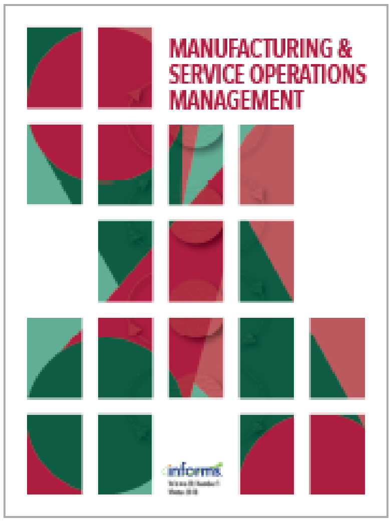

Manufacturing & Service Operations Management

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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informs
http://pubsonline.informs.org/journal/msom
MANUFACTURING & SERVICE OPERATIONS MANAGEMENT
Vol. 23, No. 6, November–December 2021, pp. 1413–1430
ISSN 1523-4614 (print), ISSN 1526-5498 (online)

New-Product Diffusion in Closed-Loop Supply Chains

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Received: July 18, 2017
Revised: August 10, 2018; April 12, 2019; October 1, 2019; November 19, 2019
Accepted: November 21, 2019
Published Online in Articles in Advance: March 11, 2020

https://doi.org/10.1287/msom.2019.0864

Abstract. ***Problem definition***: We study the sales planning problem of a producer who sells new and remanufactured versions of a durable good over a finite life cycle. We investigate whether slowing down product diffusion by choosing to partially satisfy demand might be profitable for the producer. ***Academic/practical relevance***: We provide new insights into sales management in closed-loop supply chains by uncovering the role key market characteristics play in profitability of partial demand fulfillment as well as its optimal timing and magnitude. ***Methodology***: We develop a dynamic model in which demand arrives as a slightly modified Bass diffusion process, and end-of-use products required for remanufacturing are constrained by earlier sales. ***Results***: The optimal sales plan involves partial demand fulfillment when the product diffusion rate is high, the profit margin from remanufacturing is large, and the remanufactured item is in limited demand. Partial demand fulfillment extends to earlier stages of the life cycle as the diffusion rate grows, the demand for remanufactured items shrinks, or the number of consumers who return their end-of-use items increases. It is profitable to backlog more customers when the word-of-mouth effect dominates the diffusion process or when the demand for remanufactured items is lower. Finally, the benefit of delaying product diffusion tends to increase with diffusion rate. ***Managerial implications***: Our findings suggest that deliberately backlogging some customers may be an effective lever (in the absence of flexibility to dynamically adjust prices) for durable-good producers in fast-clockspeed industries to improve their total profits from the jointly optimized sales of new and remanufactured items.

Funding: Financial support from Bilkent University is gratefully acknowledged.
Supplemental Material: The online appendix is available at https://doi.org/10.1287/msom.2019.0864.

Keywords: marketing-operations interface • new-product diffusion • sales planning • closed-loop supply chains • remanufacturing

1. Introduction

Forward supply chains (FSCs) can benefit from manipulating new-product diffusion. For example, when there are production constraints, producers may want to try to control the positive word-of-mouth feedback about their new products by avoiding sales in the early stages of the product life cycle. With this strategy, despite the potential loss of sales in the short term, there may be a better match between supply and demand in the long run, thanks to inventory that will build over time as well as delayed demand (Kumar and Swaminathan 2003, Shen et al. 2011). Closed-loop supply chains (CLSCs) have different dynamics that may motivate producers to control the word-of-mouth effect in the absence of production constraints (for new items). For instance, it may be desirable to strategically delay new-product sales of remanufacturable durable goods in fast-clockspeed industries (e.g., consumer electronics; see Fine 1996, Fine 2000, Souza et al. 2004, and Calmon and Graves 2017 for discussions of different clockspeed industries). Although remanufacturing is often viewed skeptically due to the short life cycles of products in such industries, this may be outweighed by the fact that a significant amount of material can be recovered from an end-of-use product if it has not been used extensively (Souza 2012). Curbing the initial sales volumes may amplify this value by delaying product diffusion, enabling more *high-value* returns to be remarketed in later (delayed) stages of the life cycle.

In this paper, we study the sales planning problem of a producer who sells new and remanufactured versions of a durable good over a finite selling horizon with an arbitrary number of periods. Demand arises according to the Bass diffusion model that is extended to allow for rejection of any amount of demand in any period. The Bass diffusion model was originally developed by Bass (1969) and represents a major step toward our understanding of consumer behavior regarding the timing of new-product purchase; see Bass (2004) for details. In the extended Bass diffusion model, a customer whose demand is not satisfied does not communicate feedback about the experience of the product, as is typically assumed in the FSC literature that considers sales planning for the endogenous modeling of the diffusion process (Ho et al. 2002, Kumar and Swaminathan 2003, Ho et al. 2011, Shen et al. 2011). Such an aspect of sales planning has been overlooked in the CLSC literature, despite the efforts to endogenously shape the diffusion process via pricing (Debo et al. 2006, Robotis et al. 2012, Akan et al. 2013). We refer the reader to Guide and van Wassenhove (2009), Ferguson and Souza (2010), Akçalı and Çetinkaya (2011), Hassini et al. (2012), Souza (2013), and Govindan et al. (2015) for comprehensive discussions of CLSCs. In this paper, we investigate whether the producer can benefit from delaying product diffusion by implementing a sales plan that rejects some demand in some periods (the partial-fulfillment policy) rather than meeting all demand in each period (the immediate-fulfillment policy).

In our CLSC model, similar to FSC models, a certain fraction of consumers whose demands are rejected in any period are willing to buy the product in the next period. However, unlike FSCs, a certain fraction of consumers whose demands are met in any period are willing to return their end-of-use products to the producer in the future; these end-of-use returns are required for remanufacturing. In fast-clockspeed industries, these consumers are likely to trade up to the next-generation product or trade in for credit toward their purchase of a different product in the future. In addition, a certain fraction of consumers in any period buy the remanufactured item if it is available (the functionality-oriented segment), cannibalizing demand for new items. In this setting, when there is ample supply for new-item manufacturing, we find that delaying product diffusion can be beneficial if the producer aims to maximize its total profit from selling new and remanufactured items together over the selling horizon. This finding contrasts with previous results in the FSC literature, where the profits accrue from selling only new items.

In our model, the partial-fulfillment policy can only be profitable when the remanufactured item has a greater profit margin than the new item. Focusing on this scenario, we establish conditions for the optimality of the partial-fulfillment policy (Theorem 1). Our results imply that partial fulfillment can indeed be desirable in fast-clockspeed industries: The revenue loss due to rejecting a demand is often small in fast-clockspeed industries because one can still observe almost all the diffusion demand, despite the shifted diffusion demand, before the selling horizon ends. But the revenue gain from rejecting a demand may be high because the fast diffusion process provides large return volumes during the selling horizon, enabling the delayed demand of the functionality-oriented segment to be met with remanufactured items in large quantities. Although the remanufactured-item demand is a major reason for delaying product diffusion, the partial-fulfillment policy can only be desirable when the functionality-oriented segment is small enough (but strictly positive): If this segment is too large, the gain from rejecting a demand is low because the remanufactured-item demand is likely to exceed the return volume in each period, so that any optionally delayed demand is unlikely to be met with a remanufactured item. In addition, the loss due to rejecting a demand is higher in this case because the slowdown of diffusion may lead to a situation where some customers have not yet arrived at the end of the selling horizon, *and* a larger number of these customers would prefer more profitable remanufactured items.

Numerical experiments on smartphones—a remanufacturable durable good from a fast-clockspeed industry—with calibrated data reveal that the selling horizon can be divided into three disjoint phases: *In the first phase, immediate fulfillment is optimal.* Rejecting a demand too early may significantly reduce the future diffusion demand, and a delayed demand in the initial periods cannot be met with remanufactured items due to a shortage of the used items. *In the second phase, partial fulfillment is optimal.* This partial fulfillment is advisable because it becomes possible to meet some of the resulting delayed demand with remanufactured items, thanks to the growing return volume. Unmet demand in this phase tends to be larger when the word-of-mouth component has a greater impact on product diffusion or when the functionality-oriented segment is smaller. *In the third phase, immediate fulfillment is optimal.* The accumulated returns are sufficient to meet all remanufactured-item demand in each period of the last phase, so that the remanufacturing volume cannot be increased by manipulating product diffusion in the last phase. Numerical results also indicate that the second phase appears earlier when the diffusion process is faster, when the functionality-oriented segment is smaller, or when the number of consumers who return their end-of-use items is larger. Finally, our experiments imply that the partial-fulfillment policy can improve the profit under the immediate-fulfillment policy by up to 4.2%, providing a greater benefit when the diffusion process is faster.

There are considerations not captured in our model that could affect our conclusions. First, our model does not include competition across the producer's own-brand product generations, competition against other producers' products, and endogenous pricing and market segmentation. Second, our key assumptions about consumer behavior build upon previous findings in the literature rather than on a behavioral study in any specific industry. Last, the new-product sales team of a producer is often motivated to sell as many new items as possible over the entire selling horizon and may be resistant to sales strategies aimed at improving the overall remanufacturing volume (which can only pay off in the long run). This may be a serious impediment to successful implementation of the partial-fulfillment policy in practice.

Nevertheless, despite its limitations, our proposed policy could be a novel and attractive idea when the above externalities are absent or can be overcome. One possible setting in which our conclusions might be applied concerns the world's leading smartphone producers—Apple and Samsung—which seem to have a very strong loyal customer base; only a small number of their customers whose demands are not met immediately are expected to switch to buying the competitor's product. These companies also appear to adjust the prices of their existing smartphones only when the newer generations become available; the price of a particular smartphone is often subject to only a couple of updates during the entire selling horizon. Our model may thus provide a potential strategic option for such producers with strong brand loyalty and limited pricing flexibility.

The rest of this study is organized as follows: Section 2 reviews the related literature. Section 3 describes our main model. Section 4 presents our analytical results for the main model and our numerical results in a special case of the main model. Section 5 provides several extensions. Section 6 offers a summary and conclusion. Parameter development of the base scenario for numerical analysis and detailed versions and proofs of the analytical results are contained in an online appendix.

2. Related Literature

Understanding consumer behavior is a long-standing challenge for researchers in the area of management science. In a major advance, Bass (1969) developed a behavioral rationale for the timing of the initial purchases of new products. In the Bass diffusion model, the initial purchases of products are made by "innovators" and "imitators." The timing of innovators' initial purchases is not influenced by the previous buyers. Imitators, on the other hand, are influenced by the previous buyers; imitators "learn" from those who have already bought the product. Innovators (or imitators) are thus likely to significantly contribute to the earlier (or later) stages of the adoption process. The likelihood of an initial purchase by an individual consumer at any time is a linear function of the number of previous buyers. Based on this assumption, Bass (1969) formulated his famous diffusion dynamics over the product life cycle. See Bass (2004) for details.

Our work is related to the literature on the Bass diffusion model applied to sales planning. In the FSC literature, several papers study the sales planning problem of a producer who aims to maximize her total profit over a product life cycle under supply constraints. Satisfying all current demands upon the introduction of a new product amplifies the word-of-mouth effect, potentially leading to the rapid growth of future demand and resulting in the available capacity being exceeded. In order to reduce the loss of sales due to insufficient supply, these papers focus on the following two strategies: The firm can delay the launch time of the product in order to build inventory, or it can launch the product immediately and then deliberately backlog some arriving customers, even if inventory is available, to mitigate the word-of-mouth effect (i.e., the partial-fulfillment policy). When these strategies are available, Ho et al. (2002) postulate that the partial-fulfillment policy cannot be optimal, whereas Kumar and Swaminathan (2003) show that it can be. Ho et al. (2011) prove the optimality of the immediate-fulfillment policy when all unmet demand is backordered. Shen et al. (2011) present an example that shows that the partial-fulfillment policy can be optimal when all unmet demand is lost. Similar to these papers, we also control sales to manage product diffusion. However, we show that the partial-fulfillment policy can be optimal in CLSCs in the absence of supply constraints for new items and that a larger backlogging rate favors the partial-fulfillment policy. In the FSC literature, again, under supply constraints, Shen et al. (2011, 2014) find that the partial-fulfillment policy is suboptimal when price can be dynamically adjusted: Pricing flexibility negates the need for deliberate backlogging to shape product diffusion. Unlike these two papers, there is no pricing flexibility in our diffusion model, thus encouraging partial fulfillment.

In the CLSC literature, several papers consider the diffusion process as an exogenous model input. Inspired by the Bass diffusion model, Geyer et al. (2007) model the market demand over the product life cycle as following an isosceles trapezoid. In their setting, all demand is immediately met over the life cycle, a certain fraction of the sold items become available for remanufacturing and resale after a fixed market sojourn time, and a remanufactured product is a perfect substitute for the new product. They investigate the profitability of remanufacturing when the end-of-use returns are remanufactured, as long as there is a market demand. Georgiadis et al. (2006) numerically analyze the effects of the product life-cycle pattern and the average product usage time on capacity planning for collection and remanufacturing. Georgiadis and Athanasiou (2010) extend the model in Georgiadis et al. (2006) by allowing for two sequential product types; they study two cases: (a) The sequential products are identical, and (b) the market shows preference between the products. Wang et al. (2017) consider a setting in which the demand arrives according to the Bass diffusion model and a certain fraction of the sold items become available to the producer after a fixed market sojourn time. They characterize the optimal component reuse volume and acquisition costs. Unlike these papers, we study the sales planning problem via endogenous modeling of the diffusion process.

Several other papers consider pricing as a lever to manage product diffusion. Debo et al. (2006) examine the joint pricing of new and remanufactured products in an infinite-horizon setting with variable market sojourn time, imperfect substitution between new and remanufactured items, and supply constraints. They extend the *price-dependent* Bass diffusion model (see Bass et al. 1994) by allowing for repeat purchases and modeling the coefficient of imitation as a function of the installed base of new products. They characterize the diffusion paths of new and remanufactured products, analyzing the impacts of the remanufacturability level, capacity structure, and reverse channel speed on profitability. Robotis et al. (2012) consider a producer with a constrained production and service capacity who offers a leasing contract to consumers. In their setting, a remanufactured product is a perfect substitute for the new product, and demand arrives as a diffusion process that is controlled by the producer through the leasing price and duration. They characterize the optimal pricing strategy of the producer, investigating the effects of the remanufacturing option on the leasing price and duration. Finally, Akan et al. (2013) consider a producer with ample manufacturing capacity who sells the new and remanufactured versions of a product over a finite life cycle. A remanufactured product is an imperfect substitute for the new product, and demands arrive as a price-dependent diffusion process. They characterize the optimal pricing, production, and inventory policies of the producer, showing that partially satisfying demand for the remanufactured item is never optimal. Unlike these papers, in our setting, there is no pricing flexibility, and deliberate backlogging is the only lever to manage product diffusion. Concentrating on sales decisions that are free of interactions with pricing decisions enables us to better capture the diffusion and closed-loop dynamics in our model. Specifically, we depart from the above papers by modeling that only a certain fraction of the unmet demand can be backlogged, differentiating backlogged demand from shifted diffusion demand under the partial-fulfillment policy, and allowing for consumer heterogeneity in their timing of returns.

We contribute to the literature on operations management in regards to new-product diffusion as follows:

- We incorporate the Bass diffusion process into the sales planning problem for CLSCs. We find that the producer can improve its total profit from the sales of new and remanufactured items over a finite selling horizon by delaying its product diffusion (in the absence of pricing flexibility and competition).
- We identify the key drivers for delaying product diffusion in our CLSC model: The partial-fulfillment policy can be optimal when the diffusion process is fast enough, the remanufactured-item demand exists but is not very large, and the remanufactured item has a high margin.
- Our results uncover the role the key market characteristics play in the optimal timing and magnitude of partial fulfillment: Partial fulfillment is initiated earlier if the diffusion process is faster, the functionality-oriented segment is smaller, or the return volume is larger. Unmet demand is larger when the word-of-mouth effect dominates the diffusion process or when the functionality-oriented segment is smaller.

3. Problem Formulation

We consider a producer that offers a new durable good over a finite selling horizon of T periods. Each customer buys at most one unit of the product during the selling horizon. Demand evolves over time, according to a slightly modified Bass diffusion process. In the original Bass diffusion process, a population of consumers of size m gradually purchases the product. The rate at which consumers buy the product is determined by the fraction of innovators that exist in the population and the word-of-mouth (or diffusion) effect that is a function of the number of previous purchases. *Innovators* buy the product independently of other consumers' actions, whereas *imitators'* timing of purchase is influenced by other consumers' actions. In a discrete-time framework, given that all demand is immediately met in each period, demand in period $t \geq 1$ is

$$\widetilde{d}_t = \left(p + \frac{q\widetilde{D}_t}{m}\right)\left(m - \widetilde{D}_t\right),$$

where p is the fraction of innovators (coefficient of innovation), q is a measure of the diffusion effect (coefficient of imitation), and $\widetilde{D}_t$ is the total sales volume up to period t (i.e., $\widetilde{D}_1 = 0$ and $\widetilde{D}_t = \sum_{i=1}^{t-1} \widetilde{d}_i$, $\forall t > 1$). In the literature, the term $(p + q\widetilde{D}_t/m)$ often refers to the likelihood of an initial purchase by an individual consumer in period t. According to this view, because $\widetilde{D}_t \to m$ for a very large t, we can assume that $p + q \leq 1$. See Bass (1969) and Bass (2004) for detailed descriptions of the Bass diffusion process. See also Figure 1 for an illustration. Most studies dealing with prelaunch forecasting of new-product demand have only focused on the estimation of the two parameters p and q, predicting the population size m from market research. See Goodwin et al. (2014) and Lee et al. (2014) for detailed discussions on prelaunch forecasting.

In our diffusion model, unlike the original Bass diffusion process, the producer is able to reject any amount of demand in any period. We denote by s_t the sales volume in period t. The producer is also able to remanufacture and remarket any available end-of-use product. We denote by n_t and r_t the sales volumes for new and remanufactured items, respectively, in period t. Thus $s_t = n_t + r_t$. The diffusion demand in period $t \geq 1$ is

$$d_t = \left(p + \frac{qS_t}{m}\right)(m - D_t), \tag{1}$$

where S_t is the total sales volume up to period t (i.e., $S_1 = 0$ and $S_t = \sum_{i=1}^{t-1} s_i$, $\forall t > 1$), and D_t is the total diffusion demand observed up to period t (i.e., $D_1 = 0$ and $D_t = \sum_{i=1}^{t-1} d_i$, $\forall t > 1$). This demand formulation was also proposed in the sales planning literature; see, for instance, Ho et al. (2002), Kumar and Swaminathan (2003), Shen et al. (2011), Ho et al. (2011), and Shen et al. (2014). If all demand is met in each period, our diffusion model reduces to the original Bass diffusion process. See Figure 1 for an illustration of our diffusion model for three different sales plans.

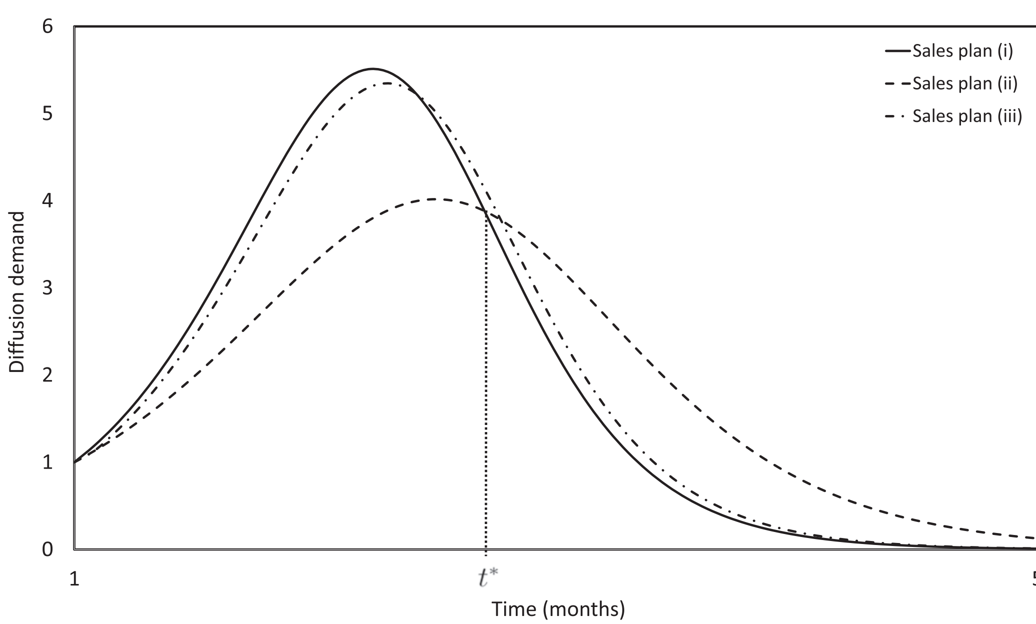
We partition the market into distinct segments according to consumers' willingness to (a) wait for product adoption, (b) return their end-of-use products, and (c) purchase remanufactured items, respectively:

(a) A fraction α of the unmet portion of the demand (newly arriving or previously backlogged) in period t is backlogged to be satisfied in period $t+1$. The remaining fraction of the unmet demand is lost. We assume that the customers whose demands were rejected in the past retain no memory about the number of periods that they have waited for the adoption of the product. These assumptions are standard in the sales planning literature; again, see, for instance, Ho et al. (2002), Kumar and Swaminathan (2003), Shen et al. (2011), Ho et al. (2011), and Shen et al. (2014).

(b) A fraction β_i of the products that have been sold in period t are returned by consumers to the producer at the end of their use and become available for remanufacturing and resale in period $t+i$, $\forall i \geq 1$. Note that $\beta \triangleq \sum_i \beta_i \leq 1$. (These consumers are likely to trade up to the next-generation product in fast-clockspeed industries.) The fraction $(1-\beta)$ of the products that have been sold in any particular period cannot be collected or remanufactured in any future period. More restricted assumptions appear in the CLSC literature; see, for instance, Ferguson and Toktay (2006), Geyer et al. (2007), Akan et al. (2013), Ovchinnikov et al. (2014), Abbey et al. (2015a), and Abbey et al. (2017).

(c) A fraction γ_1 of the newly arriving consumers in each period wants to buy only new items (the newness-conscious segment). And a fraction γ_2 wants to buy remanufactured items if available and new items otherwise (the functionality-oriented segment). The fraction γ_2 displays indifference between new and remanufactured items, preferring to buy remanufactured items at a discounted price. We assume $\gamma_1 + \gamma_2 = 1$. Experimental studies validate the existence of such consumer segments; see, for instance,

Figure 1. New-Product Diffusion when $p = 0.01$, $q = 0.20$, $m = 100$, and $\alpha = 1$ for Three Different Sales Plans



Notes. In sales plan (i), all demand is met in each period. In sales plan (ii), 70% of the diffusion demand is met in each period, but no backlogged demand is met at all. In sales plan (iii), 70% of the diffusion demand is met in each period, and all backlogged demand from each period is met in the next period. Sales plan (i) corresponds to the original Bass diffusion process.

Atasu et al. (2010), Guide and Li (2010), Ovchinnikov (2011), Ovchinnikov et al. (2014), Abbey et al. (2015a), and Abbey et al. (2015b). Consumers stick to their initial preferences (newness-conscious versus functionality-oriented) throughout the selling horizon.

We denote by b_{1t} and b_{2t} the accumulated numbers of backorders in period t from the newness-conscious customers and from the functionality-oriented customers, respectively. The total sales volume is constrained by the total demand observed in each period:

$$0 \leq s_t = n_t + r_t \leq d_t + b_{1t} + b_{2t},\ \forall t \geq 1. \tag{2}$$

The sales volume for remanufactured items is constrained by the maximum possible demand for remanufactured items in each period:

$$0 \leq r_t \leq \gamma_2 d_t + b_{2t},\ \forall t \geq 1. \tag{3}$$

We assume that, as demands for new items are met in any period, the newness-conscious customers execute their product purchases earlier than the functionality-oriented customers, who switch to buying new items after their demands for remanufactured items are rejected in this period. Suppose that $\gamma_1 d_t + b_{1t} \geq n_t$ and $\gamma_2 d_t + b_{2t} \geq r_t$. The above assumption implies that all new-item purchases in period t are made only by newness-conscious customers. The fraction α of newness-conscious customers whose demands are rejected in period t wait for the product till period $t+1$ (i.e., $b_{1(t+1)} = \alpha(\gamma_1 d_t + b_{1t} - n_t)$). Likewise, $b_{2(t+1)} = \alpha(\gamma_2 d_t + b_{2t} - r_t)$. Now, suppose that $\gamma_1 d_t + b_{1t} < n_t$, but $\gamma_2 d_t + b_{2t} > r_t$. The above assumption implies that demand of all newness-conscious customers is met in period t, whereas the demand of some functionality-oriented customers is also met with new items in period t. In this case, the backlogged demand of newness-conscious customers is cleared (i.e., $b_{1(t+1)} = 0$). Because the unmet demand of functionality-oriented customers in period t is given by the total demand minus the total sales amount in period t, $b_{2(t+1)} = \alpha(d_t + b_{1t} + b_{2t} - n_t - r_t)$. Hence, taking $(b_{11}, b_{21}) = (0, 0)$, we can calculate $(b_{1(t+1)}, b_{2(t+1)})$, $\forall t \geq 1$, with the following recursion:

$$\begin{aligned}&\left(b_{1(t+1)}, b_{2(t+1)}\right)\\ &= \begin{cases} \left(\alpha\left(\gamma_1 d_t + b_{1t} - n_t\right), \alpha\left(\gamma_2 d_t + b_{2t} - r_t\right)\right) \\ \qquad \text{if } \gamma_1 d_t + b_{1t} \geq n_t \text{ and } \gamma_2 d_t + b_{2t} \geq r_t, \\ \left(0, \alpha(d_t + b_{1t} + b_{2t} - n_t - r_t)\right) \\ \qquad \text{if } \gamma_1 d_t + b_{1t} < n_t \text{ and } \gamma_2 d_t + b_{2t} > r_t. \end{cases}\end{aligned} \tag{4}$$

The sales volume for remanufactured items is also constrained by the accumulated end-of-use return volume in each period:

$$0 \leq r_t \leq e_t,\ \forall t \geq 1, \tag{5}$$

where e_t is the end-of-use return volume available in period t. Taking $e_1 = 0$, we can calculate e_{t+1}, $\forall t \geq 1$, with the following recursion:

$$e_{t+1} = e_t - r_t + \sum_{i=1}^{t} \beta_i s_{t+1-i}. \tag{6}$$

See Figure 2 for an illustration of the evolution of the demand for remanufactured items and the accumulated return volume over the selling horizon. The above formulation does not keep track of whether a returned item is originally new or remanufactured. Thus, any particular item may be remanufactured multiple times over the entire selling horizon. But such cases are very unlikely when the values of parameters T and β_i are calibrated for fast-clockspeed industries: The length of the selling horizon is typically less than double the mean market sojourn time.

We define c_n as the unit manufacturing cost and p_n as the unit selling price of the new product. We also define c_r as the unit remanufacturing cost and p_r as the unit selling price of the remanufactured product. We assume $p_n > c_n$ and $p_r > c_r$. Hence, the producer's problem of maximizing the total profit over the selling horizon of T periods can be formulated as

$$\max_{n_1,..,n_T,r_1,..,r_T} \sum_{t=1}^{T} \left[\left(p_n - c_n\right) n_t + \left(p_r - c_r\right) r_t \right]$$

subject to (1)–(6). This optimization problem is a nonlinear program due to the presence of diffusion demand calculation in (1). Let $(n_1^*, \ldots, n_T^*, r_1^*, \ldots, r_T^*)$ denote the optimal sales plan. The optimal solution is trivial in a special case of our problem:

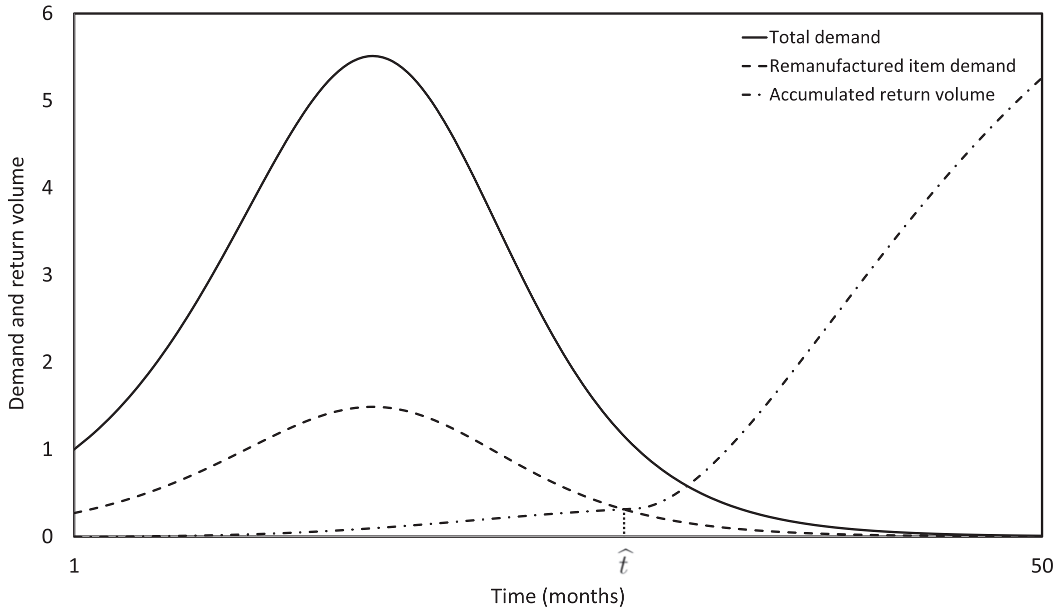
Lemma 1. *If $p_r - c_r \leq p_n - c_n$, $r_t^* = 0$ and $n_t^* = \widetilde{d}_t$, $\forall t$.*

Lemma 1 states that, if the new item has a greater profit margin than the remanufactured item, there is no positive economic return from offering remanufactured items, and there is no incentive to reject the demand for new items in any period. To eliminate this trivial case, we assume $p_r - c_r > p_n - c_n$: The producer is better off satisfying a demand with a remanufactured item (whenever possible) rather than a new item. This assumption is realistic in many cases because remanufacturing often reduces the need for new materials as well as energy consumption in manufacturing (see Atasu et al. 2010, Guide and Li 2010, and Gutowski et al. 2011).

4. Analysis of Sales Plans

In this section, we investigate whether and when slowing down the product diffusion by partially satisfying demand might be profitable for the producer. Section 4.1 establishes sufficient conditions that ensure the optimality of partial demand fulfillment

Figure 2. Evolution of Demand and Returns when All Demand Is Met, While Remanufactured-Item Demand Is Met with Available Returns to the Fullest Extent Possible, in Each Period, $p = 0.01$, $q = 0.20$, $m = 100$, $\gamma_2 = 0.27$, and $\beta_i = (12\%) \times \mathbb{P}\{i - 0.5 \leq X \leq i + 0.5\}$, Where $X \sim \text{Weibull}(25, 2)$, $\forall i \geq 1$



Note. Remanufacturing volume is bounded by accumulated return volume up to period $\widehat{t}$ and by remanufactured-item demand from period $\widehat{t}$ on.

and derives an upper bound on the optimal initiation of partial demand fulfillment under these conditions. Section 4.2 conducts numerical experiments in a simpler version of the main model to provide further insights into the exact timing and magnitude of partial demand fulfillment (if optimal).

4.1. Sufficient Conditions for Partial Demand Fulfillment

For our analysis, we classify the feasible sales plans of our optimization problem in Section 3 into two classes:

(a) Immediate-fulfillment policy: All demand is met, while the demand for remanufactured items is met with the available end-of-use returns to the fullest extent possible, in each period.

(b) Partial-fulfillment policy: Some demand is rejected in some period $t < T$. Notice that all demand is met in period T at optimality.

The sales plan in class (a) is myopically optimal and corresponds to the original Bass diffusion process. We use the tilde ($\widetilde{\ }$) to denote the variables of this myopic sales plan. Note that $\widetilde{s}_t = \widetilde{d}_t$, $\widetilde{r}_t = \min\{\widetilde{e}_t, \gamma_2 \widetilde{d}_t\}$, and $\widetilde{S}_t = \widetilde{D}_t$, $\forall t$. (Recall our definitions of $\widetilde{d}_t$ and $\widetilde{D}_t$ in Section 3.) Now, pick an arbitrary sales plan from class (b). We use the hat ($\widehat{\ }$) to denote the variables of this sales plan. We define t_p as the earliest time period in which some demand is rejected in this sales plan. Thus, $\widehat{s}_t = \widetilde{d}_t$ for $t < t_p$ and $\widehat{s}_{t_p} < \widetilde{d}_{t_p}$. Note that $\widehat{S}_t \leq \widehat{D}_t$, $\forall t$. Last, we introduce the following notation to denote the summations of positive diffusion demand differences between these two sales plans:

$$D_T^- = \sum_{t:\widetilde{d}_t > \widehat{d}_t} \left(\widetilde{d}_t - \widehat{d}_t\right) \text{ and } D_T^+ = \sum_{t:\widehat{d}_t > \widetilde{d}_t} \left(\widehat{d}_t - \widetilde{d}_t\right).$$

See Figure 1 for an illustration: For sales plans (i) and (ii) in Figure 1, D_{50}^- represents the area between solid and dashed curves up to period t^*, while D_{50}^+ represents the area from period t^* on.

Lemma 2 states that the overall diffusion rate is highest if all demand is immediately met in each period. The producer is thus better off satisfying all demand in each period when the selling horizon falls short of complete market penetration *and* remanufacturing is not possible. (Theorem 1 reveals that partial fulfillment can be desirable when the selling horizon is too short for complete market penetration but remanufacturing is possible.)

Lemma 2. *$\widehat{D}_t = \widetilde{D}_t$ if $t \leq t_p + 1$ and $\widehat{D}_t < \widetilde{D}_t$ otherwise. Furthermore, $D_T^- \geq D_T^+$.*

We denote by δ_T the highest possible market retention rate when the word-of-mouth effect is limited by partial fulfillment (i.e., the maximum of the ratio D_T^+/D_T^- over all sales plans in class (b)). Notice that $D_T^- > 0$ for each sales plan in class (b). Proposition 1 states that δ_T is nondecreasing in T. This implies that partial fulfillment is potentially less attractive on shorter selling horizons. The intuition behind this result is that partial fulfillment slows down product diffusion, leaving more customers who have not yet demanded the product at the end of the selling horizon, and thus leading to a more significant loss of diffusion demand, when T is smaller. Proposition 1 also specifies threshold levels $\underline{T}$ and $\overline{T}$, such that $\delta_T = 0$ if $T < \underline{T}$ and $\delta_T = 1$ if $T \geq \overline{T}$. Both threshold levels decrease as the innovation coefficient p grows: Partial fulfillment is potentially more attractive when the innovation effect is more dominant than the word-of-mouth effect in product diffusion—that is, when partial fulfillment can only slightly reduce the future diffusion demand.

Proposition 1. *δ_T is nondecreasing in $T \geq 2$. Furthermore, $\delta_T = 0$ if $T < \underline{T} = \min\{t \geq 3 : 2\widetilde{D}_t/m > (q-p)/q\}$, and $\delta_T = 1$ if $T \geq \overline{T} = \lceil 1 - (\ln(2pm)/\ln(1-p))\rceil$.*

Exploiting the diffusion and closed-loop dynamics available under the immediate-fulfillment policy, Theorem 1 establishes the conditions that ensure the optimality of the immediate-fulfillment policy as well as the conditions that ensure the optimality of the partial-fulfillment policy. It also derives an upper bound on the initial time period in which partial fulfillment is optimal.

Theorem 1. (a) *The immediate-fulfillment policy is optimal if, under the immediate-fulfillment policy, the remanufactured-item demand is no less than the accumulated return volume in each period. It is also optimal if the highest possible market retention rate δ_T and the backlogging rate α are below certain respective thresholds (detailed in the online appendix).*

(b) *The partial-fulfillment policy is optimal if, under the immediate-fulfillment policy, there exists a period $\widehat{t} < T$ such that* (i) *the remanufactured-item demand exceeds the accumulated return volume in each period $t \leq \widehat{t}$, whereas the reverse is true in each period $t > \widehat{t}$; and* (ii) *the rejection of a unit demand in period $\widehat{t}$ induces a loss of diffusion demand in period $\widehat{t}+1$ that is below a certain threshold (detailed in the online appendix) and a backlogged demand in period $\widehat{t}+1$ that is above a certain threshold (again detailed in the online appendix).*

(c) *If conditions* (i) *and* (ii) *hold, partial fulfillment is initiated no later than period $\widehat{t}$ at optimality.*

See the online appendix for a detailed version of Theorem 1. Theorem 1(a) shows that it is optimal to meet all demand in each period if the available returns are insufficient throughout the entire selling horizon to meet any delayed demand—backlogged demand plus shifted diffusion demand induced by partial fulfillment—with remanufactured items. Theorem 1(a) also states that it is optimal to meet all demand in each period if partial fulfillment significantly hurts the total sales volume. Theorem 1(b), on the other hand, says that it is optimal to reject some demand in some period if the available returns are sufficient in later periods to meet some delayed demand with remanufactured items (condition (i)) and if the revenue gain from improved remanufacturing volume via delayed demand is able to outweigh the revenue loss due to reduced sales induced by partial fulfillment (condition (ii)). Finally, when the conditions in Theorem 1(b) are met, Theorem 1(c) derives an upper bound on the optimal initiation of partial fulfillment. One can easily calculate this upper bound under the immediate-fulfillment policy. See Figure 2, for example. Because the backlogging rate and the profit margins have trivial effects on optimal sales decisions, we focus on the effects of the diffusion parameters (p and q) and the closed-loop parameters (γ_2 and β_i) in the remainder of this section.

We conduct numerical experiments to examine the comparative statics of the upper bound on the optimal initiation of partial fulfillment, as characterized in Theorem 1(c), with respect to the diffusion and closed-loop parameters. First, we construct a base scenario by choosing parameter values that are realistic for the smartphone industry: $T = 36$ months, $p = 0.02$, $q = 0.35$, $\alpha = 0.88$, $\beta = 0.12$, and $\beta_i = \beta \times \mathbb{P}\{i - 0.5 \leq X \leq i + 0.5\}$, where X has a Weibull distribution with scale parameter 25 and shape parameter 2 (implying a mean of 22.16), $\forall i \geq 1$, $\gamma_2 = 0.27$, and $(p_n - c_n)/(p_r - c_r) = 0.5$. See the online appendix for the derivation of these parameter values. Then, we generate instances from the base scenario by varying the values of p and q, and those of γ_2 and β, respectively. We also consider the cases in which the scale parameter of X is 18 (short market sojourn times with a mean of 15.95) and 32 (long market sojourn times with a mean of 28.36). Figure 3 exhibits the contour plots of the upper bound for the compiled instances. An important observation from Figure 3 is that the partial-fulfillment policy is optimal in the vast majority of instances.

Figure 3 indicates that the partial-fulfillment policy is optimal when p and q are sufficiently large. The upper bound on the initiation of partial fulfillment tends to decrease as p or q grows further: Large values of p and q speed up the diffusion process. This increases the available return volume, and thus the chance of meeting any delayed demand with remanufactured items earlier in the selling horizon. In addition, because a significant portion of diffusion demand arrives earlier in the selling horizon, some demand can be rejected in early periods without causing the loss of diffusion demand at the end of the selling horizon. Hence, partial fulfillment appears earlier. It is important to note that the upper bound when p is large and q is small is sooner than when p is small and q is large: Increasing p speeds up the diffusion process more than increasing q. This is because increasing p leads to not only a greater number of innovators in the initial periods, but also to a rapid spread of word-of-mouth feedback thanks to large sales volumes in the initial periods.

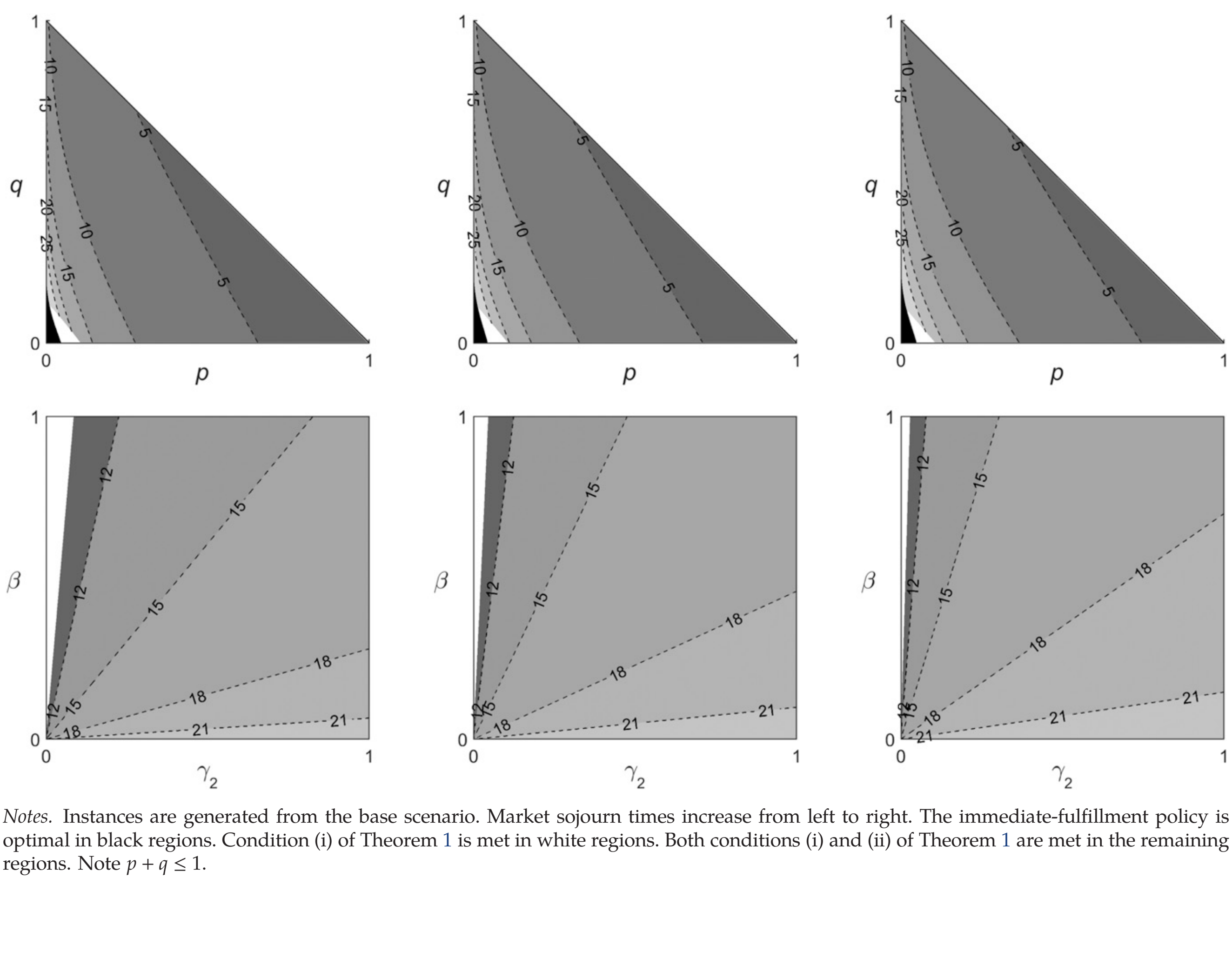
The immediate-fulfillment policy is optimal if there is no demand for remanufactured items (i.e., $\gamma_2 = 0$). Thus, one might intuitively expect partial fulfillment to be more desirable when γ_2 is large. But Theorem 1 reveals that γ_2 should be small (but strictly positive) for the optimality of the partial-fulfillment policy: When γ_2 is large, the demand for remanufactured products is likely to exceed the return volume available in each period and thus, any delayed demand is unlikely to be met with remanufactured items. In addition, when γ_2 is large, a possible loss of diffusion demand (due to partial fulfillment) may be more of a drain on the total profit because a greater fraction of customers prefer remanufactured items (recall $p_n - c_n < p_r - c_r$). The immediate-fulfillment policy is also trivially optimal if there is no product return (i.e., $\beta_i = 0, \forall i$). Figure 3 indicates that the upper bound on the initiation of partial fulfillment tends to decrease as γ_2 drops or β grows: Small values of γ_2 and large values of β induce the accumulated return volume to exceed the demand for remanufactured items in early periods, in which some delayed demand can be met with remanufactured items. Likewise, the upper bound decreases as the market sojourn times drop.

For FSCs, Kumar and Swaminathan (2003) show that production constraints may lead to the optimality of the partial-fulfillment policy. For such FSCs with production constraints, Shen et al. (2011) construct an example showing that the partial-fulfillment policy can be optimal when all unmet demand is lost (i.e., $\alpha = 0$), and Ho et al. (2011) show that the immediate-fulfillment policy is optimal when all unmet demand is backlogged (i.e., $\alpha = 1$). For CLSCs, however, Theorem 1 proves that the partial-fulfillment policy can still be optimal in the absence of production constraints (for new items). It also reveals that the backlogging rate should be large for the optimality of the partial-fulfillment policy.

4.2. Timing and Magnitude of Partial Demand Fulfillment

We now conduct numerical experiments to gain further insights into the exact timing and magnitude of partial fulfillment. We consider a simpler version of our main model that parsimoniously captures the closed-loop

Figure 3. Contour Plots of the Upper Bound $\widehat{t}$ on the Optimal Initiation of Partial Fulfillment



Notes. Instances are generated from the base scenario. Market sojourn times increase from left to right. The immediate-fulfillment policy is optimal in black regions. Condition (i) of Theorem 1 is met in white regions. Both conditions (i) and (ii) of Theorem 1 are met in the remaining regions. Note $p + q \leq 1$.

and diffusion dynamics of the problem. This allows us to solve moderately sized instances to optimality via a dynamic programming (DP) algorithm.

In our main model, the product return rate varies with the residence time, inducing the controller to keep track of the number of items sold in each of the earlier periods in order to calculate the available return volume of the current period. But this would translate into a huge state space in a DP algorithm. Thus, we assume that the number of newly available returns at the beginning of period t is determined by a fraction ζ of the total number of items sold that have not been returned to the producer prior to period t. (See Akan et al. 2013 for a similar assumption.) Such a return process is a special case of the one in Section 3 when $\beta_i = (1-\zeta)^{i-1}\zeta$, $\forall i \geq 1$. We define U_t as the total number of buyers who continue to use their items at the beginning of period t. Taking $U_1 = 0$, we can calculate U_t, $\forall t \geq 2$, with the following recursion:

$$U_t = (1-\zeta)(U_{t-1} + s_{t-1}). \tag{7}$$

We also define E_t as the accumulated return volume at the beginning of period t. Note that $r_t \leq E_t$, $\forall t$. Taking $E_1 = 0$, we can calculate E_t, $\forall t \geq 2$, with the following recursion:

$$E_t = E_{t-1} - r_{t-1} + \zeta(U_{t-1} + s_{t-1}). \tag{8}$$

We include both U_t and E_t in our state description. We also require S_t and D_t in our state description for calculation of diffusion demand in each period t. But it can be shown that $U_t + E_t = \sum_{i=1}^{t-1} n_t$ and, thus, $S_t = R_t + U_t + E_t$ where $R_t \triangleq \sum_{i=1}^{t-1} r_t$, $\forall t \geq 2$. Without loss of optimality, it can also be shown that $S_t \leq D_t$ and $R_t \leq \min\{\gamma_2 D_t, D_t - U_t - E_t\}$. Because S_t can be obtained from R_t, U_t, and E_t, and because R_t has a tighter lower bound than S_t, we include R_t (rather than S_t) and D_t in our state description. Taking $R_1 = 0$, we can calculate R_t, $\forall t \geq 2$, with the following recursion:

$$R_t = R_{t-1} + r_{t-1}. \tag{9}$$

Likewise, taking $D_1 = 0$, we can calculate D_t, $\forall t \geq 2$, with the following recursion:

$$D_t = D_{t-1} + d_{t-1}. \tag{10}$$

We assume that the demand of the newness-conscious customers is always immediately met. This assumption seems to be reasonable because if such demand is rejected, a certain fraction of the unmet demand is lost, while the remaining fraction continues to demand the new item in the future. Thus, one may intuitively expect the demand that is unmet at optimality to arise from the functionality-oriented customers. This assumption eliminates the need to calculate the backlogged demand of the newness-conscious customers.

We define B_t as the accumulated number of backorders in period t from the functionality-oriented customers, including it in our state description. Note that $n_t + r_t \leq B_t + d_t$, $\forall t$. Taking $B_1 = 0$, we can calculate B_t, $\forall t \geq 2$, with the following recursion:

$$B_t = \alpha(B_{t-1} + d_{t-1} - n_{t-1} - r_{t-1}). \tag{11}$$

The above assumption also reduces the decision space of the DP algorithm by implying that

$$\gamma_1 d_t \leq n_t \leq B_t + d_t - r_t, \ \forall t \geq 1. \tag{12}$$

Finally, we assume that demand for the remanufactured item is immediately met as long as the used items are available. This assumption is also reasonable because if such demand is rejected, a certain fraction of the unmet demand is lost, while the remaining fraction need not be met with remanufactured items in the future (recall $p_n - c_n < p_r - c_r$). This assumption further reduces the decision space of the DP algorithm by implying that

$$r_t = \min\{B_t + \gamma_2 d_t, E_t\}, \ \forall t \geq 1. \tag{13}$$

We are now ready to formulate the DP recursion under the above assumptions:

$$\begin{aligned} &v_t(B_t, D_t, E_t, R_t, U_t) \\ &\quad = \max_{n_t}\{(p_n - c_n)n_t + (p_r - c_r)r_t \\ &\qquad + v_{t+1}(B_{t+1}, D_{t+1}, E_{t+1}, R_{t+1}, U_{t+1})\}, \ \forall t \leq T, \end{aligned}$$

and $v_{T+1}(\cdot) = 0$ subject to (1) and (7)–(13). Note that $v_1(0,0,0,0,0)$ is the optimal total profit.

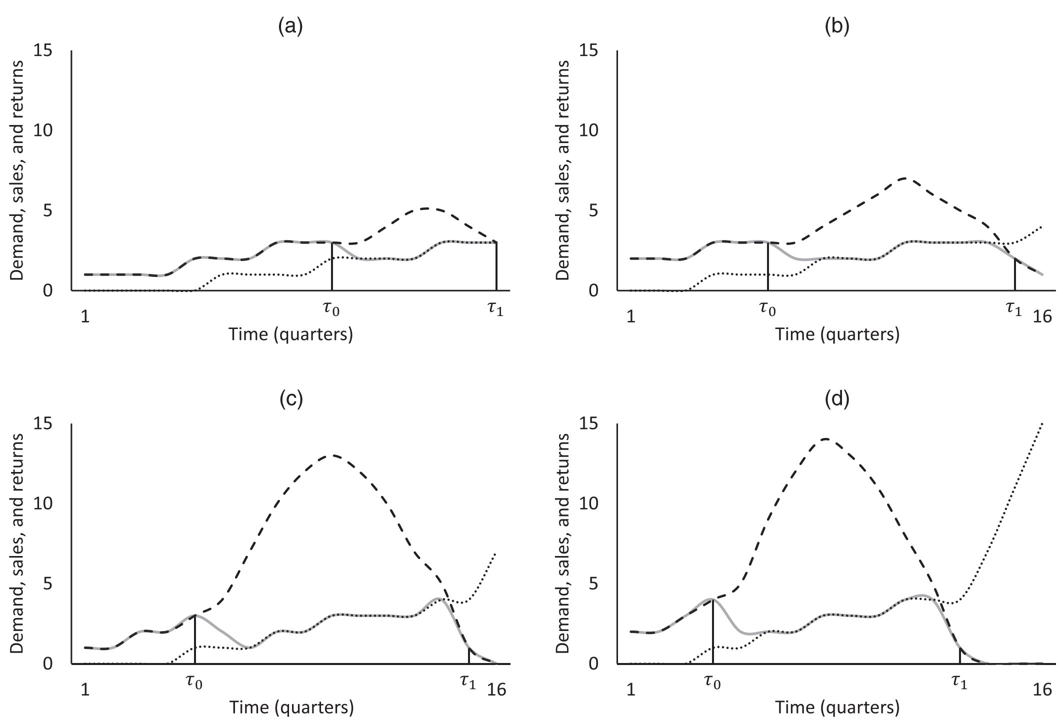
We restrict our numerical analysis to discrete state and action spaces in the DP algorithm. We consider a market of size $m = 400$ such that one unit of m corresponds to 10^k consumers (k can be 3, 4, or 5). Likewise, the state and decision variables of our DP algorithm are measured in 10^k items. The product has a life cycle of $T = 16$ quarters (i.e., 4 years). We generate the optimal sales plans for four different scenarios of the diffusion parameters p and q in Figure 4 and four different scenarios of the closed-loop parameters ζ and γ_2 in Figure 5. In all scenarios, $T = 16$ is large enough for significant market penetration: When $p \in \{0.02, 0.04\}$ and $q \in \{0.25, 0.50\}$, more than 80% of the diffusion demand is observed before the selling horizon ends if all demand is met in each period. Our choice of values for ζ is consistent with the value of β in the base scenario: When $\zeta \in \{0.01, 0.02\}$, a total of 7.7%–14.9% of the used items are returned within the first eight quarters of use. Our choice of values for γ_2 reflects pessimistic scenarios of consumers' willingness to buy remanufactured items, leading to partial fulfillment in early periods. In this way, we can pinpoint the timing and magnitude of partial fulfillment within the 16-period horizon.

We observe from Figures 4 and 5 that partial fulfillment, once initiated, appears in each period until the available return volume reaches and exceeds the remanufactured-item demand. We label this time interval (τ_0, τ_1) in Figures 4 and 5. Our explanation for the presence of partial fulfillment in such a specific time interval is as follows: Because rejecting a demand in earlier periods has a greater potential to reduce the future diffusion demand, and it is less likely that any backlogged demand will be met with remanufactured items in earlier periods (due to the used-item shortage), partial fulfillment should be postponed until it becomes possible to meet a substantial portion of the resulting delayed demand with remanufactured items. On the other hand, once the return volume becomes sufficient to meet all remanufactured-item demand in each future period, the remanufacturing volume cannot be increased by manipulating the demand in those periods, and thus partial fulfillment disappears.

Figures 4 and 5 indicate that partial fulfillment is initiated earlier when p, q, or ζ is higher, or when γ_2 is lower. All these observations confirm our findings in Section 4.1. Figures 4 and 5 also reveal that partial fulfillment is terminated earlier when p, q, or ζ is higher: The return volume exceeds the remanufactured-item demand in an earlier period when a larger portion of diffusion demand is observed earlier so that more end-of-use items arrive earlier or when more consumers return their end-of-use items. Another important observation is that the total unmet demand tends to be larger when q is larger or when γ_2 is lower: When q is larger, most diffusion demand appears in a short time interval during which the demand peaks and the remanufactured-item demand is higher than the return volume. The remanufactured-item demand sharply declines, while the return volume sharply grows, after this time interval. Because any delayed demand induced by partial fulfillment in this time interval is likely to be satisfied with remanufactured items in the near future, more demand is rejected at optimality. When γ_2 is lower, the return volume exceeds the remanufactured-item demand in more periods. This gives the controller flexibility to shape the demand in many different ways in order to improve the total remanufacturing volume. Such flexibility disappears when γ_2 is high because the return volume is insufficient to fulfill any delayed demand with a remanufactured item in each of a large number of periods.

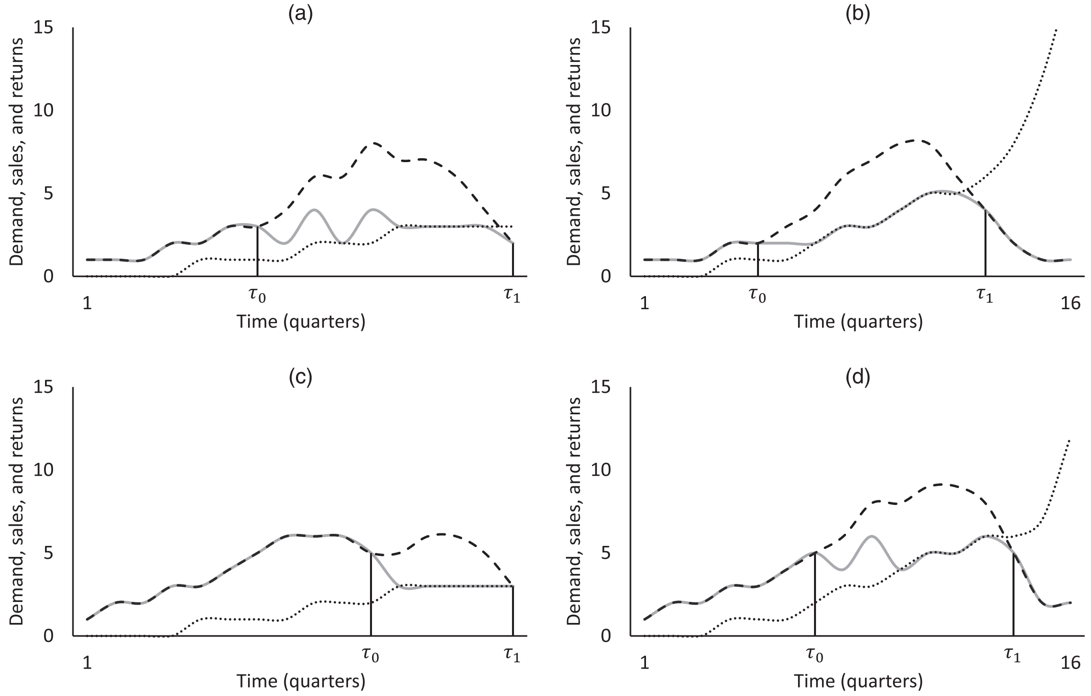
Finally, for the compiled scenarios in Figures 4 and 5, partial fulfillment has the greatest benefit when $p = 0.04$ and $q = 0.50$ and the lowest benefit when $p = 0.02$ and $q = 0.25$. The optimal total profit is greater by 4.2% and 1.3% than the total profit under the immediate-fulfillment policy in these two scenarios, respectively. (The optimal total profit is greater by

Figure 4. Optimal Sales Plans when $\zeta = 0.01$, $\gamma_2 = 0.10$, $\alpha = 0.88$, and $(p_n - c_n)/(p_r - c_r) = 0.25$



Notes. Dashed, gray, and dotted lines represent the demand for remanufactured items, the sales volume in response to this demand, and the accumulated return volume, respectively. Total unmet demand equals the area between dashed and gray lines. Total remanufacturing volume equals the area below gray and dotted lines. (a) $p = 0.02$ and $q = 0.25$. (b) $p = 0.04$ and $q = 0.25$. (c) $p = 0.02$ and $q = 0.50$. (d) $p = 0.04$ and $q = 0.50$.

Figure 5. Optimal Sales Plans when $p = 0.02$, $q = 0.35$, $\alpha = 0.88$, and $(p_n - c_n)/(p_r - c_r) = 0.25$



Notes. Dashed, gray, and dotted lines represent the demand for remanufactured items, the sales volume in response to this demand, and the accumulated return volume, respectively. Total unmet demand equals the area between dashed and gray lines. Total remanufacturing volume equals the area below gray and dotted lines. (a) $\zeta = 0.01$ and $\gamma_2 = 0.10$. (b) $\zeta = 0.02$ and $\gamma_2 = 0.10$. (c) $\zeta = 0.01$ and $\gamma_2 = 0.15$. (d) $\zeta = 0.02$ and $\gamma_2 = 0.15$.

2.6% on average for all scenarios.) The benefit is higher when p and q are larger because the loss of diffusion demand induced by partial fulfillment is lower when the diffusion rate is higher.

5. Extensions

In this section, we investigate several extensions of our main model that offer additional perspectives on the desirability and optimal timing of partial demand fulfillment: Section 5.1 considers a setting in which the word-of-mouth effect can also be generated from past unmet demand. Section 5.2 allows for a distinct consumer segment that wants to buy only remanufactured items. Section 5.3 considers a setting in which product returns arise not only from end-of-use items but also from lenient return policies and warranty claims. Section 5.4 relaxes the assumption of stationary backlogging and demand rates. Finally, Section 5.5 relaxes the assumption of zero backlogging and used-item holding costs. Detailed versions of all analytical results are contained in the online appendix.

5.1. Demand-Based Diffusion

Our main model in Section 3 assumes that customers who demand a product but are unable to purchase it (because the product is made unavailable by the producer) cannot generate the word-of-mouth effect. This assumption seems to be appropriate when the product is an experience good whose value can only be evaluated after consumption (see Nelson 1970). We now consider a variant of our diffusion model in which customers who demand the product but are unable to purchase it can still generate the word-of-mouth effect. This variant may be more realistic when the product is a search good whose value can be evaluated before purchase (again, see Nelson 1970) or when the product is an experience good but becomes more attractive if it is limited in availability. The diffusion demand in this case can be reformulated as in the original Bass diffusion process. This reformulation simplifies the problem because the diffusion demand calculation in (1) no longer depends on sales volumes. In this case, we again establish conditions for the optimality of the partial-fulfillment policy, deriving an upper bound on the initiation of partial fulfillment.

Corollary 1. *The partial-fulfillment policy is optimal if* $\alpha > (p_n - c_n)/(p_r - c_r)$ *and, under the immediate-fulfillment policy, if there exists a period* $\widehat{t} < T$ *such that the remanufactured-item demand exceeds the accumulated return volume in each period* $t \le \widehat{t}$*, whereas the reverse is true in each period* $t > \widehat{t}$*. Under these conditions, partial fulfillment is initiated no later than period* $\widehat{t}$ *at optimality.*

The conditions for partial fulfillment in Corollary 1 are less strict than in Theorem 1. This implies that partial fulfillment is more likely to be beneficial in this case: Rejecting a demand in any period does not reduce the future diffusion demand under demand-based diffusion. But our results for the upper bound in Theorem 1 remain the same under demand-based diffusion: The diffusion and closed-loop dynamics available under the immediate-fulfillment policy that we use to characterize the upper bound remain valid in this case.

5.2. Customers Demanding Only Remanufactured Items

Our main model partitions the market into two segments, according to consumers' willingness to buy remanufactured items. Recall our definitions of γ_1 and γ_2 and our assumption of $\gamma_1 + \gamma_2 = 1$ in Section 3. We now partition the market into three segments; a fraction γ_3 of the newly arriving consumers in each period wants to buy only remanufactured items (the remanufactured-item-oriented segment). We assume $\gamma_1 + \gamma_2 + \gamma_3 = 1$. Consumers stick to their initial preferences throughout the selling horizon. We denote by b_{3t} the accumulated number of backorders in period t from the remanufactured-item-oriented customers and take $b_{31} = 0$. In each period, the newness-conscious customers and the remanufactured-item-oriented customers execute their product purchases earlier than the functionality-oriented customers. We incorporate this consumer segment into our problem formulation by modifying our constraints in (2)–(4):

$$0 \le s_t = n_t + r_t \le d_t + b_{1t} + b_{2t} + b_{3t}, \quad \forall t \ge 1, \quad (14)$$
$$0 \le n_t \le (\gamma_1 + \gamma_2)d_t + b_{1t} + b_{2t}, \quad \forall t \ge 1, \quad (15)$$
$$0 \le r_t \le (\gamma_2 + \gamma_3)d_t + b_{2t} + b_{3t}, \quad \forall t \ge 1, \quad (16)$$

and

$$(b_{1(t+1)}, b_{2(t+1)}, b_{3(t+1)}) = \begin{cases} (\alpha[\gamma_1 d_t + b_{1t} - n_t], \alpha[(\gamma_2+\gamma_3)d_t + b_{2t} + b_{3t} - r_t], 0) \\ \quad \text{if } \gamma_1 d_t + b_{1t} \ge n_t \text{ and } r_t \ge \gamma_3 d_t + b_{3t}, \\ (\alpha[\gamma_1 d_t + b_{1t} - n_t], \alpha[\gamma_2 d_t + b_{2t}], \alpha[\gamma_3 d_t + b_{3t} - r_t]) \\ \quad \text{if } \gamma_1 d_t + b_{1t} \ge n_t \text{ and } \gamma_3 d_t + b_{3t} > r_t, \\ (0, \alpha[d_t + b_{1t} + b_{2t} + b_{3t} - n_t - r_t], 0) \\ \quad \text{if } n_t > \gamma_1 d_t + b_{1t} \text{ and } r_t \ge \gamma_3 d_t + b_{3t}, \\ (0, \alpha[(\gamma_1+\gamma_2)d_t + b_{1t} + b_{2t} - n_t], \alpha[\gamma_3 d_t + b_{3t} - r_t]) \\ \quad \text{if } n_t > \gamma_1 d_t + b_{1t} \text{ and } \gamma_3 d_t + b_{3t} > r_t, \end{cases} \quad \forall t \ge 1. \quad (17)$$

The producer's optimization problem is formulated as

$$\max_{n_1,..,n_T, r_1,..,r_T} \sum_{t=1}^{T} [(p_n - c_n)n_t + (p_r - c_r)r_t]$$

subject to (1), (5), (6), (14), (15), (16), (17). If demand of the remanufactured-item-oriented customers exceeds the available return volume in any period, some demand of these customers cannot be met in that period: Unlike in Section 4, the myopically optimal sales plan in this case need not meet all demand in each period, because some demand of the remanufactured-item-oriented customers may be impossible to meet. We thus modify the myopic sales plan as follows: *As much of demand as possible* is met, while the remanufactured-item demand is met with the available end-of-use returns to the fullest extent possible, in each period. We take the phrase "partial fulfillment" to refer to the deliberate rejection of some demand other than the demand that cannot be met due to insufficient returns. With these modifications, we extend our Theorem 1 to this case as follows:

Corollary 2. *The partial-fulfillment policy is optimal if, in the myopic sales plan, there exists a period $\widehat{t} < T$ such that* (i) *the remanufactured-item demand exceeds the accumulated return volume in each period $t \le \widehat{t}$, whereas the reverse is true in each period $t > \widehat{t}$; and* (ii) *the rejection of a unit demand in period $\widehat{t}$ induces a loss of diffusion demand in period $\widehat{t} + 1$ that is below a certain threshold and an increase of backlogged demand in period $\widehat{t} + 1$ that is above a certain threshold. Under these conditions, partial fulfillment is initiated no later than period $\widehat{t}$ at optimality.*

The conditions for partial fulfillment in Corollary 2 build upon the myopic sales plan defined above (rather than the myopic sales plan in Section 4). As the remanufactured-item-oriented customers grow more dominant than the functionality-oriented customers (while the total number of these customers is constant), partial fulfillment becomes less likely to be beneficial: Unmet demand of the remanufactured-item-oriented customers (due to the used-item shortage) leads to some backlogged demand for remanufactured items in the future. The existence of this backlogged demand, in addition to the newly arriving diffusion demand for remanufactured items, increases the used-item consumption in earlier periods so that the return volume may be insufficient for fulfillment of any delayed demand in any period. In addition, the unmet demand of the remanufactured-item-oriented customers also slows down the product diffusion. Rejecting extra demand decelerates the diffusion process, potentially leading to the loss of diffusion demand at the end of the selling horizon. Thus, partial fulfillment may become undesirable. If still desirable, the upper bound on the initiation of partial fulfillment is later when there are more remanufactured-item-oriented customers and fewer functionality-oriented customers. A counterintuitive observation here is that whereas condition (ii) of Corollary 2 can only be met if α is large enough, condition (i) may be violated (and partial fulfillment may be undesirable) if α is too large: Backlogged demand of the remanufactured-item-oriented customers grows with α, further draining the available returns.

5.3. Lenient Return Policies and Warranty Claims

Our main model assumes that product returns arise only from end-of-use items. We now incorporate lenient return policies and warranty claims into product returns: A fraction β_{1i} of the products that have been sold in period t are returned by consumers at the end of their use and become available for remanufacturing to remarket or fulfill the warranty demand in period $t+i$, $\forall i \geq 1$. Let $\beta_1 \triangleq \sum_i \beta_{1i}$. A fraction β_{2i} of the products that have been sold in period t are returned by consumers for a full refund within the time window allowed by the lenient return policy and again become available for remanufacturing to remarket or fulfill the warranty demand in period $t+i$, $\forall i \geq 1$. Let $\beta_2 \triangleq \sum_i \beta_{2i}$. Last, a fraction β_{3i} of the products that have been sold in period t are returned by consumers due to product failure before the warranty expires and are replaced with new or remanufactured items to honor the warranty agreement in period $t+i$, $\forall i \geq 1$. For simplicity, we drop the repair option from our analysis. Such a setting may be realistic when failed products are too expensive to repair. Let $\beta_3 \triangleq \sum_i \beta_{3i}$. Note $\beta_1 + \beta_2 + \beta_3 \leq 1$. (See Pinçe et al. 2016 for a similar setting with $\beta_1 = 0$.)

We define T_l as the length of the time window allowed by the lenient return policy and T_w as the length of the warranty agreement. Thus, $\beta_{2i} = 0$, $\forall i > T_l$, and $\beta_{3i} = 0$, $\forall i > T_w$. The products can be sold only until period T, but consumer requests regarding the lenient return policy and warranty claim must be fulfilled until periods $T + T_l$ and $T + T_w$, respectively. We define w_t as the warranty demand that arrives in period t:

$$w_t = \sum_{i=1}^{t-1} \beta_{3i} s_{t-i}, \ \forall t \in \{2, .., T + T_w\}. \tag{18}$$

We assume that the warranty demand is met immediately upon arrival to minimize negative customer experience. We also assume that $c_r < c_n$, and that the end-of-use and lenient returns available for remanufacturing in any period are used first to fulfill as much of the warranty demand in that period as possible. (See, again, Pinçe et al. 2016 for the merits of allocating more of the returns to the warranty demand rather than the remanufactured-item demand.) Implementing the latter assumption, we modify our constraints in (5) and (6) as follows:

$$r_t \leq \max\{e_t - w_t, 0\}, \quad \forall t \in \{1, .., T\}, \tag{19}$$

$$e_{t+1} = \max\{e_t - w_t, 0\} - r_t + \sum_{i=1}^{t} (\beta_{1i} + \beta_{2i}) s_{t+1-i}, \quad \forall t \in \{1, .., T + T_w - 1\}, \tag{20}$$

and

$$s_t = 0, \qquad \forall t \in \{T+1, .., T + T_w\}. \tag{21}$$

Recall that $p_r - c_r > p_n - c_n > 0$ in Section 3. We slightly modify this assumption as follows: $(1-\beta_2)p_r - c_r > (1-\beta_2)p_n - c_n > 0$. Finally, we assume that the cumulative sum of the end-of-use and lenient return volumes is no smaller than the cumulative defective volume (i.e., $\sum_{i=1}^{k} (\beta_{1i} + \beta_{2i}) \geq \sum_{i=1}^{k} \beta_{3i}$ for $k \geq 1$). This assumption is plausible for consumer electronics. (See, for instance, Pinçe et al. 2016 and Shang et al. 2019). The producer's optimization problem is formulated as

$$\max_{n_1,..,n_T, r_1,..,r_T} \sum_{t=1}^{T} \left[\left((1-\beta_2) p_n - c_n \right) n_t + \left((1-\beta_2) p_r - c_r \right) r_t \right] - \sum_{t=2}^{T+T_w} \left[c_r \min\{w_t, e_t\} + c_n (w_t - e_t)^+ \right],$$

subject to (1)–(4) and (18)–(21). We extend our Theorem 1 to this case as follows.

Corollary 3. *The partial-fulfillment policy is optimal if, under the immediate-fulfillment policy, there exists a period $\hat{t} < T$ such that* (i) *the accumulated return volume is less than the remanufactured-item demand plus the warranty demand, but greater than the warranty demand in each period $t \leq \hat{t}$;* (ii) *the accumulated return volume exceeds the remanufactured-item demand plus the warranty demand in each period $t > \hat{t}$; and* (iii) *the rejection of a unit demand in period $\hat{t}$ induces a loss of diffusion demand in period $\hat{t}+1$ that is below a certain threshold and a backlogged demand in period $\hat{t}+1$ that is above a certain threshold. If these conditions hold and $(1-\beta_2)p_n \geq c_n + \beta_3 c_r$, partial fulfillment is initiated no later than period $\hat{t}$ at optimality.*

The conditions for partial fulfillment in Corollary 3 may fail to hold when β_2 is low and β_3 is high: Partial fulfillment can only be desirable if the used items become available for remanufacturing to remarket. When β_2 is low and β_3 is high, the lenient returns have a very limited contribution to the accumulated return volume and the warranty claims consume too many used items. Thus, the used items may be insufficient for remanufacturing to remarket (in each period), and partial fulfillment may become undesirable. If still desirable, the upper bound on the initiation of partial fulfillment is later when β_2 is lower and β_3 is higher. Our numerical experiments on smartphones with calibrated data indicate that, in contrast to Theorem 1, the conditions for partial fulfillment in Corollary 3 may fail to hold when γ_2 is too small: If γ_2 is small, when β_2 is high and β_3 is low, the return volume is likely to exceed the remanufactured-item demand plus the warranty demand in an early period, when the diffusion demand is much higher than in later periods. Because lenient returns often arise from the most recent sales, the lenient return volume is also expected to be much higher in early periods; this induces the return volume to exceed the remanufactured-item demand plus the warranty demand in an even earlier period. Because partial fulfillment in such an early period may induce significant loss of future diffusion demand, it may become undesirable.

5.4. Nonstationary Backlogging and Demand Rates

We now consider an extension of our main model that allows for nonstationary backlogging and demand rates. This extension may be particularly useful when innovators exhibit a lower willingness to wait for the product adoption and a greater willingness to buy the new item than imitators. In such a market, because innovators (or imitators) contribute more heavily to the initial (or later) phases of the diffusion process, one may intuitively expect the backlogging rate and the demand rate for remanufactured items to increase over time. We define α_t as the fraction of the unmet demand in period t that is backordered. We also define γ_{1t} as the fraction of the newly arriving customers in period t that want to buy only new products and $\gamma_{2t} = 1 - \gamma_{1t}$ as the remaining fraction. We incorporate these nonstationary backlogging and demand rates into our problem formulation by modifying our constraints in (3) and (4) as follows:

$$0 \le r_t \le \gamma_{2t} d_t + b_{2t},\ \forall t \ge 1, \tag{22}$$

and

$$\begin{aligned}&\left(b_{1(t+1)}, b_{2(t+1)}\right)\\ &= \begin{cases} \left(\alpha_t\left(\gamma_{1t} d_t + b_{1t} - n_t\right), \alpha_t\left(\gamma_{2t} d_t + b_{2t} - r_t\right)\right) \\ \quad \text{if } \gamma_{1t} d_t + b_{1t} \ge n_t \text{ and } \gamma_{2t} d_t + b_{2t} \ge r_t, \\ \left(0, \alpha_t(d_t + b_{1t} + b_{2t} - n_t - r_t)\right) \\ \quad \text{if } \gamma_{1t} d_t + b_{1t} < n_t \text{ and } \gamma_{2t} d_t + b_{2t} > r_t, \end{cases} \forall t \ge 1.\end{aligned} \tag{23}$$

The producer's optimization problem is formulated as

$$\max_{n_1,..,n_T, r_1,..,r_T} \sum_{t=1}^{T} \left[(p_n - c_n) n_t + (p_r - c_r) r_t\right]$$

subject to (1), (2), (5), (6), (22), (23). We extend our Theorem 1 to this case as follows.

Corollary 4. *The partial-fulfillment policy is optimal if, under the immediate-fulfillment policy, there exists a period* $\widehat{t} < T$ *such that* (i) *the remanufactured-item demand exceeds the accumulated return volume in each period* $t \le \widehat{t}$, *whereas the reverse is true in each period* $t > \widehat{t}$; (ii) *the rejection of a unit demand in period* $\widehat{t}$ *induces a loss of diffusion demand in period* $\widehat{t}+1$ *that is below a certain threshold and a backlogged demand in period* $\widehat{t}+1$ *that is above a certain threshold; and* (iii) γ_{2t} *is nonincreasing over time for* $t > \widehat{t}$. *Under these conditions, partial fulfillment is initiated no later than period* $\widehat{t}$ *at optimality.*

Corollary 4 requires a nonincreasing γ_{2t} in later periods (after the accumulated return volume exceeds the remanufactured-item demand under the immediate-fulfillment policy) for the optimality of the partial-fulfillment policy. This requirement can still hold in the market depicted above because the number of innovators who have not yet demanded the product is likely to be small in later periods and, thus, γ_{2t} can be fixed and approximated by the imitators' willingness to buy remanufactured items in these periods.

5.5. Backlogging Costs, Used-Item Holding Costs, and Salvage Revenues

We next extend our main model by including nonzero backlogging and used-item holding costs as well as nonzero salvage revenues. Specifically, we make the following assumptions: The backlogging cost in period t is linear in the accumulated numbers of backlogged demands at the beginning of period $t > 1$ and is given by $c_{b1} b_{1t} + c_{b2} b_{2t}$, where c_{b1} is the unit backlogging cost per period for the newness-conscious customers and c_{b2} is the unit backlogging cost per period for the functionality-oriented customers. The holding cost in period $t < T$ is linear in the accumulated number of used items at the end of period t and is given by $c_e(e_t - r_t)$, where c_e is the unit holding cost per period. The salvage revenue is linear in the accumulated number of used items at the end of period T and is given by $p_s(e_T - r_T)$, where p_s is the unit salvage value. We now incorporate these cost and revenue terms into our calculation of the total profit:

$$\max_{n_1,..,n_T,r_1,..,r_T} \sum_{t=1}^{T}\left[(p_n - c_n)n_t + (p_r - c_r)r_t\right] - \sum_{t=2}^{T}(c_{b1}b_{1t} + c_{b2}b_{2t}) - \sum_{t=1}^{T-1} c_e(e_t - r_t) + p_s(e_T - r_T)$$

subject to (1)–(6). We extend our Theorem 1 to this case as follows.

Corollary 5. *The partial-fulfillment policy is optimal if, under the immediate-fulfillment policy, there exists a period* $\widehat{t} < T$ *such that* (i) *the remanufactured-item demand exceeds the accumulated return volume in each period* $t \le \widehat{t}$*, whereas the reverse is true in each period* $t > \widehat{t}$; (ii) *the rejection of a unit demand in period* $\widehat{t}$ *induces a loss of diffusion demand in period* $\widehat{t}+1$ *that is below a certain threshold and a backlogged demand in period* $\widehat{t}+1$ *that is above a certain threshold (varying with* c_e, c_{b2}, *and* p_s); *and* (iii) *the demand rate for remanufactured items is above a certain threshold.*

We generate instances for this model from the base scenario in Section 4.1 by taking $p_r - c_r = 10$ and $p_n - c_n = 5$ and by restricting c_e, c_{b2}, and p_s to take integer values that are no greater than $p_n - c_n$ (c_e, c_{b2}, and $p_s \in \{0, 1, .., 5\}$). The conditions for partial fulfillment hold in all instances with $c_e \ge 1$: More used items can be remanufactured with partial fulfillment so that fewer used items accumulate over time. Partial fulfillment is thus more desirable when c_e is nonzero. But the conditions for partial fulfillment fail to hold when $c_e = 0$ and $c_{b2} + p_s \ge 5$: Backlogged demands arise and fewer used items accumulate under partial fulfillment. There is no savings from the used-item holding cost because $c_e = 0$, but there is a significant loss due to backlogged demands and fewer used items available for salvaging at the end of the selling horizon because c_{b2} or p_s is large. Partial fulfillment is, thus, less desirable in these cases.

Finally, we extend our Theorem 1 to the discounted profit version of our problem in Section 3; see the online appendix. The conditions for partial fulfillment in the discounted-profit case are more strict than in Theorem 1: Selling an item in earlier periods is more profitable than in later periods, thus discouraging partial fulfillment.

6. Concluding Remarks

6.1. Summary of Managerial Insights

We have studied the sales planning problem of a producer who offers new and remanufactured versions of a durable good over a finite selling horizon. Demand arrives as a slightly modified Bass diffusion process, and end-of-use product returns are constrained by previous sales. In this setting, the producer may slow down product diffusion by deliberately rejecting some demand in the early periods of the selling horizon in order to exploit the benefit of remanufacturing in fulfillment of some delayed demand in later periods. We have found that partial demand fulfillment can indeed be desirable in such CLSCs, even in the absence of supply constraints for new-item manufacturing, in contrast to the FSC literature.

We provide several new insights into sales management in CLSCs: Partial fulfillment is likely to be desirable in fast-clockspeed industries when the remanufacturing profit margin is large but there is a limited demand for remanufactured items: If the remanufactured-item demand is too large, the returns collected will never be sufficient to fulfill any extra delayed demand. Partial fulfillment, if desirable, appears earlier as the diffusion rate grows, the remanufactured-item demand decreases, more consumers return their end-of-use items, or market sojourn times drop. More demand is rejected at optimality when the word-of-mouth effect is the key driver for the diffusion process or when the remanufactured-item demand is lower. Partial fulfillment provides a greater benefit when the diffusion process is faster. We also show that partial fulfillment is more likely to be desirable if the word-of-mouth feedback can be spread not only from previous purchasers but also from customers whose demands were rejected, but it is less likely to be desirable if the producer uses remanufactured items to fulfill warranty demand and/or attract price-sensitive customers who refuse to buy highly priced new items.

6.2. Limitations of Our Modeling Approach

We offer a stylized approach to a very complicated problem. CLSCs are inherently more challenging than FSCs. Our endogenous modeling of the diffusion process, together with our exogenous market segmentation along several dimensions, adds significantly to the complexity of the problem. Our proposed strategy—the partial-fulfillment policy—will clearly be less valuable in the presence of endogenous pricing and market segmentation. Consumer choices for new or remanufactured items and for timing of purchase can be manipulated by dynamically adjusting prices, thus mitigating the need for deliberate backlogging to manage product diffusion. Our proposed strategy will also be less valuable in the presence of competition against similar products of other producers. Customers whose demands are rejected can easily switch to buying other products if there is intense competition in the market, reducing the backlogged demand and the benefit of partial fulfillment. It is important to note that the partial-fulfillment policy aims to boost the remanufactured-item sales over the entire selling horizon, sacrificing some new-item sales in the short term. From a practical point of view, the remanufacturing division of a firm often has a much less impact on development of business strategies than the new-product sales team; the frictions between these business units may prevent our proposed strategy from being implemented. Finally, it is unclear whether our proposed strategy remains desirable in the presence of intergeneration product competition and/or different consumer behavior than the one we have assumed in our model.

6.3. Future Research Directions

Future extensions of this study could take into account intergeneration product competition. Most of the existing multigeneration diffusion models are inspired by Bass (1969). Among these models, Norton and Bass (1987) are often credited with proposing the pioneering work in describing multigeneration diffusion. In the Norton–Bass model, each generation has its own market potential and market-penetration process, while buyers of earlier generations can switch to newer generations. Jiang and Jain (2012) develop a generalized Norton–Bass model that counts the number of buyers who substitute an old generation with a new one by differentiating those who have already bought an earlier generation from those who have not. Our model could be extended to successive product generations by adopting the generalized Norton–Bass model, which shares the desirable mathematical properties of the Bass diffusion model. Future research could also extend our model to competitive markets with multiple producers. Several CLSC papers formulate stylized game-theoretical models to study the impacts of competition in remanufactured product markets. See, for instance, Majumder and Groenevelt (2001), Debo et al. (2005), Ferguson and Toktay (2006), and Atasu et al. (2008). These papers may guide future extensions of our study that would consider competition.

Another direction for future research is to incorporate variable conditions of used products, and product-acquisition decisions, into our analysis. Guide and van Wassenhove (2001) highlight the key role that the acquisition of used products plays in the profitability of remanufacturing. Guide et al. (2003) develop an economic analysis for calculating the optimal acquisition prices for a remanufacturer when the quantity and quality of product returns can be controlled via pricing, while Galbreth and Blackburn (2006, 2010) and Mutha et al. (2016) calculate the optimal acquisition quantities for reactive, planned, and sequential acquisition strategies, respectively. In addition, it may be more realistic to implement the time value of product returns into our analysis. See Blackburn et al. (2004) and Guide et al. (2006) for such an extension. Finally, future research could incorporate supply constraints for new-item manufacturing. Based on previous findings in the FSC literature, we intuitively expect our proposed strategy to remain useful in this extension.

Acknowledgments

The authors thank the department editor, associate editor, and two referees for their constructive comments and suggestions, which helped improve the content and exposition of this paper. The authors are also grateful to Alan Scheller-Wolf at Carnegie Mellon University for his helpful comments on an earlier version of the paper.

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