Online Appendix for ‘Multiplicity in Product Expiration Dates and Food Waste in Grocery Retail Stores.’

Ashish Kabra
Nanyang Business School, Nanyang Technological University, Singapore
ashish.kabra@ntu.edu.sg

Nitish Jain
London Business School, United Kingdom
njain@london.edu

Varun Karamshetty
School of Computing, National University of Singapore, Singapore
varun.karamshetty@nus.edu.sg

A. Mixed-Integer Linear Program (MILP) Formulation

The program $\mathtt{P}^{\mathtt{MILP}}$ below presents the mixed-integer linear program (MILP) formulation (where M is a large positive number) of $\mathtt{P}$ in Paper Section 3.3. The EW_d^{FEFO} replaces the non-linear function $\left(\widehat{CI}_{d-1,1} - S_d\right)^+$. x_d is a binary variable such that when it is 0, $EW_d^{FEFO} = 0$, while it being 1 implies $EW_d^{FEFO} = \widehat{CI}_{d-1,1} - S_d$ and $\widehat{CI}_{d-1,1} - S_d \geq 0$.

$$\mathtt{P}^{\mathtt{MILP}} = \sum_{d=1}^{D} EW_d - EW_d^{FEFO} \tag{1}$$

subject to

(a) Remaining Life Inventory Flow Equations:

$$\widehat{CI}_{d,k} = \begin{cases} DL_d - \widehat{S}_{d,l} & k = l-1 \\ \widehat{CI}_{d-1,k+1} - \widehat{S}_{d,k+1} & k \in [1, l-1) \end{cases}, \forall d \in [1, D]. \tag{2}$$

$$CI_d = \sum_{k=1}^{l-1} \widehat{CI}_{d,k}, \ \forall d \in [0, D]. \tag{3}$$

$$S_d = \sum_{k=1}^{l} \widehat{S}_{d,k}, \ \forall d \in [1, D]. \tag{4}$$

(b) Aggregate Inventory Flow Equation:

$$CI_d = CI_{d-1} - S_d - EW_d + DL_d \tag{5}$$

(c) EW Equation:

$$EW_d = \widehat{CI}_{d-1,1} - \widehat{S}_{d,1} \tag{6}$$

(d) MIP Constraints:

$$EW_d^{FEFO} \geq 0 \tag{7}$$

$$EW_d^{FEFO} \geq \widehat{CI}_{d-1,1} - S_d \tag{8}$$

$$EW_d^{FEFO} \leq \widehat{CI}_{d-1,1} - S_d + M(1 - x_d) \tag{9}$$

$$EW_d^{FEFO} \leq M \cdot x_d \tag{10}$$

(e) Integer and Positivity Constraints: (11)

$$\widehat{CI}_{d,k}, \widehat{S}_{d,k} \in \mathbb{Z}^{\geq 0}; x_d \in \{0, 1\}. \tag{12}$$

B. Appendix: Simulation Procedure

In this section, we describe the simulation analysis performed to validate the accuracy of the program $\mathtt{P}$ in identifying bounds on the actual MDEW. We first discuss the data generation process used to populate the simulated data and then expand on the validation results.

B.1. Simulation: Key Assumptions Governing the Data Generation Process

Our simulation covers a variety of demand and replenishment scenarios by parameterizing several product and supply characteristics, including the product's demand distribution, sourcing lead

	Quantity	Notation	Distribution
1	Daily Demand	$D_{p,d}$	Rounded Gamma (μ_p, σ_p)
2	Mean Demand	μ_p	Uniform[0, 75]
3	Std. Dev. of Demand	σ_p	Uniform[0, 75]
4	Shelf Life	l_p	Discrete Uniform[3, 14]
5	Safety Stock Factor	Φ_p	Uniform[0, 1]
6	Case Size Factor	c_p	Uniform(0, 2]
7	Lead Time	λ_p	Discrete Uniform[1, 7]
8	Picking Behavior Probabilities	$\rho_p^{\{FEFO,LEFO,Random\}}$	$\frac{\text{Uniform}^{\{FEFO,LEFO,Random\}}[0,100]}{\sum_{i\in\{FEFO,LEFO,Random\}}\text{Uniform}^{i}[0,100]}$

Table A1: Simulation Variables Distribution

time, case pack size, and safety stock level, over a wide range of values. We use a base stock inventory replenishment policy with case size as the minimum order quantity. Finally, we set the number of stores in our simulation to one, without loss of generality. Table A1 summarizes the generation process of the key parameters.

Product Demand: We simulate the daily demand of product p using a Gamma distribution, Gamma(μ_p, σ_p), where μ_p and σ_p denote the mean and standard deviation of the daily demand, respectively. These values are sampled uniformly from the range $[0, 75]$. Note that scaling up or down this range proportionally scales the inventory and waste counts without affecting the MDEW to EW ratio. Next, in alignment with our collaborating retailer's context, we assign each product a shelf life by drawing uniformly between 3 and 14 days.

Inventory Replenishment Policy: We follow a base-stock policy for inventory replenishment wherein the minimum order quantity is determined by the product's case size C_p. We set $C_p =$ round$(c_p \times \mu_p)$, where c_p denotes product p's case size factor sampled uniformly for a product from the range $(0, 2]$. The order-up-to level for inventory policy for the product is, O_p, calculated as,

$$O_p = \lambda_p \times (\mu_p + \Phi_p \cdot \sigma_p),$$

where λ_p denotes the sourcing lead time and Φ_p denotes the safety stock factor. We draw λ_p uniformly between 1 to 7 days , and Φ_p uniformly from $[0, 1]$. Building on these values, we calculate the order quantity for product p on any given day as

$$o_{p,d} = \begin{cases} \lceil (O_p - I_{p,d})/C_p \rceil \times C_p, & \text{if } O_p > I_{p,d}, \\ 0, & \text{if } O_p \leq I_{p,d}, \end{cases}$$

where, $\lceil \cdot \rceil$ denotes rounding up, $I_{p,d}$ represents the inventory position, which includes both on-hand inventory and units already ordered for delivery but not yet arrived. The order quantity $o_{p,d}$ is the smallest multiple of case-size C_p that takes the sum of inventory position and order quantity above the order-up-to level.

Consumer Product-Picking Behavior: We simulate all three consumer product-picking behaviors: FEFO, LEFO, and random picking. Specifically, we implement a restrictive LEFO behavior by simulating consumers picking the freshest available units (see Section B.2 for further details). We assign probabilities for these behaviors, ρ_p^{FEFO}, ρ_p^{LEFO}, and ρ_p^{Random}, such that they have identical unconditional distributions and sum to 1.

B.2. Simulation: Variable Construction

We generate the simulated data in the following sequence for each product p, sequentially across days d, starting with $d = 1$. The closing inventory count on day 0 is set to zero for each product.

Step 1. Generation of Starting Inventory Values: The delivered inventory on day d, denoted by $DL_{p,d}$, equals $o_{p,d-\lambda_p}$, i.e., the order quantity placed λ_p days earlier.[23] As per the estimation analysis in Section 3.3 of the paper, we assume for the simulation that each of the delivered product units has a remaining shelf life of l_p days. Formally,

$$DL_{p,d,k} = \begin{cases} DL_{p,d}, & \text{if } k = l_p, \\ 0, & \text{otherwise.} \end{cases}$$

The inventory position on day d, $I_{p,d}$, is computed as:

$$I_{p,d} = CL_{p,d-1} + DL_{p,d} + \sum_{d-\lambda_p < \tilde{d} < d} o_{p,\tilde{d}},$$

i.e., the sum of the closing inventory from day $d-1$, the delivered inventory on day d, and the orders placed but not yet delivered. Given the inventory position $I_{p,d}$, the order quantity $o_{p,d}$ is determined as described earlier in the section. This results in a periodic review ordering policy with a review period of daily. Further, for each product×day, we define the starting inventory with a remaining life of k using either the delivered units or closing inventory units from the previous day. Formally, we compute $SI_{p,d,k}$ as:[24]

$$SI_{p,d,k} = \begin{cases} DL_{p,d,k}, & \text{if } k = l_p, \\ CI_{p,d-1,k}, & \text{if } l_p > k \geq 1, \end{cases} \qquad \forall k \in \{1, l_p\},$$

Starting inventory for a product-day is set as $SI_{p,d} = \sum_{k=1}^{l_p} SI_{p,d,k}$.

Step 2: Generation of Sales: We compute daily aggregate sales as a minimum of randomly drawn demand value (as per the Gamma distribution) and the computed starting inventory value.

[23] We do not simulate stochasticity in sourcing lead time.

[24] To recall, we decrease the remaining life of a product at the end of the day and assume the continuity of the remaining life over the next day.

Formally, we set $S_{p,d} = \min(D_{p,d}, SI_{p,d})$. Next, we split the aggregated sales quantity as per the drawn consumer product-picking behavior probabilities:

$$S_{p,d}^{LEFO} = \lfloor \rho_p^{LEFO} \cdot S_{p,d} \rfloor,$$
$$S_{p,d}^{FEFO} = \lfloor \rho_p^{FEFO} \cdot S_{p,d} \rfloor,$$
$$S_{p,d}^{Random} = S_{p,d} - S_{p,d}^{LEFO} - S_{p,d}^{FEFO}.$$

Next, we assign the remaining lives to the sold units, $S_{p,d,k}$, such that the aggregated counts of the three product-picking behaviors are satisfied. We implement the following assignment policy: [25]

- **LEFO Sales:** $S_{p,d}^{LEFO}$ units are assigned starting from the inventory with the highest remaining life (i.e., the freshest inventory units) and moving in descending order of remaining lives until all LEFO sales are allocated.
- **FEFO Sales:** $S_{p,d}^{FEFO}$ units are assigned starting from the inventory the lowest remaining life (i.e., the oldest inventory units) and moving in ascending order until all FEFO sales are allocated.
- **Random Sales:** $S_{p,d}^{Random}$ units are assigned uniformly across the unassigned inventory units (after LEFO and FEFO sale assignments).[26]

Using the above-computed values of $S_{p,d,k}$ (step 2) and $SI_{p,d,k}$ (step 1), we define the closing inventory units for each remaining life as:[27]

$$CI_{p,d,k-1} = SI_{p,d,k} - S_{p,d,k}$$
$$CI_{p,d} = \sum_{k=1}^{l_p} CI_{p,d,k}$$

Step 3: Generation of MDEW. Consistent with our focal retailer's practice, we define the Expiration Waste (EW) count as the closing inventory with zero remaining shelf life at the end of the day. We define FEFO-EW (EW^{FEFO}) as the excess inventory units with one day of remaining shelf life at the beginning of the day over sold units that day. Finally, we compute MDEW as the difference between EW and EW^{FEFO}. Formally, we define EW, EW^{FEFO}, and $MDEW$ as:

$$EW_{p,d} = CI_{p,d,0}$$
$$EW_{p,d}^{FEFO} = \max(SI_{p,d,1} - S_{p,d}, 0)$$
$$MDEW_{p,d} = EW_{p,d} - EW_{p,d}^{FEFO}$$

[25] An alternate computationally intensive method is to simulate each sold unit's picking order to determine its remaining life. We note that our procedure provides an approximate but much simpler approach to simultaneously assign multiple units across the three product-picking behaviors.

[26] These are rounded down to the nearest integer for each value of k to maintain integer sales requirements. Any unassigned sales due to rounding are further allocated in a FEFO manner as described previously.

[27] To recall, at the end of the day, we reduce remaining life of each inventory unit by one to represent the updated remaining life for the next day.

B.3. Simulation: Validation Results

Following the data generation steps outlined in the previous section, we generate simulated data for 100 products over a 300-day period. On day 0, we set the closing inventory count for each product to zero. To eliminate any idiosyncratic spillover effects from the initial conditions on the validation results, we discard the early portion of the simulated data. Specifically, we use the final 10 weeks of simulated data to validate our MDEW estimation methodology (as specified by program `P` in Section 3.3 of the main paper, with $D = 7$). Thus, we solve ten instances of the mathematical program for each product, resulting in a total of 1000 instances. Of these, 368 instances yield zero EW. In Table A2, we present the MDEW validation results for the remaining 632 instances.

For each of the 632 instances with non-zero EW, the estimated lower and upper bounds for MDEW consistently encompass the actual MDEW value. This result validates the accuracy of our methodology in identifying bounds on the actual MDEW across a range of product and operational characteristics. Furthermore, we observe the following systematic patterns:

1. Longer shelf life results in lower MDEW bounds (both the lower and upper bounds, $p < 0.01$). On the one hand, a longer shelf life can increase the likelihood of selling a unit before its expiration, leading to lower MDEW. On the other hand, it could also result in more instances of multiple expiration dates on the shelf, thus potentially increasing MDEW. The simulation analysis suggests that the former effect systematically dominates the latter effect.
2. Larger case pack size results in lower MDEW bounds (both the lower and upper bounds, $p < 0.01$). A larger case pack size contributes to larger order sizes which, in turn, seem to result in fewer instances of multiple expiration dates on the shelf compared to a relatively smaller case pack size.
3. A higher propensity for FEFO picking results in lower MDEW bounds (both the lower and upper bounds, $p < 0.01$). This aligns with the common intuition that consumers' adherence to FEFO purchases should mitigate the waste generated by a multiplicity of product expiry dates on retail shelves. Furthermore, higher FEFO picking propensity results in wider estimated MDEW bounds.
4. A higher mean daily demand results in higher MDEW bounds (both the lower and upper bounds, $p < 0.01$). A higher demand is likely to yield more frequent orders which, in turn, could result in a multiplicity of expiration dates on shelves.
5. A higher demand variability (standard deviation) results in lower MDEW bounds (both the lower and upper bounds, $p < 0.01$).
6. With regards to the bound gap (the difference between the lower and upper MDEW bounds), we find that the bound gap increases with the increase in mean daily demand ($p < 0.01$) and decreases with the increase in case pack size ($p < 0.01$). We do not find a statistically significant change in the bound gap with respect to other factors.

Group Class	Group	N	Lower Bound	Upper Bound	Bound Gap
All		632	19.5 (30.6)	56.7 (39.6)	37.2 (33.6)
Shelf Life	Short-life (3-7 days)	284	29.2 (31.3)	68.7 (36.6)	39.4 (32.0)
	Long-life (8-14)	348	11.6 (27.6)	47.0 (39.3)	35.3 (34.9)
Case Pack Factor	Small	316	32.3 (34.5)	85.9 (26.5)	53.6 (35.6)
	Large	316	6.7 (18.9)	27.5 (27.0)	20.8 (21.6)
Fraction LEFO	Small	316	15 (26.2)	58.4 (39.3)	43.3 (34.2)
	Large	316	24.0 (33.9)	55.1 (39.9)	31.1 (32.0)
Fraction FEFO	Small	314	27.2 (35.1)	62.7 (40.2)	35.4 (34.9)
	Large	318	11.9 (23.0)	50.8 (38.1)	38.9 (32.4)
Mean Daily Demand	Small	310	15.9 (25.6)	48.9 (38.3)	32.9 (30.8)
	Large	322	23.0 (34.4)	64.2 (39.5)	41.2 (35.7)
Std. Dev. Daily Demand	Small	309	24.7 (35.6)	62.6 (39.5)	38 (35.1)
	Large	323	14.6 (23.9)	51.0 (38.9)	36.4 (32.2)
Lead Time	Small	250	26.8 (36.3)	54.6 (39.6)	27.8 (28)
	Large	382	14.8 (25.1)	58.1 (39.6)	43.3 (35.6)
Safety Stock Factor	Small	309	20.7 (32.1)	56.4 (38.2)	35.7 (31.5)
	Large	323	18.4 (29.1)	57.0 (41)	38.6 (35.6)

Table A2: Simulation Results: Average MDEW bounds across Product Characteristics.

C. Appendix: Methodology for Quantifying Sales Patterns Incurred by the Retailer

In this section, we outline a systematic approach to quantify the average fraction of sales that follow either FEFO or LEFO pattern for the retailer. Instances where sales cannot be clearly classified as either FEFO or LEFO are labeled as 'Not Classified (NC)'. The analysis is based on product-store-week (*psw*) instances where the lower and upper bounds of multiple-dates-led expiration waste ($\underline{\text{MDEW}}$ and $\overline{\text{MDEW}}$, respectively) are equal. For these instances, only one feasible life distribution (for closing inventory and sold units) matches the observed MDEW bounds.[28] For each such instance, we infer the sales sequence and calculate the fraction of FEFO or LEFO sales.

[28] In theory, multiple feasible solutions could exist with the same MDEW estimate. However, our sales pattern estimation methodology can be extended to handle such cases. We confirm that, in our dataset, all instances with equal bounds have a unique feasible solution.

C.1. Estimating Sale Sequences

For each *psw* instance with matching MDEW bounds and a feasible solution, we first compute the following latent variables: $\widehat{CI}_{d,k}$ (closing inventory) and $\widehat{S}_{d,k}$ (sales) for each day d in week w and remaining shelf life $k \in [1, l]$, where l denotes the product's shelf life.

Next, using these computed values, we derive the starting inventory $\widehat{SI}_{d,k}$ based on the previous day's closing inventory ($\widehat{CI}_{d-1,k}$) and the delivered inventory of the current day (DL_d):

$$\widehat{SI}_{d,k} = \begin{cases} \widehat{CI}_{d-1,k}, & \text{if } 1 \le k \le l-1 \\ DL_d, & \text{if } k = l \end{cases} \tag{13}$$

C.2. Classifying Sales into FEFO, LEFO, or NC

Based on the computed values of $\widehat{SI}_{d,k}$ and $\widehat{S}_{d,k}$, sales on day d of week w are classified into FEFO, LEFO, or NC using the following criteria:

- If only one age k has non-zero $\widehat{SI}_{d,k}$ (i.e., only one expiry date units are available on the shelf), all sales that day are classified as FEFO:

$$S_d^{FEFO} = S_d, \quad S_d^{LEFO} = 0, \quad S_d^{NC} = 0.$$

- If multiple ages k have nonzero inventory:
  - —FEFO sales are those derived from the older range of stock. Sale of a remaining life is counted as FEFO if units of any older life are not present in the closing inventory at the end of this day of sales. Specifically, $S_d^{FEFO} = \sum_{1 \le k < k_2} S_{d,k}$, where we determine *highest* k_2 which satisfies $S_{d,k_2} > 0$ and $CI_{d,k_1} = 0$ for all $k_1 < k_2$.
  - —LEFO sales are those derived from the fresher range of stock. Sales are counted as LEFO only when some of the older inventory remains as part of CI, ensuring that sales classified as LEFO are not simply a result of spillover of FEFO sales after depletion of older stock. Specifically,
    - ∗ determine smallest k_1 such that $CI_{d,k_2} = 0$ for all $k_1 < k_2$ (i.e., all of the stock of remaining-life higher than k_1 is depleted on day d),
    - ∗ and $\sum_{1 \le k < k_1} CI_{d,k} > 0$ (i.e., all of the stock of remaining-life less than or equal to k_1 is *not* depleted on day d).
    - ∗ if such a k_1 exists, then $S_d^{LEFO} = \sum_{k_1 \le k < L} S_{d,k}$, else $S_d^{LEFO} = 0$.
- Any remaining sales that do not fit the above FEFO or LEFO classification are categorized as 'Not Classified (NC)', S_d^{NC}. Formally, we define, $S_d^{NC} = S_d - S_d^{FEFO} - S_d^{LEFO}$.

We note that the estimates are robust to using a more conservative classification rule approach where we only count the sales of first-to-expiry units (i.e., $k_{\min,d}$) as FEFO, and last-to-expiry units (i.e., $k_{\max,d}$) as LEFO.

C.3. Illustrative Examples

We illustrate this classification with sample scenarios.

Example 1: FEFO Sales. On day d, the starting inventory and sales for a product with a shelf life of 3 days are:

k	1	2	3
SI	4	6	3
S	4	6	2
CI	0	0	1

S_d^{LEFO}	0
S_d^{FEFO}	12
S_d^{NC}	0

Since the highest k_2 is equal to 3, where the $CI_{d,k_1} = 0$ for all $k_1 < k_2$, the sales across all there remaining lives are classified as FEFO. Note that even the sales with highest remaining life with positive inventory in this setting are classified as FEFO.

Example 2: Mixed Sales (FEFO, LEFO, and NC). A different inventory and sales distribution for the same product:

k	1	2	3
SI	4	6	3
S	3	4	2
CI	1	2	1

S_d^{LEFO}	2
S_d^{FEFO}	3
S_d^{NC}	4

Here, for FEFO classification $k_2 = 1$, and therefore $S_{FEFO} = S_1 = 3$. For LEFO classification $k_1 = 3$, and therefore $S_{LEFO} = S_3 = 2$. The sales units for remaining life of 2 are classified as NC.

Example 3: FEFO, LEFO, and no NC Sales. Another inventory and sales distribution for the same product:

k	1	2	3
SI	4	6	3
S	4	3	2
CI	0	3	1

S_d^{LEFO}	2
S_d^{FEFO}	7
S_d^{NC}	0

Here, for FEFO classification, $k_2 = 2$, and therefore, $S_{d,1}$ and $S_{d,2}$ are both classified as FEFO sales. For LEFO classification, $k_1 = 3$, and therefore $S_{d,3}$ is classified as LEFO. Since all the sales are classified earlier, the NC is 0 in this case.

D. Additional Robustness Tests

D.1. Individual Products That Do Not Carry Date Labels

In our retailer's context, while some of the fresh products carry date labels, not all do. This practice is similar to other retailers. In Figure A1, we provide examples from another retailer.[29] As shown, there is mixed evidence of date label application on fresh products. In our dataset, the shown products belong to the 'Perishables Plus' category.

We do not have a column in our dataset that identifies whether a fresh product carries a date label. That said, we can find a workaround for this limitation. Our partner retailer pointed out that if a fresh product is non-saleable due to unsatisfactory appearance, it is removed from the

[29] Our NDA with the collaborating retailer prohibits us from including any pictures that could disclose the retailer's identity.

Figure A1: Examples of products with and without date labels.

Note. The top row displays fresh produce without date labels, while the bottom row shows products with clearly marked date labels. From left to right, the featured items are pears, apples, broccoli, and cauliflower. Pictures were taken on Dec 15th, 17th, and 22nd, 2024.

					Reverse CDF Prob(MDEW2EW $\geq$ x)				
#	Estimate	N($\times 10^3$)	Mean	St. Dev.	10%	20%	30%	40%	50%
			for products with quality waste ratio < 10%						
1	Lower Bound	428	25.3	39.3	0.34	0.32	0.3	0.27	0.22
2	Upper Bound	428	51.7	45.4	0.63	0.6	0.58	0.54	0.48
3	Matched Subsample	256	34.3	45.5	0.39	0.38	0.37	0.35	0.32

Table A3: Estimates for products with low quality waste ratio: Average MDEW Waste as a Percentage of EW (MDEW2EW), product×store×week.

shelf and marked as a Quality Waste (QW) unit. In the case of fresh products with no date labels, a significant fraction of the total waste would be categorized as QW.[30] In our sample, we find the majority of products exhibit a QW-to-total waste ratio much closer to 0% than to 100%. Specifically, for 77% of products, this ratio is less than 5%. However, there are nine products with a 100% QW-to-total waste ratio, all of which are loose fruits and vegetables.

[30] Note that the QW fraction for products without date labels may not reach 100%. Even if the products themselves do not carry a date label, their cases can include an expiry date. In scenarios wherein the entire case is discarded if it remains unsold until the expiration date, the corresponding product will record non-zero EW.

#	Estimate	N($\times 10^3$)	Mean	St. Dev.	Reverse CDF Prob(MDEW2EW $\geq$ x) 10%	20%	30%	40%	50%
			All categories, D = 14 days (38.9%, 96.5%)†						
1	Lower Bound	122	26.9	38.8	0.39	0.36	0.33	0.29	0.23
2	Upper Bound	122	49.7	44.8	0.63	0.59	0.56	0.52	0.46
3	Matched Subsample (61.7%, 95.7%)‡	75	33.5	44.4	0.41	0.38	0.37	0.34	0.31
			All categories, D = 28 days (18.3%, 83.5%)†						
4	Lower Bound	18	27.8	37.2	0.45	0.39	0.35	0.29	0.22
5	Upper Bound	18	48.9	43.5	0.65	0.6	0.56	0.51	0.45
6	Matched Subsample (60.1%, 76.9%)‡	11	32.8	42.7	0.44	0.39	0.37	0.33	0.29

† The first number in the bracket shows the percentage of observations with a feasible solution, and the second number shows the percentage of the initial products covered.

‡ The first number in the bracket shows the percentage of MDEW observations for which the lower bound estimate equals its upper bound estimate, and the second number shows the percentage of initial products covered.

Table A4: Robustness Results with a larger D: Average MDEW Waste as a Percentage of EW (MDEW2EW), product×store×week.

We test for the robustness of our obtained findings to the presence of products without date labels. Specifically, we classify products with a Quality Waste ratio above a certain threshold as *likely without a date label*. We utilize a threshold of 10% and note that qualitatively similar results are obtained for higher thresholds of 25% and 50%. Table A3 reports MDEW estimates after excluding the above-threshold-QW products (in total 125 products, approximately 5.6% of the total products). We note that the MDEW estimates after excluding these products are very similar to our base estimates (Table 8). In summary, our focal estimates are not sensitive to the inclusion of products without date labels.

D.2. Higher values of D

We run our analysis with $D = 14$ and $D = 28$, and present the results in Table A4. We find that the average lower and upper bounds of MDEW are largely similar to our focal estimates, with somewhat wider bounds and lower feasibility.

E. Heterogenous Patterns: Continued

To explore additional factors associated with MDEW, we append data from two additional tables. We detail them below.

Shelf Data: We utilize rich data on product shelves, which includes attributes such as the temperature regime of the shelf, whether a product has multiple locations within a store, and the shelf's

Category	N($\times10^3$)	Feasible psw†	Coverage†	Lower Bound	Upper Bound	Matched Bound	Matched psw‡	Matched Coverage‡
				Location				
Home Only	422	66.3%	97.4%	25.3 (39.4)	52.0 (45.4)	34.4 (45.6)	59.6%	97.2%
Home & Away	13	60.8%	95.4%	24.6 (38.3)	50.2 (44.3)	33.9 (45.0)	57.3%	90.0%
				Shelf Capacity				
Below Median	268	65.2%	96.3%	24.1 (39.0)	47.1 (45.5)	31.3 (44.4)	64.8%	94.8%
Above Median	166	67.7%	93.6%	27.2 (39.8)	59.8 (44.1)	40.9 (47.3)	51.0%	90.6%
				Away Shelf Capacity Ratio				
Below Median	10	60.8%	92.6%	24.6 (38.4)	49.7 (44.4)	33.7 (44.9)	58.1%	85.6%
Above Median	3	60.7%	91.1%	24.7 (38.2)	51.5 (44.0)	34.6 (45.1)	55.2%	81.5%
				Temperature				
Ambient	70	71.8%	96.7%	25.6 (39.3)	54.6 (45.0)	36.1 (46.2)	55.9%	96.1%
Chilled	364	65.2%	97.3%	25.2 (39.4)	51.4 (45.4)	34.1 (45.5)	60.3%	97.0%
				Shelf Length				
Below Median	217	67.9%	97.3%	22.1 (37.8)	46.1 (45.4)	28.9 (43.4)	63.6%	96.2%
Above Median	204	64.7%	96.0%	28.7 (40.7)	58.2 (44.5)	41.2 (47.3)	55.2%	94.17%
				Ratio of Shelf Length and Shelf Capacity				
Below Median	210	68.2%	96.5%	23.7 (38.4)	51.4 (45.5)	32.5 (45.0)	58.4%	94.8%
Above Median	211	64.5%	95.8%	26.8 (40.2)	52.6 (45.4)	36.3 (46.1)	60.7%	93.9%
				Depot Max to Shelf Life Ratio				
Below Median	155	67.8%	98.8%	27.8 (40.3)	57.6 (44.7)	39.9 (47.1)	55.1%	98.8%
Above Median	126	64.9%	99.6%	26.0 (39.6)	54.2 (45.2)	36.2 (46.1)	57.4%	99.6%
				Depot Max to Min Life Ratio				
Below Median	147	66.0%	98.7%	27.3 (40.0)	56.1 (44.9)	38.2 (46.6)	56.5%	98.7%
Above Median	134	67.0%	99.8%	26.6 (40.0)	56.0 (45.0)	38.2 (46.8)	55.7%	99.8%
				Number of Stores for a UPC				
Below Median	147	65.0%	98.7%	25.5 (39.6)	50.2 (45.5)	33.8 (45.3)	62.1%	98.7%
Above Median	134	68.2%	100.0%	28.5 (40.4)	62.4 (43.5)	44.1 (47.9)	49.5%	100.0%
				Store Gross Sale Units				
Below Median	243	70.2%	98.0%	21.7 (37.5)	45.9 (45.3)	28.6 (43.3)	62.7%	97.7%
Above Median	193	61.6%	96.1%	29.8 (41.2)	59.5 (44.4)	42.7 (47.5)	55.5%	94.3%

† Feasible *psw* is the percentage of observations with a feasible solution, and *Coverage* is the percentage of the initial products covered.

‡ Matched *psw* is the percentage of MDEW observations with equal lower and upper bound estimates, and Matched coverage is the percentage of initial products covered.

Table A5: Heterogeneous Patterns in MDEW Waste by Shelf, Store and Depot attributes (MDEW2EW), product×store×week.

maximum capacity. For about 80% of the shelves, we can also determine the horizontal shelf length based on the name of the shelf in our data. The breakdown of the average MDEW estimates by these factors is presented in Table A5. Here is a summary of the obtained patterns:

- *Shelf Temperature*: Most products are stored under 'Ambient' or 'Chilled' regimes, with Chilled regime accounting for over 85%. We find that Ambient products are associated with slightly higher MDEW bounds compared to Chilled products (25.6% vs 25.2%, $p = 0.014$ for lower bounds, and 54.6% vs 51.4%, $p < 0.01$ for upper bounds), indicating a stronger preference for freshness in Ambient products.

- *Shelf Location*: For 96.8% of *psw* instances, products are located in a single shelf (referred as 'home' location by the retailer). In the remaining 3.14% instances, products are placed in both 'home' and 'away' locations. We find that products with only home locations are associated with higher MDEW bounds (lower bound: 25.3% vs 24.6%, $p = 0.045$; upper bound: 52.0% vs 50.2%, $p < 0.01$). This could be due to an increased likelihood of units with multiple expiration dates being on the same shelf, since all units are placed in a single location.
- *Shelf Capacity*: We find that products placed on shelves with smaller capacities are associated with lower MDEW bounds (lower bound: 24.1% vs 27.2%, $p < 0.01$; upper bound: 47.1% vs 59.8%, $p < 0.01$).[31] Smaller shelf capacity may reduce the likelihood of stocking units with multiple expiration dates. Additionally, we note that when multiple locations are involved ('home' and 'away'), a higher proportion of away shelf capacity is correlated with lower upper bounds (49.7% vs 51.5%, $p = 0.05$) but similar lower bounds (24.6% vs. 24.7%, p=0.90). This indicates it is more likely to have units with multiple expiration dates when the product is placed in a single location than across two locations.
- *Shelf Length*: We have shelf length information for the 80% of *psw* instances. Using this subsample, we find that shorter shelf lengths are associated with lower MDEW bounds (lower bound: 22.1% vs 28.7%, $p < 0.01$; upper bound: 46.1% vs 58.2%, $p < 0.01$). Relatedly, we also find that a higher shelf-length-to-shelf-capacity ratio is associated with lower MDEW bounds (lower bound: 23.7% vs 26.8%, $p < 0.01$; upper bound: 51.4% vs 52.6%, $p < 0.01$). These patterns may stem from the fact that longer shelf lengths, both in absolute terms and relative to shelf capacity, increase the likelihood of stocking units with multiple expiration dates.

Product-Level Data: The second data table includes product-level variables, specifically the maximum and minimum life of products that are acceptable when receiving products at distribution centers[32] (termed as depot max and min life), and the number of stores stocking each product. The breakdown of the average MDEW estimates by these factors is presented in Table A5. Here is a brief summary:

- *Depot and Shelf Life Ratios*: We group the products using the median value of the ratio of 'depot max life' to 'shelf life'. We find that products with values below the median value are associated

[31] We aggregate shelf capacities and shelf lengths for a product when multiple locations, i.e., ('home' and 'away') are present in a store.

[32] Note that the retailer receives products from suppliers at its distribution centers. Products are then delivered from the distribution centers to retail stores as needed. The retailer has confirmed that, in most cases, fulfillment from the distribution centers to the retail stores occurs on a daily basis.

with higher MDEW bounds (lower bound: 27.8% vs. 26.0%, $p < 0.01$; upper bound: 57.6% vs 54.2%, $p < 0.01$). A similar effect is seen when the products are grouped using the ratio of depot max life to depot min life. Again, products with values below the median value are associated with higher MDEW bounds (lower bound: 27.3% vs 26.6%, $p < 0.01$; upper bound: 56.1% vs 56.0%, $p = 0.56$). These patterns suggest that a higher value of these two ratios indicates greater flexibility in fulfillment operations to meet the minimum shelf life requirements at the stores. This flexibility seems to be associated with lower MDEW.

- *Number of Stores Carrying a UPC*: We group the products using the median value of the number of stores carrying a product. We find that products with values below the median value are associated with lower MDEW bounds (lower bound: 25.5% vs 28.5%, $p < 0.01$; upper bound: 50.2% vs 62.4%, $p < 0.01$). This pattern indicates that operational uniformity, such as the same case pack size, could result in higher MDEW waste when applied across a higher number of stores.
- *Effect of Store Size:* Using our primary data, we set a store's size equal to the weekly average number of units sold at that store. We find that smaller stores (below the median size) have MDEW values that are smaller than those of larger (above-median) stores (lower bound: (21.7% vs 29.8%, $p < 0.01$); upper bound: (45.9% vs 59.5%, $p < 0.01$)).

F. Program for Model Extension: Inclusion of Quality Waste Units

Formally, we define $\mathtt{P}_{\mathrm{QW}}$ as

$$\mathtt{P}_{\mathrm{QW}} = \sum_{d=1}^{D} EW_d - \left(\widehat{CI}_{d-1,1} - S_d - \widehat{\mathbf{QW}}_{\mathbf{d,1}}\right)^+ \tag{14}$$

subject to

(a) Remaining Life Inventory flow equations:

$$\widehat{CI}_{d,k} = \begin{cases} DL_d - \widehat{S}_{d,l} - \widehat{\mathbf{QW}}_{\mathbf{d,l}} & k = l-1 \\ \widehat{CI}_{d-1,k+1} - \widehat{S}_{d,k+1} - \widehat{\mathbf{QW}}_{\mathbf{d,k+1}} & k \in [1, l-1) \end{cases}, \forall d \in [1, D] \tag{15}$$

$$CI_d = \sum_{k=1}^{l-1} \widehat{CI}_{d,k}, \ \forall d \in [0, D] \tag{16}$$

$$S_d = \sum_{k=1}^{l} \widehat{S}_{d,k}, \ \forall d \in [1, D] \tag{17}$$

$$\mathbf{QW_d} = \sum_{\mathbf{k=1}}^{\mathbf{l}} \widehat{\mathbf{QW}}_{\mathbf{d,k}}, \ \forall d \in [1, D] \tag{18}$$

(b) Aggregate Inventory Flow Equation: $\forall d \in [1, D]$.

$$CI_d = CI_{d-1} - S_d - EW_d - \mathbf{QW_d} + DL_d, \ \forall d \in [1, D] \tag{19}$$

(c) EW Equation: $\forall d \in [1, D]$.

$$EW_d = \widehat{CI}_{d-1,1} - \widehat{S}_{d,1} - \widehat{\mathbf{QW}}_{\mathbf{d,1}},\ \forall d \in [1, D] \tag{20}$$

(d) Integer and Positivity Constraints:

$$\widehat{CI}_{d,k} \in \mathbb{Z}^{\geq 0},\ \forall d \in [0, D] \tag{21}$$

$$\widehat{S}_{d,k}, \widehat{\mathbf{QW}}_{\mathbf{d,k}} \in \mathbb{Z}^{\geq 0},\ \forall d \in [1, D] \tag{22}$$

G. Program for Model Extension: The Delivered Units Meet The Minimum Life On Receipt Requiremen

Formally, we define $\mathtt{P}_{\text{MLOR}}$ as

$$\mathtt{P}_{\text{MLOR}} = \sum_{d=1}^{D} EW_d - \left(\widehat{CI}_{d-1,1} - S_d\right)^{+} \tag{23}$$

subject to

(a) Remaining Life Inventory Flow Equations:

$$\widehat{CI}_{d,k} = \begin{cases} \widehat{\mathbf{DL}}_{\mathbf{d,L}} - \widehat{\mathbf{S}}_{\mathbf{d,L}} & \mathbf{k{=}L\text{-}1} \\ \widehat{\mathbf{CI}}_{\mathbf{d\text{-}1,k+1}} + \widehat{\mathbf{DL}}_{\mathbf{d,k+1}} - \widehat{\mathbf{S}}_{\mathbf{d,k+1}} & \mathbf{k \in [l,L\text{-}1)} \\ \widehat{\mathbf{CI}}_{\mathbf{d\text{-}1,k+1}} - \widehat{\mathbf{S}}_{\mathbf{d,k+1}} & \mathbf{k \in [1,l\text{-}1)} \end{cases},\ \forall d \in [0, D]. \tag{24}$$

$$CI_d = \sum_{k=1}^{\mathbf{L\text{-}1}} \widehat{CI}_{d,k},\ \forall d \in [0, D]. \tag{25}$$

$$S_d = \sum_{k=1}^{\mathbf{L}} \widehat{S}_{d,k},\ \forall d \in [1, D]. \tag{26}$$

$$\mathbf{DL_d} = \sum_{\mathbf{k=l}}^{\mathbf{L}} \widehat{\mathbf{DL}}_{\mathbf{d,k}},\ \forall d \in [1, D]. \tag{27}$$

(b) Aggregate Inventory Flow Equation: $\forall d \in [1, D]$.

$$CI_d = CI_{d-1} - S_d - EW_d + DL_d \tag{28}$$

(c) EW Equation: $\forall d \in [1, D]$.

$$EW_d = \widehat{CI}_{d-1,1} - \widehat{S}_{d,1} \tag{29}$$

(d) Integer and Positivity Constraints:

$$\widehat{CI}_{d,k} \in \mathbb{Z}^{\geq 0},\ \forall d \in [0, D]. \tag{30}$$

$$\widehat{S}_{d,k}, \widehat{\mathbf{DL}}_{\mathbf{d,k}} \in \mathbb{Z}^{\geq 0},\ \forall d \in [1, D]. \tag{31}$$

H. Examples of legal accountability for selling expired food.

To illustrate the legal bearing associated with carrying expired food products, we summarize two representative cases from different global jurisdictions:

- **China (Punitive damages for expired food).** In a case adjudicated by the Shanghai Baoshan Court, a supermarket was ordered to refund the purchase price (RMB 9.6) for expired chocolate and to pay statutory compensation of RMB 1,000. The ruling relied on Article 148 of the *Food Safety Law of the People's Republic of China*, under which a consumer may require a producer of food failing to meet food safety standards, or a trader knowingly dealing in such food (including food sold past its marked shelf life), to pay damages and punitive compensation equal to ten times the purchase price or three times the loss, subject to a statutory minimum of RMB 1,000 (see Shanghai High People's Court).

- **United Kingdom (ASDA fined for out-of-date food).** ASDA was fined £640,000 following repeated inspections that uncovered more than 100 out-of-date food items across two stores. The offenses constituted breaches of Regulation 49(b) of the *General Food Regulations 2004*, which governs the sale of unsafe food. In imposing the fine, the court emphasized the seriousness and duration of the violations, the volume of food sold past use-by dates, the scale of the retailer's operations, and the ineffectiveness of remedial efforts at the time (see Royal Environmental Health Institute of Scotland).

I. Future Research Ideas

A few promising avenues for future research that build on our proposed MDEW methodology are:

1. **Performance Incentives.** Should stores/managers be ranked and rewarded or punished for their performance in reducing retail waste? What is the right metric to compare stores: EW or MDEW? One might conjecture that EW is more subject to external factors, while MDEW is more reflective of store operations. Future research could examine metrics that align the incentives of different stakeholders.
2. **Extending the optimization model with alternative benchmarks.** Our method is built to measure excess waste over the FEFO–EW benchmark. The method could be extended to have alternate benchmarks if deemed more desirable. For example, consumers may not purchase dairy products if remaining life is below a threshold (e.g., two days).
3. **Markdowns to reduce food waste.** Markdowns can encourage the purchase of products nearing expiration, helping to reduce MDEW and EW. Investigating their impact on waste reduction remains a valuable and promising area of research.
4. **Expiration date labels and customer behavior.** Different labels such as "best by" and "sell by" may carry different safety and quality perceptions for consumers. As a result, the extent of MDEW may vary depending on the label used.
5. **MDEW estimates across geographies.** Shopping behaviors vary across geographies, and when combined with differing food dating regulations, they significantly affect MDEW's contribution to EW. While our method is globally applicable, our estimates are specific to one European retailer and future research could extend the scope.

6. **Value of LEFO purchase in improving forecast accuracy.** Improving demand and waste forecasts is central to reducing expiration waste while avoiding stockouts. Incorporating FEFO and LEFO purchase behavior into forecasting and replenishment systems may improve alignment between inventory and demand, but the value of systematically using such signals remains an open question.

J. Additional Supporting Tables

psw	Day	Category	Store Group	Product ID	Store ID	Shelf life	Case-pack size	Delivery	Sales	Quality Waste	Expiration Waste	Closing Inventory (of previous day)
1	1	Perishables Plus	Main Chain	X	X	6	12	12	11	0	0	12
1	2	Perishables Plus	Main Chain	X	X	6	12	12	12	0	0	13
1	3	Perishables Plus	Main Chain	X	X	6	12	0	6	0	0	13
1	4	Perishables Plus	Main Chain	X	X	6	12	24	2	0	0	7
1	5	Perishables Plus	Main Chain	X	X	6	12	0	16	0	2	29
1	6	Perishables Plus	Main Chain	X	X	6	12	0	0	0	0	11
1	7	Perishables Plus	Main Chain	X	X	6	12	12	5	0	0	11
2	1	Ready to eat	Main Chain	X	X	5	10	0	1	0	0	16
2	2	Ready to eat	Main Chain	X	X	5	10	0	1	0	1	15
2	3	Ready to eat	Main Chain	X	X	5	10	0	3	0	0	13
2	4	Ready to eat	Main Chain	X	X	5	10	10	1	0	5	10
2	5	Ready to eat	Main Chain	X	X	5	10	0	2	0	0	14
2	6	Ready to eat	Main Chain	X	X	5	10	0	0	0	0	12
2	7	Ready to eat	Main Chain	X	X	5	10	0	4	0	0	12

Table A6: Anonymized daily data for two psw (product-store-week) combinations.

Group Class	Group $N(\times 10^3)$	D=7 260	D=4 396	D=10 150
Category	Bakery and Protein Deli Plus	0.45	0.41	0.48
	Perishables Plus	0.19	0.22	0.18
	Ready-to-eat	0.36	0.37	0.34
Store Type	Self-Operated	0.82	0.83	0.82
	Franchise	0.18	0.17	0.18
Shelf Life	Short-life (3-7 days)	0.81	0.86	0.76
	Long-life (8-14)	0.19	0.14	0.24
Case Pack	Small	0.31	0.34	0.30
	Large	0.69	0.66	0.70

Table A7: Distribution of Attributes for Matched Bounds Sub-samples for different D.