Advance Selling to Strategic Consumers: Preorder Contingent Production Strategy with Advance Selling Target

Mike Mingcheng Wei and Fuqiang Zhang

1 School of Management, University at Buffalo, Buffalo, NY 14260, USA
2 Olin Business School, Washington University in St. Louis, St. Louis, MO 63130, USA

Abstract
Motivated by emerging industry practices, this paper studies the effectiveness of a new advance selling strategy in counteracting strategic consumer behavior: the Preorder Contingent Production (PCP) strategy, where the seller’s production decision is contingent on an advance selling target. We find that compared to other advance selling strategies, such as the traditional advance selling strategy and the capacity rationing strategy, the PCP strategy is effective in mitigating strategic waiting behavior and thus can significantly improve the seller’s profit performance, especially when consumers’ discount factor is at a medium or high level, the production cost is not too high, or the market size has an unbalanced probability distribution. Moreover, when the market size is deterministic, we show that the PCP strategy can completely eliminate strategic waiting behavior and attain the seller’s profit performance under myopic consumer behavior. Finally, we demonstrate that the benefits of the PCP strategy are robust under other model considerations.

Key words: advance selling, preorder, strategic consumer behavior, game theory.

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*Corresponding author
1 Introduction

Advance selling is a retail practice of accepting consumers’ orders before a product is released. In the past decade, advance selling has prevailed in various industries, including consumer electronics, fashion, travel, ticketing, etc. There are various reasons why advance selling can potentially benefit the seller (e.g., see McCardle et al. 2004). Among these reasons, enabling dynamic pricing and facilitating demand learning are extensively cited. Specifically, the prolonged selling season lets the seller perform effective price discrimination via dynamic pricing (Dana 1998). Furthermore, through postponing production, the seller could mitigate the mismatch between supply and demand by reducing demand uncertainty (Prasad et al. 2011): The demand uncertainty from the advance selling period will be eliminated completely (as preorders are pre-committed), and the regular selling period’s demand can be more accurately predicted via the number of preorders (Tang et al. 2004). As a result, the potential benefits of advance selling have recently attracted increasing interest from both academics and practitioners (see Xie and Shugan 2001 and Li and Zhang 2013 for reviews).

Technological advances not only paved the way for advance selling, but also trained consumers to time their purchases strategically for anticipated future discounts. The impact of such strategic consumer behavior on the seller’s profit performance can be highly detrimental (Coase 1972, Stokey 1979, and Besanko and Winston 1990). Particularly, one of the key findings in the literature is that the seller’s ability to adjust future prices can be exploited by consumers who wait strategically for future discounts to avoid paying the premium price up-front (Aviv and Pazgal 2008, Elmaghraby et al. 2008, and Su 2007). Such waiting behavior may further interfere with the seller’s ability to respond to updated information via learning and influence the seller’s profit performance adversely (Aviv et al. 2013). Together, these negative impacts suggest that the benefits of advance selling could be substantially compromised by strategic consumer behavior. Therefore, in this research, we study an emerging advance selling practice that has the potential to curb the negative influence of strategic consumer behavior and improve the seller’s profit: the Preorder Contingent Production (PCP) strategy, in which the production quantity is contingent on preorder quantities.

Under the PCP strategy, the seller can commit to a production scheme contingent on the number of orders in the advance selling period. This strategy helps the seller adjust future price and production decisions in response to the updated information (i.e., the number of preorders) and also can mitigate strategic consumer behavior by controlling future product availability. For instance, Xiaomi, a leading Chinese cell
phone manufacturer, has adopted such a strategy (Liu 2011). When M1, Xiaomi’s first Android-based smartphone, debuted on August 2011, Xiaomi was uncertain about the market demand and concerned about savvy consumers’ potential wait-for-sale strategy. Therefore, Xiaomi adopted an advance selling strategy by announcing an advance selling target of 100,000 units. Without guaranteeing future availability, Xiaomi delivered a message to consumers: If the advance selling target is not met, then Xiaomi may discontinue M1 after the advance selling period. Fearing a shortage, eager consumers rushed to Xiaomi’s preorder website, and the advance selling target level was quickly reached (Bo 2011). Later, Xiaomi raised the advance selling target level several times (without changing the preorder price) to exploit the remaining market (Xiaomi 2013). Almost one year later, when all high-valuation consumers had preordered at the premium price, Xiaomi silently began to sell to the spot market at a discount price (Zhang 2012). Another example of such an advance selling strategy is Superpedestrian. In December 2013, when launching the Copenhagen Wheel, Superpedestrian tested the market by setting the initial advance selling target at 1,000 (Ngowi 2013). This innovative product turned out to be quite popular: More than 810 wheels were sold within just two weeks. Facing surging demand, Superpedestrian later decided to serve the whole market by accepting more orders. Along similar lines, Vividly, a web-based fashion retailer, determines its production scheme according to the number of preorders: The more preorders it receives, the more dresses Vividly will produce. Some dresses with substantial preorders will eventually hit the spot market for retailing (Vividly 2013). In the above examples, the seller determines its production scheme according to preorder quantity and could intentionally create stockout threats to influence savvy consumers: If the number of preorders is not high enough, then the seller will limit the quantity for the spot market or even serve only the preorder customers.

By modeling and analyzing the PCP strategy, we study the following two questions. First, we analyze how this strategy influences strategic consumer behavior. We demonstrate that by limiting future product availability, this strategy can effectively mitigate strategic consumer waiting behavior (i.e., more consumers will preorder in the advance selling period). Second, we identify conditions under which the PCP strategy is most effective in mitigating strategic consumer behavior. Compared to the Traditional Advance Selling (TAS) strategy, the PCP strategy could significantly improve the seller’s profit performance, especially when consumers’ discount factor is at a medium or high level, production cost is not too high, or market size has an unbalanced probability distribution. In particular, when the market size distribution is unbalanced (i.e., the probability is not evenly distributed among all possible realizations but concentrated on a small number
of market size realizations), the seller could focus its attention on a small number of market size realizations upon which it is able to choose a more accurate Advance Selling Target (AST) level and therefore improve its profit performance. In the extreme, when the market size is deterministic (e.g., the probability distribution is extremely unbalanced as all other market size realizations have zero chance to happen), we find that the PCP strategy can completely eliminate strategic waiting behavior and achieve the same profit performance as that under myopic consumer behavior.

The rest of the paper is organized as follows. In the next section, we review the related literature. §3 describes our model setting. We analyze a benchmark strategy—the TAS strategy—in §4. The PCP strategy is modeled and studied in §5. §6 considers two model extensions (i.e., a partial learning model and a valuation uncertainty model) and compares the PCP strategy to the Capacity Rationing strategy. This paper concludes with §7. All proofs are given in the Appendix.

2 Related Literature

This research studies the PCP strategy as a mechanism to counteract strategic consumer behavior under the advance selling setting. The phenomenon of strategic consumer behavior has been a topic of discussion since the seminal paper of Coase (1972). Using qualitative arguments, Coase argues that the monopolist’s pricing power can be undermined if consumers postpone their purchases for an anticipated future price drop—the idea of strategic behavior. Since then, the fast-growing literature that explicitly considers strategic behavior of individual customers has ubiquitously documented the negative influence of strategic consumer behavior on the seller’s profitability. For instance, Aviv and Pazgal (2008) demonstrate that it will cause a heavy profit loss if the seller does not consider strategic consumer behavior in pricing decisions. Furthermore, some of the above-mentioned benefits of adopting advance selling strategies (such as extending the selling season and demand learning) could be counterproductive when consumers behave strategically (Besanko and Winston 1990 and Aviv et al. 2013). See Netessine and Tang (2009) and Wei and Zhang (2017) for comprehensive surveys on this topic.

To counteract the adverse impact of such strategic consumer behavior, various mechanisms have been proposed in the literature (although not specifically under the context of the advance selling setting). One class of mechanisms can be described as capacity/production control. For example, Liu and van Ryzin (2008) consider the Capacity Rationing strategy in a deterministic two-period model where both periods’ prices
are exogenously given and announced at the beginning of the selling season. They find that it can be optimal for the seller to deliberately understock in the first period to intentionally create a rationing risk among strategic consumers to induce early purchases. Similar strategies and results can also be found in the literature, e.g., Su (2007), Su and Zhang (2009), Courty and Nasiry (2016), Agrawal et al. (2015). The literature associated with capacity/production control is closely related to our research. We will detail the connection and differences of this paper to the related literature in §6.3 when the PCP strategy is benchmarked against the Capacity Rationing strategy.

The second class of mechanisms can be generally named *pricing control*. Recent research papers have explored various pricing strategies under a single firm setting, such as responsive pricing strategy (Levin et al. 2010, Papanastasiou and Savva 2016), static pricing strategy (Su and Zhang 2008, Whang 2014), inter-temporal price matching strategy (Lai et al. 2010, Altug and Aydinliyim 2016), price commitment strategy (Cachon and Feldman 2013, Correa et al. 2016), etc. It is worth noting that the insights derived under a single firm setting do not necessarily carry over to a supply chain setting. For example, Lin et al. (2017) argue that strategic consumer behavior always benefits the manufacturer and could improve the profitability of the entire supply chain. They further show the price commitment strategy can actually be counterproductive under strategic consumer behavior.

The third class of mechanisms can be broadly described as *information-based control*. The connection of our paper to the literature on pricing-based control and information-based control is responsive pricing and demand learning. With advance selling, the seller could update demand forecast and adjust its future production and prices in response to the number of preorders. Note that the ability to learn may not always benefit the seller. Aviv et al. (2013) study a setting in which a fashion good seller has an opportunity to obtain additional demand information via early sales observation. The authors show that when all consumers are strategic, it may be better for the seller to proactively avoid learning due to the “information shading” effect. In this research, under advance selling, the seller is able to postpone and adjust its capacity and pricing decisions in response to updated preorder information. Therefore, it will be of interest to investigate the impact of the postponement ability on the seller’s profit performance. Besides the demand learning effect, we refer interested readers to several recent papers on the information-based control mechanisms in various settings. They focus on different issues that may affect strategic customer behavior, including price information (Cachon and Feldman 2013), quick response (Cachon and Swinney 2009, 2011), supply chain

Finally, we emphasize that the question of how to counteract strategic consumer behavior under advance selling deserves further research attention. Many of the widely studied strategies can actually impair, instead of improve, the effectiveness of the advance selling strategy. For instance, committing to limited initial inventory (to create a rationing risk to discourage strategic waiting behavior) could undermine the benefits of postponing production decisions—one of the key advantages of adopting the advance selling strategy. To our best knowledge, the only paper that considers strategies to counteract strategic consumer behavior in the context of advance selling is Li and Zhang (2013), where the authors demonstrate that even under the price match guarantee, strategic consumer behavior can still severely undermine the benefits of adopting the advance selling strategy. In fact, the unique features of advance selling (i.e., accepting orders before the product is released) call for innovative strategies tailored to advance selling to counteract strategic consumer behavior. Therefore, in this paper we study the emerging PCP strategy and examine the effectiveness of this strategy when the seller accepts preorders from strategic customers.

3 The Model

Consider a typical seller who sells a perishable (e.g., fashion or high technology) product in two periods. Preorders are accepted in the advance selling period (the "first period"), during which specifications of the product are available to the general public. Later, the seller releases the product to the spot market in the regular selling period (the "second period"). Similar to Nasiry and Popescu (2012), we assume all consumers are present in the market at the first period. The qualitative results in our paper will not change even with second-period arrivals (see §6.1).

The market size, $D$, is a random variable. Specifically, the realized market size $d$ can be either high ($d_h$) with probability $\alpha$ or low ($d_l$) with probability $1 - \alpha$, where $\alpha \in (0, 1)$ and $d_h > d_l > 0$. All of our analytical results can be derived similarly for general multi-points distributions. The mean and standard deviation of the market size are denoted by $\mu$ and $\sigma$, respectively. Each consumer is infinitesimally small in
the market. Their valuations are heterogeneous in nature and follow a uniform distribution between 0 and 1. Since preordered consumers are among the first to obtain the product, the valuations of consumers who wait and purchase in the second period will be discounted (see Li and Zhang 2013) by a factor $\delta \in (0, 1)$.

We model the interaction between the seller and consumers as a sequential-move game. The seller acts to maximize its total expected profit in two periods. First, before the advance selling period, the seller determines both its advance selling policy, which will be specified later, and its advance selling price $p_1$. Then, all consumers arrive in the advance selling period. Observing the seller’s advance selling policy and $p_1$, consumers time their purchases to maximize their expected surplus by taking into account all other consumers’ purchasing strategies. Such competitive interaction among consumers will be modeled under the Nash equilibrium concept, and is referred to as the consumers’ game. Next, at the beginning of the second period, the seller first collects all preorders and updates its demand forecast. Then, the seller will produce, complying with its specified advance selling strategy, to satisfy preorders and possibly to stock for the second period at a marginal cost $c \in (0, 1)$. Note that the production quantity must at least meet the demand of preordered consumers, but does not need to completely satisfy the demand from the spot market. Thus, if the production quantity $Q$ exactly equals the number of preorders, then the second period will be irrelevant. Otherwise, the seller will determine its second-period price $p_2$ to serve the spot market, in which consumers purchase if their valuations are higher than $p_2$. Finally, all unsold units can be disposed of at zero cost at the end of the second period. Strictly speaking, when the seller decides to serve the spot market, it will incur a fixed cost $F$ for expanding its capacity and investing in its channels so that its downstream retailers are incentivized to put the product on their shelves. Yet, our results and insights continue to hold true qualitatively with this fixed cost, so without deviating from the purpose of this research, we keep such cost at zero (i.e., $F = 0$).

## 4 Benchmark: Traditional Advance Selling Strategy

Before formally introducing the PCP strategy, we first present the Traditional Advance Selling (TAS) strategy as a benchmark. The TAS strategy is widely adopted for its simplicity. In this section, we present the TAS strategy as a benchmark for future comparisons. Under the TAS strategy, the seller charges a fixed advance selling price $p_1$ to all consumers in the first period. After the number of preorders $x$ is counted and demand forecast is updated accordingly at the end of the first period, the seller selects its second-period price $p_2$ and
a production quantity $Q$, where $Q$ must be larger than or equal to the number of preorders $x$. To begin with, we first analyze the TAS strategy under myopic consumers, who preorder in the first period as long as they have non-negative surpluses from immediate purchases.

### 4.1 Myopic Consumers

Utilizing the standard backward induction, we first analyze the seller’s second-period problem. When $p_1 < 1$, the first-period preorder quantity, $x$, is always positive. Observing this positive preorder quantity, the seller at the second period can perfectly predict the realized market size to be $x - p_1$. Our results and insights continue to qualitatively hold true when the seller cannot perfectly predict the market size (see §6.1 for the case where the seller can not perfectly predict the market size—the partial learning case). Clearly, to maximize its profit, the seller would set its production quantity $Q$ to be the sum of the preorder quantity and the demand induced by the second-period price:

$$Q = x + (p_1 - p_2/\delta)^+ \frac{x}{1 - p_1}. \quad (1)$$

Accordingly, the seller will maximize its second-period profit by solving the following problem:

$$\pi_2(x, p_1) \doteq \max_{c \leq p_2 \leq p_1} \left\{ (p_2 - c) \cdot (p_1 - p_2/\delta) \frac{x}{1 - p_1} - c \cdot x \right\}. \quad (2)$$

The following lemma establishes the seller’s second-period optimal decisions and its corresponding profit performance.

**Lemma 1** When $\delta p_1 \geq c$, the seller will set its second-period price at $\frac{\delta p_1 + c}{2}$, produce $\frac{2 - p_1 - c/\delta}{2(1 - p_1)} x$ units of product, and obtain the maximum second period profit $\left( \frac{(\delta p_1 - c)^2 x}{4\delta(1 - p_1)} - cx \right)$. Otherwise, if $\delta p_1 < c$, then the seller will only satisfy preorders by producing $x$ units of product and obtain the second period profit $-cx$.

Now, let’s turn to the seller’s first-period pricing decision. From Lemma 1, the seller’s first-period problem can be stated as maximizing the total profit from both periods:

$$\pi^M_{TAS} = \max_{c \leq p < 1} \left\{ E[p \cdot (1 - p) D + \pi_2((1 - p) D, p)] \right\}. \quad (3)$$

Solving Equation (3), we present the seller’s optimal profit performance of the TAS strategy under myopic consumer behavior in the following proposition.
**Proposition 1** With myopic consumers, the seller’s optimal advance selling price is

\[
P^M_{TAS} = \begin{cases} 
\frac{1+c}{2} & \text{if } c > \frac{\delta}{2-\delta}, \\
\frac{2+c}{4-\delta} & \text{if } c \leq \frac{\delta}{2-\delta}, 
\end{cases}
\]

under which the optimal expected total profit will be

\[
\pi^M_{TAS} = \begin{cases} 
\frac{(1-c)^2}{4} \mu & \text{if } c > \frac{\delta}{2-\delta}, \\
\frac{(2-3c+\delta)(2-\delta-c)}{(4-\delta)^2} \mu + \left(\frac{\delta+c-2c}{4-\delta}\right)^2 \frac{\mu}{\delta} & \text{if } c \leq \frac{\delta}{2-\delta}, 
\end{cases}
\]

It is worth noting that when the marginal production cost is high (i.e., \( c > \frac{\delta}{2-\delta} \)), the seller will only serve preordered consumers. As high-valuation consumers have already preordered the product in the advance selling period, selling in the spot market to low-valuation consumers may not cover the high production cost. Therefore, under such a scenario, the seller essentially adopts a "make-to-order" production strategy.

### 4.2 Strategic Consumers

When consumers are strategic, we will first apply the backward induction to characterize subgame perfect Nash equilibrium (SPNE) decisions for the game between the seller and consumers. Facing a first-period price \( p_1 \) and anticipated seller’s optimal second-period price \( p_2 \) and optimal production quantity \( Q \), strategic consumers will determine their purchase timing decisions by contemplating the surplus from preordering immediately versus that from waiting for a possible discount in the spot market. The following lemma characterizes each individual consumer’s purchasing strategy.

**Lemma 2** For any observed first-period price \( p_1 \), anticipated seller’s second-period price \( p_2 \) and production quantity \( Q \), and other consumers’ purchasing strategies, an individual consumer will adopt a threshold purchasing strategy with a unique threshold \( \theta \). Specifically, when this individual consumer’s valuation is higher than \( \theta \), she will purchase immediately; otherwise, she will wait.

Given the information structure, the probabilistic assessment of purchasing strategies adopted by all other consumers will be the same from each consumer’s perspective. Therefore, all consumers must adopt the same threshold \( \theta \) in equilibrium. The analysis of the seller’s profit performance for the TAS strategy under strategic consumer behavior is a standard process. In the interest of space, we will directly present the seller’s optimal profit performance in the following theorem, and the detailed analysis and optimal first-period price, consumers equilibrium threshold value, and optimal second-period price can be found in Appendix 1.
Theorem 1 With strategic consumers, the seller’s optimal expected profit under the TAS strategy is

\[
\pi_{\text{TAS}} = \begin{cases} 
\left( \frac{1-c}{2} \right)^2 \mu, & \text{if } \frac{\delta}{\delta - 1} < c < 1 \\
\frac{c(1/\delta - 1)(1 - c/\delta) \mu}{\left( \left( \frac{\delta - 1}{\delta - 1 - \delta} \right) - \frac{c}{\delta} + \frac{c^2}{\delta^2} \right)} & , \text{if } \frac{2-\delta}{2-\delta - \delta} \delta < c \leq \frac{\delta}{2-\delta} \\
0, & \text{if } 0 \leq c \leq \frac{2-\delta}{2-\delta - \delta}.
\end{cases}
\]

Similar to the myopic consumer case, the seller only serves preorder consumers when the production cost is high (i.e., \( c \geq \frac{\delta}{2-\delta} \)). As explained in §4.1, the high production cost limits the seller’s ability to serve low-valuation consumers. Therefore, serving high-valuation consumers in the advance selling period, before their valuations decline in the second period, is optimal. This observation suggests that when the seller’s production cost is high enough, the strategic consumer behavior will be less relevant, and the seller could treat all consumers as if they were myopic.

On the other hand, when the production cost is not too high (i.e., \( c < \frac{\delta}{2-\delta} \)), the strategic consumer behavior could substantially affect the seller’s profit performance. Due to strategic consumer behavior, the percentage profit loss, \( \frac{\pi_{\text{TAS}}}{\pi_{\text{TAS}}^M} - 1 \), could be nearly \(-30\%\) in our extensive numerical studies (to be detailed in §5), which suggests that there is a great potential for the seller to design other advance selling strategies to curtail such profit loss.

In the following section, we analyze an emerging strategy in advance selling: the PCP strategy. This strategy will be benchmarked against the profit performance of the TAS strategy under both strategic and myopic consumer behaviors. On one hand, by comparing the PCP strategy to the TAS strategy under strategic consumer behavior (i.e., \( \pi_{\text{TAS}} \)), we are able to assess the benefits of adopting the PCP strategy. On the other hand, as the majority of our literature demonstrates that strategic consumer behavior generally hurts the seller’s profit performance (e.g., Aviv and Pazgal 2008), we utilize the profit performance of the TAS strategy under myopic consumer behavior (i.e., \( \pi_{\text{TAS}}^M \)) to gauge the effectiveness of the PCP strategy in mitigating strategic consumer behavior.

5 Preorder Contingent Production Strategy

In this section, we will introduce and analyze a threshold-type Preorder Contingent Production (PCP) strategy. Under this strategy, the seller sets an Advance Selling Target (AST) and commits to serving the spot market only when the number of preorders is no less than this AST level. This PCP strategy reflects the practices adopted by Xiaomi and other companies mentioned in the introduction. In a nutshell, with the AST level, the PCP strategy has the potential to mitigate strategic waiting behavior by threatening to
not serve the spot market in the future when insufficient preorders are received during the advance selling period. Yet, an insufficient number of preorders may stem from either strategic waiting behavior or small market size. Particularly, in the case of a small market size, the PCP strategy may unintentionally punish consumers in the spot market who do not delay their purchases. Thus, adopting the PCP strategy requires the seller to carefully choose its AST level to balance the benefit of mitigating strategic consumer behavior and the loss from forfeiting the spot market profit.

Theoretically, it is possible for the seller to design and implement a more sophisticated PCP strategy that may further improve its profit performance. For instance, the seller might design a production menu to specify its production schedule for each and every possible preorder quantity. However, designing such a production menu is a complicated task that requires the seller to search all functional spaces of production quantities. Furthermore, even with an optimal production menu, the seller may face the issue of how to credibly communicate with consumers and implement the menu. In contrast, the threshold-type PCP strategy is considerably simpler for the seller to optimize (i.e., the seller only needs to search for the optimal AST level) and implement, and the commitment power would also be easier to obtain. Specifically, the seller could simply announce its AST level online and keep updating the number of preorders. To achieve credibility, the seller may disclose certain information such as the last few digits of customers’ phone numbers or user IDs to the public; or the seller may invite a third-party to oversee the preorder quantity. For example, since the first day of implementing Xiaomi’s PCP strategy, the public has been questioning the credibility of its claimed preorder quantity. To alleviate the public concern, Xiaomi has used both a third-party shipping vendor and the local government to confirm its preorder level (Huxiu 2014, Beijing News 2014). In another example, Meizu, a smartphone competitor to Xiaomi, announces and updates names and partial telephone numbers of its preordered customers so that its preorder quantity can be verified by the public (Meizu 2011). Therefore, in this paper we will focus on the threshold-type PCP strategy for its simplicity and implementability and leave the analysis of the full-contingent PCP strategy for future exploration.

5.1 Model Analysis

Similar to Lemma 2, it is straightforward to show that in equilibrium, all consumers will adopt a threshold policy with a unique threshold value $\theta$. Denote the AST level as $Q_{AST}$. We first analyze the seller’s production and price decisions in the second period. At this moment, we consider the equilibrium threshold
\( \theta \) to be less than 1 so that some strategic consumers will preorder in the advance selling season; the case \( \theta = 1 \) is less interesting, and we can show later that its profit performance is dominated by the case where \( \theta < 1 \). Let \( d \) represent the realized market size, \( d = \frac{x}{1-\delta} \). Further, denote \( Q^{PCP}(d, \theta, Q_{AST}) \), \( p^{PCP}_2(d, \theta, Q_{AST}) \), and \( \pi^{PCP}_2(d, \theta, Q_{AST}) \) as the optimal second-period quantity, price, and profit, respectively. Then, the following lemma establishes the seller’s optimal decisions and its corresponding profit performance in the second period.

**Lemma 3** Given the realized market size \( d \), if \( \theta > c/\delta \) and \( (1-\theta)d \geq Q_{AST} \), then the seller will charge a second-period price \( p^{PCP}_2(d, \theta, Q_{AST}) = \frac{\delta \theta + c}{2} \), order \( Q^{PCP}(d, \theta, Q_{AST}) = \frac{2-\theta-c/\delta}{2}d \), and obtain the maximum second-period profit \( \pi^{PCP}_2(d, \theta, Q_{AST}) = \frac{(\delta \theta - c)^2d}{45} - cd(1-\theta) \); otherwise, the seller will only satisfy preorder consumers by producing \( Q^{PCP}(d, \theta, Q_{AST}) = d(1-\theta) \) and charging \( p^{PCP}_2(d, \theta, Q_{AST}) = 1 \), and obtain the optimal profit \( \pi^{PCP}_2(d, \theta, Q_{AST}) = -cd(1-\theta) \).

Next, we will characterize the structure of the consumers’ equilibrium threshold \( \theta \) for any given preorder price \( p_1 \) and AST level \( Q_{AST} \). To this end, we need to define two parameters. First, consider the scenario in which all consumers act as if they believe that the number of preorders will always equal or exceed \( Q_{AST} \), and we denote the corresponding consumers’ equilibrium threshold by \( \theta_{hkl} \). Similar to the proofs of Proposition 12 and Lemma 5 in Appendix 1, this \( \theta_{hkl} \) value can be identified by the minimum between 1 and the solution \( \theta \) to the following equation:

\[
\theta - p_1 = \alpha \left( \delta \theta - \frac{\delta \theta + c}{2} \right)^+ + (1-\alpha) \left( \delta \theta - \frac{\delta \theta + c}{2} \right)^+, \tag{4}
\]

where the left side represents the surplus from an immediate purchase and the right side calculates the surplus from a wait decision where the seller serves the spot market under both high and low market size realizations.

Second, consider the setting under which all consumers act as if they believe that the number of preorders will equal or exceed \( Q_{AST} \) only under the high market size realization. Let \( \theta_h \) denote the corresponding consumers’ equilibrium threshold. Similarly, it can be shown that this \( \theta_h \) value is the minimum between 1 and the solution \( \theta \) to

\[
\theta - p_1 = \alpha \left( \delta \theta - \frac{\delta \theta + c}{2} \right)^+, \tag{5}
\]

where the right side of this equation estimates the surplus from a wait decision when the seller serves the spot market only under high market size realization. With these two parameters, we formally establish the
consumers’ unique threshold $\theta$ in equilibrium for any advance selling price $p_1$ and AST level $Q_{AST}$ in the following proposition.

**Proposition 2** Given any advance selling price $p_1$ and AST level $Q_{AST}$, the consumers’ equilibrium threshold is uniquely given by the following:

$$
\theta(p_1, Q_{AST}) = \begin{cases} 
\theta_{hkl}, & \text{if } Q_{AST} \in [0, (1 - \theta_{hkl})d_l] \\
1 - Q_{AST}/d_l, & \text{if } Q_{AST} \in ((1 - \theta_{hkl})d_l, (1 - \theta_{h})d_l] \\
\theta_h, & \text{if } Q_{AST} \in ((1 - \theta_{h})d_l, (1 - \theta_{h})d_h] \\
1 - Q_{AST}/d_h, & \text{if } Q_{AST} \in ((1 - \theta_{h})d_h, (1 - p_1)d_h] \\
p_1, & \text{if } Q_{AST} \in ((1 - p_1)d_h, \infty). 
\end{cases}
$$

Proposition 2 demonstrates that the consumers’ equilibrium threshold is a non-increasing function in the AST level. In other words, the seller can mitigate strategic waiting behavior by increasing the AST level. Figure 1 illustrates an example of the consumers’ equilibrium threshold values for different AST levels. First observe that under the PCP strategy, the consumers’ equilibrium threshold is bounded above by $\theta_{hkl}$, the same threshold under the TAS strategy. In other words, no more consumers will wait strategically under the PCP strategy than under the TAS strategy. Second, the consumers’ equilibrium threshold $\theta$ is non-increasing in the AST level, which is quite intuitive: For the seller to serve the spot market under a high AST level, more consumers need to preorder in the first period, which calls for lower $\theta$—less strategic waiting behavior. Thus, merely from the perspective of mitigating strategic consumer behavior, the seller should set its AST level as high as possible so that no consumer will wait strategically (i.e., $Q_{AST} \geq (1 - p_1)d_h$). However, doing so will sacrifice the spot market’s profit. In particular, increasing the AST level could increase the probability that the number of preorders will fall short of the AST level, which limits the seller’s ability to
serve the spot market and hurts its second-period profit.

To better understand the effectiveness of the PCP strategy, we need to determine the seller’s optimal pricing and AST level decisions in the advance selling period. Specifically, the seller’s optimal expected total profit can be stated as follows:

$$\pi_{PCP} = \max_{p_1, Q_{AST}} \left\{ E \left[ p_1 \cdot (1 - \theta(p_1, Q_{AST})) \right] d + \pi_{2PCP}^2 (D, \theta(p_1, Q_{AST}), Q_{AST}) \right\},$$

where $\theta(p_1, Q_{AST})$ is determined by Proposition 2. Further, it can be shown that for any given first-period price $p_1$, there are only three possible candidates for the optimal AST level.

**Proposition 3** For any given first-period price $p_1$, the seller’s optimal AST level is one of the following three values: $0$, $(1 - \theta_h) d_i$, or $(1 - p_1) d_h$, under which the consumers’ equilibrium threshold is $\theta_{hlk1}$, $\theta_h$ or $p_1$, respectively.

Notice that the optimal AST level will be no larger than $(1 - p_1) d_h$, which suggests that it will be optimal for the seller to serve the spot market at least under the high market size realization. Furthermore, based on Proposition 3, to determine the optimal profit under the PCP strategy, we only need to analyze the profit performance under three AST candidates: Case I: $Q_{AST}^I = 0$, Case II: $Q_{AST}^II = (1 - \theta_h) d_i$, and Case III: $Q_{AST}^III = (1 - p_1) d_h$. Observe that Case I is, de facto, the TAS strategy, whose profit performance has already been given in Theorem 1. We will, therefore, only discuss the other two cases. In the second case where the AST level is set to $(1 - \theta_h) d_i$, the optimal profit performance is given by the following proposition.

**Proposition 4** When the AST level is set to $Q_{AST}^II$, it is optimal for the seller to charge the optimal first-period price at

$$p_{1II} = \left\{ \begin{array}{ll}
\theta^{II} - \alpha \cdot \left( \frac{\delta^{II} - c}{\delta} \right), & \text{if } c/\delta \leq \theta^{II} \leq 1 \\
0, & \text{if } 0 \leq \theta^{II} < c/\delta
\end{array} \right.,$$

where $\theta^{II}$ is the equilibrium threshold value in consumers’ game and

$$\theta^{II} = \left\{ \begin{array}{ll}
\frac{1 + c}{\delta} \cdot \frac{1}{c/\delta}, & \text{if } \frac{c}{\delta} < c \leq \delta \\
\frac{\delta}{\delta - \alpha c + c}, & \text{if } \frac{\delta}{\delta - \alpha c} \delta < c \leq \frac{\delta}{\delta - \alpha c} \\
\frac{\delta}{\delta - \alpha c + c}, & \text{if } 0 \leq c \leq \frac{\delta}{\delta - \alpha c} \\
\end{array} \right..$$

Accordingly, the seller’s optimal profit is

$$\pi_{PCP}^{II} = \left\{ \begin{array}{ll}
\frac{(1 - c)^2}{\delta} \mu, & \text{if } \frac{\delta}{\delta - \alpha c} < c \leq 1 \\
\frac{c (1/\delta - 1) (1 - c/\delta)}{\mu}, & \text{if } \frac{\delta}{\delta - \alpha c} \delta < c \leq \frac{\delta}{\delta - \alpha c} \\
\left( 1 - \frac{\alpha c}{\delta} \right) \theta^{II} + \frac{\alpha c}{\delta} - c \cdot (1 - \theta^{II}) \mu + \frac{(\delta^{II} - c)^2}{4\delta}, & \text{if } 0 \leq c \leq \frac{\delta}{\delta - \alpha c}.
\end{array} \right.$$
From Proposition 4 and Theorem 1, we can directly show that the profit performance under Case I is dominated by that under Case II. Immediately, this observation implies that the PCP strategy ($\pi_{PCP}$) dominates the TAS strategy ($\pi_{TAS}$) in terms of profit performance.

**Corollary 1** $\pi_{PCP}^{II} \geq \pi_{TAS}$, and therefore $\pi_{PCP} \geq \pi_{TAS}$.

Next, to characterize the profit performance of the PCP strategy, we need to consider the last case, where the AST level is set to $Q_{AST}^{III}$.

**Proposition 5** When the AST level is set to $Q_{AST}^{III}$, it is optimal for the seller to charge the optimal first-period price at

$$p_{1}^{III} = \begin{cases} \frac{1+c}{2} & \text{if } \frac{\delta}{2-\delta} < c \leq \frac{\delta}{2} \text{ and } \frac{\delta}{2} \leq c \leq \frac{\delta}{2-\delta}, \\
\frac{2\mu+2\mu-c\theta d_{h}}{4\mu-c\theta d_{h}} & \text{if } 0 \leq c \leq \frac{\delta}{2-\delta}, 
\end{cases}$$

under which consumers will preorder as long as their valuations are higher than the first-period price (i.e., $\theta^{III} = p_{1}^{III}$). Accordingly, the seller’s optimal profit is

$$\pi_{PCP}^{III} = \begin{cases} \frac{(1-c)^2}{4} \mu & \text{if } \frac{\delta}{2-\delta} < c \leq 1 \\
(p_{1}^{III} - c)(1-p_{1}^{III}) \mu + \alpha \frac{(\delta p_{1}^{III} - c)^2 d_{h}}{45} & \text{if } 0 \leq c \leq \frac{\delta}{2-\delta}, 
\end{cases}$$

Together, the profit of the PCP strategy can be identified by the maximum profit among Case II, Case III, and the case $\theta = 1$. Note that it is more profitable for the seller to serve only preorder consumers than to serve only the spot market (i.e., the case of $\theta = 1$), which suggests that the profit performance under Case III is greater than or equal to that under $\theta = 1$. Therefore, the profit performance of the PCP strategy is the maximum between the profit of Case II and the profit of Case III.

**Theorem 2** Under the PCP strategy, the seller can maximize its profit performance by setting the AST level to $Q_{AST}^{II}$ or $Q_{AST}^{III}$, i.e. $\pi_{PCP} = \max \{ \pi_{PCP}^{II}, \pi_{PCP}^{III} \}$, and the corresponding optimal first-period price and consumers’ equilibrium threshold value are given in Proposition 4 or Proposition 5.

Before discussing the impact of market parameters (e.g., the production cost and the consumers’ discount factor) on the selection of the AST level and on the profit performance of the PCP strategy, we introduce a special case to illustrate the effectiveness of the PCP strategy in mitigating strategic consumer behavior.

### 5.2 Deterministic Market

Suppose the market size is deterministic with the value $\mu$. We can show that the profit benchmark under myopic consumer behavior can be achieved by the PCP strategy even in the presence of strategic consumers.
Proposition 6 Under the deterministic market size, $\pi_{TAS}^M = \pi_{PCP} = \pi_{TAS}$ for $\frac{\delta}{2-\delta} \leq c \leq 1$ and $\pi_{TAS}^M = \pi_{PCP} > \pi_{TAS}$ for $0 < c < \frac{\delta}{2-\delta}$.

As mentioned in previous sections, so far various approaches have been proposed in the literature to mitigate strategic consumer behavior. However, the question of what strategy can eliminate strategic consumer behavior has not been formally explored. We show that under certain scenarios (e.g., when the market uncertainty is low), the PCP strategy can completely eliminate strategic consumer behavior and achieve the optimal profit benchmark under myopic consumers.

5.3 Stochastic Market

The analysis behind Proposition 6 can be similarly carried through to that under stochastic market demand. Particularly, we have the following proposition:

Proposition 7 Under the stochastic market size, $\pi_{TAS}^M = \pi_{PCP} = \pi_{TAS}$ for $\frac{\delta}{2-\delta} \leq c \leq 1$ and $\pi_{TAS}^M \geq \pi_{PCP} \geq \pi_{TAS}$ for $0 < c < \frac{\delta}{2-\delta}$.

Yet, compared to Proposition 6, Proposition 7 states that the PCP strategy might not be able to completely eliminate the negative influence of strategic consumer behavior (i.e., $\pi_{TAS}^M \geq \pi_{PCP}$). In the following, we should quantitatively gauge the benefits of the PCP strategy. As it is challenging to analytically measure the profit difference under different strategies, we conduct a comprehensive numerical study to derive additional insights. Our numerical study spans over (i) 11 levels of marginal production cost $c \in \{0, 0.05, ..., 0.5\}$; (ii) 9 levels of consumers’ discount factor $\delta \in \{0.1, 0.2, ..., 0.9\}$; (iii) 9 levels of low market size $d_l \in \{1, 2, ..., 9\}$; and (iv) 9 levels of high market size $d_h \in \{11, 12, ..., 19\}$. Without loss of scope, we hold the mean of market size $\mu$ at 10, and allow $\alpha$ (i.e., the probability of the high market size) to vary accordingly (i.e., $\alpha = (\mu - d_l) / (d_h - d_l)$). There are 8,019 parameter combinations in total that cover a wide range of scenarios. Below we first examine the optimal AST level.

5.3.1 The optimal AST level

According to Theorem 2, there are two candidates for the optimal AST level: $Q_{AST}^{III}$ and $Q_{AST}^{III}$. Under the higher AST level (i.e., $Q_{AST}^{III}$), the seller will sacrifice its potential future profit—the profit from serving the spot market under the low market size realization—to induce more preorders from strategic consumers. It is worth noting that we are not suggesting that a lower AST level (e.g., $Q_{AST}^{III}$) is not optimal. On the
contrary, adopting the AST level at $Q_{\text{AST}}^H$ could be quite effective in containing strategic waiting behavior under certain scenarios. In this section, we are interested to see when it is optimal for the seller to raise its AST to the high level.

We find that at most scenarios (i.e., 91% in our numerical experiments), the seller sets the high AST level. The market uncertainty (i.e., the probability distribution of market size $\alpha$) plays a significant role in determining the optimal AST level, but the exact values of high and low market sizes ($d_l$ and $d_h$) have a secondary effect. In particular, we observe that as the probability of the high market size realization rises, the percentage of scenarios with a high AST level tends to increase. When $\alpha$ is no less than 0.4, the seller will always select the high AST level. The rationale behind this observation is straightforward. By not serving the spot market under the low market size realization, the seller partially removes consumers’ waiting incentives and hence induces more preorders. In addition, if the probability of the low market size realization is insignificant (i.e., $\alpha$ is large), then the direct cost associated with forfeiting the spot market profit under the low market size realization will be less severe, which further incentivizes the seller to set a high AST level.

5.3.2 The magnitude of profit improvement

So far, our analyses suggest that the negative effect of strategic consumer behavior can be completely eliminated under two situations: (i) There is no stochasticity (Proposition 6); or (ii) the marginal production cost is high (large $c$) or the product is fashionable (small $\delta$) (Proposition 7). However, due to strategic consumer behavior, under other scenarios, even the PCP strategy may not always attain the profit benchmark under myopic consumers (i.e., $\pi_{TAS}^M$). Across all 8,019 scenarios in our numerical study, the percentage profit improvement of the PCP strategy over the TAS strategy (i.e., $\pi_{PCP}/\pi_{TAS} - 1$) ranges from 0% to 40.96%, with an average of 13.58%. Compared to the profit benchmark under myopic consumers $\pi_{TAS}^M$, the minimum, maximum, and average of the profit loss ($\pi_{PCP}/\pi_{TAS}^M - 1$) are 0%, -12.23%, and -1.62%, respectively. Yet by adopting the PCP strategy, the seller on average can close 93% of the profit gap from the TAS strategy (i.e., the mean of $(\pi_{TAS}^M - \pi_{PCP}) / (\pi_{TAS}^M - \pi_{TAS})$ is 93%). In addition, the PCP strategy nearly attains the profit benchmark under myopic consumers (i.e., profit gap $\pi_{PCP}/\pi_{TAS}^M - 1$ is within 1%) for 61% of scenarios. Below, we proceed to examine how market parameters affect the profit performance of the PCP strategy.
We first investigate the influence of market uncertainty. Similar to early findings about the optimal AST level, the profit comparison between PCP and TAS strategies is significantly affected by the probability of the high market size realization (i.e., $\alpha$), but not much by the exact values of the high and low market sizes ($d_l$ and $d_h$). Figure 2(a) reports the average profits for TAS and PCP strategies where the marginal production cost equals 0.05 (i.e., $c = 0.05$). The figures for other cost values exhibit similar patterns and are therefore omitted. First note that the profit performance under the TAS strategy is invariable to $\alpha$. This observation reinforces our previous discussions on the benefits of adopting advance selling: The seller benefits from postponing production decisions after resolving market size uncertainty via observing the number of preorders. However, this argument does not hold under the PCP strategy, as its profit depends on the AST level, which is set before the uncertainty is revealed to the seller and has a complicated influence on the seller’s profit performance.

Specifically, the PCP strategy performs extremely well when there is an unbalanced probability distribution between two market size realizations—either large $\alpha$ or small $\alpha$. It is worth noting that under general multiple-point distributions, the unbalanced probability distribution implies that the probability is not evenly distributed among all possible realizations but concentrated on a small number of market size realizations. Under such unbalanced probability distribution, this small number of realizations can be scattered in the distribution support and do not necessarily have to be near each other, i.e., the unbalanced distribution does not necessarily imply a distribution with a low variability. As observed in §5.3.1, the low AST level (i.e., $(1 - \theta_h) d_l$) is sufficient to mitigate strategic consumer behavior under a low $\alpha$. From Proposition 4, setting the AST level at $(1 - \theta_h) d_l$ will not limit the seller’s ability to serve the spot market under both
Therefore, we observe that the profit performance under the PCP strategy converges to the profit upper-bound as $\alpha$ approaches zero. On the other hand, a large $\alpha$ reduces the opportunity cost of setting a high AST level and therefore favors the adoption of the high AST level (detailed in §5.3.1). Hence, under a high $\alpha$, the profit performance of the PCP strategy approaches the profit upper-bound as $\alpha$ increases. To the extreme, when $\alpha$ is either zero or one, we return to the deterministic case, where the PCP strategy always attains the profit upper-bound (Proposition 6).

The PCP strategy is least effective when $\alpha$ is in the medium range, where the strategic consumer behavior is most detrimental (so that a low AST level is less advantageous) but it is too costly to counteract strategic consumer behavior (so that a high AST level is less favorable). Nevertheless, compared to the TAS strategy, the seller still prefers the PCP strategy, which significantly improves the seller’s profit as shown in Figure 2(a) and Figure 2(b).

Next, we consider how consumers’ discount factor ($\delta$) affects the seller’s profit under these three strategies. On one hand, under a high $\delta$, consumers will not heavily discount the valuation of the product later on, so the

Figure 3: The influence of the consumer’s discount factor ($\delta$) on PCP strategy.
seller may benefit from charging a high price to those high-valuation consumers in the second period. By this argument, when all consumers are myopic, the profit performance (i.e., $\pi_{MTAS}^M$) is expected to increase in $\delta$. Similarly, through mitigating strategic consumer behavior by setting an optimal AST level, the PCP strategy seems to benefit from a high $\delta$ as well. On the other hand, a high $\delta$ could potentially encourage strategic waiting behavior, which in turn hurts the seller’s revenue performance. Together, these two conflicting effects of $\delta$ lead to a non-monotonic pattern of the seller’s profit performance under the TAS strategy (i.e., the dash line in Figure 3(a)). In particular, when $\delta$ is in the medium range, where the strategic consumer behavior is the most detrimental, the profit performance under the TAS strategy would be hurt severely, which is consistent with the findings in the strategic consumer behavior literature (e.g., Aviv and Pazgal 2008). Accordingly, this non-monotonic profit performance of the TAS strategy explains the non-linear shape in Figure 3(b)—the benefit of adopting the PCP strategy over the TAS strategy peaks at the medium range of $\delta$.

At last, it is intuitive that the marginal cost has a negative influence on the seller’s profit performance. Comparing Figure 3(a) to Figure 3(c), the profit performance monotonically decreases as the marginal cost increases from 0.05 to 0.15. Yet, as the profit performance proportionally decreases at a similar rate from each strategy’s perspective, the benefits of adopting the PCP strategy are less sensitive to such marginal cost increase (see Figure 3(d)).

To summarize, we find that the PCP strategy could effectively mitigate strategic consumer behavior and, therefore, significantly improve the seller’s profit performance. In particular, when the discount factor is at a medium or high level or the production cost is not too high, the PCP strategy performs exceptionally well. Furthermore, when the market size has an unbalanced probability distribution, the PCP strategy can nearly eliminate strategic waiting behavior and achieve the profit benchmark under myopic consumer behavior.

6 Extension and Discussion

In this section, we examine the robustness of our results and insights by considering two model extensions (i.e., a partial-learning model in §6.1 and a valuation uncertainty model in §6.2) and comparing the PCP strategy to the Capacity Rationing strategy in §6.3.
6.1 Partial Demand Learning with Second-Period Arrivals

For analytical tractability, in previous sections we presented the full-learning model in which the seller could completely resolve the demand uncertainty in the second period from the number of preorders. Particularly, we have shown that under both the TAS strategy and the PCP strategy, it is optimal for the seller to charge a preorder price that induces non-zero preorders and facilitates the seller to fully resolve demand uncertainty in the spot market. Although models without demand uncertainty are not uncommon in the advance selling literature (e.g., Xie and Shugan 2004), it will be of interest to investigate the benefits of the PCP strategy when the spot market demand cannot be fully resolved from preorders (e.g., Tang et al. 2004).

To this end, we extend our analysis to a partial-learning model that includes a new stream of arrivals in the second period, whose market size can be positively/negatively correlated with the first-period market size. Specifically, we denote the market size for the second period to be $M$, which is a random variable, with two possible realizations of $m_h$ and $m_l$, where $m_h > m_l > 0$. If the first-period market size is $d_h$, then the second-period market size will be $m_h$ and $m_l$ with probability $\beta_h \geq 0$ and $(1 - \beta_h) \geq 0$, respectively. On the other hand, when the realized first-period market size is $d_l$, the second-period demand will be $m_h$ or $m_l$ with probability $\beta_l \geq 0$ and $(1 - \beta_l) \geq 0$. Clearly, when $\beta_h$ is larger than $\beta_l$, the two-period market sizes are positively correlated. Therefore, the demand in the spot market can only be learned partially through the preorder quantity. Further, the advance selling literature often assumes that high valuation consumers (e.g., informed or tech-savvy consumers) arrive in the first period and consumers arriving in the second period have lower valuations (e.g., Li and Zhang 2013). Therefore, we allow the second-period arriving consumers' base valuations to be discounted by a factor of $\kappa \in (0, 1]$.

In the following, we will briefly summarize the benefits of the PCP strategy under this partial-learning model. For detailed discussions of the model, analysis, and results, please refer to Appendix 2. Denote the profit performance for the PCP and TAS strategies under this partial-learning model to be $\tilde{\pi}_{PCP}$ and $\tilde{\pi}_{TAS}$. We can show that the PCP strategy continues to dominate the TAS strategy in terms of profit performance.

**Proposition 8** When there are second-period arrivals and the seller could partially learn the second-period market size through the first-period preorders, the PCP strategy dominates the TAS strategy in terms of profit performance i.e., $\tilde{\pi}_{PCP} \geq \tilde{\pi}_{TAS}$.

To understand the quantitative impact of the second-period arrivals and the partial demand learning, we
conduct comprehensive numerical studies that cover a wide range of scenarios (360,855 parameter combinations). Across all scenarios, the percentage profit improvement of the PCP strategy over the TAS strategy (i.e., $\tilde{\pi}_{PCP}/\tilde{\pi}_{TAS} - 1$) ranges from 0% to 65.67%, with an average of 14.25%.

We further find that results and insights derived in the full-learning model (i.e., the main model) continue to qualitatively hold true under this partial-learning model. Particularly, the PCP strategy still can significantly improve the seller’s profit over the TAS strategy, especially when consumers’ discount factor $\delta$ is at a medium or high level, the production cost $c$ is not too high, or the first-period market size exhibits an unbalanced probability distribution. At last, we observe that the benefits of the PCP strategy can be influenced by the size and valuations of the second-period arrivals. Clearly, a large market size (i.e., $m_l$ and $m_h$) or high consumers’ valuations (i.e., $\kappa$) of the second-period arrivals will potentially undermine the relative influence of strategic consumer behavior, as only consumers arriving in the first period could behave strategically to postpone their purchases.

6.2 Valuation Uncertainty

In previous sections, we assume that consumers have heterogeneous but certain valuations for the product. This assumption is widely adopted in the literature (e.g., Li and Zhang 2013, Tang et al. 2004, McCardle 2004, etc.) and well justified for a search good where product characteristics can be fully observed and thoroughly evaluated before purchase (e.g., screen size, memory size, and CPU for smartphones). However, the valuation uncertainty may emerge when consumers face an experience good whose characteristics can only be determined when the product is physically available for consumers to evaluate (e.g., comfortable to hold, compatible to specific Apps, etc.). In this subsection, we examine the robustness of our results by extending our model to incorporate the valuation uncertainty. Specifically, we assume that consumers have heterogeneous and uncertain valuations that consist of two independent parts (Chu and Zhang 2011): $v = v_o + v_u$. The consumers’ observable base valuations (observable during advance selling period) are denoted by $v_0$, and the unobservable experience-based features (only revealed in the regular selling period) are denoted by $v_u$.

In the following, we will briefly summarize the impact of this valuation uncertainty model on our results. For detailed discussions of the model, analysis, and insights, please refer to Appendix 3. We first confirm that the results and insights derived in the original model continue to hold. In particular, the PCP strategy
dominates the TAS strategy in terms of profit performance.

**Proposition 9** *The PCP strategy dominates the TAS strategy in terms of profit performance.*

In addition, we consistently find that compared to the TAS strategy, the PCP strategy can significantly improve the seller’s profit, especially when consumers’ discount factor is at a medium or high level, the production cost is not too high, or the first-period market size exhibits an unbalanced probability distribution. Across all scenarios (433,026 parameter combinations) in our numerical study, the percentage profit improvement of the PCP strategy over the TAS strategy ranges from 0% to 52.11%, with an average of 6.48%.

### 6.3 Capacity Rationing Strategy

The strategic consumer literature has lauded the *Capacity Rationing* (CR) strategy, in which the seller commits to a limited capacity/quantity at the beginning of the selling season, for its effectiveness in mitigating strategic consumers’ behavior by limiting the initial inventory level (e.g., Su 2007 and Liu and van Ryzin 2008). In comparison, the PCP strategy proposed in this paper facilitates the seller to design a preorder contingent production plan that may allocate no products to strategically waiting consumers if there are insufficient preorders. Conceptually, the CR strategy and the PCP strategy share some similarities, as both strategies may benefit from discouraging strategic waiting behavior via rationing. Yet, besides the modeling differences from the CR strategy literature (e.g., we model both dynamic pricing and capacity decisions), the PCP strategy further grants the seller the flexibility to responsively adjust its capacity level contingent on the updated demand information. Therefore, it will be of interest to gauge the potential benefits, if any, of the PCP strategy over the CR strategy.

Below, we briefly summarize the results of comparing the CR strategy to the TAS strategy and the PCP strategy; for detailed analysis please refer to Appendix 4. Generally speaking, the seller’s profit function under the CR strategy is not unimodal in consumer’s threshold value $\theta$ and the committed capacity level $Q$, thus characterizing and comparing the seller’s profit performance will be quite tedious. Yet, under a special case (i.e., deterministic market size), we can show the PCP strategy continues to outperform the CR strategy, which dominates the TAS strategy. Denoting $\pi_{CR}$ as the profit performance under the CR strategy, the following proposition formally states the discussion above.
Proposition 10  Under the deterministic market size, \( \pi_{PCP} \geq \pi_{CR} \geq \pi_{TAS} \).

Under the stochastic market size, we gauge the benefits of the PCP strategy via the same parameter combinations as in §5.3. We first observe that CR strategy is not necessarily better than the TAS strategy under the advance selling setting, because the potential benefit of the CR strategy (i.e., mitigate strategic consumers’ waiting behavior) is achieved at the cost of not being able to utilize updated market size information to optimize its production decision. Across all 8,019 scenarios in our numerical study, the percentage profit improvement of the CR strategy over the TAS strategy (i.e., \( \pi_{CR}/\pi_{TAS} - 1 \)) ranges from \(-90.00\%\) to \(15.53\%\), with an average of \(-21.39\%\). Only when the probability of the high market size realization \( \alpha \) is either very high or very low (i.e., the market uncertainty is low) and the production marginal cost \( c \) is low (e.g., the cost of overstocking is low), it is beneficial for the seller to utilize the CR strategy.

As we have shown that the PCP strategy dominates the TAS strategy in §5, it is not surprising that the PCP strategy could significantly improve the seller’s profit performance from the CR strategy. For all scenarios, the percentage profit improvement of the PCP strategy over the CR strategy (i.e., \( \pi_{PCP}/\pi_{CR} - 1 \)) ranges from \(1.27\%\) to \(900.33\%\), with an average of \(66.83\%\). Analogous to previous comparisons between the TAS strategy and CR strategy, the PCP strategy is most beneficial compared to CR strategy when the marginal production cost \( c \) is not too small or when \( \alpha \) is neither too high nor too low. Under either condition, the benefits from postponing the production decision are quite significant, either because of the high costs for overstock (e.g., high production cost) and understock (e.g., high market size realization), or because of the benefits from demand learning (e.g., medium value of \( \alpha \)).

7 Conclusion

The advent of Internet technologies has facilitated the proliferation of the advance selling strategy that significantly improves sellers’ operational flexibility and profit performance. At the same time, such technology advances also provide affluent information to consumers so that they can strategically time their purchases for anticipated future discounts. In recent years, the negative impact of such strategic consumer behavior on advance selling has received an increasing amount of attention in the literature. In this paper, we study the emerging preorder contingent production (PCP) strategy, where the seller will produce to serve the spot market only when the number of preorders is no less than a pre-determined advance selling target, and we investigate the PCP strategy’s effectiveness in mitigating the negative influence of strategic consumer
behavior.

We find that the PCP strategy is competent in counteracting strategic waiting behavior and can substantially improve the seller’s profit, compared to the Traditional Advance Selling strategy and the Capacity Rationing strategy. When there is no market size uncertainty, the PCP strategy can completely eliminate strategic waiting behavior and achieve the profit benchmark under myopic consumers (i.e., the seller’s profit under the traditional advance selling strategy when selling to myopic consumers). Even when the market size is stochastic, we show that the benefit of using the PCP strategy can be significant, especially when the production cost is not too high, consumers’ discount factor is at a medium or high level, or there is an unbalanced probability distribution among market size realizations. In particular, when the market size distribution is unbalanced (i.e., the probability is not evenly distributed among all possible realizations but concentrated on a small number of possible market size realizations), the seller could focus its attention on a small number of market size realizations, which helps the seller target an accurate advance selling target level and therefore improves its profit performance. Finally, we demonstrate that the benefits of the PCP strategy are robust under other model considerations. These results call for practitioners’ attention to this emerging PCP strategy for its significant benefits.

This line of research can be extended in several directions. In this paper, we consider the PCP strategy, and a natural research question will be whether and when a preorder contingent pricing strategy can benefit the seller. Another natural extension is to include additional behavioral characteristics such as trust and regrets (Nasiry and Popescu 2012). Finally, this paper considers a monopolist seller; it would be interesting to examine the performance of advance selling in a competitive setting.

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