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Extracting Maximum Value from Consumer Returns: Allocating Between Remarketing and Refurbishing for Warranty Claims

Çerağ Pinçe
Kühne Logistics University, 20457 Hamburg, Germany, cerag.pince@the-klu.org

Mark Ferguson
Moore School of Business, University of South Carolina, Columbia, South Carolina 29208, mark.ferguson@moore.sc.edu

Beril Toktay
Scheller College of Business, Georgia Institute of Technology, Atlanta, Georgia 31200, beril.toktay@scheller.gatech.edu

The high cost of lenient return policies force consumer electronics original equipment manufacturers (OEMs) to look for ways to recover value from lightly used consumer returns, which constitute a substantial fraction of sales and cannot be resold as new products. Refurbishing to remarket or to fulfill warranty claims are the two common disposition options considered to unlock the value in consumer returns, which present the OEM with a challenging problem: How should an OEM dynamically allocate consumer returns between fulfilling warranty claims and remarketing refurbished products over the product's life cycle? We analyze this dynamic allocation problem and find that when warranty claims and consumer returns are jointly taken into account, the remarketing option is generally dominated by the option of refurbishing and earmarking consumer returns to fulfill warranty claims. Over the product's life cycle, the OEM should strategically emphasize earmarking of consumer returns at the early stages of the life cycle to build up earmarked inventory for the future warranty demand, whereas it should consider remarketing at the later stages of the life cycle after enough earmarked inventory is accumulated or most of the warranty demand uncertainty is resolved. These findings show that, for product categories with significant warranty coverage and refund costs, remarketing may not be the most profitable disposition option even if the product has strong remarketing potential and the OEM has the pricing leverage to tap into this market. We also show that the optimal dynamic disposition policy is a price-dependent base-stock policy where the earmarked quantity is capacitated by the new and refurbished product sales quantities. We compare with the myopic policy and show that it is a good heuristic for the optimal dynamic disposition policy.

Keywords: consumer returns; consumer electronics; warranty; refurbishing; closed-loop supply chains
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1. Introduction

Consumer returns are products that are purchased by the consumer from the manufacturer or a retailer and then returned for a refund within the time window allowed by the return policy. In the U.S. market, consumer returns have been estimated at $200 billion per year and average 8.2% of total retail sales (Greve and Davis 2012). In the consumer electronics sector, which is the focus of this paper, consumer returns require testing prior to the disposition decision and are typically returned to the original equipment manufacturer (OEM) for full credit for this purpose. Despite the fact that the majority of these returns are found to have no defects in their intended functionality (Accenture 2008, Ferguson et al. 2006), litigation concerns prevent OEMs from returning them to the new product distribution channel. Thus, consumer returns represent a significant cost to consumer electronics manufacturers (King 2013); yet, prevalent industry practice reinforces the notion that full-refund return policies will continue to be offered because of competitive pressures (Shang et al. 2016a, b). These companies view no-defect-found consumer returns as a necessary cost of doing business and are increasingly focusing on the ways to recapture value from them.

Refurbishing consumer returns provides the OEM with the possibility of recapturing value in two ways: savings in the cost of warranty claims or revenues from remarketing (selling as refurbished product). To honor warranty agreements, OEMs are obliged to either repair the failed product, which is usually not cost effective for most failure categories of consumer electronics, or replace it with a *functional* product, which can be a refurbished product.[1] When

[1] For example, Apple states in the warranty policy that the failed Apple product can be replaced with a device that is "formed from new and/or previously used parts that are equivalent to new in performance and reliability" (https://www.apple.com/legal/warranty/).

refurbishing is cheaper than manufacturing, fulfilling a warranty claim with a refurbished product instead of a new product generates savings in cost. However, refurbishing a consumer return to fill a warranty demand has an opportunity cost: the potential margin that can be earned by remarketing it. On the other hand, remarketing cannibalizes new product sales, and the price of refurbished products should be set in relation to the new product price and in coordination with the amount of expected warranty claims. Thus, identifying the best dynamic disposition strategy in face of consumer returns and warranty claims received during the product's life cycle is a challenging but important decision.

The prior academic literature provides guidelines on the profitability of remarketing when warranty claims are ignored and remarketing is considered as the only disposition option (e.g., Debo et al. 2005, Ferguson and Toktay 2006, Ferrer and Swaminathan 2006, Atasu et al. 2008). Other independently developed research streams (cost minimizing disposition strategies and inventory management under warranty service) do not bring together pricing and refurbishing for the dual purposes of remarketing and fulfilling warranty claims. For consumer electronics OEMs, however, the disposition decision lies at the intersection of pricing new and remarketed products and stocking refurbished consumer returns to meet future warranty demand. While prior research concludes that remarketing is a valuable disposition option as long as new product cannibalization concerns do not dominate the cost recovery benefits, there is little guidance about how warranty claims and money-back guarantees jointly affect the profitability of remarketing as well as the OEM's dynamic disposition strategy. With these motivations, we address the following question: How should an OEM dynamically allocate consumer returns between fulfilling warranty claims and remarketing refurbished products over the product's life cycle? While answering this question, we also study how the OEM's dynamic disposition strategy is shaped by the inter-temporal changes in the consumer return rate and warranty demand.

We first study a single-period setting where, at the beginning of each period, the OEM decides the prices of the new and refurbished products along with the quantity to be refurbished and earmarked to fulfill uncertain warranty demand.[2] Our main finding is that when using consumer returns to meet warranty claims is taken into account, the profitability of remarketing requires a stricter parameter condition than the one suggested by the earlier literature. Moreover, our numerical analysis shows that the remarketing option is dominated by earmarking in most cases. This counterintuitive result is driven by the fact that each remarketed product can potentially generate a future warranty coverage cost or refund cost, and therefore, when earmarking is economically attractive, the OEM optimally allocates some consumer returns to the earmarking option to reduce these costs. Interestingly, the cost reduction effect of earmarking can enable the OEM to remarket returned products more aggressively than when she relies solely on remarketing.

We next consider a multiperiod setting where, in every period, the surplus earmarked inventory is available to meet warranty demand in subsequent periods, and the OEM jointly decides the quantity to be earmarked in that period together with the prices of new and refurbished products. We show that the optimal dynamic disposition policy in each period is a price-dependent base-stock policy where the earmarked quantity is capacitated by the new and refurbished product sales quantities, which are endogenously determined by the OEM's pricing decisions. Via a numerical analysis, we study the behavior of the optimal dynamic disposition policy with respect to the inter-temporal changes in the consumer return rate and failure rate. We find that if the consumer return rate is decreasing over time, the optimal earmarking quantity is also decreasing while the optimal refurbished product sales are increasing. This is because a decreasing consumer return rate implies an increasing warranty demand (as more consumers keep their products) and a decreasing refurbishing capacity, therefore favoring a buildup of earmarked inventory at the early stages in the life cycle. If the consumer return rate is increasing, the OEM faces a relatively high warranty demand with a relatively low refurbishing capacity at the beginning of the life cycle, yet the optimal dynamic policy again favors emphasizing earmarking at the early stages in the life cycle to fulfill the immediate warranty claims. When the product's failure rate decreases over time, we continue to observe a similar behavior in the optimal dynamic policy. Thus, although the behavior of the optimal dynamic policy can vary depending on the underlying inter-temporal changes, its overall pattern prescribes a consistent disposition strategy.

We conduct an extensive numerical study and find that, in the majority of the instances, a larger percentage of the consumer returns are allocated to the earmarking option, and throughout the life cycle, the percentage allocated to earmarking decreases while the percentage allocated to remarketing increases. As such, our earlier result regarding the behavior of the optimal dynamic policy generalizes to the majority of our practical cases. We also find that the percentage of consumer returns allocated to the earmarking option

[2] For brevity, in the rest of the paper, we refer to the disposition option of refurbishing and earmarking consumer returns to fulfill warranty claims shortly as the *earmarking* option.

is robust since earmarking dominates both remarketing and salvaging. Moreover, when compared to the myopic policy, the optimal dynamic policy is most beneficial for high values of consumer return rate, warranty demand uncertainty, remarketing potential, manufacturing cost, and for low values of refurbishing cost and salvage value.

The rest of the paper is organized as follows. In Section 2 we review the relevant literature and position our paper. In, Sections 3 and 4 we present and analyze the single-period and multiperiod problems. In Section 5 we report our numerical study. In Section 6 we conclude. We refer the reader to the online appendix (available as supplemental material at http://dx.doi.org/10.1287/msom.2016.0584) for all proofs.

2. Literature Review

Our paper draws on three different research streams: closed-loop supply chains (CLSC), consumer return policies, and inventory management under warranty service. The literature from the CLSC stream that are closest to our problem consider the disposition decision for returned products and market-related issues. The former focuses on the allocation of the limited amount of returned products to appropriate recovery options such as disposal, dismantling for parts, and remanufacturing to sell. The papers considering a single disposition option (typically dismantling) focus on spare parts recovery either for usage throughout the life cycle (e.g., Fleischmann et al. 2003, Ferguson et al. 2011) or to reduce the final order/buy quantities (e.g., Teunter and Fortuin 1999), or multiple remanufacturing options (e.g., Inderfurth et al. 2001). These papers focus on the cost side of the disposition decision rather than the value of the recovered products in the refurbished product market with two exceptions. Ferguson et al. (2011) consider a scenario where a returned product can be dismantled for parts to meet the uncertain spare parts demand, or remanufactured to be sold at an exogenous price under demand uncertainty. Similarly, Calmon and Graves (2015) study the inventory system of refurbished products that are used to serve warranty claims or sold through side-sales channel at an exogenous price. Nevertheless, all papers in the disposition decision literature have two common assumptions: (i) the return and demand streams, as well as product prices, are exogenous and independent; and (ii) consumers do not differentiate between new and remanufactured products. As such, our model differs from this literature in that we endogenize the OEM's pricing decisions for new and remanufactured products and take into account consumer preferences over these products.

The papers on market-related issues in closed-loop supply chains essentially focus on the profitability of remarketing under different operational and market conditions (see, e.g., Guide and Van Wassenhove 2001, Debo et al. 2005, Ferrer and Swaminathan 2006, Ferguson and Toktay 2006, Atasu et al. 2008, and for a comprehensive review, Souza 2013). Similar to these papers, we also assume a heterogenous consumer base and use a vertical market segmentation model to capture the impact of cannibalization and consumer valuations on the OEM's remanufacturing strategy. In contrast, however, we consider an additional disposition option, refurbishing consumer returns to fulfill warranty claims, which is also influenced by the pricing decisions of the OEM. Moreover, a significant portion of this literature focuses on the end-of-use or end-of-life returns that are received after long durations of use, resulting in high levels of variability in their quality (e.g., Guide and Van Wassenhove 2001, Debo et al. 2005, Ferguson and Toktay 2006). In contrast, we study consumer returns, the vast majority of which are barely used. Other papers considering lightly used consumer returns in the closed-loop supply chains context focus on different aspects, such as coordination mechanisms to reduce returns (Ferguson et al. 2006), time-sensitive products (Guide et al. 2006), returns processing (Ketzenberg and Zuidwijk 2009), and profitability of money-back guarantees (Akçay et al. 2013). To our knowledge, the dynamic joint pricing and stocking decisions of the OEM have not been investigated for consumer returns.

Outside the closed-loop supply chains context, the literature on consumer returns focuses on the issue of how, and to what extent, the seller should refund product returns arising from buyers' remorse or from the lack of fit between product attributes and consumer expectations. Davis et al. (1995), Che (1996) and Moorthy and Srinivasan (1995) analyze the benefits of a full refund policy when consumers are not opportunistic. In case of opportunistic consumers, Davis et al. (1998) and Chu et al. (1998) show that full refund policies are suboptimal. In a series of papers, Shulmann et al. (2009, 2010, 2011) study the impact of the provision of product fit information, competition, and reverse channel structure on the form of the return policy. Su (2009) investigates the impact of return policies on supply chain performance and proposes coordination mechanisms taking into account consumer returns. Using transactions data from a major U.S. consumer electronics retailer, Shang et al. (2016a) propose an econometric model to estimate consumers' experience duration and the probability of a return, whereas Shang et al. (2016b) empirically investigate the value of money-back-guarantee policies in online retailing. The majority of this literature is devoted to analyzing the trade-off between enforcing stricter return policies (via restocking fees) versus increasing sales by a more service-oriented sales policy. In practice, and counter to the recommendations of this literature stream, the major consumer electronics OEMs and retailers still offer free return policies, at least in the U.S. market (Shang et al. 2016a, b). In our paper we take the return policy as given (full refund) and, rather than focusing on the cost versus customer service trade-off, we explore how OEMs can more effectively utilize the products that are returned.

Finally, the literature on inventory management under warranty demand focuses on the effects of future warranty claims on production and stocking decisions of an OEM providing warranty service. As such, the focus of this literature is on operational issues such as the optimal inventory-warranty policy, quality uncertainty of returned products, and the impact of production lot sizes on quality (e.g., Khawam et al. 2007, Huang et al. 2008, Djamaludin et al. 1994). Although these papers consider the impact of warranty service on the OEM's stocking decisions, we approach this problem from a more integrated perspective and show how the OEM's stocking decision under warranty service is influenced by the OEM's pricing decisions of new and refurbished products.

3. Formulation as a Single-Period Problem

Our focus is on consumer electronics, which typically have short product life cycles and high depreciation rates in their market values. Consequently, consumer returns (as compared to end-of-use or end-of-life returns) requiring low-touch refurbishing are the main option for selling refurbished products or meeting warranty demand with anything other than new products. To understand the underlying drivers of the OEM's joint pricing and stocking problem, we begin with a single-period setting where, at the beginning of the period, the OEM sets the new and refurbished product prices to determine the sales volumes and decides the quantity of the consumer returns that will be refurbished and earmarked to fulfill the warranty demand. In other words, the OEM first makes the planning for the whole period in expectation of the consumer returns and warranty claims that it will receive during the period, then allocates the arriving consumer returns to one of the disposition options (refurbishing to remarket or refurbishing to earmark for warranty demand) based on the initially planned allocation quantities. As such, the single-period framework provides a convenient starting point to analyze the OEM's complex disposition decisions at an aggregate and strategic level, and it is commonly used in the context of consumer returns and closed-loop supply chains (e.g., Akçay et al. 2013, Ferguson et al. 2006, Su 2009).

For consumer electronics products, there is often a significant difference between the return time windows of the consumer returns and the warranty claims. The consumer returns typically depend only on recent sales, because of short time windows of money-back guarantees (14 or 30 days), whereas warranty agreements span a significant portion of the product life cycle (one or two years). This implies that, for the majority of the life cycle, the warranty claims depend on a larger number of sales compared to the consumer returns, and therefore the relative uncertainty in total warranty demand is typically much higher than the uncertainty in the number of consumer returns. We discussed this point with the CEO of a third party refurbisher and learned that the consumer return rates are consistently in the 8%–12% range across all brands, while the warranty demand rates can range from 2%–30% (Francis 2012). Moreover, the consumer return rate can sometimes be reduced by target rebate contracts offered to retailers by OEMs (Ferguson et al. 2006) while warranty demand can usually be reduced through design and manufacturing improvements that require longer periods of time (e.g., over successive product generations). Thus, to maintain tractability while capturing the primary drivers of the optimal disposition strategy of a consumer electronics OEM, we attribute all the uncertainty to the warranty demand.

To model the firm's pricing decisions, we assume that consumers are heterogenous according to their willingness-to-pay and that a consumer's willingness-to-pay for the new product θ is uniformly distributed within the interval $[0, 1]$. Furthermore, we assume that a consumer's willingness-to-pay for the refurbished product is a known fraction of its willingness-to-pay for the new product, i.e., $\delta\theta$ with $\delta \in (0, 1)$. Let p_n and p_r denote the prices for the new and refurbished products, respectively. These assumptions lead to the inverse demand functions $p_n = 1 - D_n - \delta D_r$ and $p_r = \delta(1 - D_n - D_r)$, with D_n and D_r denoting the demand (sales) for new and refurbished products. This demand model derivation is frequently used in the closed-loop supply chain literature (e.g., Agrawal et al. 2012, Atasu et al. 2008, Ferguson and Toktay 2006, Debo et al. 2005). The OEM incurs a unit cost of c_n to produce a new product and a unit cost of c_r to refurbish a consumer return. To eliminate trivial cases, we let $0 < c_r < c_n$.

Consumer returns are a fraction (α) of the total sales, i.e., $R_c(D_n, D_r) = \alpha(D_n + D_r)$ with $\alpha \in (0, 1)$. We refer to αD_n as the *new-product* consumer returns and αD_r as the *refurbished-product* consumer returns. For each type of consumer return, the OEM refunds the selling price of the product to the customer; thus, the total refund cost is equal to $p_n \alpha D_n + p_r \alpha D_r$. Warranty demand (warranty claims), on the other hand, form a separate stream from consumer returns given by $R_w(D_n, D_r, \xi) = \gamma(1-\alpha)(D_n + D_r) + \xi$, where $\gamma \in (0, 1)$ is the (known) base product failure rate, $1-\alpha$ is the fraction of sales not returned as consumer returns, and $\xi \in [0, \bar{\xi}]$ is a nonnegative continuous random variable distributed according to $F(\cdot)$. For analytical convenience, we assume that $\xi \sim F(\cdot)$ is strictly increasing in the interval $[0, \bar{\xi}]$ and therefore has an inverse. $R_w(D_n, D_r, \xi)$ is similar to the additive demand function in the price-setting newsvendor models, where the objective is to jointly decide on the replenishment quantity and price of a product to meet stochastic price-dependent demand (e.g., Petruzzi and Dada 1999, Dana and Petruzzi 2001).

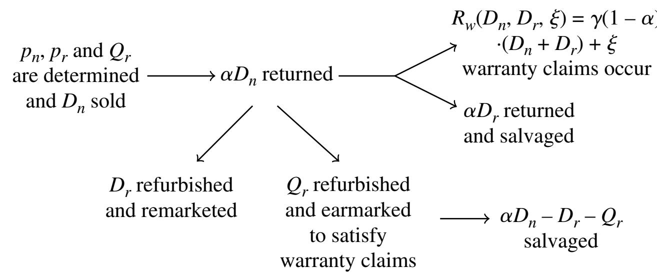
The OEM can meet the warranty demand by using new products or refurbishing consumer returns. Let Q_r denote the earmarked quantity of consumer returns, which is refurbished to satisfy warranty demand during the period. We assume warranty demand not met by refurbished products is met by new products at the end of the period.[3] Thus, $c_n E(R_w(D_n, D_r, \xi) - Q_r)^+$ is the expected cost of covering the surplus warranty demand (warranty demand exceeding the earmarked quantity) by using new products. Similarly, there is an overage cost h per unit of leftover earmarked products. Hence, $hE(Q_r - R_w(D_n, D_r, \xi))^+$ is the expected overage cost of the surplus earmarked quantity.

Consumer returns that are not refurbished for either remarketing or warranty demand coverage are salvaged (e.g., recycled or cannibalized for parts) at the end of the period. To keep the model tractable, we assume that the OEM refurbishes a product only once and all refurbished-product consumer returns are salvaged. This also reflects the most common policy from practice, as cores are rarely refurbished more than once. Because the total number of refurbished products cannot be larger than the number of new-product consumer returns, there is a refurbishing capacity constraint $D_r + Q_r \le \alpha D_n$. Consequently, the total salvage revenue earned at the end of the period is equal to $s(\alpha D_n - D_r - Q_r + \alpha D_r)$, where s is the unit salvage value, $\alpha D_n - D_r - Q_r$ is the amount of new-product consumer returns that are not refurbished by the end of the period, and αD_r is the amount of refurbished-product consumer returns. We set the salvage value for products returned because of warranty claims to zero.

Figure 1 depicts the sequence of events occurring during a single period. At the beginning of the period, the OEM simultaneously determines the new

[3] In the multiperiod setting, we relax this assumption and allow warranty demand to be backlogged until enough consumer returns are available.

Figure 1 **Sequence of Events in a Single Period**



and refurbished product prices (p_n, p_r) and the quantity of new-product consumer returns to be refurbished and earmarked to satisfy warranty claims (Q_r). Subsequently, the demand for both products, consumer return quantities, and base warranty demand received during the period are determined. As the new-product consumer returns arrive, the OEM refurbishes these returns to either remarket or earmark them to satisfy warranty claims. The OEM then begins to receive the refurbished-product consumer returns, which are salvaged at the end of the period, and the warranty claims, which are fulfilled by the new products or the refurbished and earmarked quantity.

The OEM's single-period disposition problem is given as follows:

$$\begin{aligned}
&\max \Pi(D_n, D_r, Q_r)\\
&= ((1-\alpha)p_n - c_n)D_n + ((1-\alpha)p_r - c_r)D_r - c_r Q_r\\
&\quad - hE(Q_r - R_w(D_n, D_r, \xi))^+ - c_n E(R_w(D_n, D_r, \xi) - Q_r)^+\\
&\quad + s(\alpha D_n - (1-\alpha)D_r - Q_r), \qquad (1)
\end{aligned}$$

subject to $D_r + Q_r \le \alpha D_n$ and $D_n, D_r, Q_r \ge 0$. The first two terms are the net profit from selling new and refurbished products after the refunds for consumer returns are deducted, the third term is the refurbishing cost of the earmarked quantity, the fourth term is the expected overage cost of the earmarked quantity left at the end of the period, the fifth term is the expected cost of covering the surplus warranty demand by new products, and the sixth term is the salvage revenue.

It is straightforward to show that (1) is jointly concave in (D_n, D_r, Q_r). The characterization of the optimal earmarking quantity for a given new and refurbished product demand is given by the following lemma.

Lemma 1. *For a given (D_n, D_r), the optimal earmarking quantity is given by*

$$Q_r^* = \min(\gamma(1-\alpha)(D_n + D_r) + \tilde{z}, \alpha D_n - D_r), \qquad (2)$$

with $\tilde{z} = F^{-1}((c_n - c_r - s)/(c_n + h))$.

Lemma 1 states that the optimal earmarking quantity either attains its interior solution, which is equal to the base warranty demand ($\gamma(1-\alpha)(D_n+D_r)$) plus the safety stock ($\tilde{z}$) against warranty demand uncertainty, or is found at its boundary, which is equal to the new-product consumer returns minus the quantity allocated to the remarketing option ($\alpha D_n - D_r$). We refer to this boundary as the *earmarking capacity*. When the earmarking capacity is binding, all new-product consumer returns are allocated to the remarketing and earmarking options, and no new-product consumer returns are salvaged, whereas in the interior solution some of those returns are salvaged. Moreover, in the interior solution, the optimal safety stock is determined by a critical fractile, where $c_n - c_r - s$ is the marginal savings from filling a warranty demand by refurbishing (or equivalently, the underage cost of not filling a warranty demand by refurbishing), and $c_r + s$ is the marginal cost of filling a warranty demand by refurbishing, where c_r and s represent the direct and opportunity costs of refurbishing for warranty demand, respectively. Thus, for the rest of the analysis, we assume that the marginal saving from filling a warranty demand by refurbishing is positive ($c_n - c_r - s > 0$); otherwise, the earmarking option is not economically attractive.

3.1. Unconstrained Earmarking

Next, we focus on the case where the OEM sets new and refurbished product prices such that the optimal earmarked quantity has an interior solution.

Proposition 1. *If it is optimal to set new and refurbished product prices such that the optimal earmarking quantity has an interior solution, the optimal policy is characterized in Table 1.*

The functions of parameters M_n and M_r represent the maximum marginal values of a new and remarketed product, respectively. In M_n, the term $1-\alpha-c_n+\alpha s$ is the maximum net marginal revenue earned from selling a new product, where $1-\alpha-c_n$ is the maximum direct profit from a new product, considering that α portion of each new product sold is returned and refunded, and αs is the salvage revenue generated by the return. Since each new product sold also contributes to the base warranty demand, M_n includes the marginal cost of filling the base warranty demand by refurbishing, which is given by the term $(c_r+s)\gamma(1-\alpha)$. Similarly, in M_r, the term $\delta(1-\alpha)-c_r-(1-\alpha)s$ is the net maximum marginal revenue from selling a refurbished product, where $\delta(1-\alpha)-c_r$ is the maximum direct profit from a remarketed product after the refund cost is deducted. Because consumer returns from remarketed products are only salvaged, each remarketed product generates a salvage revenue of αs. On the other hand, each remarketed product incurs an opportunity cost of s, since it prevents a consumer return from being salvaged before refurbishing. Thus, $(1-\alpha)s$ is the net marginal opportunity cost of remarketing a returned product. Since selling a refurbished product also contributes to the base warranty demand, M_r includes the term $(c_r+s)\gamma(1-\alpha)$.

Proposition 1 prescribes two different disposition strategies in the interior: If M_n is sufficiently low ($M_n < M_r/\delta$), remarketing is profitable. Thus, consumer returns are allocated to both remarketing and earmarking options, and the rest are salvaged. The optimal earmarking quantity in this case is the base warranty demand ($\gamma M_r/2\delta$) plus the safety stock ($\tilde{z}$). On the other hand, if M_n is sufficiently high, remarketing is not profitable and the consumer returns are either earmarked or salvaged. In this case the earmarked safety stock remains the same, but the base warranty demand depends on the failure rate and maximum marginal value of a new product ($\gamma M_n/2$).

When remarketing is profitable, the optimal fill rate for warranty demand fulfilled by earmarking is $1-2\delta L(\tilde{z})/(\gamma M_r + 2\delta\mu)$, where $L(z) := E(\xi - z)^+$ and $\mu := E(\xi)$ denote the loss function and expected value of ξ, respectively. The optimal fill rate is increasing in γ, μ, M_r, and δ, since an increase in these parameters suggests a higher warranty demand and larger optimal earmarking quantity. Thus, although earmarking and remarketing are seemingly competing disposition options, when the optimal earmarking quantity is unconstrained, more profitable remarketing conditions imply less salvaging rather than less earmarking.

Corollary 1. *When it is optimal to set new and refurbished product prices such that the optimal earmarking quantity has an interior solution, remarketing is profitable if*

$$c_r < \delta c_n - s(1-\alpha+\alpha\delta) - (c_r+s)\gamma(1-\alpha)(1-\delta). \quad (3)$$

Earlier literature on closed-loop supply chains concludes that when the refurbishing cost structure is linear and there are no fixed costs (for collecting and processing the returned products), remarketing is profitable only if the unit refurbishing cost is sufficiently lower than the unit manufacturing cost ($c_r < \delta c_n$). Corollary 1 generalizes this result and shows that when consumer returns, warranty demand, and salvaging are taken into account, the profitability of remarketing not only depends on the remarketing potential, refurbishing cost, and manufacturing cost but also on the consumer return rate, failure rate, and salvage value. As such, for products with relatively high consumer return rates, salvage values, or warranty coverage costs, the classical profitability condition for remarketing is incomplete, and,

Table 1 Optimal Policy Under Unconstrained Earmarking

Condition	D_n^*	D_r^*	Q_r^*	p_n^*	p_r^*
$M_r < M_n < \frac{M_r}{\delta}$	$\frac{M_n - M_r}{2(1-\alpha)(1-\delta)}$	$\frac{M_r - \delta M_n}{2(1-\alpha)(1-\delta)\delta}$	$\frac{\gamma M_r}{2\delta} + \tilde{z}$	$1 - \frac{M_n}{2(1-\alpha)}$	$\delta - \frac{M_r}{2(1-\alpha)}$
$M_n \geq \frac{M_r}{\delta}$, $M_n > 0$	$\frac{M_n}{2(1-\alpha)}$	0	$\frac{\gamma M_n}{2} + \tilde{z}$	$1 - \frac{M_n}{2(1-\alpha)}$	—

Note. $M_n := 1 - \alpha - c_n + \alpha s - (c_r + s)\gamma(1-\alpha)$, $M_r := \delta(1-\alpha) - c_r - (1-\alpha)s - (c_r + s)\gamma(1-\alpha)$.

as (3) shows, a stricter condition is required for remarketing to be profitable. Moreover, (3) reveals a substitution effect between c_r, γ and α: As refurbishing becomes more costly, not only does the profit margin of the remarketed products decrease but the warranty coverage cost increases. Thus, to keep the refurbished products in the market, the OEM needs to reduce the failure rate or receive more consumer returns, since a lower failure rate or higher consumer return rate implies a lower base warranty demand rate ($\gamma(1-\alpha)$).

Corollary 2. *A higher consumer return rate decreases the optimal new product sales and optimal earmarking quantity but increases the optimal refurbished product sales.*

As the consumer returns become more abundant, the OEM incurs higher refund costs and optimally charges more for new and refurbished products. Since refunding a new product is more expensive than refunding a refurbished product, when remarketing is profitable, the new product price increases in the consumer return rate faster than the refurbished product price. Thus, although both products become more expensive in absolute terms, a higher consumer return rate makes the new products relatively more expensive compared to the refurbished products and favors the refurbished product sales.[4] The optimal earmarking quantity is decreasing in the consumer return rate because when the earmarking quantity is unconstrained, a higher consumer return rate implies a lower warranty demand because of a lower total sales quantity.[5]

3.2. Optimal Single-Period Policy

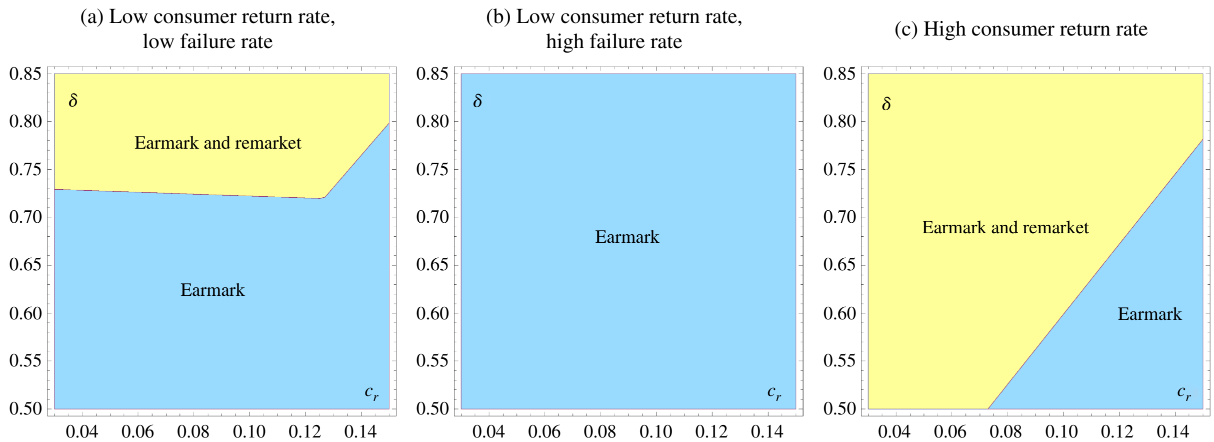
As previously discussed, when the earmarking quantity is unconstrained, the optimal policy can be characterized in closed form. When the earmarking quantity is constrained, the analytical expressions are tedious and not amenable to comparative static analysis. Thus, we use representative numerical examples to obtain insights about the overall optimal disposition strategy, including the constrained cases (Figure 2). For these examples, we choose parameter values that demonstrate typical shifts in the dominant strategy and are anchored in realistic ranges, which are developed for the numerical study in Section 5. This discussion captures the main dynamics in the single-period setting that are worthy of discussion and shed light on the dynamics of the multiperiod problem. For brevity, in the figures, we do not differentiate between the cases where new-product consumer returns are salvaged or not (i.e., unconstrained and constrained earmarking cases) and refer to the optimal policy with the names of the disposition options it includes.

3.2.1. Consumer return rate vs. failure rate. We begin by studying how the interaction between the refurbishing capacity and warranty demand shape the optimal disposition strategy. Figure 2 shows that for low consumer return rates, the dominant policy is earmarking. This is because a low consumer return rate implies a high base warranty demand rate (i.e., more consumers keep and use their product until the end of the period) and low earmarking capacity. Thus, to avoid high warranty coverage costs, the optimal policy generally prioritizes earmarking over remarketing (Figures 2(a)–2(b)). In particular, when a low consumer return rate is combined with a high failure return rate, the OEM foregoes remarketing for all refurbishing cost and remarketing potential values to obtain the maximum possible warranty savings by earmarking all the consumer returns (Figure 2(b)). On the other hand, when the consumer return rate and failure rate are both low and the remarketing potential is sufficiently high, the OEM allocates consumer returns to both the earmarking and remarketing options (Figure 2(a)). For high consumer return rates, the OEM allocates consumer returns to both disposition options in the majority of the cases (Figure 2(c)), since refurbishing capacity is abundant and remarketed products are preferred over new products because of their relatively low refund costs. Similar figures and insights are obtained when the failure rate

[4] This effect can be seen more clearly from the gap between the optimal new and refurbished product prices, i.e., when remarketing is profitable, by Proposition 1, $p_n^* - p_r^* = (c_n - c_r - s)/(2(1-\alpha)) + (1-\delta)/2$. Thus, a higher α increases the gap between new and refurbished products and makes the new products relatively more expensive.

[5] The optimal total sales quantity ($D_n^* + D_r^*$) is given by $M_r/(2(1-\alpha)\delta)$, and it can be easily verified that it is decreasing in α. The same can also be easily verified when remarketing is not profitable ($D_r^* = 0$).

Figure 2 **(Color online) Optimal Single-Period Policy** ($c_n = 0.30, s = 0.09, \bar{\xi} = 0.05, h = 0$)†



†$\alpha = \{0.05, 0.30\}$, $\gamma = \{0.01, 0.05\}$, ξ is assumed to be uniformly distributed.

is fixed and the warranty demand uncertainty is varied. We also find that when both warranty demand uncertainty and consumer return rate are low, the optimal single-period policy is determined by the failure rate (i.e., for a high failure rate, the optimal policy is pure remarketing as in Figure 2(b) and for moderate to low failure rates, the optimal policy is more balanced as in Figure 2(c)).

3.2.2. Remarketing potential vs. refurbishing cost. Next, we study the interaction between the remarketing potential and the refurbishing cost. When consumer return rates are sufficiently high and the refurbishing cost becomes more expensive, the remarketing potential threshold above which remarketing is profitable is increasing (Figure 2(c)). Note that as the refurbishing cost increases, the OEM shuts down the refurbished product market but still refurbishes and earmarks consumer returns to cover warranty demand because, as discussed in Corollary 1, the profitability of remarketing depends not only on the profit margins of the remarketed products but also on the warranty coverage costs generated by them. Thus, for sufficiently high refurbishing costs, the remarketing profit does not offset the warranty coverage cost generated by remarketing and the optimal policy leans toward earmarking or salvaging. When the consumer return rate and failure rate are both low, for sufficiently low refurbishing costs, the remarketing potential threshold is either constant or very slowly decreasing (Figure 2(a)), implying that remarketing might have a slight advantage over earmarking for these parameter combinations. Observe that pure remarketing is not an optimal strategy by itself, i.e., some level of earmarking is always optimal even though the earmarked quantity can be relatively small. This is because when earmarking is economically attractive ($c_n - c_r - s > 0$), it helps offset the warranty costs generated by the remarketed products.

4. Formulation as a Multiperiod Problem

To investigate how the OEM's disposition decision is affected by intertemporal changes, we extend the single-period model to a multiperiod setting. To this end, the planning horizon is divided into T periods where the decision epochs are denoted by $t = 0, 1, 2, \ldots, T-1$. In each period, the events unfold as in the single-period model illustrated by Figure 1. At the beginning of period t, the OEM reviews the level of the earmarked inventory (x_t), which is used to satisfy warranty claims. The OEM then simultaneously decides the new and refurbished product prices (p_t^n, p_t^r) and the quantity (Q_t^r) to be refurbished and added to the earmarked inventory. Analogous to the single-period model, the inverse demand functions for new and refurbished products at period t are given as $p_t^n = 1 - D_t^n - \delta_t D_t^r$ and $p_t^r = \delta_t(1 - D_t^n - D_t^r)$, where D_t^n and D_t^r denote the new and refurbished product sales quantities in period t and δ_t is the remarketing potential in period t. Similarly, α_t denotes the fraction of the total sales the OEM receives as consumer returns in period t. After p_t^n, p_t^r, and Q_t^r are decided, D_t^n is sold and the new-product consumer returns arrive ($\alpha_t D_t^n$). The OEM refurbishes these returns for remarketing or earmarking as planned at the beginning of period t (i.e., D_t^r units of returns are refurbished and remarketed, and Q_t^r units of returns are refurbished and added to the earmarked inventory). The OEM then receives the refurbished-product consumer returns ($\alpha_t D_t^r$) and warranty demand, which is given by $R_t^w(D_t^n, D_t^r, \xi_t) = \gamma_t(1 - \alpha_t)(D_t^n + D_t^r) + \xi_t$, where γ_t is the base failure rate in period t and ξ_t is the random portion of warranty demand in period t. Similar to the single-period model, $\xi_t \in [0, \bar{\xi}_t]$ is a continuous nonnegative random variable with cumulative distribution function $F_t(\cdot)$.

The state of the system is x_t, the earmarked inventory level at the beginning of period t *before* the refurbishing decision is taken. We define y_t $(:=x_t+Q_t^r)$ as the earmarked inventory level at the beginning of period t *after* the refurbishing decision is taken. Thus, the earmarked inventory dynamics satisfy the equation $x_{t+1}=x_t+Q_t^r-R_t^w(D_t^n,D_t^r,\xi_t)=y_t-R_t^w(D_t^n,D_t^r,\xi_t)$, that is, the earmarked inventory level at the beginning of period $t+1$ before the refurbishing decision is equal to the earmarked inventory level in period t after the refurbishing decision minus the warranty demand received in period t. The expected earmarked inventory cost charged to period t is based on x_{t+1}. The OEM can backorder the unfilled warranty demand until there is enough earmarked inventory. Thus, at the end of period t, the backordering cost b_t is incurred for each backlogged warranty demand. The practical examples of backordering cost in warranty inventory systems are the loss of good will caused by an increase in customer waiting time for replacement products as well as the additional production and transportation costs caused by congestion due to backlogged warranty demand (see e.g., Huang et al. 2008, Khawam et al. 2007). If there are no backorders, the holding cost h_t is incurred per unit of surplus earmarked inventory kept in stock.

All refurbished-product consumer returns received in period t $(\alpha_t D_t^r)$ and the new-product consumer returns received in period t but not earmarked or remarketed $(\alpha_t D_t^n-D_t^r-Q_t^r)$ are salvaged at the end of the period at a salvage value s. For short life-cycled consumer electronics products, the changes in c_n, c_r, and s are typically much slower compared to the changes in the consumer return rate and failure rate. Thus, for analytical convenience, we take these parameters as fixed throughout the life cycle.

The OEM profit in period t is given by

$$\begin{aligned}&\Pi_t(y_t,D_t^n,D_t^r)\\&=((1-\alpha_t)p_t^n-c_n)D_t^n+((1-\alpha_t)p_t^r-c_r)D_t^r-c_r(y_t-x_t)\\&\quad-h_tE(y_t-R_t^w(D_t^n,D_t^r,\xi_t))^+-b_tE(R_t^w(D_t^n,D_t^r,\xi_t)-y_t)^+\\&\quad+s(\alpha_tD_t^n-(1-\alpha_t)D_t^r-(y_t-x_t)),\end{aligned}$$

where the first two terms are the net profit from selling new and refurbished products, the third term is the cost of refurbishing the period's earmarking quantity, the fourth and fifth terms are the expected holding and backordering costs incurred for the earmarked inventory, and the last term is the total salvage revenue.

As in the single-period model, the total quantity that is refurbished in period t cannot exceed the total new-product consumer returns received in period t $(D_t^r+Q_t^r\le\alpha_tD_t^n)$, and all decision variables are nonnegative $(D_t^n,D_t^r,Q_t^r\ge 0)$. For brevity, we express this set of constraints by letting $0\le Q_t^r\le\alpha_tD_t^n-D_t^r$ (or equivalently, $x_t\le y_t\le x_t+\alpha_tD_t^n-D_t^r$) and confining (D_t^n,D_t^r) to the set $\Omega=\{(D_t^n,D_t^r)\mid D_t^n\in[0,1],D_t^r\in[0,\alpha_tD_t^n]\}$. Since all variables driving the system state are continuous, the state space is $\mathbb{R}$. The OEM's dynamic disposition problem is related to the single product joint dynamic pricing and replenishment problem under stochastic demand (e.g., Zabel 1972, Federgruen and Hetching 1999). Our model differs from those models, however, in that we consider pricing of two vertically differentiated products and there is a capacity constraint limiting the maximum quantity that can be "ordered" (earmarked) in each period.

In the rest of the analysis, we suppress the time index unless necessary and use the notation defined in Section 3 whenever possible (e.g., D_n for D_t^n). Define the functions $\pi_t(D_n,D_r):=((1-\alpha)p_n-c_n+\alpha s)D_n+((1-\alpha)p_r-c_r-(1-\alpha)s)D_r$ and $G_t(y,D_n,D_r):=hE(y-R_w(D_n,D_r,\xi))^++bE(R_w(D_n,D_r,\xi)-y)^+$. Reorganizing the terms yields the profit in period t as $\Pi_t(y,D_n,D_r)=(c_r+s)x+\pi_t(D_n,D_r)-(c_r+s)y-G_t(y,D_n,D_r)$.

Let $V_t(x)$ denote the maximum expected discounted profit in periods $t,t+1,\dots,T$, if period t begins in state x. At the end of the planning period, the unfilled warranty demand is covered by the new products and the surplus earmarked inventory is salvaged. Thus, $V_T(x)=c_T(x)$ where $c_T(x)=sx^+-c_nx^-$ with the conventions $x^+=\max(0,x)$ and $x^-=\max(0,-x)$. Note that $c_T(x)$ is a concave increasing function since $c_n>s$. For $t=0,1,\dots,T-1$, we can state the dynamic programming formulation of the multiperiod problem as follows:

$$V_t(x)=(c_r+s)x+\max_{x\le y\le x+\alpha D_n-D_r,\,(D_n,D_r)\in\Omega}J_t(y,D_n,D_r),$$

with $J_t(y,D_n,D_r)=\pi_t(D_n,D_r)-(c_r+s)y-G_t(y,D_n,D_r)+\beta E(V_{t+1}(y-R_w(D_n,D_r,\xi)))$. A more convenient representation of this formulation can be obtained by defining the function $V_t^+(x)=V_t(x)-(c_r+s)x$ and reorganizing the terms in $J_t(y,D_n,D_r)$. Then, for $t=0,1,\dots,T-1$:

$$V_t^+(x)=\max_{x\le y\le x+\alpha D_n-D_r,\,(D_n,D_r)\in\Omega}J_t(y,D_n,D_r),\qquad(4)$$

with

$$\begin{aligned}&J_t(y,D_n,D_r)\\&\quad=W_t^+(y,D_n,D_r)+\beta E(V_{t+1}^+(y-R_w(D_n,D_r,\xi))),\qquad(5)\\&W_t^+(y,D_n,D_r)\\&\quad=\pi_t(D_n,D_r)-\beta(c_r+s)(\gamma(1-\alpha)(D_n+D_r)+E(\xi))\\&\qquad-(c_r+s)(1-\beta)y-G_t(y,D_n,D_r),\qquad(6)\end{aligned}$$

and $V_T^+(x)=(c_n-c_r-s)x-(c_n-s)x^+$. Without loss of generality, we assume that $(c_r+s)(1-\beta)<b$.

Otherwise, backordering is cheaper than covering a warranty demand by refurbishing and it would be optimal to backorder all warranty demand.

Proposition 2. *For $t = 0, 1, \ldots, T-1$, the following statements hold*:

(a) *$J_t(y, D_n, D_r)$ is jointly concave in (y, D_n, D_r) and $V_t^+(x)$ is concave in x.*

(b) *$J_t(y, D_n, D_r)$ has a finite maximizer denoted by $(\hat{y}_t, \hat{D}_t^n, \hat{D}_t^r)$.*

(c) *Let $\hat{K}_t := \alpha \hat{D}_t^n - \hat{D}_t^r$,*

(c.1) *if $x > \hat{y}_t$, it is optimal not to earmark any consumer returns, i.e., $y_t^*(x) = x$, and to sell the quantities $(D_t^{n*}(x), D_t^{r*}(x)) = \arg\max_{(D_n, D_r)\in\Omega} J_t(x, D_n, D_r)$.*

(c.2) *if $\hat{y}_t - \hat{K}_t \le x \le \hat{y}_t$, it is optimal to earmark up to the level $\hat{y}_t$ and sell the global optimal quantities, i.e., $(y_t^*(x), D_t^{n*}(x), D_t^{r*}(x)) = (\hat{y}_t, \hat{D}_t^n, \hat{D}_t^r)$.*

(c.3) *if $x < \hat{y}_t - \hat{K}_t$, the optimal earmark-up-to level and optimal sales quantities are given by*

$$\big(y_t^*(x), D_t^{n*}(x), D_t^{r*}(x)\big) = \underset{x \le y \le x + \alpha D_n - D_r, (D_n, D_r)\in\Omega}{\arg\max} J_t(y, D_n, D_r),$$

and $y_t^*(x) < \hat{y}_t$.

Proposition 2 shows that the optimal policy is essentially a price-dependent base-stock policy where the earmarked quantity is capacitated by the new and refurbished product sales quantities, which are endogenously determined by the OEM's pricing decisions. $\hat{K}_t$ is the capacity level if the OEM can sell new and refurbished products at the global optimal levels $(\hat{D}_t^n, \hat{D}_t^r)$. If the earmarked inventory at the beginning of the period is sufficiently large $(x > \hat{y}_t)$, earmarking is not a concern, and the new and refurbished product sales quantities (prices) are decided under this high level of protection against the warranty demand uncertainty. If the earmarked inventory at the beginning of the period is sufficiently low $(x < \hat{y}_t - \hat{K}_t)$, the OEM can optimally set a new capacity for earmarking, denoted by $K_t^*(x)(:= \alpha D_t^{n*}(x) - D_t^{r*}(x))$, by adjusting the new and refurbished product sales quantities accordingly. Even with an adjustment in the sales quantities, however, the optimal earmark up-to level $(y_t^*(x))$ does not exceed its global optimal level $(\hat{y}_t)$.

Our numerical experiments show that as the consumer return rate decreases or failure rate increases, the average $y_t^*(x)$ is decreasing. This is because when the consumer return rate is low, the OEM cuts the new product price aggressively to increase the refurbishing capacity by selling more new products. On the other hand, for higher failure rates, the OEM charges higher prices for both new and refurbished products and decreases the total product sales to balance the increase in the base warranty demand. Yet, the increase in the prices are such that the refurbished product sales shrink faster than the new product sales to keep the earmarking capacity in check. For sufficiently low consumer return rates and sufficiently high failure rates, these price adjustments are not enough to bring $y_t^*(x)$ to a positive level, the earmarked inventory is insufficient to keep up with the warranty demand and the backlog grows until the end of the planning horizon.

4.1. Optimal Dynamic Policy

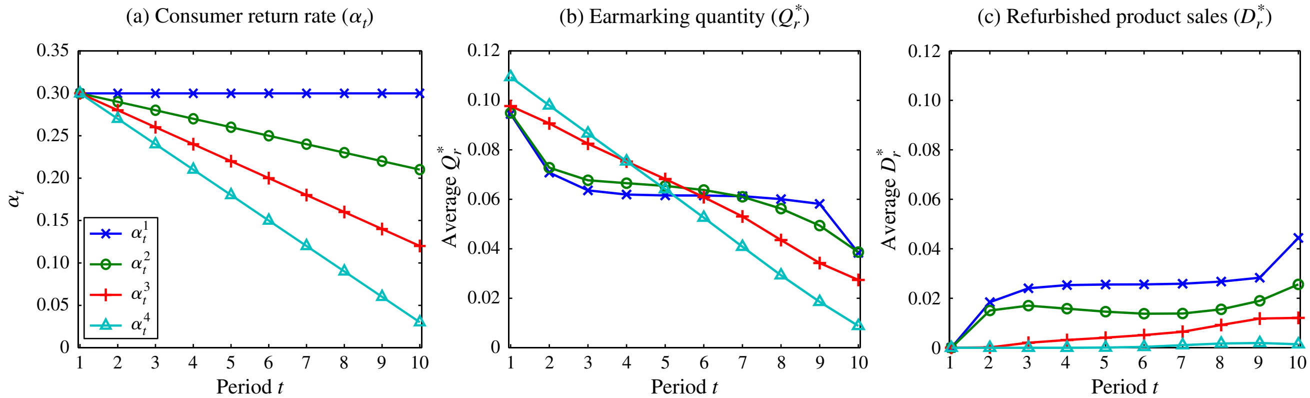
In this section we explore the inter-temporal behavior of the optimal dynamic disposition policy during the life cycle of the product. In particular, we focus on the inter-temporal changes in the consumer return and failure rates to better understand how the evolution of these parameters affects the optimal policy. To study the dynamic behavior of the optimal new and refurbished product sales and earmarked quantity, we divide the life cycle of the product into 10 periods and compute the optimal policy for each period. We then simulate sample paths of the state and decision variables and compute their averages.[6] Representative numerical results showing the inter-temporal behavior of D_r^* and Q_r^* under different scenarios, capturing various characteristics of products, consumers, and business environment, are reported in Figures 3–5. The parameters used in these representative examples are drawn from the parameter set developed for the numerical study in Section 5. The behavior of the optimal new product sales (D_n^*) is relegated to Online Appendix A.2.

4.1.1. Impact of the consumer return rate. For new-generation products with a disruptive technology and design, the consumer return rates are typically higher in the earlier stages of the life cycle because of a larger likelihood of mismatch between the product's functionality and the consumers' expectations. As the product reaches its maturity phase, consumers are better informed about the product's functionality (e.g., because of the OEM's or retailer's efforts) and less likely to return the product. Consequently, the consumer return rates of such products often show a decreasing pattern throughout the life cycle. Figure 3 shows that in such scenarios, the optimal policy emphasizes earmarking at the early stages of the life cycle and gradually decreases the earmarked quantity towards the end of the life cycle. This is because a decreasing consumer return rate implies an increasing number of warranty claims[7]

[6] Averages are calculated over at least 5,000 simulation runs. The initial state of the system (i.e., earmarked inventory at the beginning of the life cycle) is assumed to be zero $(x_0 = 0)$.

[7] As in the single-period model, a lower consumer return rate implies a higher base warranty demand rate $(\gamma(1-\alpha))$ and a higher total sales, and therefore increases the warranty demand.

Figure 3 (Color online) Dynamics Under a Decreasing Consumer Return Rate ($\delta = 0.7$, $c_n = 0.3$, $c_r/c_n = 0.2$, $s/c_n = 0.1$, $\bar{\xi} = 0.1$, $h/c_n = 0.02$, $b = 0.21$, $\beta = 1$, $\gamma = 0.05$)



and a decreasing refurbishing capacity. Thus, it is optimal to prioritize earmarking consumer returns early in the life cycle to build up earmarked inventory to hedge against the large number of warranty claims that will arrive at the later stages in the life cycle when refurbishing capacity is more constrained. Depending on the speed of the inventory buildup, which is driven by the warranty demand rate, warranty demand uncertainty, and consumer return rate, remarketing may become more pronounced relatively later in the life cycle. Even if the consumer return rate is stationary (α_t^1 in Figure 3), for sufficiently high warranty demand uncertainty, it is optimal to build up some level of earmarked inventory at the early stages in the life cycle to protect against the future warranty claims.

For consumer electronics products that are less disruptive in their technology and design, consumer return rates can be primarily driven by the competitive product offerings that are launched during the product's short life cycle. For such products, the consumer return rate can be increasing over time since the alternative products launched at different points in the life cycle can encourage consumers to try multiple products during the money-back return periods and increase the likelihood of a return. In such scenarios, the optimal earmarking quantity shows a concave inter-temporal behavior (Figure 4). The reason is as follows: For sufficiently high failure rates, a low consumer return rate implies a relatively high base warranty demand, causing the optimal policy to allocate scarce consumer returns to cover warranty demand rather than remarketing them, since the latter option also generates warranty demand. As the consumer return rate increases, however, the warranty demand decreases and the refurbishing capacity increases. Consequently, the earmarking quantity decreases while the refurbished product sales increase. The increase in the refurbished product sales is driven by not only the ample refurbishing capacity but also the refund cost advantage of the refurbished products; i.e., as discussed in the single-period model, a high volume of consumer returns favors remarketing, since refunding a refurbished product is cheaper than refunding a new product.

Interestingly, for sufficiently high warranty demand uncertainty, the above observations point to a consistent overall disposition strategy: At the early stages in the life cycle, the OEM should emphasize earmarking of consumer returns to either fulfill the current warranty claims or build up earmarked inventory for the future warranty claims, whereas remarketing should be considered later in the life cycle after enough earmarked inventory is accumulated.

4.1.2. Impact of the failure rate. Because of design and manufacturing problems, the OEMs can receive higher amounts of warranty claims at the early stages in the life cycle. As these design and manufacturing problems are resolved throughout the life cycle, the product's failure rate drops. Figure 5 shows that under this scenario, the OEM should allocate most of the consumer returns to the earmarking option because of high warranty demand at the early stages of the life cycle. As the failure rate decreases, the warranty demand decreases and, consequently, the refurbished product sales increase. As such, the inter-temporal behavior of the optimal refurbished product sales and optimal earmarking quantity in the face of a decreasing failure rate can be considered as qualitatively similar to the case of a decreasing consumer return rate. There is a difference, however, in that a steeper drop in the failure rate encourages a higher level of remarketing, whereas a steeper drop in the consumer return rate discourages it.

We also analyze the inter-temporal price changes for the cases considered in Figures 3–5. When the refurbishing capacity is scarce at the early stages in

Figure 4 (Color online) Dynamics Under an Increasing Consumer Return Rate
($\delta = 0.7$, $c_n = 0.3$, $c_r/c_n = 0.2$, $s/c_n = 0.1$, $\bar{\xi} = 0.05$, $h/c_n = 0.02$, $b = 0.21$, $\beta = 1$, $\gamma = 0.05$)

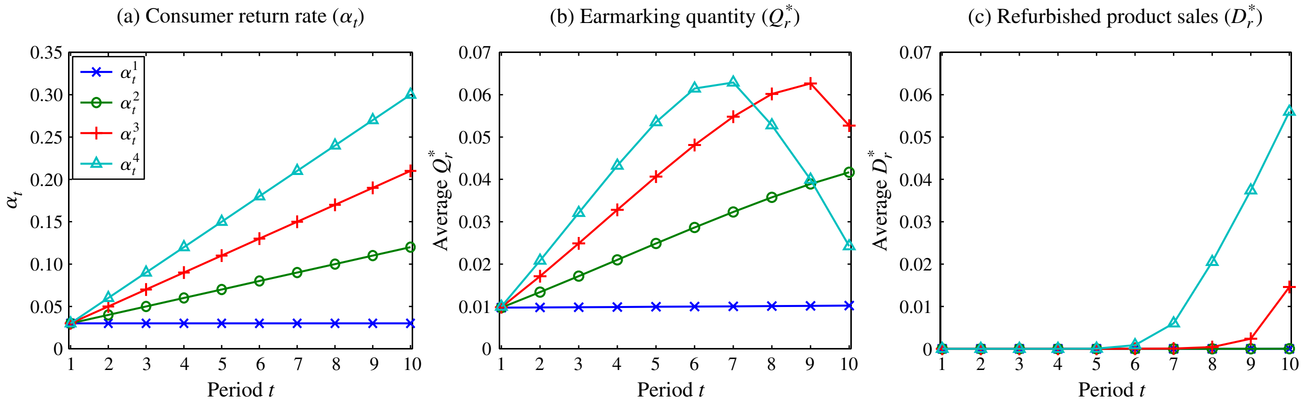
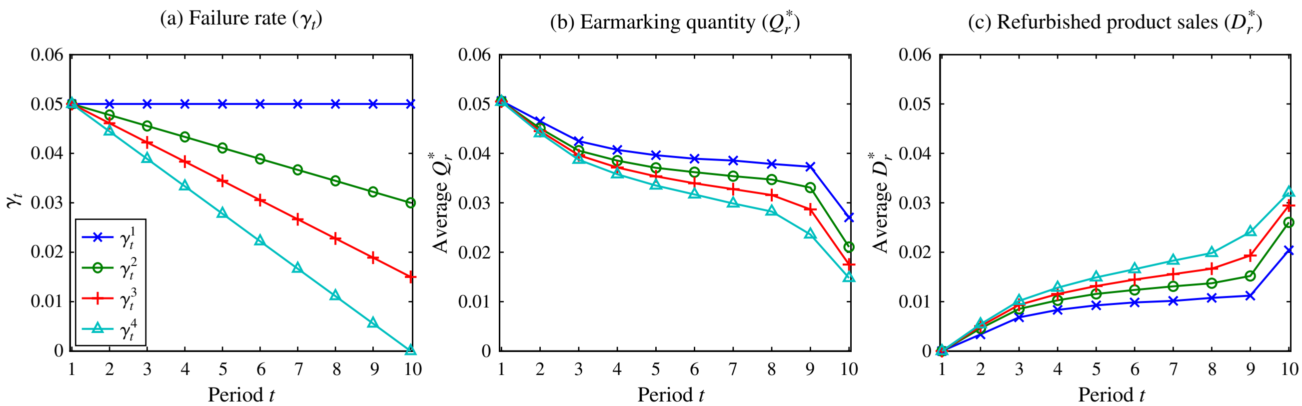


Figure 5 (Color online) Dynamics Under a Decreasing Failure Rate
($\delta = 0.7$, $c_n = 0.3$, $c_r/c_n = 0.2$, $s/c_n = 0.1$, $\bar{\xi} = 0.05$, $h/c_n = 0.02$, $b = 0.21$, $\beta = 1$, $\alpha = 0.15$)



the life cycle (Figure 4), the OEM first decreases the new product price to increase the refurbishing capacity via new product sales and then gradually increases it to balance the warranty demand and introduce the refurbished product to the market. On the other hand, when the consumer return rate is decreasing over time (Figure 3), this behavior is reversed and the optimal new product price shows a weakly concave behavior since a decreasing consumer return rate implies a higher warranty demand and a lower refurbishing capacity later in the life cycle. We find that the optimal refurbished product price is fairly stable over time (i.e., it changes in the narrow band of 0.45 to 0.47) and closely follows the pattern of the optimal new product price. Thus, the changes in the optimal refurbished product sales are mainly driven by the interactions between the refurbishing capacity and warranty demand rather than the changes in the optimal refurbished product price.

The interplay between the consumer return rate and the product prices reflects how the product prices are affected by the backlogged warranty demand. In particular, when the refurbishing capacity is scarce, the OEM uses the new product price to moderate the accumulation of the warranty demand backlog by first increasing the new product sales to generate more refurbishing capacity and then decreasing the new product sales to balance the warranty demand. Moreover, our analysis of the inventory level shows that when the consumer return rate or failure rate is decreasing, the inventory level is mostly positive and shows a concave behavior. On the other hand, for the cases where the consumer return rate is increasing over time, the inventory level is mostly negative and shows a weakly convex behavior.

5. Dynamic Allocation of Consumer Returns and Value of the Optimal Dynamic Policy

Section 4.1 shows that the optimal disposition strategy prescribes emphasizing different disposition options at different stages in the product's life cycle. To better understand how the allocation of consumer returns between remarketing and earmarking change throughout the life cycle as well as when a dynamic policy is most beneficial, we carry out a numerical study.

5.1. Parameter Development

To be consistent with our model development, we choose parameter ranges that are typically observed for consumer electronics having short product life cycles. The manufacturing cost of a new product (c_n) is estimated by using the reported price and material costs of various consumer electronics products and normalized to the range of $[0, 1]$ for convenience (see Online Appendix A.3 for details on estimation and normalization). The refurbishing cost (c_r) is taken within the range of 10% to 50% of the manufacturing cost since most consumer electronics returns are characterized as *no-trouble-found* returns and therefore can be brought back to almost new condition by simple buff-and-polish operations (Accenture 2008, Francis 2012, Gventer 2012). Reported consumer return rates (α) for consumer electronics vary from 2% to 20% depending on the product category and geographical location of the market (e.g., Accenture 2008, Shang et al. 2016a). Thus, in our experiments, we vary α from 5% to 30% to capture the reported rates and possible high-return scenarios. Based on our discussions with industry experts, we learned that most OEMs try to keep their failure rate (γ) below 5%. However, because of the uncertainties involved in the production and distribution process, the realized warranty demand rates can be very high (Gventer 2012). Therefore, the OEMs suffer from a high upside risk of warranty demand, which we represent in our numerical experiments by a uniformly distributed ξ in the interval $[0, \bar{\xi}]$ in each period, and vary $\bar{\xi}$ from 1% to 10%. For many products, the ratio of the new product price to the refurbished product price lies within the range of 30% to 100% (Subramanian and Subramanyam 2012). This ratio can be taken as a proxy for the relative willingness-to-pay (remarketing potential) for the refurbished products (δ). Accordingly, we vary δ from 50% to 85% to capture the reported ranges as well as some relatively low willingness-to-pay scenarios. The unit holding cost of earmarked inventory per period (h) is taken as 2% of the manufacturing cost of a new product, corresponding to the 20% annual inventory holding cost rate. The backordering cost per warranty claim per period (b) is approximated by the marginal saving of covering a warranty demand by refurbishing, or equivalently, the underage cost of not filling a warranty demand by refurbishing ($c_n - c_r - s$). Consumer electronics returns have relatively small salvage value compared to the potential value created by refurbishing; therefore, the OEMs commonly consider salvaging (e.g., recycling, parts harvesting) as a fallback to decrease the congestion in the refurbishing facility (e.g., Geyer and Blass 2010, Guide et al. 2008). Thus, we vary the salvage value (s) from 5% to 30% of the manufacturing cost. This range is in line with the values reported in previous work, and it captures different scenarios where salvaging is more or less valuable compared to refurbishing. The salvage value also affects the marginal cost of covering a warranty demand by refurbishing ($c_r + s$), which should be less than the manufacturing cost of a new product; otherwise, refurbishing for warranty coverage is not economically attractive and the problem trivially boils down to the one with a single disposition option ($Q_r = 0$). As such, in our experimental design, $c_r + s$ varies between 15% to 85% of the manufacturing cost of a new product, reflecting a relatively rich set of cases for the marginal warranty coverage cost. We set the per period discount factor (β) to 0.98 and 1 to capture scenarios with high discounting (20% annual cost of capital) and no discounting, respectively.

Table 2 **Parameter Values Used in Numerical Experiments**

c_n	c_r/c_n	α	δ	$\bar{\xi}$	γ	s/c_n	β	h/c_n
0.25	0.10	0.05	0.50	0.01	0.01	0.05	0.98	0.02
0.30	0.50	0.15	0.70	0.05	0.03	0.15	1.00	
		0.30	0.85	0.10	0.05	0.30		

Table 2 provides a summary of the parameters used in the numerical experiments. While these parameter estimates are not directly based on data reported by firms, they are realistic as discussed above; thus, they provide insights that are close to those that a firm, using its own proprietary data, should obtain. We generate a numerical set consisting of 1,944 instances obtained from all possible combinations of this parameter set.

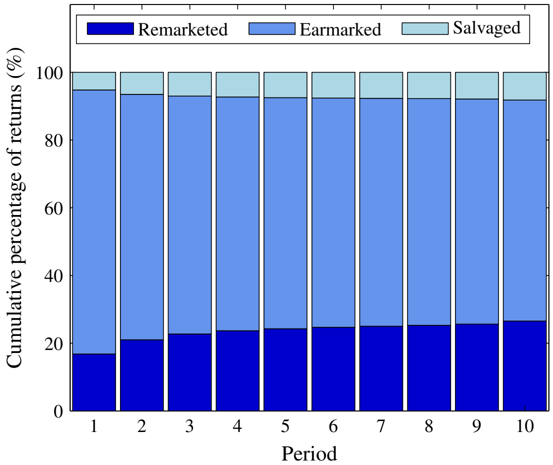
5.2. Dynamic Allocation of Consumer Returns

Figure 6 shows the optimal dynamic allocation of consumer returns among the three options. The allocation quantities are presented in terms of cumulative percentages of consumer returns[8] averaged over all instances at each time period. This is because the changes in the allocation percentages across periods are relatively small for the majority of the life cycle and the allocation of total consumer returns over time is observed more clearly by cumulative percentages. As such, the percentage allocation of the total consumer returns quantity received during the life cycle is given by the last column in each figure.

Over all the experiment instances, we find that the majority of the consumer returns are allocated to the earmarking option throughout the life cycle. On average, about 27% of all returns are allocated to the remarketing option, about 65% of all returns are allocated to the earmarking option, and the rest

[8] Cumulative quantity of consumer returns allocated to a disposition option by period t divided by the cumulative consumer returns received by period t.

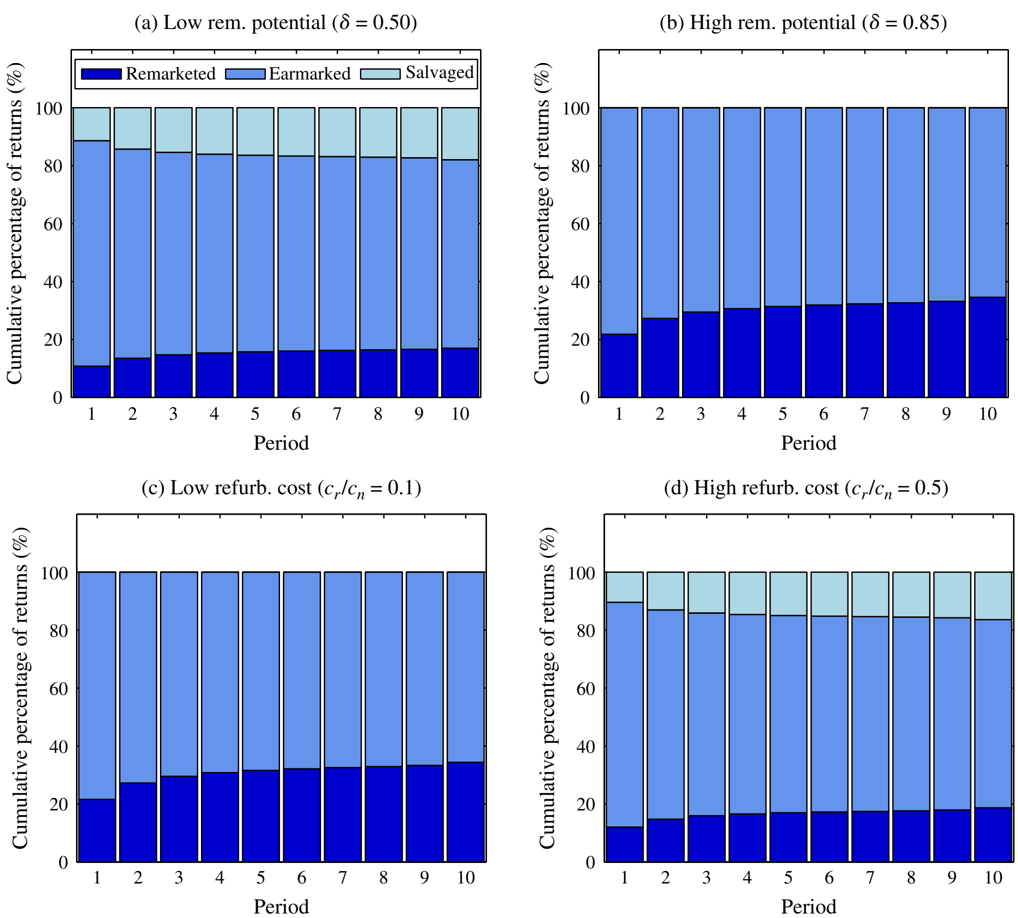
Figure 6 (Color online) Dynamic Allocation of Consumer Returns (All Instances)



are salvaged (see last column in Figure 6). These ratios change in favor of remarketing for low warranty demand uncertainty and high consumer return rates, e.g., when $\bar{\xi} = 0.01$ or $\alpha = 0.3$, about 46% of all returns are allocated to remarketing and 40% are allocated to earmarking. Yet, even for such parameter combinations where the remarketing option has an advantage over the earmarking option (as a result of low warranty uncertainty and high consumer return rate), almost half of the consumer returns are still earmarked. On the other hand, for the parameter combinations where the earmarking option has an advantage (e.g., high warranty uncertainty and low consumer return rate), the fraction of returns allocated to the remarketing option decreases significantly. For example, when $\bar{\xi} = 0.1$ or $\alpha = 0.05$, less than 10% of all consumer returns are allocated to the remarketing option, and more than 87% of returns are allocated to the earmarking option. These findings confirm our earlier intuition, developed in Section 3.2, and show that even in a multiperiod setting, earmarking generally dominates remarketing, since earmarked consumer returns can offset the warranty claim and refund costs generated by new and refurbished products.

We also observe from Figure 6 that over time, the percentage of consumer returns allocated to the earmarking option is decreasing while the percentage of consumer returns allocated to the remarketing and salvaging options is increasing, and this overall inter-temporal behavior is consistent under different parameter combinations (Figure 7). Thus, our

Figure 7 (Color online) Dynamic Allocation of Consumer Returns



earlier observations that the OEM should strategically emphasize earmarking at the early stages in the life cycle and postpone remarketing to the later stages appear to be robust.

Intuitively, it is expected that the percentage of returns allocated to the earmarking would be lower when the remarketing potential or refurbishing cost is high. Figure 7 shows, however, that an increase in the remarketing potential or refurbishing cost does not significantly affect the fraction of consumer returns allocated to the earmarking option but instead changes the allocation between remarketing and salvaging. For example, as δ increases, about 65% of all returns are consistently allocated to the earmarking option, while the percentage of returns allocated to salvaging shifts to remarketing. Similarly, as c_r/c_n increases, the percentage allocated to earmarking is preserved (about 65%), and the rest is reallocated in favor of salvaging. This is because the remarketing and salvaging options are generally dominated by earmarking (Figure 6). Consequently, when parameters change in favor of remarketing or salvaging, the optimal policy shifts the allocation of returns beginning from the least valuable disposition option rather than the earmarking option.

We also investigate how warranty demand variability affects the overall optimal earmarking quantity[9] and the overall optimal refurbished product sales. We find that as the warranty demand becomes more variable, the overall optimal earmarking quantity increases and becomes more variable, whereas the overall optimal refurbished product sales decreases and becomes less variable. This is because a higher warranty demand variability requires a higher level of earmarked inventory to hedge against the stockout risk, but also implies a larger fluctuation in the optimal earmarking quantity because of a higher risk of overstocking and understocking.

5.3. Comparison with the Myopic Policy

To shed light into the value of the dynamic disposition policy, we benchmark its performance vis-à-vis the myopic policy. The myopic policy in period t is found by maximizing (6) over (y, D_n, D_r) subject to the original constraint set $x \le y \le x + \alpha D_n - D_r$ and $(D_n, D_r) \in \Omega$. We emphasize that the definition of the myopic policy function (6) is in line with the previous literature on inventory theory (e.g., Zipkin 2000) but slightly different than the definition of the profit incurred in period t $(\Pi_t(y, D_n, D_r))$ because of the reformulation of the value function. We define the performance measure as the percentage profit penalty incurred by the myopic policy ($\Delta_M\%$). Table 3 reports the frequency distribution of the percentage profit penalty among all experiment instances.

Table 3 **Frequency Distribution of Profit Penalty Under Myopic Policy**

Profit penalty ($\Delta_M\%$)	Number of instances	Cumulative percentage (%)
≤0.5	1,277	65.7
≤1	1,482	76.2
≤3	1,786	91.9
≤5	1,870	96.2
≤10	1,932	99.4
≤15	1,944	100

Our results show that the myopic policy performs well compared to the optimal policy. Over all the experiment instances, the mean and median $\Delta_M\%$ are found to be 0.91% and 0.23%, respectively. Table 3 shows that for 96.2% of all instances, the percentage profit penalty is less than or equal to 5%. The maximum profit penalty is 15%, and there are 12 instances (out of 1,944 instances) where the percentage profit penalty can be considered as high (between 10% and 15%).

To better understand which parameters drive the performance of the myopic policy, in Table 4 we provide an overview of the differences in the average values of the system parameters between the *high* ($\Delta_M\% \le 3\%$) and *low* ($\Delta_M\% > 3\%$) performing instances of the myopic policy. We find that for all measured parameters except β and γ, the average parameter values for the high performing instances are significantly different than the average parameter values for the low performing instances. In particular, we find that the myopic policy performs better for smaller values of $\bar{\xi}, \alpha, \delta, c_{\underline{n}}$, and larger values of c_r/c_n, s/c_n, $c_r + s$. A small $\bar{\xi}$ positively impacts $\Delta_M\%$ since lower demand variability requires less strategic buildup of the earmarked stock and hence favors the myopic policy (e.g., for 1,296 instances with $\bar{\xi} \le 0.05$, the mean and max $\Delta_M\%$ are

Table 4 **Tests for Parametric Differences**

	Parameter means			
	$\Delta_M\% \le 3\%$	$\Delta_M\% > 3\%$	H_1	P-value
$\bar{\bar{\xi}}$	0.050	0.096	$\bar{\bar{\xi}}_l < \bar{\bar{\xi}}_u$	0.0000***
$\bar{\beta}$	0.990	0.990	$\bar{\beta}_l < \bar{\beta}_u$	0.3705
$\bar{\alpha}$	0.164	0.202	$\bar{\alpha}_l < \bar{\alpha}_u$	0.0000***
$\bar{\gamma}$	0.030	0.031	$\bar{\gamma}_l < \bar{\gamma}_u$	0.1561
$\bar{\delta}$	0.677	0.753	$\bar{\delta}_l < \bar{\delta}_u$	0.0000***
$\overline{c_n}$	0.274	0.283	$\overline{c_{nl}} < \overline{c_{nu}}$	0.0000***
$\overline{c_r/c_n}$	0.316	0.123	$\overline{(c_r/c_n)_l} > \overline{(c_r/c_n)_u}$	0.0000***
$\overline{s/c_n}$	0.170	0.127	$\overline{(s/c_n)_l} > \overline{(s/c_n)_u}$	0.0000***
$\overline{c_r+s}$	0.133	0.071	$\overline{(c_r+s)_l} > \overline{(c_r+s)_u}$	0.0000***

***P-value < 0.01.

[9] Defined as the average optimal earmarking quantity over the entire planning horizon. The overall optimal refurbished product sales are defined analogously.

found to be 0.4% and 3.7%, respectively). Similarly, under scarce refurbishing capacity (small α), it is optimal to allocate most of the returns for warranty coverage immediately without keeping them as earmarked stock, implying less benefit from strategic earmarking. Higher c_r, s, and a lower δ improve the performance of the myopic policy since they encourage more salvaging of consumer returns instead of remarketing and therefore give more weight to the immediate salvaging revenues in the overall profit. Finally, a smaller c_n implies less marginal saving from warranty coverage by refurbishing, which benefits the myopic policy. We conclude that the myopic policy can be used with confidence in practice when the consumer return rate, remarketing potential, manufacturing cost, and warranty demand uncertainty are low, and refurbishing cost and salvage value are high.

6. Conclusion

The high cost of lenient return policies forces consumer electronics OEMs to look for ways to recover value from lightly used returned products, known as consumer returns. Refurbishing these returns to remarket them or fulfill warranty claims are two common disposition options. These options, however, present the OEM with a challenging dynamic allocation problem that lies at the intersection of pricing new and refurbished products and stocking refurbished consumer returns to meet future warranty demand. Since consumer electronics are sold in rapidly changing markets and have short life cycles, the allocation of refurbished products between remarketing and warranty demand is also influenced by inter-temporal changes in critical parameters such as the consumer return rate and the product's failure rate. In this paper we analyze this dynamic allocation problem and provide managerial insights for consumer electronics OEMs.

Earlier research on closed-loop supply chains concluded that remarketing can be profitable when the new product cannibalization is low. Our study, on the other hand, reveals that when warranty claims and consumer returns are jointly taken into account, refurbishing and earmarking consumer returns to fulfill warranty claims generally dominate the remarketing option, and the OEM should strategically emphasize earmarking consumer returns at the early stages in the life cycle while switching to remarketing at the later stages in the life cycle. These results are driven by the fact that remarketed products also generate warranty coverage costs, and the OEM is exposed to much larger total warranty demand uncertainty at the early stages in the life cycle than at the later stages, when most of the warranty demand uncertainty is resolved. Thus, the option of refurbishing to fulfill warranty claims gives the OEM the opportunity to build up earmarked inventory of refurbished consumer returns that can be used to reduce the cost of warranty claims and hedge against future warranty demand uncertainty. Our analytical results reveal that, in certain cases, refurbishing consumer returns to fulfill warranty claims can even increase the refurbished product sales because of this warranty cost reduction effect. These findings contribute to the previous academic literature on closed-loop supply chains by showing that, for product categories with significant warranty coverage and refund costs, remarketing may not be the most profitable disposition option even if the product has strong remarketing potential and the OEM has the pricing leverage to tap into this market. Also, they provide an alternative explanation to the question of why most OEMs are reluctant to sell refurbished products. As such, the predictions of our model can be used to develop testable hypotheses about the impact of warranty service on the remarketing activities of OEMs.

To obtain more granular insights about the OEM dynamic allocation strategy, we study the impact of inter-temporal changes in the consumer return rate and the failure rate on the optimal disposition policy. Our numerical results show that if the consumer return rate is decreasing over time, the optimal earmarked quantity is decreasing while the optimal refurbished product sales are increasing. This happens because a decreasing consumer return rate implies an increasing warranty demand and a decreasing refurbishing capacity, making it optimal to refurbish and earmark most of the consumer returns early in the life cycle and remarket more aggressively after enough earmarked inventory is accumulated. On the other hand, if the consumer return rate is increasing, the OEM faces a relatively high warranty demand with a relatively low refurbishing capacity early in the life cycle compared to warranty demand and refurbishing capacity it faces later in the life cycle. Thus, to bridge this gap between the warranty demand and consumer returns, the OEM optimally allocates the majority of the consumer returns to fulfill the immediate warranty demand and postpones remarketing to later in the life cycle. The optimal disposition policy behaves similarly for a decreasing failure rate because of a similar inter-temporal mismatch between the warranty demand and consumer returns. These observations provide a useful managerial insight: when the warranty demand uncertainty is sufficiently high, regardless of the inter-temporal changes in the consumer return and failure rates, the OEM should allocate the majority of the consumer returns to the earmarking option early in the life cycle and consider remarketing only after enough earmarked inventory is built up or most of the warranty demand uncertainty is resolved.

To our knowledge, this paper is the first to analyze a dynamic joint pricing and stocking problem with dual disposition options in a closed-loop supply chain setting. We show that the optimal dynamic disposition policy for this problem is a price-dependent base-stock policy where the maximum quantity that can be earmarked is limited by the new and refurbished product sales quantities, which are endogenously determined by the OEM's pricing decisions. To better understand the operating conditions where the optimal dynamic disposition policy is most valuable, we numerically quantify the value of the optimal dynamic disposition policy by comparing its profit with the profit obtained under a myopic disposition policy, when all parameters are stationary. We find that, overall, the profit penalty incurred by the myopic policy is low, and therefore it can be considered as a good heuristic for the optimal dynamic policy. The optimal dynamic policy is most valuable for product categories with high warranty demand uncertainty, high consumer return rates, and high manufacturing cost since these parameters imply higher benefits from strategically earmarking at the early stages of the life cycle. Similarly, high remarketing potential, low refurbishing cost, and low salvage values imply less salvaging and more remarketing, and so these conditions also benefit more from a dynamic disposition policy.

We assume that all warranty claims and consumer returns occur in the same period in which the products are sold. Numerical analysis (available from the authors upon request) reveals that the performance of our myopic policy, which is found by maximizing (6), is not significantly affected when there is one-period dependence for warranty claims (i.e., a sold product can be returned as a warranty claim in the same or the next period); therefore, our original conclusions about the performance of the myopic policy stated above remain valid. This is because one-period dependence on warranty claims increases the warranty demand in a given period, but it does not change the refurbishing capacity. Consequently, one-period dependence implies relatively less refurbishing capacity and diminishes the value of strategic earmarking.

On the other hand, when there is multiperiod dependence on both warranty claims and consumer returns, a bigger performance difference between the myopic and optimal policies is expected, since the consumer returns arriving from the sales in the previous periods also contribute to the refurbishing capacity. With this more general model, however, we identify two major issues. First, when the consumer returns can be returned and refunded in periods other than when they are purchased, the concavity of the optimal value function is not guaranteed. Second, the state-space grows exponentially in the number of dependent periods and renders the problem computationally intractable. Addressing these problems (e.g., establishing structural properties for optimization other than concavity) and extending our model to the multiperiod dependence case is an interesting future research direction that would yield a more comprehensive understanding of the multiperiod dynamics and the value of a dynamic disposition policy.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/msom.2016.0584.

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