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# Throwing out food before expiration and still reducing food waste: online vs. offline retail

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**Abstract**

Online retailers throw out food that has not yet expired. This gives rise to the question whether online retailers generate more food waste than offline retailers, who typically throw out food only after it has expired. We focus on the food waste at the retailer which inherently ensues from the logistical set-up. We first provide a theoretical analysis to establish whether throwing out food before expiration indeed results in an increase in food waste, putting online retailers at a disadvantage compared to offline retailers. We show the relevance of this question by providing a theoretical example, showing an inventory control policy which counter-intuitively results in a decrease in food waste. Nonetheless, we show for well-behaved inventory control policies, including the optimal policy, that food waste increases when food is thrown out before expiration. Next, we compare the food waste of the online retailer with that of an offline retailer in numerical experiments. Note that the online retailer has some advantages over offline retailers as well. Online retailers benefit from full control of order picking, which is instead often done by the consumer in offline retail. Moreover, the online retailer often benefits from the pooling effect, as offline retailers might use multiple stores to satisfy the same demand volume as an online retailer from a single warehouse. Our numerical experiments with a base-stock policy suggests that online retail actually yields less food waste for many products, despite throwing out food before expiration.

## 1 Introduction

Online retailers throw out food that has not yet expired. This food is repurposed, donated to charity, or simply wasted. Food is thrown out before expiration because it is currently uncommon for online retailers to know the consumption date of sold products. Therefore, they need to decide on the minimum remaining time until expiration of sold products, while food that expires sooner is unsalable. The minimum remaining time should reasonably allow for consumption to avoid dissatisfaction. See Cho (2011) for a study on the effect of dissatisfaction with perishables on future sales.

Our study is inspired by the case of online supermarkets, where consumers buy food to be consumed even up to a week in the future. An online supermarket might, for example, sell yogurt that is valid for one more week, while yogurt valid for six days or less is thrown out. This is different from traditional offline retail, where consumers commonly pick their products themselves. This allows consumers to assess whether a product expires before the intended date of consumption. Knowing that today you will consume the yogurt that expires tomorrow, you might purchase it. As a result, offline retailers throw out food only after it has expired, while online retailers typically throw out food that has not yet expired.

At the same time, online retail is growing, arguably at the expense of offline retail. There has been steady growth in recent years, with an acceleration during the current Covid-19 pandemic (Zissis et al., 2018; www.grandviewresearch.com, 2020; www.supermarketnews.com, 2020; Dannenberg et al., 2020). As a consequence, the amount of retail food waste which has been thrown out before expiration, might also be growing. This observation seems to stand in stark contrast to the sustainable development goals of the United Nations (United Nations , 2016). Goal 12 is to ensure sustainable production and consumption patterns, and target 12.3 states specifically: "*By 2030, halve per capita global food waste at the retail and consumer levels.*"

Still, even if throwing out food before expiration would increase food waste, this does not necessarily imply that a shift from offline to online retail would increase the total retail food waste. There are also some redeeming factors for online retail. i) Online retailers may employ strict order picking procedures, such that first-in first-out (FIFO) inventory depletion can be ensured. In offline retail this is not always possible. For instance, if consumers pick their own products it is rational to pick the freshest product, i.e., apply last-in first-out (LIFO) inventory depletion. FIFO inventory depletion usually yields less food waste than LIFO, see Nahmias (1982). ii) Online retailers typically satisfy the same quantity of demand from a single warehouse, as satisfied by offline retailers using multiple stores. Therefore, online retail may benefit from the pooling effect; less safety stock needs to be maintained, resulting in lower food waste as well.

In this paper, we investigate the net-effect on food waste of a shift from offline to online retail. We do this by comparing the food waste generated by two inventory control systems, which reflect modern day online and offline retail in the context of this paper. We refer to the first system as online, and characterize it by throwing out food before expiration, FIFO inventory depletion, and pooled inventory. We refer to the second system as offline, in which food is only thrown out after expiration, but we do vary between LIFO, FIFO and mixed LIFO and FIFO inventory depletion.

Our goal is to lay bare the food waste *inherent* to the logistical set-up of online and offline retail. That is, we only consider food waste at the retailer, and not at the consumer. The latter is not inherent to the logistical set-up, but dependent on how conscientious the consumer treats food. Such consumer behavior is dependent on commodity, company, culture, etc. and therefore susceptible to change. See Schanes et al. (2018) for a recent in-depth analysis on causes of consumer food waste. For the same reason, we consider the demand generating process as fixed, and focus on demand satisfaction instead. We assess what happens if demand which is currently satisfied by an offline retailer, in the future would be satisfied by an online retailer, to answer the research question: Does more food waste *inherently* ensue from an increase in the market share of online retail?

Note that food waste may also be generated at the interface of retailers and consumers (Audet and Brisebois, 2019). For instance, there are differences between demand patterns of online and offline customers, see e.g. Danaher et al. (2003) and Kim and Krishnan (2015). These differences in turn affect the effectiveness of inventory control of retailers. Furthermore, in Belavina (2021) it is suggested that offline store density results in different amounts of food waste generated by the consumer. These and similar effects described in the literature are also dependent on consumer behavior. Although consumer behavior clearly has an effect on food waste, we do not consider these effects as inherent to the logistical set-up. Therefore, we disregard such effects in this paper.

The contributions of this paper are as follows. Firstly, we answer the question whether food waste increases if food is thrown out before expiration. We answer this question by providing sufficient conditions for food waste generated by an inventory control policy to monotonically increase in the lifetime of the product. We do this for a perishable inventory control model with lost sales and a service level constraint, and with the objective to minimize food waste. This implies that the earlier food is thrown out, the more food waste is generated. We show that this applies to the optimal order policy and the optimal constant order policy. Note that a similar statement about the optimal policy is made by Abouee-Mehrizi et al. (2019) for a closely related model. They claim without proof that the optimal holding plus back-order plus disposal cost, with a one-period discount factor, of a perishable inventory control model, with back-orders and multiple demand classes, is decreasing in the lifetime. Perhaps contrary to intuition, we also show that food waste can theoretically increase in the lifetime of a product. This implies that, for some suboptimal policies, food waste might actually decrease by throwing out food before expiration. Secondly, we quantify the food waste resulting from online and offline retail, using a numerical analysis. We identify the tipping point of the minimum remaining time before expiration that leads to lower food waste of each product when sold by an online retailer. We conclude that in realistic settings, online retail actually yields lower food waste for many products. The increase in food waste resulting from throwing out food before expiration, is outweighed by the decrease in food waste resulting from LIFO inventory depletion and the pooling effect. Note that, although we use the term food throughout this paper, of course our results apply to any perishable product in general.

Our results have the following implications. First consider the result that food waste decreases monotonically in the lifetime of the product for well-behaved policies. This result provides an argument for extending the lifetime of a product, which goes beyond mere convenience. Our result implies that an increased lifetime can help reduce food waste of the retailer. The increased lifetime can be achieved for example by investing in better packaging, preservatives, and storage. But we emphasize that our result actually applies to the lifetime at the retailer. This means that food waste is also reduced by decreasing the lead time, e.g. by local sourcing. Secondly, our numerical results suggest that online retail yields lower food waste than offline for many products, despite throwing out food before expiration. A shift from offline to online retail might therefore aid in achieving the SDG goals. Moreover, for online retailers this provides a sales argument which can be used in marketing campaigns to compete with offline retailers.

The remainder of this paper is organized as follows. Our theoretical results are found in Section 2 and our numerical results are found in Section 3. We conclude this paper with a discussion in Section 4.

# 2 Theoretical results

In this section, we provide a theoretical analysis of the effect on food waste of throwing out food before expiration. Recall that the online retailer decides on the minimum remaining time until expiration. Observe that effectively this is equivalent to shortening the lifetime of the product during which it can be sold. For example, if yogurt has a lifetime of 21 days but is thrown out 6 days before expiration, the lifetime from the perspective of the retailer is 15 days. Therefore, we are interested in answering the question whether food waste is monotonically decreasing in the lifetime of a product. This would imply that indeed throwing out food before expiration leads to an increase in food waste.

In Section 2.1, we define the model of the inventory control problem which forms the basis of our analysis. In Section 2.2, we provide a sufficient condition for inventory control policies that exhibit decreasing food waste for increasing lifetime. This allows us to show that the optimal policy and constant order policy yields food waste that is decreasing in the lifetime of the product. The importance of these seemingly intuitive results, is indicated by a theoretical example showing that a poorly designed policy might actually yield an increase in food waste when the lifetime of the product increases.

## 2.1 Model

We consider a single perishable product, periodic review, stochastic demand inventory control problem with lost sales. For ease of notation, we assume a finite horizon and FIFO inventory depletion, but the results presented here can straightforwardly be extended to the case of an infinite horizon and LIFO (or a mix of FIFO and LIFO) inventory depletion.

We denote time periods as integers, where 1 is the first and the $T$ is the last period. Let $d_t$ be the random demand in period $t \in (1, \ldots, T)$. In each period, a decision is taken on the non-negative quantity of products that is ordered. We denote this quantity by $q_t \geq 0$ for $t \in (1, \ldots, T)$. The ordered products are added to the inventory after an integer non-negative lead time, $L$. Let $m$ be the integer lifetime of the product, indicating the number of consecutive periods in which it can be used to satisfy demand, starting at the day the product is added to the inventory. If the product remains in inventory for $m$ consecutive periods, it perishes and is removed from the inventory. The order of events in each period is: i) products arrive and are added to the inventory, ii) a new order is placed, iii) the demand realization is revealed and inventory depletes to satisfy demand, and iv) items that expire after the current period are removed from inventory.

The amount of products in inventory in period $t \in (1, \dots, T)$, after new products have been added to the inventory, but before inventory depletes to satisfy demand, which perish after $i \in (1, \dots, m)$ periods is denoted by $x_{it} \geq 0$. Similarly, $y_{it}$ denotes the amount of products which perish after $i \in (1, \dots, m)$ periods, which are used to satisfy demand in period $t \in (1, \dots, T)$. It holds that

$$y_{it} = \min \left\{ x_{it}, \left( d_t - \sum_{j=1}^{i-1} x_{jt} \right)^+ \right\} \text{ for } i \in (1, \dots, m),\ t \in (1, \dots, T), \tag{1}$$

where $(x)^+ = \max\{x, 0\}$. Furthermore,

$$x_{i(t+1)} = \begin{cases} x_{(i+1)t} - y_{(i+1)t} & \text{for } i \in (1, \dots, m-1),\ t \in (1, \dots, T), \\ q_{t+1-L} & \text{for } i = m,\ t \in (1, \dots, T), \end{cases} \tag{2}$$

where we define $q_t = 0$ for all $t \leq 0$ and $x_{i0} = 0$ for all $i \in (1, \dots, m)$, for notational convenience.

Observe that the amount of food that is wasted at the end of period $t \in (1, \dots, T)$ is $x_{1t} - y_{1t}$. Hence, we can express the expected amount of total food waste as

$$E\left( \sum_{t=1}^{T} (x_{1t} - y_{1t}) \right).$$

Furthermore, we can express the expected fill rate as

$$E\left( \frac{\sum_{t=1}^{T} \sum_{i=1}^{m} y_{it}}{\sum_{t=1}^{T} d_t} \right),$$

We impose a service level constraint, which is that the expected fill rate should be greater than or equal to a target fill rate $f \in [0, 1]$.

We use the description of Powell (2014), and say that a state at time $t \in (1, \dots, T)$ is a representation of all information which is known before making a decision at time $t$, limited to that information which is necessary to make the decision, but sufficient to ensure the Markov property. For example, if demand is independently and identically distributed, we can define a state at time $t' \in (1, \dots, T)$ as $S = \left( [q_t]_{t=t'-L+1}^{t'-1}, [x_{it'}]_{i=1}^{m}, \sum_{t=1}^{t'-1} d_t, \sum_{t=1}^{t'-1} \sum_{i=1}^{m} y_{it} \right)$. Let $\mathcal{S}$ be the set of all possible states of the system. A policy is a function $\pi : \mathcal{S} \to \mathbb{R}$ which provides an order quantity for each state. Hence, deciding on order quantities $q_t$ per state, is equivalent to deciding on which policy to use. We call a policy feasible if it satisfies the fill rate constraint. Let $\Pi$ be a set of policies to choose from.

The inventory control problem that we consider here, is to find a feasible policy $\pi \in \Pi$ that minimizes the expected daily food waste. Note that we choose as objective the minimization of food waste for two main reasons. Firstly, we think it makes the interpretation of our results most clear. Since we are interested in assessing food waste, it is sensible to consider the case in which this is minimized, i.e., the best-case scenario. Secondly, this objective seems reasonable from a business perspective as well. It is commonly argued in the setting of perishable items and supermarkets, that costs like holding costs and ordering costs can be neglected, see e.g. Haijema and Minner (2016). This is not because these costs are negligibly small, but because it is not reasonable to include them as marginal cost of a product. Of course, a business would suffer the procurement cost per product that perishes before being sold. But these costs are proportional to the total food waste, and are thus minimized simultaneously.

We wish to introduce some terminology to clearly distinguish between two separate optimality concepts. Let $\mathcal{P}$ be the set of all conceivable policies. Although $\Pi \subseteq \mathcal{P}$, note that the set $\Pi$ is not necessarily equal to $\mathcal{P}$. Hence, there could exist a feasible policy in $\mathcal{P}$ that has less expected total food waste than the optimal solution to our inventory control problem, for which we are limited to policies in $\Pi$. That is, when limited to $\Pi$, the optimal solution might not correspond to the best possible policy. Still it is common to limit $\Pi$ for purposes of tractability. Therefore, we refer to a policy in $\Pi$ which corresponds to an optimal solution as $\Pi$-optimal. Moreover, we refer to the best conceivable policy as an optimal policy, which could be obtained as optimal solution to the inventory control problem with $\Pi = \mathcal{P}$. Similarly, we refer to the solution value as $\Pi$-optimal food waste or optimal food waste. We further refer the reader to Powell (2014) for an intriguing discussion on the representation of decisions in a stochastic setting using policies.

Finally, note that our model admits some pathological cases. For the purposes of this paper, it is suitable to assume that $L < T$ such that decisions on order quantities matter. It is also suitable to assume $d_t = 0$ for $t \in (1, \ldots, L)$, such that the fill rate is not affected by the start up period during which orders have not arrived yet. Alternatively, one might assume specific inventory levels and outstanding orders in the first period, but we will not do this here.

## 2.2 Monotonicity

Next, we address the question whether food waste is monotonically decreasing in the lifetime of a product. However, this question requires some refinement before we are ready to provide meaningful answers. To that end, we define an instance of the inventory control problem by lifetime, the set of periods, demand distribution, lead time, and target fill rate. Consider an instance $I(m)$ with lifetime $m$. A second instance $I(m')$ is straightforwardly obtained from $I(m)$ by changing the lifetime from $m$ to $m'$, and leaving the rest the same. This way we can create a family of instances $(I(1), \ldots, I(T))$, and we could consider the instance $I(m)$ a function of $m$. Hence, a more precise question is: does the food waste corresponding to instance $I(m)$ monotonically decrease in the lifetime $m$?

Still this question is ill-defined, because food waste is not a property of an instance. Food waste also depends on the selected policy, since it is the property of a solution to an instance. Because any reasonable instance admits multiple solutions, we need to refine our question further. We provide two avenues forward, which we think are both important.

Firstly, we can consider in particular the optimal food waste, as opposed to $\Pi$-optimal food waste, which may be seen as a property of the instance. We prove in this section that the optimal food waste corresponding to instance $I(m)$ is indeed monotonically decreasing in the lifetime $m$. This result validates our intuition, that if a product has a longer lifetime there is more potential to avoid food waste. However, this result has limited practical relevance. In practice, finding an optimal policy is typically intractable, and we usually optimize over policy classes that do not necessarily include an optimal policy. Given a particular policy class, we now might wonder whether this policy class valorizes the potential for reducing food waste when the lifetime increases. This brings us to the second avenue forward.

Secondly, we can compare the food waste resulting from policies that are actually selected for various values of the lifetime. That is, denoting by $\Pi(m)$ the set of allowed policies for instance $I(m)$, we investigate whether the $\Pi$-optimal food waste of an instance $I(m)$ is monotonically decreasing in $m$. We demonstrate that this is the case for some choices of $\Pi(m)$, although this is not the case in general. In fact, we show a theoretical example in Appendix A, in which the $\Pi$-optimal food waste resulting from the selected policies is actually increasing in the lifetime $m$.

Next, we present a sufficient condition on the relation between $\Pi(m)$ and $\Pi(m+1)$ such that food waste is monotonically decreasing in $m$. Applying this condition allows us to prove that the optimal food waste is monotonically decreasing. It also allows us to prove that a more tractable policy, in particular the optimal constant order policy, provides food waste that is monotonically decreasing in $m$. This condition makes use of the concept of a *mimicking policy*, which we define as follows. Consider the lifetimes $m, m' \in (1, \ldots, T)$, such that $m \neq m'$. The policy $\pi' \in \Pi(m')$ is a mimicking policy of $\pi \in \Pi(m)$ if it orders precisely the same quantity as $\pi$ in each period for any sample path of demand realizations.

**Lemma 1.** *The $\Pi$-optimal food waste of instance $I(m)$ is monotonically decreasing in $m \in (1, \ldots, T)$, if for each $m \in (1, \ldots, T-1)$ there is a mimicking policy $\pi' \in \Pi(m+1)$ of a $\Pi$-optimal policy $\pi \in \Pi(m)$.*

A proof of Lemma 1 can be found in Appendix B. The main argument is obtained by investigating a $\Pi$-optimal policy $\pi \in \Pi(m)$, and a corresponding mimicking policy $\pi' \in \Pi(m+1)$. For a fixed sample path of demand, both policies order the same quantities in each period. Any product that would expire in case the lifetime is $m$, can still be sold for one more period if the lifetime would be $m+1$. Roughly stated, this product can then be used to satisfy an additional unit of demand, or it results in an expired product in a later period. The prove in the Appendix consists essentially of checking this claim by induction. We arrive at the conclusion that, because this is valid for any sample path of demand, the expected food waste and fill rate of the mimicking policy is at least as good, and therefore the Π-optimal food waste is monotonically decreasing.

It follows immediately that the optimal food waste is monotonically decreasing.

**Theorem 1.** *The optimal food waste of instance $I(m)$ is monotonically decreasing in the lifetime $m \in (1, \dots, T)$.*

*Proof.* Proof. Let $\Pi(m)$ be the set of all conceivable policies for instance $I(m)$, for each $m \in (1, \dots, T)$. Note that $\Pi(m)$ includes an optimal policy $\pi$, and $\Pi(m+1)$ includes a mimicking policy of $\pi$. It follows from Lemma 1, that the optimal food waste is monotonically decreasing in the lifetime $m$. □

Because finding the optimal policy is usually not tractable, the set of policies Π is typically limited to a specific policy class which is more tractable. Consider for example the class of constant order policies. A constant order policy is a policy $\pi$ that always orders the same constant quantity $q$, i.e., $\pi(S) = q$ for all $S \in \mathcal{S}$. See Haijema and Minner (2016) for an application of constant order policies to a perishable inventory control problem. Denote $\pi(q, m)$ as the constant order policy for instance $I(m)$ which always orders $q \geq 0$ and let $\Pi(m) = \{\pi(q, m) : q \in \mathbb{R}_+\}$. We refer to the $\Pi(m)$-optimal policy as the optimal constant order policy of instance $I(m)$.

**Theorem 2.** *The expected total food waste of the optimal constant order policy of instance $I(m)$ is monotonically decreasing in the lifetime $m \in (1, \dots, T)$.*

*Proof.* Proof. Observe that the constant order policy $\pi(q, m+1) \in \Pi(m+1)$ is a mimicking policy of the constant order policy $\pi(q, m) \in \Pi(m)$. Therefore, by Lemma 1 the expected total food waste of the optimal constant order policy is monotonically decreasing in the lifetime $m$. □

Unfortunately, the sufficient condition in Lemma 1 does not apply to all policy classes. For instance, another frequently used policy class is the base-stock policy; in each period order a quantity such that the sum of the current inventory and outstanding orders equals a constant. Again, see Haijema and Minner (2016) for an application of base-stock policies to a perishable inventory control problem. A mimicking policy of a base stock policy, is in general not itself a base-stock policy, and hence Lemma 1 does not apply. Of course, this does not mean that the food waste of the optimal base-stock policy is not decreasing in the lifetime $m$, so this remains an open question.

# 3 Numerical results

We perform numerical experiments to assess the net effect on food waste of a shift from offline to online retail. We demonstrate that some products yield lower food waste when sold online and others when sold offline, dependent on the lifetime and demand distribution. Hence, it depends on the assortment of a retailer, whether a shift from offline to online reduces food waste. However, our experiments indicate that many products are actually better sold online, despite being thrown out before expiration. Next, we first describe the used instances, then the used inventory control policy, and lastly we discuss the results from our numerical experiments.

We consider 1000 periods each representing a day. We vary the lifetime of the products $m \in (2, \ldots, 22)$. Observe that many types of food have a longer lifetime than 22 days (European Comission , 2018), but our results with these lifetimes overwhelmingly favor online retail in terms of food waste. We also do not consider products that perish after one day in our comparison, because it is meaningless to throw them out before expiration. The target fill rate $f$ is 0.99, and we set the lead time to zero. This is common in our setting, see Zhang et al. (2018), and has the added benefit of simplifying the optimization, as highlighted later. We consider independent and identical discrete demand distributions. We obtain these distributions by choosing a mean $\mu$ and standard deviation $\sigma$, and fitting a discrete distribution using the procedure of Adan et al. (1995). Unless stated otherwise, we consider as mean $\mu$ the values $\{5, 10, 50, 100\}$ and as coefficient of variation $CV = \frac{\sigma}{\mu}$ the values $\{0.5, 0.7, 1.0, 1.5, 2.0\}$. In our experiments, we explore a full combinatorial design, totaling 410 instances.

To model the offline setting, we incorporate both LIFO and FIFO inventory depletion. Similar to e.g. Haijema and Minner (2016) we introduce a FIFO demand and LIFO demand, and update equations (1) accordingly. The fraction of demand which is FIFO demand is represented by the value $\alpha \in \left\{0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1\right\}$, while the remainder is LIFO demand. FIFO and LIFO demand are independently distributed. Given a mean $\mu$ and standard deviation $\sigma$ of the online demand, for the FIFO demand of offline retail we use $\alpha\mu$ as mean and $\sqrt{(\alpha)}\sigma$ as standard deviation, and for the LIFO demand we use $(1 - \alpha)\mu$ and $\sqrt{(1 - \alpha)}\sigma$ as standard deviation.

Furthermore, in our experiments we distinguish between comparisons with and without the pooling effect. To incorporate the pooling effect, we use a ratio of one online store to 20 offline stores. This ratio is inspired by the largest Dutch multi channel supermarket Albert Heijn, whose online distribution centers each satisfy roughly the same demand as 20 of their offline stores (*personal communication with Marcel Holtmaat, VP Online Operations Albert Heijn, December 2020*). Consequently, for every original combination of $\mu$ and $\sigma$ in our experiments, we replace the mean demand of the online store with $20\mu$ and the standard deviation with $\sqrt{20}\sigma$. We then compare the resulting food waste with 20 times the corresponding offline food waste.

A compelling argument is made by Zhang et al. (2018), to use the base-stock policy when faced with a perishable inventory control problem as described in this paper. They provide evidence from the literature of both computational tractability and near optimality of this policy, and mention its wide use in practice. Given a choice for an order-up-to-level $S$, the base-stock policy is to order a quantity $q_t$ in each period $t \in P$ such that the inventory position gets back to $S$, i.e., $q_t = S - \sum_{i=1}^{m} x_{it} - \sum_{p=t-L+1}^{t-1} q_p$. We use this policy in our numerical experiments. Note that there is a plethora of other policies for perishable inventory control problems, see Nahmias (2011).

We optimize the order-up-to-level $S$ as follows. Note that according to Zhang et al. (2018), when the lead time is zero, the expected food waste and expected fill rate are convex in $S$. Since both quantities are non-negative and zero for $S = 0$, this even implies that they are monotonically increasing in $S$. The optimal value of $S$ might now be found by iteratively trying increasing values of $S$ starting at zero. As soon as the expected fill rate exceeds the target $f$, the optimum is found. The fill rate is assessed using an approach similar to that used in e.g. Minner and Transchel (2018). A batch of 10 sample paths is generated, and the expected fill rate is estimated. Iteratively new batches are added, until the size of the 95% confidence interval of the fill rate is smaller than 0.004. When the value $S$ is determined, but still less than 1000 sample paths are generated, they are supplemented to 1000. Therefore, the final set consists of at least 1000 sample paths, which are used to estimate the expected food waste corresponding to the choice of $S$.

We apply the base-stock policy to each of the 410 instances, in ten different configurations, i.e., for five different FIFO fractions $\alpha$, and with or without pooling. Note that in all our experiments, we observe that the expected food waste resulting from the base-stock policy is monotonically decreasing in the lifetime. That is, all thing equal, the expected food waste increases when food is thrown out more days before expiration.

Next, we compare the expected total food waste resulting from offline and online retail. As a statistic used in our comparison, we introduce the *tipping point*, which is the largest number of days that food can be thrown out before expiration, for which online food waste is smaller than or equal to offline food waste. For example, if the tipping point is six, this means that even if food is thrown out six days before expiration, online retailers still generate less or equal food waste compared to offline retailers.

In Figure 1, we show five graphs that illustrate the tipping points per lifetime of the product, corresponding to the five values of the FIFO fraction $\alpha$, without pooling. In particular, per lifetime the expected food waste is averaged over all instances, i.e., over all configurations of mean and coefficient of variation. The graphs show the tipping points with respect to this average, which we refer to as 'Average tipping point'. For example, from the blue, topmost graph corresponding to the offline FIFO fraction $\alpha = 0$, we can conclude that when offline customers always pick the freshest item on the shelve, for food with a lifetime of nine days the online retailer yields less expected food waste than the online retailer even when the offline retailer throws out food six days before expiration.

From Figure 1, we see that as expected, the lower the offline FIFO fraction $\alpha$, the more favourable are the results for the online retailer. Suppose that we are interested in ensuring that sold food is consumable for a week, so we throw out food six days before expiration. Then, if all offline customers pick the freshest item, the online retailer has on average a lower food waste if the lifetime of the products is 9 days or higher, and if the lifetime of the product is 17 days or higher, the online retailer yields less or equal expected food waste for any offline FIFO fraction $\alpha$, despite throwing out food before expiration.

We refer to the lifetime $m$ minus the amount of days before expiration that food is thrown out,

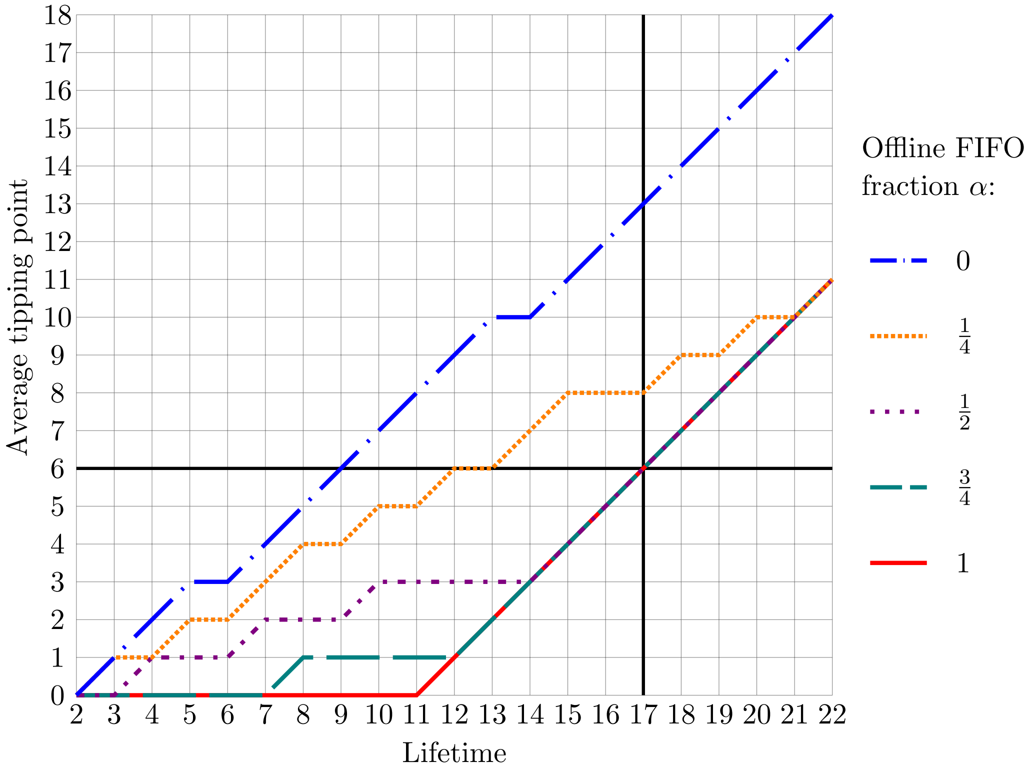


Figure 1: Average tipping points, without pooling.

Table 1: The minimum net lifetime such that the expected food waste of the online retailer is zero, without pooling.

| $\mu$\CV | 0.5 | 0.7 | 1.0 | 1.5 | 2.0 |
|---|---|---|---|---|---|
| 5 | 6 | 6 | 7 | 9 | 11 |
| 10 | 4 | 4 | 5 | 6 | 7 |
| 50 | 2 | 2 | 3 | 3 | 3 |
| 100 | 2 | 2 | 2 | 2 | 3 |

as the net lifetime. In our experiments, the expected food waste of the online retailer is zero in all instances with a net lifetime of eleven days or more. This explains the peculiar shape of the the red, bottom graph in Figure 1 corresponding to the offline FIFO fraction $\alpha = 1$, i.e., the case that offline customers pick the oldest product first. In this case, the online retailer has no advantage over the offline retailer, and both the offline and online retailer have zero expected food waste when the net life time is at least eleven.

In Table 1, we provide the minimum net lifetime such that the expected food waste of the online retailer is zero, individually per mean $\mu$ and coefficient of variation CV. For example, with $\mu = 100$ and CV$= 0.5$, the online retailer has zero food waste if the net lifetime is two days or more. Observe that as mean demand gets lower, and the coefficient of variation gets higher, the higher the net lifetime of the product needs to be before zero expected food waste is achieved.

When we include the pooling effect, the results are even more pronounced. In all but one of our instances we observed zero expected food waste at the online retailer if the net lifetime is at

Table 2: Percentage of satisfied demand per age category for the instance with mean demand 5, coefficient of variation 2 and lifetime 22.

| Age category | 0-2 | 3-5 | 6-8 | 9-11 | 12-15 | 16-18 | 19-22 |
|---|---|---|---|---|---|---|---|
| $\alpha = 0$ | 87.7 | 6.8 | 2.4 | 1.2 | 0.8 | 0.5 | 0.5 |
| $\alpha = \frac{1}{4}$ | 75.8 | 12.8 | 8.6 | 2.5 | 0.3 | 0.0 | 0.0 |
| $\alpha = \frac{1}{2}$ | 69.2 | 27.1 | 3.7 | 0.1 | 0.0 | 0.0 | 0.0 |
| $\alpha = \frac{3}{4}$ | 73.0 | 26.3 | 0.7 | 0.0 | 0.0 | 0.0 | 0.0 |
| $\alpha = 1$ | 81.0 | 18.9 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 |
| Pooling | 100.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

least two days. That is, the online retailer yields food waste that is lower than, or equal to that of the offline retailer in virtually all cases. The only exception is the case that $\mu = 5$ and CV= 2, for which our estimated expected food waste is 0.004 for a net lifetime of two days, and zero food waste if the net lifetime is at least three days.

Note that in our experiments, not only does the online retailer often yield lower expected food waste, also the consumer seems to receive fresher products. This is because when some customers of the offline store pick the freshest product, an older product might remain in inventory for a prolonged time and is eventually used to satisfy demand of a customer on a later day. To illustrate this with an example, in Table 2 we show the percentage of satisfied demand per age category, with one decimal precision, for the instance with mean demand 5, coefficient of variation 2 and lifetime 22, which is the instance from our experiments in which the highest age products are observed. The age category indicates the age of the product, e.g. 0-2 corresponds to all products that have been in inventory for 0, 1 or 2 days. Each row in Table 2 corresponds to a different offline FIFO fraction $\alpha$, where $\alpha = 1$ corresponds equivalently to the online retailer and offline retailer with LIFO inventory depletion. The row 'Pooling' corresponds to the case with pooling and FIFO inventory depletion. As expected, we observe that at an offline retailer, the customer might receive food that is even in the age category 19-22. In fact cases arise where the food is 22 days old, while this does not happen at the online retailer. Still, we remark that the percentage of satisfied demand with an age of 0 days, is highest at the online retailer with LIFO inventory depletion.

# 4 Discussion

It seems intuitive that an increased lifetime will result in decreased food waste. However, in this paper we have made this intuition more precise to overcome a fallacy. In particular, we would connect this intuition to the *potential* for food waste decrease, as we have shown that when the lifetime of a product increases, the optimal food waste decreases. However, we also demonstrate that not every policy valorizes this potential. We provide a sufficiency condition that can be used to determine for specific policy classes whether food waste decreases when the lifetime increases, and we show as an example that this applies to the constant order policy.

This study was initiated by our observation that online retailers necessarily throw out food before expiration. Hence, we can now conclude that this increases the potential for food waste, and well-behaved policies might indeed suffer from this. Still, online retailers benefit from better control of order picking and the pooling effect. In fact, our numerical results show that many products have lower food waste when sold online despite food being thrown out before expiration. This seems due to the simple fact that even for relatively short net lifetimes, all inventory is sold before expiration in case of FIFO inventory depletion, resulting in zero food waste. Our analysis seems to explain and support claims of (near) zero food waste by online retailers in practice, such as the U.K. based online supermarket Ocado (Ocado group, 2020).

An important reason for online retailers to throw out food before expiration, is because they are unaware of the consumption date by the consumer. This situation might be improved. However, this does not seem easy. It does not simply require an appropriate interface for consumers to communicate this, e.g., allowing the selection of a product with a particular expiration date. Also, warehousing and order picking would become more complex. Additional research would be required on how to manage this. However, our results suggest that the benefit of such efforts might be limited, because most food is sold before getting to an age at which it might be thrown out.

We remark that in practice, the difference between offline and online might even be greater than in our numerical experiments. We have used equal inventory control policies when comparing offline to online, while in practice online and offline stores might use different policies. For example, offline supermarkets typically have as objective to keep their shelves fully stocked, because it is believed that full shelves attract customers. When considering food waste, this is a disadvantage compared to online supermarkets, which might simply have efficiency as objective. Moreover, online retailers may benefit from the fact that there is time in between a sale and delivery, which might be used to further increase the efficiency of inventory control. Finally, food which is thrown out by the online retailer is still fit for consumption for a short amount of time. Therefore, it might be repurposed instead of wasted. For example, the largest Dutch online supermarket AH.nl donates unsold food to the food banks (*personal communication with Marcel Holtmaat, VP Online Operations Albert Heijn, December 2020*).

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# A Example

We provide a theoretical example which demonstrates that not every policy class $\Pi$ results in monotonically decreasing $\Pi$-optimal food waste. Even though the presented policies do not seem suitable for application, the example demonstrates that a poorly designed inventory control policy might fail to valorize the potential for food waste reduction of an increased lifetime.

**Example 1.** *We define the set of policies as the singleton* $\Pi(m) = \{\pi(m)\}$ *for any* $m \in (1, \ldots, T)$. *Each policy* $\pi(m)$ *is obtained by ordering a sufficiently large constant quantity in each period* $t \in (1, \ldots, T)$*, such that the service level constraint is satisfied. Additionally, a large quantity is added to the order in period 1. This additional quantity is dependent on* $m$ *and chosen sufficiently large, such that the expected food waste is monotonically increasing in* $m$.

*We provide a simple concrete example to demonstrate existence of this construction. Consider an instance* $I(m)$ *such that the probability distribution of* $d_t$ *has bounded support for all* $t \in (1, \ldots, T)$. *This implies there exists a sufficiently large value* $q$ *such that* $P(q > d_t) = 1$. *Consider the constant order policy* $\pi(q, m)$ *for instance* $I(m)$, $m \in (1, \ldots, T)$. *Observe that* $\pi(q, m)$ *achieves an expected fill rate of 1, and satisfies the service level constraint.*

*We construct* $\pi(m)$ *from* $\pi(q, m)$ *by adding an additional quantity* $M(m)$ *to the order of period 1. Denote the expected total food waste generated by policy* $\pi(q, m)$ *as* $W(\pi(q, m))$*, and denote the difference between the largest and smallest expected total food waste as* $W^\delta = \max_{m \in (1,\ldots,T)}\{W(\pi(q, m))\} - \min_{m \in (1,\ldots,T)}\{W(\pi(q, m))\}$. *We define* $M(m) = 1 + mW^\delta$. *It follows that the resulting policies* $\pi(m)$ *satisfy the service level constraint and that the expected food waste is monotonically increasing in* $m$.

# B Proof of Lemma 1

In this Appendix, we provide a proof of Lemma 1, which we first repeat.

**Lemma 1.** *The $\Pi$-optimal food waste of instance $I(m)$ is monotonically decreasing in $m \in (1, \ldots, T)$, if for each $m \in (1, \ldots, T-1)$ there is a mimicking policy $\pi' \in \Pi(m+1)$ of a $\Pi$-optimal policy $\pi \in \Pi(m)$.*

*Proof.* Proof. Consider a $\Pi$-optimal policy $\pi \in \Pi(m)$ and let $\pi' \in \Pi(m+1)$ be a mimicking policy of $\pi$. The bulk of this proof consists of showing that the expected total food waste and fill rate of $\pi'$ are less than or equal to those of $\pi$. Since $\pi' \in \Pi(m+1)$, this would immediately imply that the $\Pi$-optimal food waste of instance $I(m)$ is monotonically decreasing in $m$.

Denote by $x_{it}^{m}$ and $x_{it}^{m+1}$ the inventory for instances $I(m)$ and $I(m+1)$, respectively, for $t \in (1, \ldots, T)$ and $i \in (1, \ldots, m)$. Similarly let $y_{it}^{m}$ and $y_{it}^{m+1}$ be the satisfied demand for instances $I(m)$ and $I(m+1)$. We proceed as follows. i) We prove by induction on $t \in (1, \ldots, T)$ that, given a sample path $[d_i]_{i=1}^{t}$, the total inventory corresponding to $\pi'$ is greater than or equal to that of $\pi$. In particular, $x_{it}^{m} \leq x_{(i+1)t}^{m+1}$ for all $t \in (1, \ldots, T)$ and $i \in (1, \ldots, m)$. ii) We continue by showing that the total satisfied demand is greater or equal when using $\pi'$ instead of $\pi$, i.e., $\sum_{t=1}^{T} \sum_{i=1}^{m} y_{it}^{m} \leq \sum_{t=1}^{T} \sum_{i=1}^{m+1} y_{it}^{m}$. iii) We conclude by showing that if $\pi$ satisfies the service level constraint, then so does $\pi'$, and moreover the expected total food waste of $\pi'$ is less than or equal to that of $\pi$, showing that the best food waste is monotonically decreasing in $m$.

i) For time period $t = 1$, trivially $x_{it}^{m} \leq x_{(i+1)t}^{m+1}$ for all $i \in (1, \ldots, m)$. We make the induction hypothesis that for $t \in (1, \ldots, T-1)$ it holds that $x_{it}^{m} \leq x_{(i+1)t}^{m+1}$ for all $i \in (1, \ldots, m)$. Next, we take the induction step, proving that also $x_{i(t+1)}^{m} \leq x_{(i+1)(t+1)}^{m+1}$ holds for all $i \in (1, \ldots, m)$. Observe that because $\pi'$ is a mimicking policy of $\pi$, they order the same quantity in each period, and so $x_{m(t+1)}^{m} = q_{t+1-L} = x_{(m+1)(t+1)}^{m+1}$. Next, we consider the remaining lifetimes $i \in (1, \ldots, m-1)$. We distinguish two cases. As the first case, suppose that in period $t$ the demand for products with remaining lifetime $i+1$ was less than or equal to the inventory, i.e., $x_{(i+1)t}^{m} \geq d_t - \sum_{j=1}^{i} x_{jt}^{m}$. It follows from (1), the induction hypothesis and $x_{1t}^{m+1} \geq 0$ that

$$y_{(i+1)t}^{m} = \left( d_t - \sum_{j=1}^{i} x_{jt}^{m} \right)^{+} \geq \left( d_t - \sum_{j=1}^{i+1} x_{jt}^{m+1} \right)^{+} \geq y_{(i+2)t}^{m+1}.$$

Combining this with (2), we derive that

$$x_{i(t+1)}^{m} = x_{(i+1)t}^{m} - y_{(i+1)t}^{m} \leq x_{(i+2)t}^{m+1} - y_{(i+2)t}^{m+1} = x_{(i+1)(t+1)}^{m+1}.$$

As the second case, suppose that in period $t$ the demand for products with remaining lifetime $i+1$ was greater than the inventory, i.e., $x_{(i+1)t}^{m} < d_t - \sum_{j=1}^{i} x_{jt}^{m}$. In this case, the inventory $x_{(i+1)t}^{m}$ is completely used up. Indeed, from (1) it follows that $y_{(i+1)t}^{m} = x_{(i+1)t}^{m}$, and it follows subsequently from (2) that $x_{i(t+1)}^{m} = 0$. By non-negativity of the inventory, we conclude $x_{i(t+1)}^{m} \leq x_{(i+1)(t+1)}^{m+1}$.

ii) Observe that, because $x_{it}^m \leq x_{(i+1)t}^{m+1}$ for all $i \in (1, \ldots, m)$ and $t \in (1, \ldots, T)$, it follows for the total satisfied demand and each sample path that

$$\sum_{t=1}^{T}\sum_{i=1}^{m} y_{it}^m = \sum_{t=1}^{T} \min\left\{\sum_{i=1}^{m} x_{it}^m, d_t\right\} \leq \sum_{t=1}^{T} \min\left\{\sum_{i=1}^{m+1} x_{it}^{m+1}, d_t\right\} = \sum_{t=1}^{T}\sum_{i=1}^{m+1} y_{it}^{m+1}.$$

That is, the total satisfied demand by $\pi'$ is higher than that by $\pi$.

iii) Because for every sample path, the total satisfied demand by $\pi'$ is higher, it follows that if $\pi$ satisfies the service level constraint then also $\pi'$ satisfies the service level constraint. Furthermore, observe that the total food waste of instance $I(m)$ can be expressed as the difference between the cumulative quantity ordered until period $T - m - L$, which is at risk of perishing before period $T$, and the total satisfied demand. For each sample path, it holds that the total food waste is larger for $\pi'$ than $\pi$ since

$$\sum_{t=1}^{T-m-L} q_t - \sum_{t=1}^{T}\sum_{i=1}^{m} y_{it}^m \geq \sum_{t=1}^{T-(m+1)-L} q_t - \sum_{t=1}^{T}\sum_{i=1}^{m+1} y_{it}^{m+1}.$$

Since this holds for each sample path, the expected total food waste is also larger for $\pi'$ than $\pi$. We conclude that the best food waste is monotonically decreasing in $m$. □