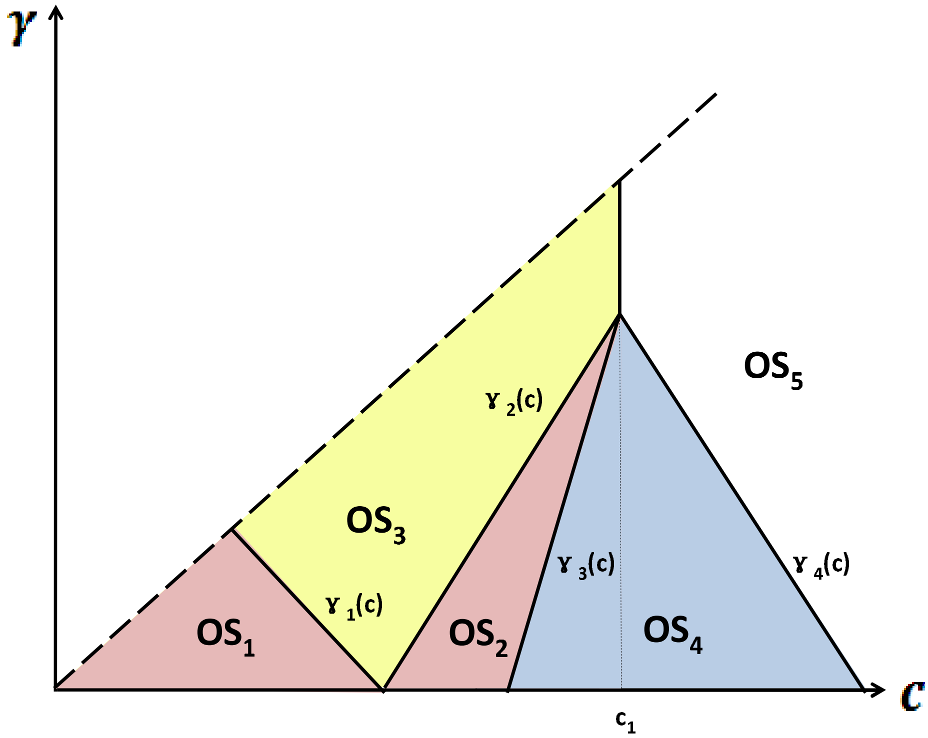
The optimal cutoff points $\boldsymbol{w}^*$ for each of the optimal strategy set are provided in Appendix D.

As can be seen from Table 4.5, six consumption strategies, Strategy 1 (N, N, N, N),

Table 4.5: Optimal Strategy Sets and Corresponding Conditions

Conditions	The Optimal Strategy Set
$\gamma \leq \gamma_1(c)$	$OS_1 = \{S1, S2, S5, S11, S12\}$
$\gamma_3(c) < \gamma \leq \gamma_2(c)$	$OS_2 = \{S2, S5, S7, S11, S12\}$
$\gamma > \gamma_1(c)$ & $\gamma > \gamma_2(c)$ & $c \leq c_1$	$OS_3 = \{S2, S5, S12\}$
$\gamma \leq \gamma_3(c)$ & $\gamma \leq \gamma_4(c)$	$OS_4 = \{S7, S11, S12\}$
$\gamma > \gamma_4(c)$ & $c > c_1$	$OS_5 = \{S12\}$

Figure 4.1: Optimal Strategy Sets



Strategy 2 (N, N, K, N), Strategy 5 (K, N, K, N), Strategy 7 (K, N, N, N), Strategy 11 (K, I, K, U), and Strategy 12 (I, I, I, I), make to the optimal strategy sets. To understand them better, Strategy-(N, N, N, N) consumers are the highest-valuation consumers who highly value both new technology and a product's physical newness and therefore demand a new product in every period. Strategy-(N, N, K, N) consumers also highly value new technology and adopt immediately, but unlike Strategy-(N, N, N, N) consumers, they keep their used units as long as the featured technology is still current. These consumers are technology conscious, but do not consider physical newness a must. Strategy-(K, N, N, N) consumers are the opposite to Strategy-(N, N, K, N) consumers: they delay their new technology adoption whenever possible (i.e., when they have a used product on hand), but require a brand-new unit every period after they start to adopt. These consumers can be regarded as a technology skeptical type since they tend to wait for other consumers to try out a new technology first. Strategy-(K, N, K, N) consumers are insensitive to technological innovations. They always keep a product for its entire physical lifetime regardless of the technology it features. Strategy-(K, I, K, U) consumers are low-end consumers who adopt a current technology only when used products that feature it become available. Finally, Strategy-(I, I, I, I) consumers remain inactive the entire time. Among the six strategies, Strategy 1 (N, N, N, N) involves both state-0 and state-1 trade-ins, Strategy 2 (N, N, K, N) trades in at state 0 only, while Strategy 7 (K, N, N, N) and Strategy 11 (K, I, K, U) participate in state-1 trade-in. Based on these six strategies, $OS_1 - OS_5$ are defined as shown in Table 4.5. OS_1 includes Strategies 1, 2, 5, 11, and 12; OS_2 includes Strategies 2, 5, 7, 11, and 12; OS_3 includes Strategies 2, 5, and 12; OS_4 includes Strategies 7, 11, and 12; and OS_5 only includes Strategy 12, which is the inactive region. Note that OS_1 and OS_2 (represented by the pink regions in Figure 4.1) invoke trade-ins at both states 0 and 1, while OS_3 (represented in yellow) is a state-0 trade-in only scenario and OS_4 (represented in blue) is a state 1 trade-in only scenario.

Figure 4.1 presents the optimal strategy sets on the $c-\gamma$ space, i.e., for a given set of $(q_0, \theta_1^U, \theta_0^U)$ values, it shows the change of optimal strategy set as c and γ change. First we discuss the impact of resell cost γ on the choice of optimal strategy set. When production cost c is not too high, as resell cost increases, the optimal strategy set changes from OS_1, OS_2, or OS_4, where the first two offer trade-in at both state 0 and state 1 and the latter one is the state-1 trade-in only scenario, to OS_3, which is the state-0 trade-in only scenario. This is straightforward because when secondary market activities cost more, the manufacturer inclines to stop offering used products at state 1. On the other hand, when production cost is very high where OS_4 is chosen as the optimal strategy set when resell cost is low (the blue area to the right of the $c = c_1$ vertical line in Figure 4.1), as resell cost increases, it becomes unprofitable for the manufacturer to remain active. Note that under this situation, the manufacturer cannot benefit from a state-0 trade-in only scenario (i.e., OS_3) because of the high production cost.

Next, we examine the impact of production cost on the optimal strategy set. When γ is low, a typical change of the optimal strategy set as c increases is from OS_1 to OS_3 to OS_2 to OS_4. Recall that Strategy-(N, N, N, N) requires a brand-new product in every period; hence, a manufacturer needs to have both low production cost and low resell cost in order to induce Strategy-(N, N, N, N) as an optimal strategy. Hence, as c increases, Strategy-(N, N, N, N) is no longer optimal and the optimal set adjusts to OS_3, with the dropping out of Strategy-(N, N, N, N) and its companion strategy due to secondary market clearance condition, Strategy-(K, I, K, U). However, a more interesting change is that when production cost becomes even higher, the manufacturer is better off to choose OS_2, which induces Strategy-(K, N, N, N) and Strategy-(K, I, K, U) addition to the three strategies in OS_3. The intuition is as follows. When c is even higher (while γ stays the same), the manufacturer can offset the high production cost to some degree by engaging in state-1 trade-in to facilitate the transaction of used products, and therefore should switch to an optimal strategy set that offers both state-0 and state-1 trade-ins. Moreover, because Strategy-(N, N, N, N) should be invoked only under low c and low γ situation, the manufacturer in this case should induce Strategy-(K, N, N, N), the other strategy that serves as a supplier to the secondary market, instead. For even higher c, the manufacturer stops offering state-0 trade-in and changes to a state-1 trade-in only scenario, OS_4, before she goes out of business entirely. It is also worth noticing that under an extreme case where $\gamma = 0$ (which approximates to cases where secondary markets are extremely efficient and mature or the condition of used products can be tested and evaluated easily), regardless of values of the other parameters, the manufacturer should always play the intermediary role in the secondary market, as shown by Figure 4.1) that OS_3 is never optimal.

In summary, facing the same innovation process and product wear and tear situation, manufacturers with different cost structures should induce different combinations of consumption strategies in order to maximize their expected profit. Low-c and low-γ manufacturers should take advantage of both state-0 and state-1 trade-ins and induce the highest-valuation consumers to adopt Strategy-(N, N, N, N) (i.e., choose OS_1). Low-c and high-γ manufacturers clearly should choose the state-0 trade-in only scenario, OS_3, because state-1 trade-in is too expensive to offer and the low production cost allows to promote new technology aggressively. High-c and low-γ manufacturers should choose OS_2 which uses a lower-valuation strategy, Strategy-(K, N, N, N) (compared to Strategy-(N, N, N, N)) to take advantage of the low resell cost by offering state-1 trade-in. Apparently OS_2 sustains for a certain range of the production cost, and for even higher c, the state-1 trade-in only scenario OS_4 should be selected.

4.6.2 The Impact of Parameter Values on the Manufacturer's Maximum Expected Profit

Although we have explicit expressions for the optimal strategy sets, the optimal prices, and the resulting maximum long-run average profit for the manufacturer, these expressions are rather cumbersome for analytical examination. Hence, we design a numerical study to understand the model results. Specifically, the value sets of the five parameters are as follows: q_0 is between 0.01 and 0.97, with an interval of 0.04, θ_1^U is between 0.01 and 0.97, with an interval of 0.06, θ_0^U is between 0 and 0.96 with an interval of 0.06, c is between 0.1 and 1.1, with an interval of 0.2, and γ is between 0 and 0.6, with an interval of 0.1. As discussed, we limit the parameter values to: (1)

$\theta_0^U < \theta_1^U$, (2) $\gamma < c$, and (3) $\theta_1^U > \frac{1+q_0\theta_0^U}{1+q_0}$ (from (4.1)). Taking these three assumptions into account, there are a total of 33342 cases in the numerical study, which are the basis of the discussion in this section.

When the parameters assume different values, the optimal strategy set that the manufacturer should induce changes according to the results presented in Section 4.6.1. We examine in this section the impact of the five parameters on the manufacturer's maximum long-run average profit assuming that the optimal strategy set is induced. The numerical study reveals that the impact of c and γ are monotonic and rather obvious: as either cost increases, the manufacturer's expected profit decreases. We now focus on the other three parameters: innovation frequency q_0, and the valuations of state-0 and state-1 used products, θ_0^U and θ_1^U, respectively. In order to make the discussion more straightforward, we use functional depreciation (FD) and technological obsolescence (TO) as substitutes for θ_0^U and θ_1^U. Recall that their relationships are: $\mathrm{FD} = 1 - \theta_1^U$ and $\mathrm{TO} = \theta_1^U - \theta_0^U$.

We first examine the impact of technological obsolescence (TO) on the manufacturer's expected profit. Under the majority of the parameter value ranges in the numerical study, when TO increases, the manufacturer's expected profit decreases. The explanation is that everything else holds equal, higher technological obsolescence implies that consumers value state-0 used products lower, i.e., θ_0^U is lower; consequently, lower willingness-to-pay translates to lower profit for the manufacturer. However, the numerical study shows that there are exceptions where the manufacturer's expected profit increases along with increasing TO. As summarized by Table 4.6 (where "I" and "D" indicate the increasing and decreasing trends of the manufacturer's expected profit, respectively), these exceptions are characterized by parameter value regions where production cost is low, functional depreciation is not severe, and innovation doesn't occur very frequently. As shown in Table 4.6, in the region that has low c, low FD, and low q_0, "I" is observed for 38.32% of the cases in that region;

and it is not detected in any other regions.

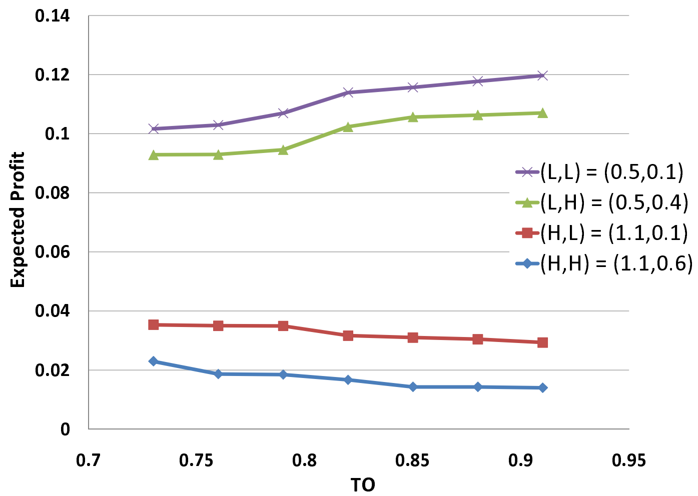
The intuition is as follows. When functional depreciation is not severe, state-1 trade-in is not as attractive to high-valuation consumers because the gain from replacing a one-period-old product by a brand-new unit featuring the technology is not much. Along with the fact that innovation frequency is relatively low, the manufacturer does not have much opportunities to implement state-0 trade-in either. Under such situation, if the degree of technological obsolescence can be broadened, she can better incentivize consumers to adopt new technology as soon as it becomes available because keeping a previous-generation product is valued less by the consumers. Coupled with low production cost, which ensures that state-0 trade-in is not too costly to offer, the manufacturer can actually benefit from more severe technological obsolescence. Figure 4.2 provides an illustrative example. We consider four different cost structures as shown in Figure 4.2, which are defined by the pairs of c and γ: $(L, L) = (0.5, 0.1)$ represents low production cost (which is 0.5 in this case) and low resell cost (which is 0.1), $(L, H) = (0.5, 0.4)$ represents low production cost and high resell cost, $(H, L) = (1.1, 0.1)$ represents high production cost and low resell cost, and $(H, H) = (1.1, 0.6)$ represents high production cost and high resell cost. The four cost structures are compared under the same FD of 0.09 and q_0 of 0.13, which qualify for the low functional depreciation and low innovation frequency region. It is clear to see that when production cost is low (as represented by (L, L) and (L, H)), as technological obsolescence increases, the expected profit increases; however, this is not the case when production cost is high (as represented by (H, L) and (H, H)).

Table 4.6: The Impact of Technological Obsolescence on Expected Profit

	Low c (0.1-0.5)						High c (0.7-1.1)	
	Low FD (0.03 - 0.15)				High FD (0.21 - 0.45)		All FD	
	Low q_0 (0.05 - 0.29)		High q_0 (0.33-0.97)		All q_0		All q_0	
As TO ↑,	I	D	I	D	I	D	I	D
% Cases	38.32%	61.68%	0%	100%	0%	100%	0%	100%

Next, we examine the impact of functional depreciation (FD) on the manufac-

Figure 4.2: Illustrative Example of the Impact of TO on Expected Profit with $q_0 = 0.13$ and FD $= 0.09$

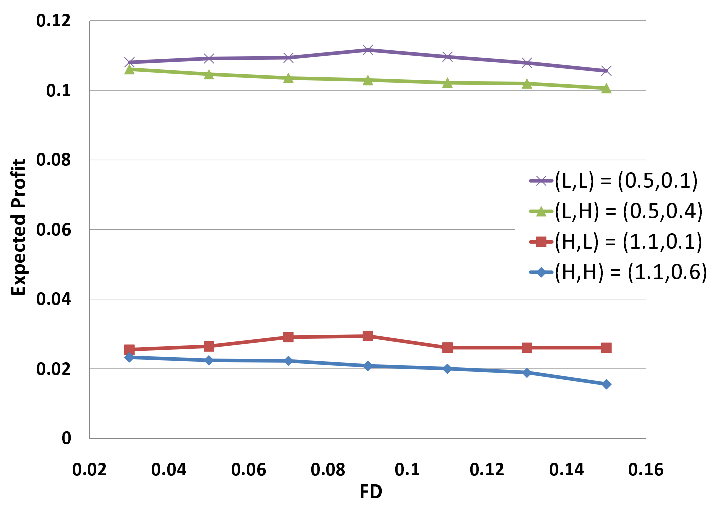


turer's expected profit. Following the same logic, we can argue that as FD increases, the manufacturer's expected profit decreases due to lowered consumer valuation of state-1 used product (i.e., lower θ_1^U). This, again, is supported by the majority of the parameter value ranges in the numerical study. However, there are also exceptions where as FD increases, the manufacturer's profit increases as well, which are identified by regions with low resell cost, moderate innovation frequency, and low technological obsolescence. As summarized by Table 4.7, in the region with low γ, moderate q_0, and low TO, 22.15% of the cases exhibit "I", i.e., increasing expected profit when functional depreciation increases; and "I" is not observed in any other regions. The explanation for the profit increase is as follows. When q_0 is moderate, state-0 and state-1 activities contribute balanced to the manufacturer's profit (as opposed to scenarios where q_0 is too low or too high); when technological obsolescence is not severe, which means that consumers are not well-incentivized to participate in state-0 trade-in, the manufacturer should resort to state-1 trade-in for improved profitability. Under such scenarios, making the product perfectly durable is not favorable; rather, the manufacturer can benefit from making it less durable physically to some degree as long as she is cost-efficient when serving as the intermediary in the secondary market, i.e., γ is low. Figure 4.3 gives an example where the four cost structures are defined the same as those in Figure 4.2, and q_0 and TO values are set at 0.61 and 0.25, respectively. It shows that as FD increases, low resell cost structures ((L, L) and (H, L)) experience profit increase, while high resell cost structures ((L, H) and (H, H)) do not. Also note that profit improvement sustains only for low to moderate functional depreciation; when FD becomes excessive, further increase starts to hurt profitability.

Table 4.7: The Impact of Functional Depreciation on Expected Profit

	Low γ (0.1-0.3)								High γ (0.7-1.1)	
	Low q_0 (0.05-0.33)		Moderate q_0 (0.37-0.77)				High q_0 (0.81-0.97)		All q_0	
	All TO		Low TO (0.07-0.43)		High TO (0.49-0.97)		All TO		All TO	
As FD ↑,	I	D	I	D	I	D	I	D	I	D
% Cases	0%	100%	22.15%	77.85%	0%	100%	0%	100%	0%	100%

Figure 4.3: Illustrative Example of the Impact of FD on Expected Profit with $q_0 = 0.61$, TO $= 0.25$

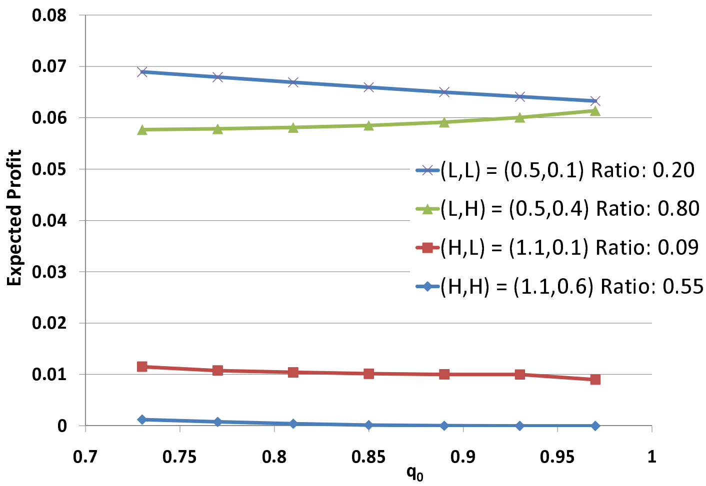


Lastly, we discuss the impact of innovation frequency on the manufacturer's expected profit. The impact of innovation frequency is mixed and depends on the values of the other parameters. On the one hand, everything else holds equal, as innovation becomes more frequent, it reduces the manufacturer's expected profit because higher frequency means shorter "realized" product lifespan in the market where the manufacturer makes profit from (because technologically obsolete products are disposed elsewhere), and hence the manufacturer has shorter time to recover the production cost of a product. On the other hand, higher innovation frequency gives the manufacturer more opportunities to increase product sales by encouraging early technology adoption through trade-ins. The dominance of the two forces depends on the other aspects of the business environment that the manufacturer faces. We summarize in Table 4.8 the net effect of the two forces in different parameter value ranges. We explain here the scenario under which the latter dominates the former, i.e., as q_0 increases, the manufacturer's expected profit increases (which is represented by "I" in the table). As seen from Table 4.8, in the region where γ/c ratio (the ratio of resell cost to production cost) and FD/TO ratio (the ratio of functional depreciation to technological obsolescence) are high, 65.05% of the cases show profit increase as q_0 increases; none of the other regions has the phenomenon. With high FD and high γ, the manufacturer cannot make much profit by engaging in secondary market activities at state 1 because used products are not valued much by consumers, but the cost of offering them are high. Given that functional depreciation has already greatly deteriorated the value of a one-period-old product, the manufacturer is better off by deliberately introducing innovation to fully depreciate the product from the technology perspective and using state-0 trade-in to promote innovation adoption. Figure 4.4 provides an illustrative example where the high FD/TO ratio of 0.71 remains the same for the four cost structures as defined in Figure 4.2. Among the four cost structures, the high γ/c ratio one, (L, H), exhibits profit increase as q_0 increases. Note that high resell cost alone doesn't guarantee an increasing-profit scenario (as shown by (H, H)); relatively low production cost is essential because it ensures that expedited obsolescence and state-0 trade-in are profitable.

Table 4.8: The Impact of Innovation Frequency on Expected Profit

	Low γ/c (0-0.60)				High γ/c (0.61-0.86)			
	Low FD/TO (0.03-0.40)		High FD/TO (0.41-0.92)		Low FD/TO (0.03-0.40)		High FD/TO (0.41-0.92)	
As q_0 ↑,	I	D	I	D	I	D	I	D
% Cases	0%	100%	0%	100%	0%	100%	65.05%	34.95%

Figure 4.4: Illustrative Example of the Impact of Innovation Frequency on Expected Profit with FD/TO Ratio = 0.71 (FD=0.39, TO =0.55)



4.7. Conclusions and Future Research

In this paper, we study the problem of a monopolistic manufacturer offering a technology product to a heterogeneous consumer population where trade-in programs can be provided either as an incentive to accelerate innovation adoption or as a means to facilitate replacing used products by brand-new ones that feature the same technology. We characterize the optimal stationary pricing strategy for the manufacturer and the resulting optimal consumption strategies that heterogenous consumers should choose to maximize their own utility.

Several key insights provided by our analysis are summarized as follows. First, given the same exogenous innovation process and degree of functional depreciation, low production and resell cost manufacturers should take advantage of trade-in programs regardless of innovation occurrence; low production cost and high resell cost manufacturers should offer trade-in programs only when innovation occurs; and high production cost and low resell cost manufacturers should do the opposite. Second, although technological obsolescence and functional depreciation reduce the value of used products, when innovation is infrequent, manufacturers who face gentle functional depreciation and low production cost can benefit from higher technological obsolescence; when innovation frequency is moderate and technological obsolescence is mild, low resell cost manufacturers can profit from making their products less durable physically. Third, manufacturers with high resell cost and severe product wear and tear should increase innovation frequency to achieve higher profit.

Leasing is another commonly used strategy by companies to encourage product upgrades and to gain better control over the secondary market. Therefore, for future research, it is interesting to study leasing under the same setting and compare its result to that of the trade-in strategy.

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Appendix A

Summary Statistics

	Relative Frequency									
Count	B1	R1	B2	R2	B3	R3	B4	R4	B5	R5
0	0.08	0.34	0.06	0.32	0.07	0.34	0.05	0.41	0.35	0.27
1	0.32	0.24	0.42	0.35	0.37	0.30	0.46	0.31	0.17	0.24
2	0.21	0.12	0.11	0.09	0.13	0.08	0.18	0.10	0.10	0.17
3	0.07	0.07	0.06	0.04	0.06	0.04	0.06	0.03	0.05	0.06
4	0.06	0.04	0.06	0.04	0.07	0.03	0.05	0.04	0.03	0.05
5	0.02	0.02	0.03	0.02	0.03	0.02	0.04	0.03	0.03	0.02
6	0.04	0.03	0.05	0.03	0.03	0.02	0.02	0.02	0.03	0.03
7	0.02	0.01	0.01	0.00	0.04	0.04	0.02	0.00	0.02	0.02
8	0.01	0.01	0.01	0.00	0.01	0.01	0.02	0.01	0.01	0.02
9	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01
10	0.02	0.02	0.02	0.00	0.02	0.01	0.01	0.01	0.03	0.01
> 10	0.13	0.09	0.15	0.09	0.17	0.09	0.08	0.03	0.16	0.11
Sample Size	302		414		103		410		454	
Sample Mean	5.04	3.41	8.61	3.36	6.63	3.47	4.10	1.87	9.29	3.87
Sample SD	23.48	22.00	32.78	22.43	32.15	22.04	18.34	14.44	32.27	22.01
Count	B6	R6	B7	R7	B8	R8	B9	R9	B10	R10
0	0.54	0.21	0.17	0.20	0.06	0.59	0.21	0.31	0.11	0.35
1	0.15	0.29	0.19	0.21	0.27	0.13	0.23	0.22	0.21	0.22
2	0.09	0.19	0.10	0.10	0.16	0.10	0.10	0.11	0.14	0.13
3	0.04	0.08	0.07	0.07	0.10	0.06	0.08	0.07	0.11	0.07
4	0.04	0.04	0.06	0.05	0.07	0.03	0.08	0.08	0.08	0.06
5	0.01	0.04	0.06	0.05	0.06	0.03	0.02	0.02	0.05	0.04
6	0.02	0.02	0.04	0.03	0.06	0.01	0.04	0.03	0.04	0.02
7	0.01	0.01	0.03	0.03	0.04	0.01	0.01	0.00	0.02	0.00
8	0.00	0.02	0.02	0.01	0.01	0.00	0.05	0.02	0.00	0.01
9	0.01	0.00	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01
10	0.01	0.02	0.04	0.04	0.03	0.01	0.02	0.01	0.02	0.00
> 10	0.09	0.09	0.19	0.18	0.14	0.03	0.14	0.11	0.20	0.09
Sample Size	140		297		224		284		110	
Sample Mean	3.43	3.72	13.29	6.70	5.91	1.57	6.00	4.05	9.39	3.03
Sample SD	24.25	22.01	25.96	30.77	24.92	13.75	26.04	22.51	24.19	20.17

	Relative Frequency									
Count	B11	R11	B12	R12	B13	R13	B14	R14	B15	R15
0	0.20	0.05	0.19	0.48	0.61	0.22	0.76	0.14	0.28	0.43
1	0.18	0.24	0.28	0.19	0.07	0.11	0.05	0.33	0.05	0.08
2	0.12	0.17	0.15	0.13	0.09	0.25	0.08	0.19	0.28	0.19
3	0.07	0.07	0.08	0.04	0.02	0.03	0.03	0.09	0.01	0.02
4	0.07	0.07	0.04	0.03	0.03	0.13	0.03	0.06	0.15	0.14
5	0.04	0.04	0.05	0.04	0.02	0.01	0.01	0.06	0.02	0.03
6	0.03	0.05	0.04	0.02	0.04	0.05	0.02	0.03	0.04	0.01
7	0.02	0.02	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.02
8	0.01	0.01	0.03	0.02	0.02	0.04	0.00	0.03	0.04	0.02
9	0.02	0.02	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00
10	0.03	0.04	0.03	0.01	0.01	0.03	0.02	0.00	0.02	0.00
> 10	0.21	0.22	0.10	0.03	0.09	0.13	0.02	0.06	0.10	0.05
Sample Size	397		98		142		138		201	
Sample Mean	7.02	7.23	4.12	2.03	3.34	5.03	1.16	3.01	4.41	2.72
Sample SD	26.50	30.00	16.68	14.98	24.21	22.84	13.70	14.13	17.66	15.10
Count	B16	R16	B17	R17	B18	R18	B19	R19	B20	R20
0	0.67	0.19	0.70	0.16	0.21	0.42	0.11	0.37	0.11	0.44
1	0.01	0.15	0.03	0.05	0.34	0.28	0.21	0.16	0.14	0.11
2	0.05	0.14	0.03	0.16	0.14	0.13	0.13	0.09	0.10	0.04
3	0.00	0.05	0.09	0.18	0.10	0.05	0.08	0.06	0.08	0.08
4	0.01	0.07	0.00	0.07	0.05	0.02	0.08	0.06	0.09	0.05
5	0.01	0.05	0.01	0.03	0.03	0.02	0.03	0.04	0.07	0.04
6	0.01	0.05	0.03	0.11	0.01	0.01	0.04	0.04	0.02	0.02
7	0.00	0.02	0.02	0.01	0.00	0.00	0.02	0.00	0.02	0.02
8	0.02	0.03	0.01	0.01	0.01	0.02	0.02	0.01	0.05	0.02
9	0.00	0.00	0.01	0.05	0.01	0.01	0.01	0.02	0.02	0.02
10	0.01	0.02	0.00	0.02	0.01	0.01	0.04	0.03	0.02	0.01
> 10	0.18	0.22	0.07	0.16	0.08	0.03	0.24	0.13	0.29	0.14
Sample Size	180		85		137		265		277	
Sample Mean	13.16	7.47	2.39	6.49	3.48	1.74	14.86	5.00	16.14	4.92
Sample SD	35.91	31.35	15.96	23.83	16.89	13.14	34.47	29.85	34.16	29.17

Appendix B

Cluster Analysis Based on MAD

Tables B.1 and B.2 provide Pseudo-F statistics and composition of customers in different segments, respectively. MAD results in the same number of customer segments for all twenty products as MSE does, except P6 and P7 where the number of customer segments decreases from four to three. As for customer composition, we observe a slight increase in the number of customers belonging to Segment 4, but overall the total number of customers in each segment and its composition do not change significantly.

Table B.1: Pseudo-F for Cluster Analysis Based on MAD

# Clusters	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
2	22.29	147.66	6.06	143.96	477.33	245.18	126.21	42.72	119.51	49.37
3	45.80	**756.78**	15.88	307.36	**786.19**	**648.31**	**485.81**	**99.68**	**168.85**	**131.20**
4	**140.30**	665.56	**39.07**	**572.58**	684.23	381.05	381.66	80.52	161.34	71.91
5	102.76	458.11	18.49	492.29	541.13	323.08	229.19	60.74	101.77	111.07
# Clusters	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
2	54.08	333.31	70.71	117.72	94.55	3.86	172.48	153.65	266.43	46.84
3	89.56	569.78	**165.65**	**132.57**	**217.44**	20.03	**603.67**	236.18	**706.26**	**105.02**
4	**120.36**	**838.50**	122.10	92.29	115.76	**66.53**	518.82	**825.37**	667.88	97.31
5	117.74	640.17	111.86	87.37	96.02	48.41	276.51	794.42	400.45	82.98

Table B.2: Customer Composition of Cluster Analysis Using MAD

Enterprise Size	Seg 1	Seg 2	Seg 3	Seg 4	Total # of Customers
Small	39 25.00%	21 14.79%	26 22.81%	0 0.00%	86
Medium	80 51.28%	58 40.85%	19 16.67%	11 17.19%	168
Large	37 23.72%	63 44.37%	69 60.53%	53 82.81%	222
# of Customers in Each Segment	156	142	114	64	-

Appendix C

Parameter Estimation of Products 1 &7

Product 1										
Strategy	Segment	Parent Distribution								
		B1	B2	B3	B4	B5	B6	B21	Intercept	Ln(alpha)
S1		0.067*	0.233	-0.092	0.025*	0.021*	0.039*	0.055*	0.277*	2.083*
		(0.031)	(2.455)	(0.078)	(0.011)	(0.010)	(0.018)	(0.026)	(0.122)	(1.033)
S2A	Seg 1	0.132*							0.779*	1.809*
		(0.057)							(0.331)	(0.906)
	Seg 2	0.128*							0.917*	2.024*
		(0.061)							(0.365)	(0.828)
	Seg 3	0.093*							0.995*	1.639*
		(0.046)							(0.415)	(0.688)
S3A	Seg 1	0.111*	0.285	0.425	0.238	0.012*	0.044*	0.395	0.144*	1.200*
		(0.034)	(39.669)	(1.748)	(0.316)	(0.005)	(0.017)	(4.817)	(0.069)	(0.589)
	Seg 2	0.091*	0.170	0.214	-0.014	0.013*	0.050*	0.039*	0.092*	0.926*
		(0.044)	(0.950)	(0.259)	(0.014)	(0.006)	(0.024)	(0.016)	(0.044)	(0.465)
	Seg 3	0.081*	0.479	0.203	0.023*	0.011*	0.023*	0.036*	0.117*	1.366*
		(0.031)	(0.862)	(0.402)	(0.009)	(0.005)	(0.009)	(0.013)	(0.058)	(0.374)
	Seg 4	0.072*	0.345	0.170	0.031*	0.020*	0.048*	0.041*	0.188*	1.492
		(0.031)	(0.347)	(0.243)	(0.012)	(0.009)	(0.023)	(0.018)	(0.081)	(2.060)
		Proportion of Structural Zeros								
		B1	B2	B3	B4	B5	B6	B21	Intercept	
S1										
S2A	Seg 1	0.083*							0.146*	
		(0.033)							(0.067)	
	Seg 2									
	Seg 3	0.079*							0.250*	
		(0.029)							(0.122)	
S3A	Seg 1									
	Seg 2									
	Seg 3	0.007*	0.008	0.432	0.018*	0.006*	0.122	0.020*	0.092*	
		(0.003)	(0.008)	(0.341)	(0.007)	(0.002)	(0.236)	(0.008)	(0.045)	
	Seg 4	0.009*	0.517	-0.113	0.026*	0.013*	0.192	0.423	0.071*	
		(0.003)	(5.906)	(0.265)	(0.011)	(0.005)	(0.199)	(1.620)	(0.028)	

* indicates 5% significance level.

Strategy	Segment	B7	B8	B9	B10	B11	B27	B30	Intercept	Ln(alpha)
		Product 7								
		Parent Distribution								
S1		0.149*	0.091	0.033*	0.093	0.020	0.051*	0.098	0.222*	2.839*
		(0.074)	(0.116)	(0.015)	(0.099)	(0.073)	(0.021)	(0.119)	(0.095)	(1.210)
S2A	Seg 1	0.136*							0.508*	1.331*
		(0.068)							(0.199)	(0.610)
	Seg 2	0.111*							0.697*	1.578*
		(0.054)							(0.300)	(0.640)
	Seg 3	0.121*							0.660*	2.909*
		(0.057)							(0.302)	(1.320)
	Seg 4	0.092*							0.735*	2.092
		(0.045)							(0.323)	(1.382)
S3A	Seg 1	0.156*	0.065	0.059	-0.024	0.086	0.044*	0.045	0.199*	0.675*
		(0.071)	(0.033)	(0.033)	(0.103)	(0.249)	(0.020)	(0.541)	(0.080)	(0.320)
	Seg 2	0.109*	0.077	0.049*	0.460	0.055	0.038*	0.176	0.206*	1.630*
		(0.038)	(0.108)	(0.021)	(0.397)	(0.221)	(0.017)	(0.365)	(0.096)	(0.603)
	Seg 3	0.094*	0.044	0.056*	0.032	0.486	0.049*	0.318	0.490*	2.959*
		(0.047)	(0.048)	(0.026)	(0.02)	(0.258)	(0.019)	(0.474)	(0.214)	(1.220)
	Seg 4	0.064*	0.480	0.051*	0.081	0.366	0.083*	0.106	0.525*	1.628
		(0.031)	(0.375)	(0.017)	(0.111)	(0.718)	(0.035)	(0.057)	(0.195)	(2.248)
		Proportion of Structural Zeros								
		B7	B8	B9	B10	B11	B27	B30	Intercept	
S1										
S2A	Seg 1	0.169*							0.014*	
		(0.085)							(0.005)	
	Seg 2									
	Seg 3	0.056*							0.331*	
		(0.020)							(0.105)	
	Seg 4	0.044*							0.597*	
		(0.020)							(0.263)	
S3A	Seg 1									
	Seg 2	0.143*	0.147	0.024*	0.105	0.247	0.155	0.019	0.096*	
		(0.065)	(0.222)	(0.011)	(0.089)	(0.252)	(2.120)	(0.073)	(0.041)	
	Seg 3	0.146*	0.257	0.052*	0.240	0.208	0.240	0.149	0.481*	
		(0.061)	(0.338)	(0.022)	(0.577)	(0.214)	(0.338)	(0.541)	(0.220)	
	Seg 4	0.192*	0.043	0.041*	0.194	0.209	0.002*	0.216	0.587*	
		(0.095)	(0.027)	(0.015)	(0.251)	(0.315)	(0.001)	(1.151)	(0.238)	

* indicates 5% significance level.

Appendix D

Optimal Cutoff Points

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$$OS_1 = \{S1, S2, S5, S11, S12\}$$

$$w_1^* = \frac{c(q_0\theta_0^U - 2\theta_1^U - q_0\theta_0^U\theta_1^U + \theta_1^{U^2} + 1) + \gamma((-q_1^3)\theta_0^{U^2} + (2q_1)\theta_1^{U^2} + (q_1^3 + q_1^2 - 2q_1)\theta_0^U\theta_1^U + (q_1 - q1^2)\theta_0^U + (-2q_1)\theta_1^U + q_1) - q_1\theta_1^{U^3} - q_0\theta_0^U\theta_1^{U^2} + (2q_1-1)\theta_1^{U^2} + 2q_0\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (2-q_1)\theta_1^U}{(-q_1^4 + 2*q1^3 + q_1^2 - 5q_1)\theta_0^{U^3} + (-q_1^3)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (q_1^4 - q_1^3 - 3q_1^2 + 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (7q_1-1)\theta_1^{U^2} + (2q_1^2 - 4q_1 + 2)\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (-3q_1+2)\theta_1^U - 1}$$

$$w_2^* = \frac{c((q_1^4)\theta_0^{U^3} + (-3q_1^3 + 5q_1)\theta_1^{U^3} + (q_1^4 - q_1^3 - q_1^2 + q_1)\theta_0^{U^2}\theta_1^U + (-2q_1^4 + 4q_1^3 + 2q_1^2 - 5q_1 + 1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (2q_1^3 - 6q_1 + 1)\theta_1^{U^2} + (-2q_1^3 + q_1^2 + 4q_1 - 2)\theta_0^U\theta_1^U + q_0\theta_0^U + (-2q_1^2 + 2q_1 - 2)\theta_1^U + 1)}{(-q_1^4 + 2*q1^3 + q_1^2 - 5q_1)\theta_0^{U^3} + (-q_1^3)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (q_1^4 - q_1^3 - 3q_1^2 + 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (7q_1-1)\theta_1^{U^2} + (2q_1^2 - 4q_1 + 2)\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (-3q_1+2)\theta_1^U - 1}$$

$$\frac{\gamma((q_1^5 - q_1^4 - 3q_1^3)\theta_1^{U^3} + (q_1^5 + q_1^4 - 2q_1^3 - q_1^2 + q_1)\theta_0^{U^2}\theta_1^U + (-2q_1^5 + 6q_1^3 + 2q_1^2)\theta_0^U\theta_1^{U^2} + (q_1^3 - q_1)\theta_0^{U^2} + (2q_1^4 + q_1^3)\theta_1^{U^2} + (-2q_1^4 - 4q_1^3 + 2q_1^2)\theta_0^U\theta_1^U + (-2q_1^2)\theta_0^U + (q_1^3 - 4q_1^2 + 3q_1^2 - q_1)\theta_1^U + q_1)}{(-q_1^4 + 2*q1^3 + q_1^2 - 5q_1)\theta_0^{U^3} + (-q_1^3)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (q_1^4 - q_1^3 - 3q_1^2 + 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (7q_1-1)\theta_1^{U^2} + (2q_1^2 - 4q_1 + 2)\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (-3q_1+2)\theta_1^U - 1}$$

$$+ \frac{q_1^3\theta_0^{U^3} + (q_1^4 - 10q_1^2 + 6q_1)\theta_1^{U^3} + (-q_1^4 + 3q_1^3 - q_1^2 - 3q_1 + 2)\theta_0^{U^2}\theta_1^U + (-6q_1^3 + 16q_1^2)\theta_0^U\theta_1^{U^2} + (q_1^2 - 1)\theta_0^{U^2} + (-q_1^3 + 6q_1^2 + 1)\theta_1^{U^2} + (2q_1^3 - 8q_1^2 + 4q_1)\theta_0^U\theta_1^U + (-2q_1)\theta_0^U + (-q_1^2 - 10q_1 - 2)\theta_1^U + q_1}{(-q_1^4 + 2*q1^3 + q_1^2 - 5q_1)\theta_0^{U^3} + (-q_1^3)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (q_1^4 - q_1^3 - 3q_1^2 + 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (7q_1-1)\theta_1^{U^2} + (2q_1^2 - 4q_1 + 2)\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (-3q_1+2)\theta_1^U - 1}$$

$$w_5^* = \frac{c(2q_1\theta_0^{U^2} + (q_1^3 - 3q_1^2 + 1)\theta_1^{U^2} + (-q_1^3 + 2q_1^2 - q_1)\theta_0^U\theta_1^U + ()\theta_0^U - (2+q_1)\theta_1^U + 1) + \gamma((-q_1^3 - q_1^2)\theta_0^{U^2} + (q_1^4 + 2q_1)\theta_1^{U^2} + (-q_1^4 + 2q_1^2 - q_1)\theta_0^U\theta_1^U + (-q_1^2 + q_1)\theta_0^U + (q_1^3 - 3q_1)\theta_1^U + q_1)}{(-q_1^4 + 2*q1^3 + q_1^2 - 5q_1)\theta_0^{U^3} + (-q_1^3)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (q_1^4 - q_1^3 - 3q_1^2 + 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (7q_1-1)\theta_1^{U^2} + (2q_1^2 - 4q_1 + 2)\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (-3q_1+2)\theta_1^U - 1}$$

$$+ \frac{(q_1^4 - q_1^3 - 4q_1^2 + 9q_1)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (-q_1^4 + 5q_1^2 - 5q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (4q_1^2 - 14q_1)\theta_1^{U^2} + (q1^3 - 4q_1^2 - 5q_1 - 2)\theta_0^U\theta_1^U + (-q_0)\theta_0^U + (-q_1^2 + 6q_1 - 2)\theta_1^U}{(-q_1^4 + 2*q1^3 + q_1^2 - 5q_1)\theta_0^{U^3} + (-q_1^3)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (q_1^4 - q_1^3 - 3q_1^2 + 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (7q_1-1)\theta_1^{U^2} + (2q_1^2 - 4q_1 + 2)\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (-3q_1+2)\theta_1^U - 1}$$

$$w_{11}^* = \frac{c((q_1^3 - 3q_1^2 + 2q_1 + 2)\theta_1^{U^2} + (-q_1^3 + 2q_1^2 - 1)\theta_0^U\theta_1^U + (-q_1 + 1)\theta_0^U + (q_1^2 - q_1 - 4)\theta_1^U + 2) + \gamma((q_1^4 - 2q_1^3 - q_1^2 + 4q_1)\theta_1^{U^2} + (-q_1^4 + q_1^3 + 3q_1^2 - 3q_1)\theta_0^U\theta_1^U + (-2q_1^2 + 2q_1)\theta_0^U + (q_1^3 - 5q_1)\theta_1^U + 2q_1)}{(-q_1^4 + 2*q1^3 + q_1^2 - 5q_1)\theta_0^{U^3} + (-q_1^3)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (q_1^4 - q_1^3 - 3q_1^2 + 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (7q_1-1)\theta_1^{U^2} + (2q_1^2 - 4q_1 + 2)\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (-3q_1+2)\theta_1^U - 1}$$

$$+ \frac{(q_1^4 - q_1^3 - 4q_1^2 + 8q_1)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (-q_1^4 + 5q_1^2 - 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (4q_1^2 - 12q_1)\theta_1^{U^2} + (q_1^3 - 4q_1^2 + 3q_1)\theta_0^U\theta_1^U + ()\theta_0^U + (-q_1^2 + 5q_1)\theta_1^U}{(-q_1^4 + 2*q1^3 + q_1^2 - 5q_1)\theta_0^{U^3} + (-q_1^3)\theta_1^{U^3} + ()\theta_0^{U^2}\theta_1^U + (q_1^4 - q_1^3 - 3q_1^2 + 4q_1)\theta_0^U\theta_1^{U^2} + ()\theta_0^{U^2} + (7q_1-1)\theta_1^{U^2} + (2q_1^2 - 4q_1 + 2)\theta_0^U\theta_1^U + (q_1-1)\theta_0^U + (-3q_1+2)\theta_1^U - 1}$$

$$OS_2 = \{S2, S5, S7, S11, S12\}$$

$$w_1^* = 1$$

$$w_2^* = \frac{1}{2} + \frac{c}{2(q_1\theta_1^U - (q_1+1)\theta_0^U + 1)} -$$

$$- \frac{q_1 c(1 + 2q_0\theta_0^U - 2(1+q_0)\theta_1^U + (1-2q_1)\theta_0^{U^2} + (3-2q_1)\theta_1^{U^2} + q_1^2\theta_0^{U^2} - 2(q_1^2 - 3q_1 + 2)\theta_0^U\theta_1^U - q_1\gamma((q_1^3 + q_1^2 - q_1 - 1)\theta_0^{U^2} - (q_1^3 - q_1^2 - 2q_1)\theta_1^{U^2} + (2q_1^3 + 2q_1^2 + 2q_1 - 2)\theta_0^U\theta_1^U - (1 - 2q_1^2)(\theta_1^U - \theta_0^U) - 1)}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

$$- \frac{q_1((2q_1^2 - 3q_1)\theta_1^{U^3} + q_0^2\theta_0^{U^2}\theta_1^U - 3q_0^2\theta_0^U\theta_1^{U^2} - q_0^2\theta_0^{U^2} - (2q_1^2 - 6q_1 + 3)\theta_1^{U^2} + (3q_1^2 - 8q_1 + 5)\theta_0^U\theta_1^U - 2q_0\theta_0^U + (4 - 3q_1)\theta_1^U)}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

$$w_5^* = \frac{c((-2q_1^3 + 5q_1^2 - 4q_1 + 1)\theta_0^{U^2} + (-3q_1^3 + 8q_1^2 - 5q_1 - 2)\theta_1^{U^2} + (5q_1^3 - 13q_1^2 + 10q_1 + 2)\theta_0^U\theta_1^U + (3q_1^2 - 5q_1)\theta_0^U + (-3q_1^2 + 5q_1 - 2)\theta_1^U - q_0)}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

$$\frac{\gamma((-q_1^4 + q_1^3 + q_1^2 - q_1)\theta_0^{U^2} + (-q_1^4 + q_1^3)\theta_1^{U^2} + (2q_1^4 - 2q_1^3)\theta_0^U\theta_1^U + (2q_1^3 - 2q_1^2)\theta_0^U + (-2q_1^3 + 2q_1^2)\theta_1^U - q1^2 + q1) +}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

$$\frac{(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + (-3q_1^4 + 4q_1^3 + 13q_1^2 - 20q_1)\theta_1^{U^3} + (-4q_1^4 + 6q_1^3 + 6q_1^2 - 14q_1 + 6)\theta_0^{U^2}\theta_1^U + (6q_1^4 - 7q_1^3 - 20q_1^2 + 29q_1 - 8)\theta_0^U\theta_1^{U^2} + (-q_1^3 - 3q_1^2 + 9q_1)\theta_0^{U^2} + (-2q_1^3 - 11q_1^2 + 31q_1 - 8)\theta_1^{U^2} + (2q_1^3 + 14q_1^2 - 32q_1 - 5 + 16)\theta_0^U\theta_1^U + (-q_1^2 + 8q_1 - 7)\theta_0^U}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

$$w_7^* = \frac{1}{2} -$$

$$\frac{c((q_1^3 - q_1^2 + q_1 - 1)\theta_0^{U^2} + (3q_1^3 - 7q_1^2 + q_1 + 4)\theta_1^{U^2} - (4q_1^3 - 7q_1^2 - q_1 + 4)\theta_0^U\theta_1^U - (q_1^2 + q_1 - 2)\theta_0^U + 2(q_1^2 - 2)\theta_1^U + 1) - \gamma((q_1^4 - q_1^3 - q_1^2 + q_1)\theta_0^{U^2} + (2q_1^4 - 3q_1^3 - 2q_1^2 + 4q_1)\theta_1^{U^2} + (-3q_1^4 + 3q_1^3 + 4q_1^2 + 4q_1)\theta_0^U\theta_1^U + (-q_1^3 - q_1^2 + 2q_1)\theta_0^U + (2q_1^3 - 4q_1)\theta_1^U + q_1)}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2} -$$

$$- \frac{(q_1^3\theta_0^{U^2} - (4q_1^3 - 7q_1^2 - q_1 + 4)\theta_0^U\theta_1^U + (3q_1^3 - 7q_1^2 + q_1 + 4)\theta_1^{U^2} - (q_1^2 + q_1 - 1)\theta_0^{U^2} - (q_1^2 + q_1 - 2)\theta_0^U + (2q_1^2 - 4)\theta_1^U + 1)}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

$$w_{11}^* = \frac{c((q_1^3 - 3q_1 + 2)\theta_0^{U^2} + (3q_1^3 - 7q_1^2 + 6)\theta_1^{U^2} + (-4q_1^3 + 6q_1^2 + 5q_1 - 7)\theta_0^U\theta_1^U + (-q_1^2 - 3q_1 + 4)\theta_0^U + (2q_1^2 + q_1 - 7)\theta_1^U + 2)}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

$$+ \frac{\gamma((q_1^4 - q_1^3 - q_1^2 + q_1)\theta_0^{U^2} + (2q_1^4 - 4q_1^3 - 2q_1^2 + 6q_1)\theta_1^{U^2} + (-3q_1^4 + 4q_1^3 + 5q_1^2 - 6q_1)\theta_0^U\theta_1^U + (-q_1^3 - 2q_1^2 + 3q_1)\theta_0^U + (2q_1^3 - 6q_1)\theta_1^U + 2q_1)}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

$$+ \frac{(-q_1^4 + 2q_1^3 - 8q_1^2 - 2q_1 + 1)\theta_0^{U^3} + (3q_1^4 - 5q_1^3 + 14q_1)\theta_1^{U^3} + (4q_1^4 - 7q_1^3 - q_1^2 + 7q_1)\theta_0^{U^2}\theta_1^U + (-6q_1^4 + 9q_1^3 + 10q_1^2 - 15q_1 + 2)\theta_0^U\theta_1^{U^2} + (2q_1^3 - 2q_1^2 - 2q_1 + 2)\theta_0^{U^2} + (3q_1^3 + 4q_1^2 - 17q_1 + 2)\theta_1^{U^2} + (-4q_1^3 - 2q_1^2 + 10q_1 - 4)\theta_0^U\theta_1^U + (-q_1^2 + 1)\theta_0^U + (5q_1 - 1)\theta_1^U}{2(-3q_1^4 + 6q_1^3 + 4q_1^2 - 10q_1)\theta_1^{U^3} + 2(q_1^4 - 2q_1^3 + 2q_1 - 1)\theta_0^{U^3} + 2(6q_1^4 - 10q_1^3 - 8q_1^2 + 16q_1 - 4)\theta_1^{U^2}\theta_0^U - 2(4q_1^4 + 7q_1^3 + 2q_1^2 - 9q_1 + 4)\theta_1^U\theta_0^{U^2} - (8q_1^3 + 2q_1^2 + 24q_1 - 8)\theta_1^{U^2} + (4q_1 - 2q_1^3 + q_1^2 - 3)\theta_0^{U^2} + 2(5q_1^3 - 13q_1 + 8)\theta_1^U\theta_0^U + 8q_0\theta_1^U + 2(2q_1 - 3)\theta_0^U - 2}$$

.

$OS_3 = \{S2, S5, S12\}$

$$w_1^* = 1$$

$$w_2^* = \frac{c((q_1^2-1)\theta_0^{U^2}+(q_1^2-q_1-2)\theta_1^{U^2}+(-2q_1^2+q_1+3)\theta_0^U\theta_1^U-(q_1+1)\theta_0^U+(1+q_1)\theta_1^U)}{2((1+q_1)\theta_0^U-q_1\theta_1^U-1)((2-q_1^2)\theta_1^{U^2}+(q_1^2+q_1-2)\theta_0^U\theta_1^U+(q_0)\theta_0^U-2\theta_1^U+1)}+$$

$$+\frac{(q_1^3+q_1^2-2q_1)\theta_1^{U^3}+(q_1^3+3q_1^2-q_1-3)\theta_0^{U^2}\theta_1^U+(-2q_1^3-4q_1^2+4q_1+2)\theta_0^U\theta_1^{U^2}+(-2q_1^2+2)\theta_0^{U^2}+(q_1^2-2)\theta_1^{U^2}+(2q_1^2-6q_1)\theta_0^U\theta_1^U+(4q_1)\theta_0^U+(4q_1+3)\theta_1^U-2)}{2((1+q_1)\theta_0^U-q_1\theta_1^U-1)((2-q_1^2)\theta_1^{U^2}+(q_1^2+q_1-2)\theta_0^U\theta_1^U+(q_0)\theta_0^U-2\theta_1^U+1)}$$

$$w_5^* = \frac{cq_0(\theta_1^U-\theta_0^U)+(-q_1^2-q_1+4)\theta_1^{U^2}+(q_1^2+2q_1-3)\theta_0^U\theta_1^U+2q_0\theta_0^U+(-5+q_1)\theta_1^U+2}{2((1+q_1)\theta_0^U-q_1\theta_1^U-1)((2-q_1^2)\theta_1^{U^2}+(q_1^2+q_1-2)\theta_0^U\theta_1^U+(q_0)\theta_0^U-2\theta_1^U+1)}$$

$OS_4 = \{S7, S11, S12\}$

$$w_1^* = 1$$

$$w_7^* = \frac{1}{2} + \frac{(1+q_0)c+(2q_1-q_1^2)\gamma+(3q_1-q_1^2)\theta_1^U}{(-4q_1^2+10q_1)\theta_1^U+2(q_1^2-3q_1+2)\theta_0^U-2q_1+4}$$

$$w_{12}^* = \frac{q_0}{2(1+q_0)} + \frac{(q_1-3)((1+q_0)c+(2q_1-q_1^2)\gamma+(3q_1-q_1^2)\theta_1^U)}{(-4q_1^2+10q_1)\theta_1^U+2(q_1^2-3q_1+2)\theta_0^U-2q_1+4}$$

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