QUANTIFYING THE BENEFITS AND COSTS OF GROCERY CLICK-AND-COLLECT SERVICE

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ABSTRACT

To combat the rising fulfillment cost of online grocery, this paper investigates the benefits of receiving online orders from customers and taking advantage of the time difference between order placement and order fulfillment to optimize stock levels. We describe methods to quantify the value of demand information and compare the benefits to the marginal labor cost of fulfilling online orders. Our numerical illustration shows the crucial role of the amount of short-life items in cart, item pick rate, and in-store fulfillment setup.

INTRODUCTION

The grocery retailing industry has undergone dramatic changes in recent years. Due to unforeseen circumstances, customer demand for online grocery services had accelerated faster than even the more optimistic, pre-pandemic estimates. According to one survey of internet users in the United States, the number of participants that have made at least one online grocery order in the past calendar year has risen from 33.8% (2019) to 47.8% (2020), and online grocery sales increased from $62.2 to $95.8 in the same period [1].

This development has led to higher fulfillment operation expenses for grocers. In order to provide omnichannel services, such as click-and-collect (or buy online, pickup in-store), the retailer incurs additional costs from order picking and fulfillment handing of the online orders. For a 25-items order, the marginal increase in fulfillment cost can range from $10.25 per pickup order to $17.75 per delivery order [2]; though these figures are likely to differ across geographical regions and customer demographics.

Some chains choose to pass on the last-mile portion of the fulfillment cost to customers in the form of a delivery fee. However, most stores today offer pickup services free of charge. This means that the incremental expenses associated with pickup orders are currently being absorbed by retailers. While cost is not the immediate concern as we progress in overcoming the pandemic, it will be important again once these services become convenience features rather than necessities. A portion of consumers that have acclimated to the process of online grocery could later do so on occasions, and those that have adopted buying groceries online into their lifestyles may continue that routine.

One advantage that online ordering brings, though, is access to advance demand information (ADI). In earlier research, Siawsolit & Gaukler (2019) identify that if online orders are placed with a demand lead time duration that is greater than the supply lead time, the value of ADI can be significant for perishable products [3]. This applies in particular to products with short shelf life durations, where the retailer's goal is to simultaneously minimize both the stockout rate and the spoilage rate. The U.S. Department of Agriculture estimates that the retail-level inventory shrink rates for fruits, vegetables, meat, and seafood products are all higher than 10% [4].

As suggested by Song et al. (2021), "… *when produce is more perishable, omni-channel strategy improves the retailer's profits and the consumer surpluses with either a (delivery) or (store pickup) mode. Therefore, omni-channel operation should be implemented especially for fresh produce with high loss rates*" [5]. Another prior research by Siawsolit & Gaukler (2021) also provides evidence of this. Essentially, the shorter the product's lifetime, the higher the chance of product loss, which translates to higher ADI value. Therefore, we posit that the ADI value obtained through advance online orders of perishables may be able to help alleviate some portion of the marginal fulfillment cost of online grocery [6].

On the other hand, perishable items are also more challenging to manage in regards to omnichannel fulfillment. As noted by a participant of the online grocery satisfaction survey by Weber-Snyman & Badenhorst-Weiss (2018), "… *tomatoes, they always pick the ripest tomatoes. Now everything is ripe and now you have to either make sauce or soup or something just to make use of it, and that was not necessarily the plan*" [7]. Since consumers have differing expectations when picking their produce items, online grocery ordering systems often include the option to communicate these preferences to the store's pickers. Consequently, perishable products tend to take a longer time to pick relative to non-perishables, and hence, incur higher fulfillment cost due to the slower pick rate per item.

Apart from the need to have local delivery vehicles capable of maintaining temperature zones, or at least cool temperature, the grocer is also taking more responsibilities during the last steps of fulfillment. If the quality of an item delivered is sub-standard, the customer may distrust the entire omnichannel shopping process and not simply the one sub-standard order fulfilment. Thus, in order to quantitatively explore in-store fulfillment strategies, we are interested to find out how the benefits obtained from advance online orders of perishables compare to the incremental costs of offering omnichannel services.

Specifically, our research goals include: i) Comparing the potential value of ADI for perishables and non-perishables, ii) Characterizing the relationship between ADI value and marginal omnichannel fulfillment cost, and iii) Identifying key performance markers for profitable curbside pickup fulfillment operations. We address these queries by first describing the process of deriving the value of ADI from advance orders, and then show how ADI value can be related on a dollar-per-cart basis to the fulfillment cost of online ordering. Included is a numerical example that considers various inputs such as number of items per cart, proportion of short-life items, and item pick rate, with outputs ranging from net dollar gain/loss per each online order, to the minimum pick rate required to breakeven.

The remainder of this paper is organized as follows. The Literature Review section discusses past contributions relevant to our study. Next, the Value of ADI section introduces the concept of ADI, when it occurs, and how the value from ADI is obtained. The Marginal Fulfillment Cost section defines fulfillment-related expenses attributed to online orders; taking into account the pick rate and added handling requirements. The Benefit-Cost Comparison section then relates the potential benefits of ADI to the labor costs required to prepare each pickup order, and the equations derived here allow for a comparison of several parameters in the Numerical Illustration section. Finally, the Conclusion section summarizes key observations, limitations, along with future research avenues.

LITERATURE REVIEW

This research applies knowledge from several distinct streams of literature, ranging from decision support science to e-commerce and fulfillment operations. To provide a brief context on important topics, the following subsections discuss relevant past contributions according to the research domains that our work aims to bridge.

Perishable inventory management

The common motivation in all perishable inventory management literatures stem from the fact that these products are subjected to deterioration in value over time. For perishable groceries, the main challenge is to minimize the cost incurred due to expiration. It is long established that, when possible, the retailer should issue the oldest inventory that can satisfy demand first [8].

In order to better characterize day-to-day inventory levels when there are products with differing remaining shelf lives at the same time, we look to the framework of Markov Decision Processes [9]. MDPs can accommodate problems where events are influenced by both stochastic variables and decision variables, allowing us to observe the system in 'states' of replenishment decisions.

The advantages of using the MDP approach to find the optimal replenishment policy for perishables have resulted in numerous studies that make use of the tracking of shelf life information, such as Ketzenberg et al. (2015, 2018) and Gaukler et al. (2017) [10, 11, 12]. Still, much of the research in this domain limit the scope of analysis to traditional grocery retailing.

Few studies are specifically geared toward capitalizing on the potential benefits of online grocery. Siawsolit et al. (2018) report that retailers selling perishable products and having access to shelf life information are able to significantly improve profit when online backlog order placements are allowed [13]. In a similar spirit, we are trying to improve the management of perishable grocery products by making use of demand information from online grocery.

Advance demand information

The time duration between when an online order is placed and when it is required for fulfillment, is referred to as the demand lead time [14]. Gallego & Özer (2003) study inventory systems with advance demand information and indicate that the cost impact depends on both the demand and supply lead times. We apply their finding that ADI available with a demand lead time duration at least as long as the supply lead time provides the best improvement to the optimal stock level under stationary demand distributions [15].

Karaesmen et al. (2004) study the value of ADI using various assumptions on the cost of obtaining the information. They also suggest that significant ADI benefits exist, but are dependent on the supply lead time [16]. Wang and Toktay (2008) further extend this line of research by considering scenarios where early fulfillment of advance orders are allowed. In contrast, we consider that fulfillment must occur at the time specified by the customer upon order placement [17].

Omnichannel fulfillment

One of the contributions of this study is to quantify the marginal labor requirement that can be attributed to the fulfillment of online grocery orders. As described by Wollenburg et al. (2018), grocery retailers use different transportation, order picking, warehousing, and last-mile delivery approaches depending on product, customer, market, and retailer specifics [18]. Therefore, we focus on two of the costs that incur on all online grocery orders, namely the picking cost and additional fulfillment handling cost.

Contrary to customers performing the picking in traditional in-store purchases, all online orders irrespective of fulfillment option are put together using the grocer's resources. For instance, one estimate in Hübner et al. (2016) puts the pick rate of store workers at 80-120 line items per hour [19]. The faster the pick rate, the lower the cost to prepare each online order.

Waitz et al. (2018) considers a decision support system that compares omnichannel service offerings to customer preferences and logistics operations, taking into account delivery fee, time slot, and freshness guarantee factors [20]. Siawsolit & Gaukler (2021) also explore how retailers can obtain ADI value from advance orders of perishables, but we extend that perspective to the cart level that considers non-perishable grocery items as well [6].

THE VALUE OF ADVANCE DEMAND INFORMATION

The general premise of this paper stems from the finding that advance demand information from online grocery orders placed in advance of fulfillment can be of significant value to the retailer [3]. The time difference between order placement and order fulfillment allows the grocer to more effectively plan inventory holding to achieve higher profit levels. To that end, the following two sections describe the processes of deriving the values of ADI for grocery products belonging in the perishables category and non-perishables category, respectively.

MODEL DEVELOPMENT: PERISHABLES

Products with short lifetimes, such as loaf bread or packaged spinach, are subject to deterioration in quality over time. These products are uniquely at risk of being removed from inventory (or outdated), if the perceived quality or other freshness measures degrade beyond acceptable levels prior to the items being sold. By having access to ADI with adequate demand lead time, the grocer can eliminate safety stock for the advance order portion of demand. The risk of product outdating also decreases as more customers place advance orders [3]. In situations where the cost of product loss is high or demand is highly uncertain, the ADI-equipped grocer can safely increase stock level to some degree and achieve higher sales.

With the main idea above in mind, the value of ADI for perishables is then a function of the stockout rate, outdate rate, and advance order rate, along with other factors such as product cost, shelf life, and demand and supply lead times. The Markov Decision Process-based, inventory decision support model developed in Siawsolit & Gaukler (2019) offers a periodic-review replenishment policy that already considers these factors [3]. As such, we employ an abbreviated form of that model for the purpose of quantifying the potential benefits of ADI for perishable items.

The model's objective is to identify the optimal replenishment quantity that maximizes the grocer's long-run expected profit, given the presence of demand uncertainty. Key model assumptions include: 1) Replenishment requests can only be made at the start of every period and supply lead time is 1 period, 2) There is no supply shortage, no order size limit, and no fixed ordering cost, 3) Products are issued according to a first-to-expire, first-out policy, 4) Promotions and substitutions are excluded, and 5) Incoming demand is composed of Poisson-distributed demand streams, each with differing demand lead time durations.

Using a period of 1 day as an example, a two-day advance order with demand lead time exceeding 1 day would grant the maximum ADI value for our analysis purpose. As established by Gallego and Özer (2003), increasing the demand lead time beyond the supply lead time horizon would not further improve the optimal stock level under stationary demand distributions [15].

MDP model components

In-store demand requiring immediate fulfillment in period t is denoted by $d_{t,t}$, and is distributed according to the p.m.f. $\phi\left(d_{t,t}\right)$ with mean μ. In this manner, a two-day advance demand originating in period t to be fulfilled in period t+2 can be represented by $d_{t,t+2}$ that follows the p.m.f. $\theta(d_{t,t+2})$. Alternatively, the amount required in period t to fulfill advance orders from period t-2 is $d_{t-2,t}$.

Inventory units are classified according to the remaining shelf lives in periods, or age class a. If a decreases to 0 while the item remains in stock, the unit is considered outdated. The number of units in each age class is individually tracked through i_a. Using M as the maximum age class, the inventory profile of a single product is indicated by $\{i_1, i_2, \dots, i_M\}$, with the total on-hand inventory being $I = \sum_{a=1}^{M} i_a$.

The replenishment order quantity, denoted by q, is the decision of interest. The system moves from a current decision state S to the next decision state S' through the choice of q and a transition probability matrix $\bar{P}$. The current state's inventory profile and the online demand to be fulfilled in the upcoming and subsequent periods provide the needed information to be transferred between states. For each decision q, the probability of going from state S to state S' is written as $P_q\left(\{i_1, \dots, i_M, d_{t-2,t}, d_{t-1,t+1}\}, \{i'_1, \dots, i'_M, d'_{t-2,t}, d'_{t-1,t+1}\}\right)$, or abbreviated as $P_q(S, S')$.

The following inventory transfer equation is used to find the next state's starting inventory, for any integer age class k in $1 \le k < M$.

$$i'_k = \left[i_{k+1} - \left(d_{t,t} + d_{t-2,t} - \sum\nolimits_{j=1}^{k} i_j\right)^+\right]^+ \qquad (1)$$

with $(\_)^+ = max(0, \_)$, and $i'_M = q$. The transition probability, given choice of q, for all combinations of $d_{t,t}$ and $d_{t,t+2}$ that can bring the system from state S to state S' is:

$$P_q(S, S') = \sum\nolimits_{d_{t,t}} \sum\nolimits_{d_{t,t+2}} \phi(d_{t,t}) \cdot \theta(d_{t,t+2}) \qquad (2)$$

All non-zero terms of equation (2) are computed to form the complete transition probability matrix $\bar{P}$.

To account for the expected revenue and costs of being in a certain state and taking a certain action, we consider one reward and three cost terms. For each unit of replenishment, the grocer incurs a cost c which includes the cost of the item along with any incoming transportation/handling cost. Each stockout event may incur a penalty s in addition to the loss in profit, to represent the potential long term effects on store loyalty. All inventory units that are held across periods are subjected to a holding cost h per period. With p denoting the retail price, we have the four terms:

$$p \cdot min\left(I, d_{t,t} + d_{t-2,t}\right) \qquad (3)$$

$$-c \cdot q \qquad (4)$$

$$-s \cdot \left(d_{t,t} + d_{t-2,t} - I\right)^{+} \quad (5)$$
$$-h \cdot \left[I - max\left(i_1, d_{t,t} + d_{t-2,t}\right)\right]^{+} \quad (6)$$
The cost of product outdating is not included here since it is accounted as a loss of inventory without corresponding revenue. Therefore, the net reward of being in state S and taking action q is:
$$R_q(S) = \sum_{d_{t,t}} [(3) + (4) + (5) + (6)] \cdot \phi(d_{t,t}) \quad (7)$$
Similar to matrix $\bar{P}$, the expected rewards matrix $\bar{R}$ consists of $R_q(S)$ for all possible states and choice of q.

Optimal policy and ADI value

After computing the required $\bar{P}$ matrix and $\bar{R}$ matrix based on desired inputs of M, p, c, s, h, $\phi(d_{t,t})$, and $\theta(d_{t,t+2})$, we proceed to solve the MDP. To find the optimal long run expected profit, the following profit-maximization value iteration function is applied.
$$V_{f+1}(S) \coloneqq \max_{q} \left\{ \sum_{S'} P_q(S, S') \left(R_q(S) + \gamma V_f(S')\right)\right\} \quad (8)$$
where f signifies the iteration number, and the time-discount rate γ is specified at 0.9999.
The iteration process continues to calculate V_{f+1} until reaching convergence. The obtained policy is a list of optimal order quantity q, for each possible states S, that leads to the highest expected profit. From this policy we find the stationary distribution vector π of the Markov chain, such that $\pi = \pi\bar{P}_{optimal\ q}$.
The states' information and the irreducible vector π together allow us to compute the expected number of inventory units sold in each period. Let $sold_S = min(I, d_{t,t} + d_{t-2,t})$, and we have the average units sold per period as the product of a vector containing $sold_S$ for all states and the vector π. It is also possible to differentiate between in-store and advance order sales by considering $d_{t,t}$ or $d_{t-2,t}$ individually.
From here, we obtain the expected profit levels for comparable scenarios with and without advance online ordering. The maximum ADI value occurs when 100% of incoming demand comprise of advance orders that provide longer demand lead time than the supply lead time period. We take the difference in the attained profit level of the advance order-only scenario and the baseline zero-advance-order scenario, and divide it by the average number of units sold per period to arrive at the *potential ADI value per unit of perishables sold through advance ordering*, or x_{peri}.
As a side note, although the overall ADI value is closely proportional to the advance order rate, the ADI value per unit sold is much less influenced by the advance order rate. For instance, using the same parameters for short-life perishables found in Siawsolit & Gaukler (2021), the average ADI value per unit sold when advance orders make up 20% of demand is around 60% of the all-advance-orders scenario [6].

MODEL DEVELOPMENT: NON-PERISHABLES

Next, we discuss the potential ADI value for non-perishables. Products with very long shelf lives, such as canned peaches or frozen dinners, are able to remain in inventory for extended periods with minimal risk of product loss. The primary expenses associated with the management of non-perishables include the acquisition, lost sale, and holding costs. Consequently, these items generate less expenses on a per-unit basis, relative to stocking and handling of perishable products.

By having access to ADI with sufficient demand lead time, the retailer can stock the needed amount to fulfill demand, thereby avoiding *lost sale costs* and cross-period *holding costs*. For our purpose of comparing the value of ADI between the two product categories, we apply all of the same assumptions from Section 3.1 here as well. Because these assumptions exclude the fixed component of the replenishment ordering cost, we note that the resulting ADI value obtained here should provide a conservative estimate.

Finding the optimal replenishment quantity is considerably more straightforward for non-perishables. We consider a periodic review, order-up-to (OUT) policy, with a 1 period decision interval and 1 period supply lead time. This policy is optimal under our assumptions. The main idea of the OUT policy is to first decide the optimal OUT stock level, then review current inventory and request for replenishments to bring the stock level up to the OUT quantity.

Using the same notations for c, p, s, h, μ, and I from earlier, the cost of under-stocking is as follows.

$$Underage\ cost = p - c + s \qquad (9)$$

This represents the loss of opportunity to earn profit from selling the product, as well as any additional stockout penalty due to potential degradation of store loyalty. On the other hand, if the grocer holds more inventory than the demand turns out to be, the remaining products are carried over across selling periods and incur a holding cost h per unit per period. Thus, for each set of input parameters, we can compute a critical ratio CR (similar to the newsvendor model's CR) to obtain the optimal in-stock probability.

$$CR = \frac{p - c + s}{p - c + s + h} \qquad (10)$$

For a Poisson-distributed demand stream $\phi(d_{t,t})$, the OUT quantity is the minimum quantity such that: $Prob.(demand\ over\ lead\ time\ +\ 1\,period\ \leq\ OUT\ quantity) \geq CR$. By subtracting the expected demand over the supply lead time plus review period from the OUT quantity, we obtain the mean quantity of products held across periods. This quantity along with h provide the holding cost component of the grocer's expenses.

Let $\psi(d_{LT+1})$, with mean $(lead\ time + 1) \cdot \mu$, represent the demand distribution during the lead time plus review period. The amount of lost sales expected to occur on an average period is calculated as:

$$Exp.loss\ sale = \sum_{d_{LT+1}} (d_{LT+1} - I)^+ \cdot \psi(d_{LT+1}) \quad (11)$$

The costs incurred from shortages is then the product of the expected lost sale per period and the underage cost from equation (9). By combining the holding and shortage-related costs that can be eliminated by demand visibility, we obtain the *potential ADI value per unit of non-perishables sold through advance ordering* with sufficient demand lead time, or x_{np}.

Potential ADI value per cart

Because the ADI values for perishables and non-perishables are expected to be significantly different, we define x_{cart} as the potential ADI value per average cart; given average number of items per cart n and proportion of short-life items in the cart λ. The ADI value per cart increases linearly with n, and is given by:

$$x_{cart} = n \cdot \left[\left(x_{peri} \cdot \lambda \right) + \left(x_{np} \cdot (1 - \lambda) \right) \right] \quad (12)$$

Equation (12) is important since different grocery chains (or even stores of the same chain in various settings) may generate differing sales levels from products in the perishables category. Moreover, we can then directly compare the benefits afforded by ADI to the marginal fulfillment cost of obtaining the ADI on a very simple dollar-per-cart basis.

MARGINAL FULFILLMENT COST

The quick adaptations of many grocers in ramping up their online grocery services during the coronavirus outbreak had been pivotal in helping high-risk individuals reduce their exposures to crowded settings. Omnichannel fulfillment offerings such as curbside pickup or home delivery are crucial in supporting and retaining customers at the moment. As we transition back to normalcy, the operational expenses associated with these services may force some retailers to increase prices, or add a service fee based on the customer's fulfillment option.

We propose that brick-and-mortar retailers capable of acquiring and integrating ADI into their replenishment decisions are able to better absorb the costs of offering these services; making them well-positioned to capture the demand of customers that wish to continue using online grocery going forward. To that end, the next step is to quantify the expenses specifically incurred when fulfilling online orders.

Using the classification scheme found in Fransoo et al. (2019), we limit our scope of analysis to business model 3 (online ordering and store-based fulfillment) due to current prevalence in the United States [21]. It is assumed that a home delivery service is optional; with a separate fee passed on to consumers who prefer the convenience. For a buy online, pickup in-store scenario, there are two primary expenses not present in the traditional walk-in scenario, namely the cost of *picking* the products to prepare the customer's online cart order, and the labor cost of additional *handling* required to pass on the completed orders to customers.

In contrast to the customers performing the task of picking products, online orders require labor on the part of store employees to put together the customer's cart. The average number of line items that one picker can pick in one hour is referred to as the pick rate r. Because of varying product mixes, store layouts, or levels of information technology support, the pick rate can differ significantly from store to store.

As an example, the pick rate for Walmart's in-store pickup service is estimated at 80 line items per hour [22]. However, as described in Section 1, perishable items are expected to have a lower pick rate than non-perishables. Therefore, we account for the labor costs required to pick items from each category separately by designating r_{peri} for perishables pick rate and r_{np} for non-perishables pick rate.

Once the required items have been picked, the completed orders must be navigated by store associates to reach the customers' hands; per the fulfillment pickup time specified upon order placement. We assume there is a fixed amount of labor time associated with this final step of fulfillment. In essence, this additional handling time covers the transfer of goods to the fulfillment location, such as a pickup kiosk or an assigned parking space, and may include reviewing the order with the customer. The average handling time needed per each pickup order is represented by z.

Let w be the wage in dollars per hour, and we can then approximate the marginal fulfillment cost of each pickup order, y_{cart}, through the following equation:

$$y_{cart} = w \cdot \left(\frac{n \cdot \lambda}{r_{peri}} + \frac{n \cdot (1 - \lambda)}{r_{np}} + z \right) \qquad (13)$$

Equation (13) takes into account the pick rates of products in the perishables and non-perishables sections, the proportion of cart items in each category, as well as the average fixed amount of time needed in handing over completed orders to customers.

BENEFIT-COST COMPARISON

Equations (12) and (13) capture the potential benefits and added challenge, respectively, of perishable products within the context of omnichannel grocery retailing. The proportion of perishables in an average cart can be adjusted by scaling λ from 0% to 100%, allowing for a convenient comparison of ADI values between perishables and non-perishables to address our research goal (i).

In addition, we can observe the effects of increasing the cart size, which simultaneously increases both the ADI benefit and the marginal fulfillment cost of each online order. And above all, by quantifying x_{cart} and y_{cart} on the same dollar-per-cart scale, we can better characterize the net impact on profits from receiving advance online orders and taking full advantage of the accompanying ADI. For our research goal (ii), we define the percentage of marginal fulfillment cost that is offset by ADI as:

$$percent\ cost\ offset = \frac{x_{cart}}{y_{cart}} \qquad (14)$$

The percent cost offset ratio provides a crude insight on whether a brick-and-mortar retailer can economically offer a buy online pickup in-store service free of charge. The higher this ratio is, the more effective the strategy to obtain ADI for omnichannel fulfillment becomes. The breakeven condition, where the dollar benefits obtained from ADI per cart is equal to the marginal fulfillment cost per cart is: $x_{cart} = y_{cart}$.

Apart from lowering z, the grocer can attempt to increase the pick rate to reduce y_{cart}. Let us assume that the pick rates for perishables and non-perishables are equal at $r_{eq} = 80$ items per hour, and that there are $n = 20$ items in an average cart. Under this scenario the picking labor time is already 15 minutes, which is likely to be longer than the incremental handling time of pickup orders (given that the in-store cashier's time requirement would also decrease in the presence of online orders). For this reason, it should be worthwhile for grocers to explore new methods and technologies that can improve the in-store pick rate.

To find the target pick rate that can fully offset the fulfillment cost of pickup orders, equation (15) considers the hourly wage, number of cart items, ADI value per cart, and pickup orders handling time.

$$breakeven\ r_{eq} = \frac{w \cdot n}{x_{cart} - w \cdot z} \qquad (15)$$

Being able to estimate the breakeven pick rate can assist in identifying which key performance markers, if any, the grocer should focus on in their effort to achieve profitable curbside pickup fulfillment operations (research goal iii). In the case that $r_{peri} \neq r_{np}$, we can find the breakeven pick rate for perishables, given some r_{np}, such that $x_{cart} = y_{cart}$.

$$breakeven\ r_{peri} = \frac{w \cdot n \cdot \lambda}{x_{cart} - w \cdot z - \frac{w \cdot n \cdot (1-\lambda)}{r_{np}}} \quad (16)$$

Alternatively, equation (16) can also be reformulated to find the target r_{np} instead.

$$breakeven\ r_{np} = \frac{w \cdot n \cdot (1-\lambda)}{x_{cart} - w \cdot z - \frac{w \cdot n \cdot \lambda}{r_{peri}}} \quad (17)$$

NUMERICAL ILLUSTRATION

Using the methods and equations described up to here, we illustrate through a small numerical example how a grocer might specify the necessary parameters to conduct what-if analyses regarding omnichannel fulfillment strategy. The cost of each unit of product to the retailer, c, is considered at \$2 and \$5. Products are marked up by either 50% or 100%, creating prices p of \$3, \$4, \$7.5, and \$10. The stockout penalty s is 50% of c when included, leading to values of \$0, \$1, and \$2.5. All products carried over across selling periods are subject to a holding cost h of \$0.05 per unit per period.

Demand is characterized by the Poisson distribution with mean μ of 5 units per period and a maximum of 15 units per period. We use fixed product shelf life M of 1, 2, 3, 4, and 5 periods to represent short-life perishables, and one additional non-perishables category where products do not deteriorate at all. The experiments comprise a full-factorial design of the parameters described here. It is worth noting that, although the parameter values used here have been chosen to cover a wide range of grocery product types, the following results and general observations may vary based on each grocer's unique set of input parameters.

ADI benefits

To compare the potential values of ADI from perishables and non-perishables, we start at their optimal replenishment policies. The MDP policy described in Sections 3.1.1 & 3.1.2 and the OUT policy from Section 3.2 allow us to obtain the optimal levels of inventory held across selling periods for perishables and non-perishables, respectively. Figure 1 indicates the average amounts of inventory units that are held across selling periods; categorized by product shelf lives. Each data point marks the average value of 8 experiments, each containing a distinctive combination of c, p, and s.

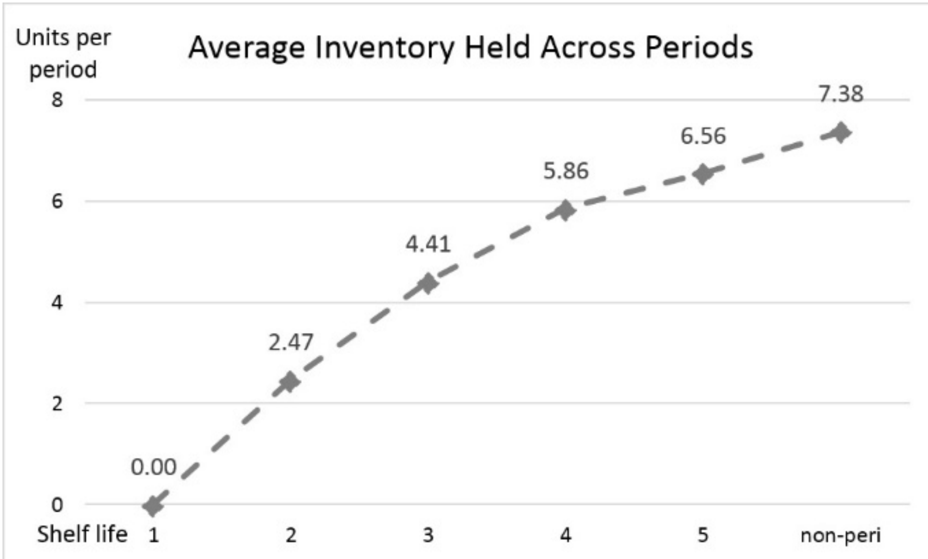

Figure 1. Cross-period inventory by shelf lives

For instance, replenishment products that arrive with a 1-period life are either sold or outdated by the end of the same period, therefore cross-period holding is always zero units. On the other hand, the mean OUT quantity is 17.38 for non-perishables, which indicates that around 7.38 units are held as safety stock to cover the demand during lead time plus one period. Intuitively, the optimal stock level increases as the risk of product outdating decreases.

Another observation is that products having different prices and stockout penalty costs may end up generating the same ADI value. Let us consider two products with a 3-periods shelf life, $\{c$=\$2, p=\$3, s=\$1$\}$ and $\{c$=\$2, p=\$4, s=\$0$\}$. These two products produce the same optimal fill rate at 97.6%. However, the first item achieves 87.3% of the theoretical maximum profit level (if given full demand visibility), while the second attained a much better 93.7% of max profit (and a little over double the net profit in dollars).

Given these results, it would be reasonable to infer that the potential value of ADI is higher when the loyalty-degradation stockout penalty s is high. But in fact, the ADI values are exactly the same for the above two products at \$0.127 per unit sold. This is because their CR values (equation 10 with outdate cost) are the same, and by extension, the costs associated with lost sales and outdating as well.

Figure 2 shows the potential value of ADI per each unit of product sold through advance ordering, averaged and sorted by shelf lives. Products with a 1-period shelf life face the highest risks of outdating, which translate to the highest ADI values. In addition, we note that products in the 5-periods shelf life category achieve an average fill rate of 99.2%. As a result, their ADI values are very close to that of non-perishables. This is partly due to the fixed shelf life parameters used here. They do not contain variability, which has been shown to negatively impact inventory management costs [6]. Therefore, if shelf life variability is involved, the difference between the potential ADI values of perishables and non-perishables would be greater than currently shown in Figure 2.

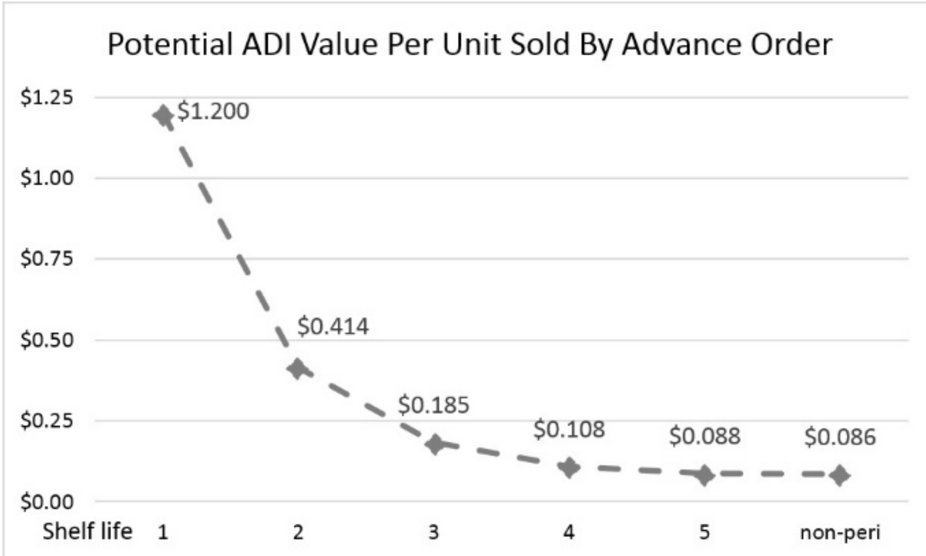

Figure 2. Potential ADI value per unit sold

For this illustration purpose, we take the average of the ADI values for product shelf lives of 1 through 5 periods as the ADI value for perishables, or x_{peri} = \$0.399. A more in-depth analysis of ADI values for short-life perishables can be found in Siawsolit & Gaukler (2021) [6]. The ADI value for non-perishables is taken directly as shown in Figure 2, x_{np} = \$0.086.

While Figure 2 suggests that the potential reward of incorporating ADI into replenishment decisions is more significant for perishables, the proportion of these items in an average customer cart must also be taken into account. We consider λ at two levels, including 20% and 40%, along with n = 15 and 30 items per average cart. For an example using equation (12) with λ = 20% and n = 15, we can obtain x_{cart} = \$2.23.

Fulfillment operations

Next, we investigate the factors within the retailer's control that can influence the marginal fulfillment cost. Due to statistics on the difference between the pick rates of perishables and non-perishables being relatively scarce at this time, we specify two pick rates for each of these categories; based on Walmart's estimated 80 line items per hour. These include $\{r_{peri}$=40, r_{np}=80$\}$, {80, 80}, and {80, 160}. The pick rates selected here should provide a reasonable range of values that are applicable to many retailers competing in this space.

In terms of the additional handling time, we consider two scenarios of pickup orders fulfillment. The first is a conventional curbside pickup fulfillment scenario, where the customer is asked to park within a designated area and notify the store upon arrival. A store member will then bring out the entire order in a cart and help to unload the bagged items into the customer's vehicle. It is assumed that each curbside pickup order requires around 5 minutes of store labor time.

The second scenario is a hypothetical self-pickup fulfillment, where completed orders are placed in temperature-controlled lockboxes near the store entrance. The customer must scan their smartphone or loyalty card to retrieve the items inside. For this setting, we assume an associate takes 2 minutes to fill each lockbox and register the identifying information for pickup. And lastly, we set the labor cost per hour at w = \$15 (CA minimum for 2022).

As an example with w=\$15, r_{eq}=80 items per hour, z=5 minutes, and n=15 items, the marginal fulfillment cost is y_{cart} = \$4.06, or \$0.27 per unit sold by pickup. If we shift to a self-pickup fulfillment and 30 items per cart, y_{cart} increases to \$6.13, whereas the per-unit cost decreases to \$0.20 due to the effects of shorter handling time and larger cart size.

Putting these results into perspective, one estimate place the "*incremental cost per unit (of) sale of merchandise through online order picked by instore shopper valet (where) customer picks up order at curbside*" at \$0.41 per unit [2]. If we specify the same w=\$20, r_{eq}=65, and n=25 as in their case, equation (13) gives a comparable y = \$0.37 per unit sold via curbside pickup fulfillment.

Cost offset potential

We now review the net financial impacts to the grocer per customer order. In Table 1, columns 2 to 6 represent our input parameters, comprising of the percentage of perishables in an average cart, fulfillment handling time, number of items in cart, and the pick rates for perishables and non-perishables. We keep the same ADI values obtained in Section 6.1, namely x_{peri}=\$0.399 and x_{np}=\$0.086, along with w=\$15 for all of the experiments shown in Table 1.

The net per order column highlights some of the most costly scenarios considered here, with darker shades signifying a higher loss-per-cart to fulfill pickup orders. The highest net cost observed here is \$3.54 per cart, which is due to the small percentage of short-life items and the slow pick rates. For instance, if we double the pick rates in experiment #4, experiment #6 gives a much more palatable \$0.17 net cost per pickup order.

Figure 3 displays the percentages of marginal fulfillment cost offset by ADI for n=15 items per cart; categorized by z, λ, and pick rates. For instance, the 55% number on top of the dashed line marks the percent cost offset for z=5 minutes, λ=20%, and r_{eq}=80 items per hour. Halving r_{peri} to 40 items per hour gives the solid line, while doubling r_{np} results in the dotted line. Overall, Figure 3 visually captures the cost-advantages of increasing the item pick rates and reducing the handling time associated with pickup orders.

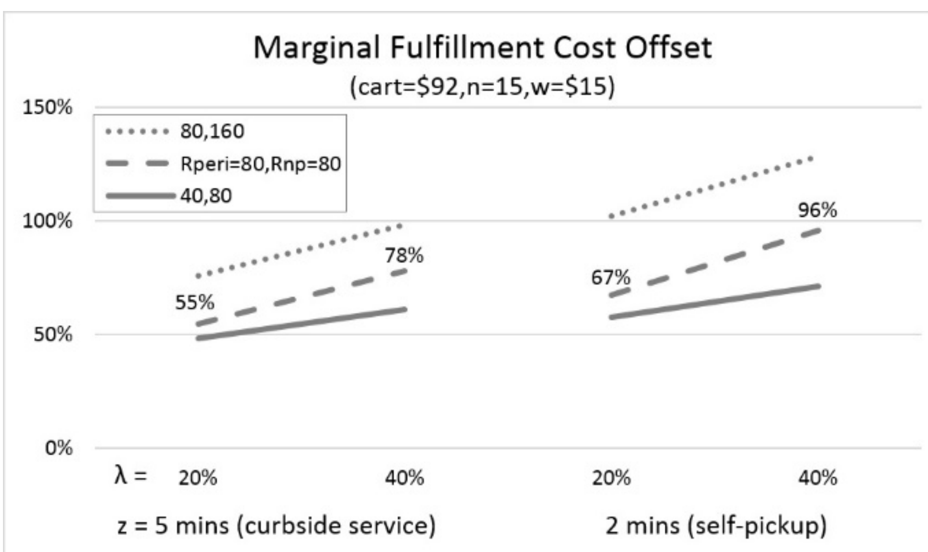

Figure 3. Percent cost offset at various pick rates

The 100% horizontal line in Figure 3 indicates the point where the potential benefit from ADI is equal to the incremental cost to fulfill the online orders. The right-most value of 96% cost offset for r_{eq}=80 items per hour is very close to the breakeven condition. Therefore, experiments #19, #20, and #21 in Table 1 produce a breakeven r_{eq} that is just 5% higher than the estimated pick rate for Walmart.

Another interesting observation occurs when comparing experiments #3 and #22, where none of the inputs in columns 2 to 6 are identical. Both of these scenarios lead to the same 76% cost offset, but the net cost per online cart is $0.71 versus $2.04; nearly a three-fold difference. Conversely, the breakeven r_{eq} for #3 is very high due to the smaller cart size and fewer perishable items.

Even with r_{np} of 160 items per hour, r_{peri} can never be fast enough to attain the breakeven condition for experiment #3. Hence, we emphasize the importance of reviewing several key performance measures together when quantifying the cost-benefits of receiving advance online orders. For scenario #3, some of the options for the retailer include reducing handling time, increasing prices/service fees, and to consider shifting fulfillment of online orders to app-based service providers or possibly investing in automated fulfillment warehouses.

At this time, there are numerous automated picking systems being tested and improved. Walmart's version of the structures of robotic arms is named Alphabot, and it is designed to achieve a pick rate of 800 lines per hour [22]. Although it is unclear how these automated systems can handle perishable products, the cost implications are still significant given that the 800 pick rate applies only to non-perishables. Taking values from experiment #4 (our worst dollar-per-cart performer) and changing r_{np} to 800, the percent cost offset greatly improves to 113%; exceeding the breakeven condition. In this hypothetical scenario, the breakeven in-store pick rate for perishables is still under 60 items per hour. This is true even when we disregard the ADI value from products with shelf lives of 1 period and instead use x_{peri}=$0.199 per unit (the average value from shelf lives M=2,3,4,5 in Figure 2).

The insights obtained from this numerical illustration are made possible by bridging the gap between advance demand information and omnichannel fulfillment literatures. Brick-and-mortar grocers can use a similar method as described here to conduct several analyses in identifying the potential opportunities and challenges of offering online grocery services.

Table 1. Summary of net cost & breakeven pick rate

#	λ	z mins	n	r_{peri}	r_{np}	x_{cart}	y_{cart}	Net / order	B. r_{eq}	B. r_{peri}	B. r_{np}
1	20%	5	15	40	80	\$2.23	\$4.63	-\$2.40	230	NA	NA
2	20%	5	15	80	80	\$2.23	\$4.06	-\$1.83	230	NA	432
3	20%	5	15	80	160	\$2.23	\$2.94	-\$0.71	230	NA	432
4	20%	5	30	40	80	\$4.46	\$8.00	-\$3.54	140	NA	376
5	20%	5	30	80	80	\$4.46	\$6.88	-\$2.42	140	NA	173
6	20%	5	30	80	160	\$4.46	\$4.63	-\$0.17	140	94	173
7	20%	2	15	40	80	\$2.23	\$3.88	-\$1.65	130	NA	298
8	20%	2	15	80	80	\$2.23	\$3.31	-\$1.08	130	NA	154
9	20%	2	15	80	160	\$2.23	\$2.19	\$0.04	130	75	154
10	20%	2	30	40	80	\$4.46	\$7.25	-\$2.79	114	NA	211
11	20%	2	30	80	80	\$4.46	\$6.13	-\$1.67	114	NA	127
12	20%	2	30	80	160	\$4.46	\$3.88	\$0.58	114	53	127
13	40%	5	15	40	80	\$3.17	\$5.19	-\$2.02	117	390	NA
14	40%	5	15	80	80	\$3.17	\$4.06	-\$0.89	117	390	170
15	40%	5	15	80	160	\$3.17	\$3.22	-\$0.05	117	84	170
16	40%	5	30	40	80	\$6.34	\$9.13	-\$2.79	88	105	461
17	40%	5	30	80	80	\$6.34	\$6.88	-\$0.54	88	105	95
18	40%	5	30	80	160	\$6.34	\$5.19	\$1.15	88	53	95
19	40%	2	15	40	80	\$3.17	\$4.44	-\$1.27	84	92	323
20	40%	2	15	80	80	\$3.17	\$3.31	-\$0.14	84	92	87
21	40%	2	15	80	160	\$3.17	\$2.47	\$0.70	84	49	87
22	40%	2	30	40	80	\$6.34	\$8.38	-\$2.04	77	73	202
23	40%	2	30	80	80	\$6.34	\$6.13	\$0.21	77	73	75
24	40%	2	30	80	160	\$6.34	\$4.44	\$1.90	77	43	75

CONCLUSION

We set out to address the rising cost of omnichannel grocery retailing. To combat the increase in fulfillment expenses, we propose the use of ADI obtained when receiving advance online orders with a sufficient demand lead time. Noteworthy findings of this study are summarized according to our research goals as follows.

The first objective (i) is to compare the potential value of ADI obtained from advance order sales of perishable and non-perishable products. We describe the methods to obtain ADI values for both of these product categories. Using equations 1 through 11 and a range of product-specific parameters, we find that the average ADI value per unit of perishables sold is over four times higher than for non-perishables.

The value of ADI is dependent upon a newsvendor-type CR ratio, as well as the replenishment product's shelf life and incoming demand distributions. Products facing the highest risks of outdating naturally give the highest ADI values. In addition, the ADI value per cart depends also on the proportion of short-life items and the number of items in each cart.

Our next aim (ii) is to characterize the relationship between the potential benefits of ADI and the marginal costs to fulfill online orders. Equation (13) allows us to quantify the incremental labor cost of preparing each pickup order, taking inputs from wage per hour, item pick rates, and fulfillment handling time. For both the curbside pickup and the self-pickup scenarios, we equate the ADI value to the marginal cost on a dollar-per-cart basis. We also observe a number of scenarios where the potential benefits from ADI outweigh the incremental fulfillment costs.

Finally, the overarching goal of this study (iii) is to identify key performance markers for a profitable omnichannel operation. We find that the pick rate is one of the most decisive performance marker, and that the more perishable items sold, the stronger the impact of improving pick rate. The same is true when increasing the cart size of online orders. However, we must caution that in some scenarios, there exists no pick rate that can achieve a cost-breakeven condition. In these cases, it should be more worthwhile to explore solutions aside from trying to improve the pick rate alone.

On a more optimistic note, we have identified scenarios where a reasonable pick rate of 80 items per hour can fully offset the marginal fulfillment cost. This condition is at least 40% short-life items in a cart size of at least 30 items, and fulfillment handling time is 2 minutes or less at $15 wage. Thus, our work validates that it is possible to completely offset omnichannel costs through achievable performance measures.

In conclusion, the methods described in this paper allow for a multitude of analyses to support grocery retailers when making high-level decisions concerning omnichannel fulfillment. Retailers that stand to gain the most are those already receiving online orders in advance, but are not yet utilizing ADI to its full potential. The takeaway from our numerical illustration is that perishables with a high loss-rate, even with their hard-to-handle characteristics, are still good targets for omnichannel grocery because of the ADI benefits. In other words, grocers selling more perishables are better-positioned to promote advance online ordering.

The limitations of this research are primarily attributable to the assumptions used in estimating the value of ADI and the marginal fulfillment cost. These range from excluding the fixed component of the ordering cost and the delivery component of omnichannel fulfillment cost, to not considering the variability in the shelf lives of replenishment items. Still, our study indicates that there are untapped rewards for online grocery retailing. Future research is needed to incorporate the last-mile delivery cost into total cost, or compare the long run return on investment of automated fulfilment centers, as well as develop new best-practices to reduce the handling time of in-store pickup orders.

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