Dynamic pricing to reduce dairy food waste:
Evidence from lab and grocery store experiments

Saumya Desai, Cornell University, sd963@cornell.edu
Yixuan Wang, Cornell University, wyxuan1999@163.com
Leonie Kemmerling, Cornell University, lk483@cornell.edu
Aljosa Trmcic, Cornell University, at543@cornell.edu
Martin Wiedmann, Cornell University, martin.wiedmann@cornell.edu
Aaron Adalja, Cornell University, aaa362@cornell.edu

Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-30, 20

INTRODUCTION

Food waste is a substantial issue in the US that impedes larger goals for future sustainable development. An estimated 40% of total food produced in the US goes uneaten because of waste or loss throughout the food supply chain (Hall et al., 2019). It is estimated that more than 55 million metric tons of food waste in the US is avoidable per year, which is nearly 29% of annual food production (Venkat, 2011); and per capita food waste disposal exceeds 0.6 pounds per day, totaling more than 35.5 million pounds annually (Thyberg, Tonjes and Gurevitch, 2015). Perishable food waste, including dairy waste, makes up a considerable portion of overall food waste. According to past estimates, approximately 25 billion pounds of dairy products are lost and wasted annually, the second largest category of food waste behind fruits and vegetables, with consumers making up 64% of the total contribution (Buzby et al., 2014). For retail, food service, and households, dairy food waste accounts for 19% of total food waste (Gunders and Bloom, 2017). In 2010, it was estimated that 15.7% of energy consumption was used for food production annually (Canning et al., 2010). Food waste therefore contributes to excess usage of water and fossil fuels and exacerbates climate change by producing greenhouse gas emissions from decomposing food (Hall et al., 2009).

Food waste causes a substantial financial loss in the US nationally and at the household level. In the US, food loss and food waste cost an estimated 218 billion dollars or 1.3% of GDP annually. The amount of food wasted annually for a four-person family is equivalent to $1500. Furthermore, food waste hinders the ability to feed a growing world population by decreasing food availability and therefore has adverse impacts on food security as well. Continued population and consumption growth will result in an increase in food demand over the next 40 years, potentially leading to competition for natural resources (Godfray et al., 2010). In the US alone, 33.8 million individuals live in food insecure household (USDA, 2021). With a projected global population of 9.3 billion people by 2050, the fact that one third of the world's edible food is lost or wasted along the supply chain raises concerns about future food shortages (Qi and Roe, 2016).

Additionally, across the whole supply chain, consumer-level food waste comprises a substantial share of total food waste, particularly in developed countries, and could be considered the most prevalent and devasting. Indeed, compared with other steps along supply chain, such as handling, processing, transportation and storage, consumer-related food waste is the largest contributor of total food waste (Commission for Environmental Corporation, 2017). In 2010, about 31% of total food produced was unavailable for consumption at retailer or consumer level. American households discard approximately 25% of food and beverages they buy (Buzby et al., 2014), and food wasted by consumers continues to grow and has risen 50% since 1970s (Gunders and Bloom, 2017). In 2010, around 218.9 pounds of edible food was wasted and sent for disposal per person in the US (Gao, 2019). Food waste at consumer level is more environmentally damaging than waste that occurs earlier in the supply chain because food products disposed at the consumer-level encompass the cumulative value added and resources used prior to reaching the consumer (Campbell and Feldpausch, 2022). The food discarded by consumers cannot be recovered and repurposed. Given the apparent magnitude of the consumer food waste issue, it is imperative that researchers, policymakers, and the food industry work together to develop novel solutions to reduce food waste. In this study, we focus on dairy milk waste as it contributes to a significant share of the overall food waste.

It is critical to first understand consumer attitudes toward milk waste and promote their awareness of waste reduction. Understanding consumer perceptions of milk waste would help us prioritize potential interventions. Misunderstanding date labels, poor planning of purchases, spoilage before consumption, and improper storage are commonly referenced reasons for consumer-level food waste (Campbell and Feldpausch, 2022). Qi and Roe (2016) used survey as an instrument to learn about US residents' attitudes toward food waste Most households feel guilty of throwing waste but also care about the quality and taste of the waste food product. Most respondents agreed that throwing away food after the label date passed could reduce illness odds and that there is a trade-off between food waste and taste (Qi and Roe, 2016). The current study aims to extend previous studies, where we quantify the shelf, we hypothesize that providing either general or personal information on food waste will change consumer's WTP for remaining shelf-life attribute.

Gao and Schroeder (2019) suggest that consumer willingness to pay (WTP) for food attributes changes due to an interaction of various label information which affects consumer preferences. When confronted with perishable food products, consumers tend to be more sensitive to shelf-life information delivered by label date. Shelf-life based pricing models could be applied to represent the value degradation. (Fauza et al., 2015). Another study of inventory models for perishable products reveals that the increasing health consciousness of consumers increases demand for fresh food products. Demand for products is influenced by various factors, including the freshness condition of food products, thus leading to freshness value degradation (Macías-López et al., 2021). Even if expiration dates are not explicitly present, consumers tend to believe that the quality of products goes down monotonically with time (Li et al., 2020). These studies suggest that consumer WTP tends to decrease as time passes. Based on this information, this study we hypothesize that consumer willingness to pay for fluid milk is increasing in the remaining shelf-life attribute.

In this study, we implement a series of lab-based auction experiments to test whether consumers exhibit positive WTP for greater shelf life, as operationalized by a date label on fluid milk products; to investigate the impact of providing general (industry-wide) and personal (individual-level) information about food waste on consumers' valuations of fluid milk products; to evaluate whether providing that information changes consumer WTP for an additional day of shelf life; and to develop a shelf-life based pricing model.

We find that consumers have a positive WTP for an additional day of shelf life. Based on results from a Tobit model, we find that, on average, consumers are willing to pay a premium of $0.37 for one additional day of shelf life in half a gallon of fluid milk. Providing information about food waste increases overall consumer WTP for fluid milk, and providing personal information is more impactful than general information; but providing food waste information does not affect consumer WTP for an additional day of shelf life.

Based on these results, we then explore the application of dynamic pricing in retail settings using a field experiment in a local supermarket. Dynamic pricing, which involves adjusting prices based on product shelf-life, demand, and supply factors, has shown potential in reducing waste while enhancing sales and customer satisfaction (Ellickson and Misra, 2008). Such strategies are particularly pertinent for managing perishable goods, where the risk of spoilage is high, and the opportunity for waste reduction is significant. We implemented a dynamic pricing model based on the shelf life of milk in a retail environment to evaluate its impact on consumer purchasing behavior and overall retail economics.

Our results indicate that the dynamic pricing model has had a noticeable impact on consumer purchasing patterns and retail economics. We observed a shift in consumer preference towards purchasing milk with shorter shelf lives. This shift suggests that dynamic pricing can be an effective tool in reducing food waste while maintaining consumer engagement. Additionally, our findings suggest a weak increase in retailer revenue, indicating that dynamic pricing can be economically sustainable. These outcomes underscore the potential of dynamic pricing strategies to balance economic viability with environmental sustainability.

The rest of the paper is organized as follows. In the next section, we present the experimental design and the auction mechanism for Study 1, followed by the results of that study. After that, we present the design and implementation strategy for the retail field experiment, along with results from that study. We then provide a general discussion of the results and findings of both studies, and finally we conclude with a discussion of policy and managerial implications as well as opportunities for future research.

STUDY 1

Materials and Methods

The data for this study was collected from an incentivized lab auction experiment administered using a Qualtrics survey on January 30th, January 31st, and February 1st, 2023. Cornell University Institutional Review Board reviewed the research protocol and granted an exemption (see Appendix 1). A total of 152 participants were recruited through the LEEDR Lab at Cornell University. The sample of participants were prescreened with three criteria in mind: be at least 18 years old, consume dairy milk, and not be an undergraduate student. The first pre-screener made sure that participants have the capacity to understand bid process and the ability of making purchase decisions based on the experience they developed. The second pre-screener ensured that participants may be interested in purchasing dairy milk products, and thus, the bids they offer will not be attenuated due to the absence of milk consumption habits. The third pre-screener ensured that participants were familiar with shopping for groceries for their household and that their preferences reflect those of the typical grocery shopping public.

Required activities, benefits, including a $20 compensation payment, and rights associated with this study were communicated through a consent form. Additionally, participants were free to choose one session time slot of the experiment out of nine sessions without being informed about any potential differences between sessions. Each day we conducted three experimental sessions, and each session was assigned to one of three information treatment groups: Control, Treatment 1, and Treatment 2. We varied the order of the treatment groups each day to balance the number of registered participants across all three groups each day.

The auction experiment uses the Becker-DeGroot-Marschak (BDM) mechanism to elicit consumer WTP for fluid milk with differing label dates when they are exposed to one of the three information treatments. The BDM mechanism (Becker, Degroot and Marschak, 1964) is commonly used in experimental economics to elicit values people place on commodities (Bohm et al., 1997). In BDM, we show or describe the product to the bidders (in this case the subjects) and ask them what is their maximum willingness to pay for the product. Then we draw a random price p from an interval (0, T) where T is a fixed number we set. If the random price p is below the bidders' reported wiliness to pay, they will pay and get the product. If it is above, then the bidders will not get the product or pay for it. Thus, each bidder's dominant strategy is to bid their true maximum WTP, so BDM is an incentive compatible valuation method. Compared with other valuation methods, BDM has the advantage that it produces an exact measure rather than yielding only a bound on WTP (Berry et al., 2020). As a demand revealing mechanism, the BDM method is more successful at eliciting true valuations for certain distributions of sale prices than others (Irwin et al. ,1998). Compared with other auction mechanisms, such as the Vickery auction (sealed bid second price auction), the BDM auction gives the subjects of individual choice without posing interaction or competition between subjects (Noussaire at al., 2004).

Prior to the official bidding process, a tutorial auction was conducted for practice purposes. After that, participants were introduced to a ten-round bid auction where they were asked to submit bids for the item in each round equal to their maximum willingness to pay. Their WTP was limited from \$0 to \$20 for each product presented. In each round, subjects were asked to read an information chart about a fluid milk product (including the size, the retailer, the minimum number of days from the experiment date to the label date, and fat content information). Using that product information, subjects submitted their bids based on their preferences. In each round, all characteristics of the milk product remained the same except for the days remaining until the label date (i.e., shelf-life). The milk product presented in each round had a different minimum number of days remaining until the label date: NA, -1, 0, 1, 3, 5, 7, 10, 14, 19. This “remaining shelf-life attribute” was not assigned to auction rounds in a monotonically increasing or decreasing manner, and the sequence was randomized each day to avoid any bias (See Table 2). To help subjects make rational bid decisions, a summary table of the bids they made in previous rounds was presented on their screen when they were prompted to provide the next bid. The summary table included the label date information and the bids they provided for each of the previous auction rounds.

Table 1: Minimum number of days to the label date assigned to milk product in each round

Round	Sessions 1-3	Sessions 4-6	Session 7-9
1	NA	NA	NA
2	7	1	7
3	1	14	10
4	3	0	1

5	-1	7	0
6	5	5	14
7	14	10	5
8	0	19	-1
9	9	-1	3
10	10	3	19

Participants in Treatment 1 and Treatment 2 both read information about the milk industry in New York State before the first-round bid. The information was presented as control information. Participants in Treatment 1 read *general* information about milk waste in the US before submitting their bids for the second round; and they were reminded of this information every two rounds during the remaining rounds. Participants in Treatment 2 read *personal* information about milk waste in the US before submitting their bids for the second round; and they were reminded of this information every two rounds during the remaining rounds (Appendix A).

The conditions for purchasing the milk were defined as follows. At the end of the experiment, a participant was randomly invited to draw a ping-pong ball from a satchel of balls. Each ball was labeled with an auction round number on one side and a randomly assigned binding market price for that round on the other side. If a participant's bid for the item in that round was equal to or greater than the randomly selected market price, they would purchase the specified product for the market price. The purchased milk product was delivered by a voucher which could be exchanged for the specified milk product at Cornell Dairy Bar. The sample of voucher is presented in Appendix Figure 4. After the ten auction rounds, participants were then asked to complete a survey consisting of questions about their dairy product consumption habits and demographic characteristics.

Results

We conducted a series of one-way ANOVAs to test for differences in demographic and behavioral characteristics of subjects across the three treatments (Table 2 and Table 3). Each column represents the mean value of each variable in the respective treatment group. Some of the survey variables are numeric, but many are categorical in nature. We address each categorical variable in one of two ways. For variables with two categorical levels, we coded them as binary indicator variables. For instance, for "household primary shopper" we generate a variable that takes a of 1 when the response is "Yes;" otherwise, it takes a value of 0.

For variables that used a Five-point Likert scale, we followed standard protocol to code them numerically. The five-point Likert scale is the most common scale and uses a range from "strongly disagree" on one end to "strongly agree" on the other, with "neither disagree nor agree" in the center. Each level on the scale is assigned a numeric value starting at one and incremented by one for each level (Bertram, 2007). For instance, to code the variable "help reduction," we generate a variable that takes a numeric value from -2 to 2 based on the response level: 2 for "strongly agree", 1 for "somewhat agree", 0 for "neither agree nor disagree", -1 for "somewhat disagree", -2 for "strongly disagree". The mean value therefore represents the average level of each group's agreement with wanting to help reduce milk waste.

As expected, there are very few differences across the three treatment groups, indicating that our sampling strategy did not introduce any significant bias. Only the p-values of the variables "Age", "Significant issue" and "Smell milk" (0.00779, 0.00444 and 0.0102, respectively) are less than 0.05. We therefore conclude that these variables have significant differences across treatment groups and will need to be included as control variables in our subsequent econometric analysis.

Table 2: ANOVA summary of the demographic characteristics of subjects in each group

Variable	Control	Treatment 1	Treatment 2	P-value
Mean bid	1.5	1.5	1.9	0.115
Min bid	0.2	0.27	0.32	0.57
Max bid	2.7	2.6	3.3	0.108
Medium bid	1.6	1.6	2	0.159
Min difference	-2.2	-2	-2.3	0.51
Max difference	0.28	0.38	0.65	0.132
Age	38	35	30	0.00779
Gender	0.73	0.56	0.75	0.0932
Education	0.76	0.78	0.73	0.808
Income	0.31	0.18	0.24	0.294
Marital status	0.45	0.38	0.25	0.115
Family Size	0.8	0.68	0.71	0.338
Milk consumption frequency	0.35	0.38	0.22	0.164
Milk consumption frequency	1.8E-17	2.9E-17	0.02	0.374
Label date mark meaning	0.35	0.3	0.22	0.309
Vegetarian	0.039	0.04	0.059	0.869
Child	0.14	0.12	0.059	0.404
Household primary shopper	0.69	0.74	0.71	0.837
Consumption period	0.39	0.5	0.55	0.272
Pick the longest remaining SL	0.59	0.56	0.63	0.79
Min remaining SL	0.61	0.64	0.55	0.644

Table 3: ANOVA summary of behavioral characteristics of subjects in each group

Variable	Control	Treatment 1	Treatment 2	P-value
Significant issue	0.88	1.5	1.1	0.00444
Feel bad for waste	1.5	1.6	1.6	0.708
Feel wrong for waste	1.5	1.2	1.4	0.228

Consideration	0.8	0.82	0.7	0.853
Help reduction	1.1	0.92	1.1	0.544
Social contributes	-0.67	-0.63	-0.7	0.966
Network	0.098	0.28	-0.078	0.327
Discard after label date	0.61	0.2	0.064	0.13
Discard on label date	-0.14	-0.58	-0.54	0.176
Smell milk	1.7	1.3	1.1	0.0102
Taste milk	0.31	0.12	0.38	0.646
Label date indication	-0.04	-0.041	0.44	0.0914
Label date text	0.82	0.35	0.67	0.138

The boxplot in Figure 5 provides visual intuition on the positive relationship between remaining shelf life and consumer WTP across the three treatment groups. It also suggests that the demand curve may not be perfectly linear. While the relationship seems relatively linear for moderate levels of remaining shelf life, it appears that WTP for a half gallon of milk plateaus when shelf life is 7 days or more and drops off steeply when it there are less than 3 days remaining. Therefore, to isolate systematic differences in consumer WTP for remaining shelf life for fluid milk, while controlling for confounding factors, we turn to multiple regression to analyze the data.

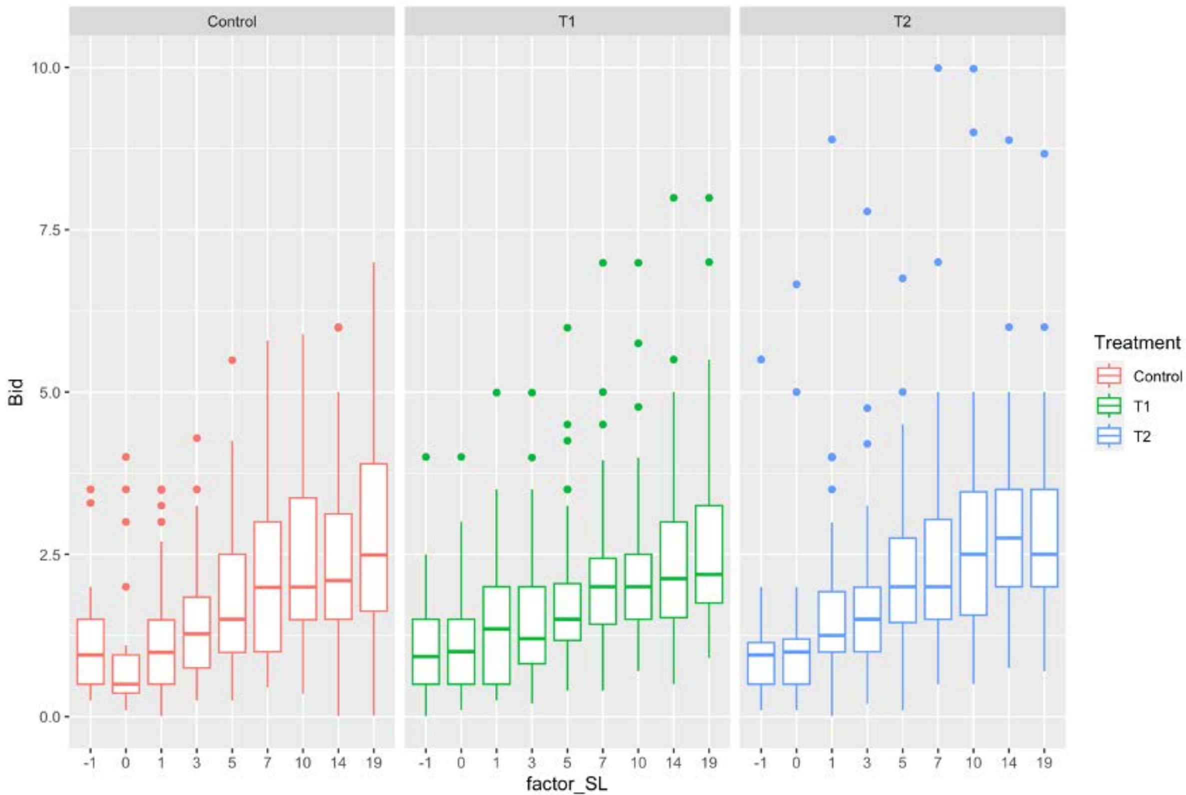


Figure 5: Milk bids based on remaining shelf-life by information treatment group

The marginal effects of the information treatment and the days of remaining shelf on consumer WTP are analyzed using multiple regression analysis. Our baseline OLS specification takes the form.

$$WTP_{ij} = \alpha + \beta_1 Treatment_i + \beta_2 SL_{ij} + \beta_3 SLSq_{ij} + \beta_4 Age_i + \beta_5 smellmilk + \beta_6 sig\_issue_i + \beta_7 \left(Treatment_i * SL_{ij}\right) + \beta_8 \left(Treatment_i * SLSq_{ij}\right) + \varepsilon_{ij}$$

Here, i denotes subjects and j indicates the auction round. The constant is α, $Treatment_i$ is a dummy variable for the three possible group assignments. SL_{ij} and $SLSq_{ij}$ are defined both by the subject (based on their session) and round number. *SL* represents remaining shelf-life which refers to the "number of days from experiment date to the label date." *SLSq* represents the square of *SL*. In order to avoid order bias, we randomize the sequence each day for remaining shelf-life days displayed in each round, and the remaining shelf-life changes each round (Table 1). Age_i, *smellmilk* and sig_issue_i are control variables that we include based on the ANOVA results previously presented. The treatment interaction terms ($Treatment_i*SL_{ij}$ and $Treatment*SLSq_{ij}$) are used to test whether either information treatment has an effect on consumers' valuation on remaining shelf-life attribute and square of remaining shelf-life, respectively.

To control for individual heterogeneity more effectively, we leverage the panel structure of our data and estimate a one-way fixed effects model to as well. The model is specified as

$$WTP_{ij} = \alpha + \zeta_i + \beta_1 SL_{ij} + \beta_2 SLSq_{ij} + \varepsilon_{ij}$$

where ζ_i is an individual fixed effect that absorbs any static individual-level characteristics, including $Treatment_i$.

The lower bound of allowed bids in each auction round is restricted to $0, and subjects were instructed to enter a bid of $0 if they had no interest in buying the fluid milk product. Therefore, our bid data is subject to left censoring at 0. A Tobit model is commonly used to estimate a linear relationship when the response variable is left- or right-censored. In our data, a total of 280 $0 bids were observed, indicating that 22% of the observations are left-censored at 0. We therefore estimate a series of Tobit model to recover $WTP_{ij}*$, the true value of WTP_{ij} in the case that there are no limits on bids. The variable $WTP_{ij}*$ is formulated as:

$$WTP_{ij}^{*} = X\beta + \varepsilon_{ij}$$

$$WTP_{ij} = \min\left(WTP_{ij}^{*}, 0\right)\ if\ WTP_{ij}^{*} > 0$$

$$WTP_{ij} = 0\ if\ WTP_{ij}^{*}\ < 0$$

In the model, X is the same vector of independent variables which are specified in the baseline OLS specification, β is the vector of coefficients and ε_{ij} is the normally distributed random error term with mean zero. The response variable is observable for the submitted bids of $0 or greater. To test for heterogeneous treatment effects, we also estimate a specification with fully saturated interaction effects between the treatment indicators and control, and we conduct a subsample analysis by estimating a separate model for observations in each treatment group.

Table 4: Multiple Regression Analysis of Consumer WTP

Variable	**(1) OLS model**	**(2) Fixed Effect model**	**(3) Tobit model 1**	**(4) Tobit model 2**
Constant	0.634*** (0.168)		-0.232 (0.219)	-1.887*** (0.393)
SL	0.234*** (0.033)	0.241*** (0.011)	0.372*** (0.372)	0.372*** (0.042)
SLSq	-0.007*** (0.002)	-0.007*** (0.001)	-0.012*** (0.002)	-0.012*** (0.002)
Treatment General	0.326* (0.157)		0.494* (0.209)	2.055*** (0.482)
Treatment Personal	0.379* (0.156)		0.647** (0.207)	3.020*** (0.460)
Age	0.005 (0.003)		0.007* (0.003)	0.013* (0.006)
smellmilk	-0.002 (0.039)		0.023 (0.048)	0.541*** (0.150)
sig_issue	-0.290*** (0.043)		-0.316*** (0.053)	0.190 (0.098)
Treatment General:SL	-0.019 (0.046)		-0.048 (0.059)	-0.051 (0.058)
Treatment Personal:SL	0.044 (0.046)		0.009 (0.058)	0.007 (0.057)
Treatment General:SLSq	0.000 (0.003)		0.002 (0.003)	0.002 (0.003)
Treatment Personal:SLSq	-0.002 (0.003)		-0.000 (0.003)	-0.000 (0.003)
Treatment General:Age				0.001 (0.008)
Treatment Personal:Age				-0.021* (0.009)

Treatment General:smellmilk				-0.418* (0.169)
Treatment Personal:smellmilk				-0.591*** (0.165)
Treatment General:sig_issue				-0.686*** (0.139)
Treatment Personal:sig_issue				-0.670 (0.128)
N	1,268	1,268	1,268	1,268

Notes: Control group is the excluded treatment level. *** P ≤ 0.01; ** P ≤ 0.05; * P ≤ 0.1. Each column represents a separate regression. For OLS and fixed effects models, robust standard errors are calculated. For Tobit models, standards errors are clustered at the individual level.

Table 5: Tobit model with lower limit of $0 by treatment group subsample

Variable	**Control**	**TreatmentGeneral**	**TreatmentPersonal**
Constant	**-1.778*** (0.368)	0.259 (0.254)	**1.068*** (0.275)
SL	**0.362*** (0.039)	**0.309*** (0.036)	**0.395*** (0.045)
SLSq	**-0.012*** (0.002)	**-0.010*** (0.002)	**-0.013*** (0.002)
Age	**0.013*** (0.005)	**0.014**** (0.005)	-0.008 (0.008)
smellmilk	**0.527***** (0.139)	0.125 (0.071)	-0.043 (0.079)
sig_issue	**0.183*** (0.091)	**-0.498***** (0.089)	**-0.490***** (0.094)
N	413	423	432

Notes: *** P ≤ 0.01; ** P ≤ 0.05; * P ≤ 0.1. Standard errors clustered at the individual level in parentheses.

Table 4 reveals consistent positive marginal WTP for an additional day of shelf life as well as positive effects for sharing information about food waste on consumer WTP. In the OLS model (Table 4, Column 1), the coefficient of SL is 0.234 (p<0.01), indicating that with one more day remaining shelf-life, consumer WTP increases by about \$0.23. The coefficients for the general and personal information treatment are 0.326 ($p< 0.1$) and 0.379 ($p<0.1$), respectively, which indicates provision of general or personal information on food waste are both associated with a higher consumer WTP for a half gallon of dairy milk. Notably, the personal information treatment is slightly more powerful than general information treatment, resulting in about \$0.05 in additional WTP. However, we do not find that providing either type of information on food waste changes marginal WTP for an additional day of shelf life, as indicated by the lack of statistically significant estimates for the treatment interaction terms.

The results of fixed effect model (Table 4, Column 2), the estimated coefficients for SL and *SLSq* are 0.241 ($p< 0.01$) and -0.007 ($p< 0.01$, respectively., indicating that one more day of remaining shelf-life increases consumer WTP by \$0.241 for a half gallon of fluid milk. The negative coefficient of SLSq provides evidence of decreasing marginal utility of remaining shelf-life.

Comparing the baseline OLS estimates (Table 4, Column 1) to the analogous Tobit results (Table 4, Column 3), the estimates for TreatmentGeneral, TreatmentPersonal, SL and SLSq remain statistically significant when we control for left censoring of bids. Unsurprisingly, the point estimates in the Tobit model are larger in magnitude, thus indicating a greater marginal effect of the significant factors after controlling for left censoring. Based on the results of Tobit model, both information treatments result higher consumer WTP for fluid milk, with general information group participants paying \$0.494 ($p<0.1$) more on average, and personal information group participants paying \$0.647 ($p<0.05$) more on average. The more positive effect of personal information treatment is consistent with the results in OLS model, suggesting that personal information on food waste is more powerful for changing consumer WTP for fluid milk. The lack of any statistically significant statistic treatment interaction terms in the Tobit model is consistent with the OLS model, once again indicating that providing information on food waste does not affect consumer WTP for an additional day of shelf life in fluid milk.

To test for heterogeneous treatment effects, we estimate a fully saturated Tobit interaction model (Table 4, Column 4) along with separate Tobit models in which the sample is restricted to each of the three treatment groups (Table 5). Our results from these models suggest that the treatment effects exhibit some heterogeneity over the sample based on some statistically significant estimates for the interaction terms between treatment and the control variables (Table 4, Column 4). In particular, we find statistically significant estimates for the interaction terms between the personal information treatment and *age* and *smellmilk*, as well as between the general information treatment and *smellmilk* and *sig_issue*, suggesting that the treatment may have differing effects for subjects with specific characteristics. Furthermore, the differences between the estimated coefficients for *SL* and *SLSq* across the three subsample groups (Table 5) suggest that WTP for shelf life may differ slightly across the three treatments.

Discussion

The results of the baseline OLS model, the fixed effects model, and the full sample Tobit models (Table 4) provide valuable insights into consumers' marginal WTP for additional shelf life for fluid milk products. In short, subjects tend to place more value on fluid milk with longer remaining shelf-life, and the finding of diminishing marginal value of shelf-life is consistent in all three models, indicating that that consumers place higher value on remaining shelf-life in a decreasing way.

Summarizing the results of OLS model and Tobit models, the effect of general and personal information treatments about food waste on consumer's valuation on fluid milk is robust and economically meaningful. By providing information about milk waste and the environmental damage, economic loss, and ethical problems it triggers, consumers tend to pay more for fluid milk. Furthermore, personal information about milk waste is more powerful than general information, which may be due to the fact that individual information is more relatable and therefore has more influence on consumer behavior.

STUDY 2

Materials and Methods

The milk we chose for our study was half-gallon (1.89 L) Cornell Dairy Milk as it was the same milk used in the previous lab study to determine the consumer willingness to pay. This consistency is required as the consumers are only willing to pay the price used in this study for brands known for high quality milk such as Cornell Dairy.

We decided to categorize the shelf lives of the milk into three groups- High Shelf-Life milk, Medium Shelf-Life milk, and Low Shelf-Life milk. From the previous study's information, we determined that High Shelf-Life Milk could be sold at a premium price at $3.39.

For Medium Shelf-Life Milk, it could be at the price it is normally sold as at $2.59. For a Low Shelf-Life Milk, it could be at a discounted price at $1.39 per half gallon milk carton.

Milk Shelf Life and Milk Type

We chose to observe all the three types of dairy milk being sold by Cornell Dairy. These were- Whole milk, Reduced (2%) milk, and Fat-Free (Skim) milk. The high shelf-life milk had a shelf-life range of 21 to 8 days. The medium shelf-life milk had shelf-life range of 7 to 4 days. The low shelf-life milk had a shelf-life range of 3 to 0 days.

Milk Sample Preparation

We processed the milk fresh at the Cornell dairy plant. Then we manipulated the best before dates, such that we always had all the three types of shelf-life milks available on the shelf during the study. To help us track the different shelf-life milks and implement dynamic pricing, we had three different Universal Product Code of high, medium, low shelf-life milk. For example, we set and used barcode with UPC number ending with 253 for low shelf life, 252 for medium shelf life, and 231 for high shelf-life milk. With unique UPCs for the three shelf-life categories of milk, we were able to program dynamic pricing in the store’s system. Despite these adjustments, it's critical to note that all milk remained fresh, with the manipulation serving solely to investigate consumer perceptions and purchasing decisions.

To ensure that the consumers were aware of the shelf life of the milk, we placed round color-coded stickers prominently on the top left corner. These stickers indicated shelf-life status: blue for high shelf life stating, "8 to 21 Days Remaining", green for medium shelf life stating, "4 to 7 Days Remaining", and purple for low shelf life stating, "0 to 3 Days Remaining".

Retail Execution

We conducted this study at a medium sized traditional retail grocery store based in Ithaca. We performed this study from September 12, 2023, to September 25, 2023, where we expected a traditional year-round consumer behavior. We checked that these dates did not coincide with any major holidays or college events.

We placed the milk strategically on the middle shelf to ensure optimal visibility and access, surrounded by other dairy products for a conventional shopping experience. During the first week, a uniform price of $2.59 per unit was maintained for all milk variants to establish a baseline for consumer behavior. In the following week, we introduced dynamic pricing—$3.39 for High shelf-life milk, $2.59 for Medium, and $1.39 for Low shelf-life milk. (Figure 6)

We also displayed an informational sign, measuring 21 7/8" wide by 27 7/8" high, to detail the study's objectives and encourage thoughtful selection based on individual needs to aid in reducing food waste. (Appendix B, Figure 1)

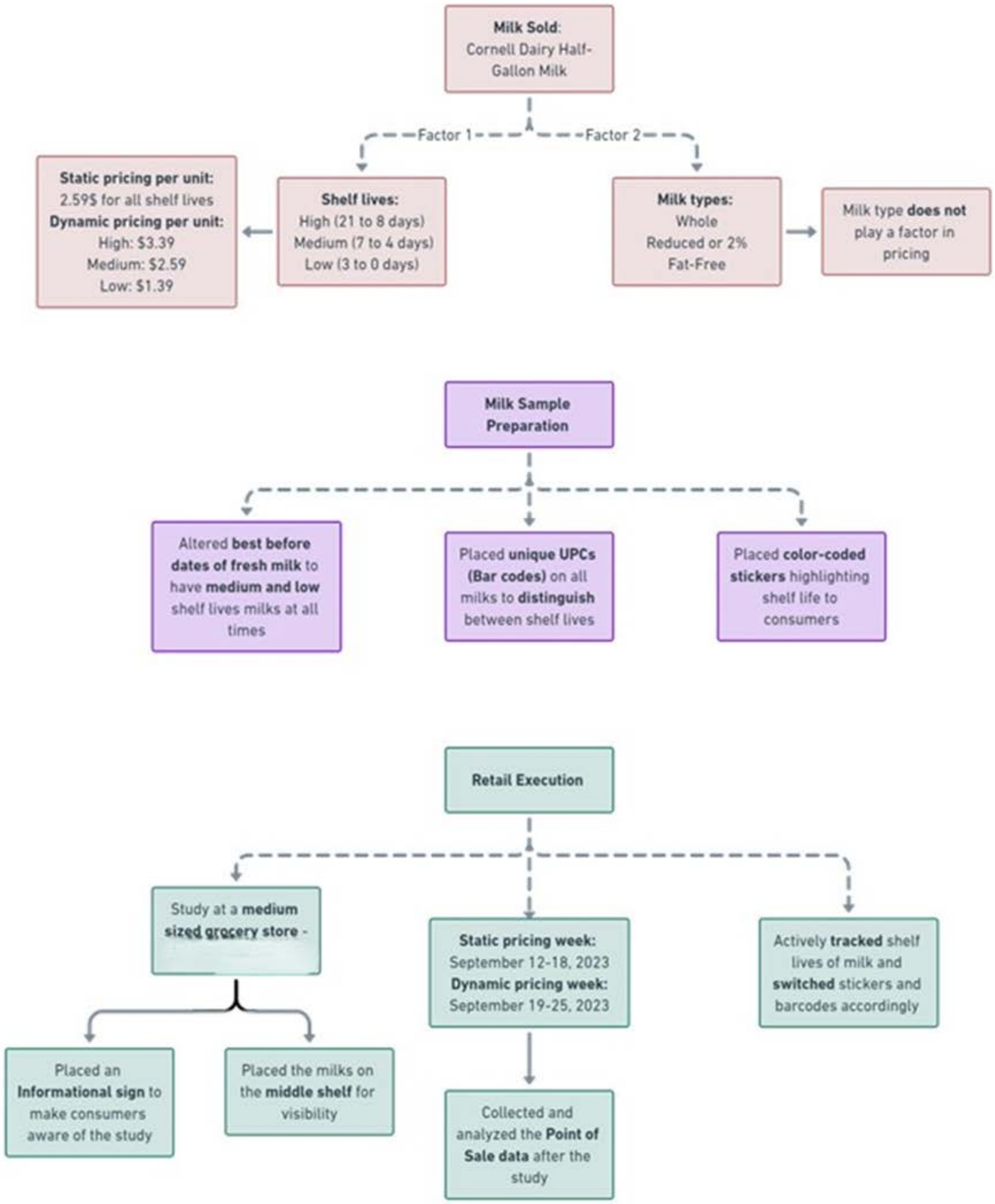


Figure 6: Flow diagram with planning and execution of the study to evaluate the dynamic pricing model in retail environment.

Statistical Analysis:

We collected the point-of-sale data from the retailers, where the dataset encompassed sales from the study period and two weeks prior (8/29/2023 to 9/11/2023). We primarily used the UPC label data to distinguish between different shelf life and milk type products. The data was collected in .csv format and we it cleaned using Microsoft Excel (Microsoft Corp., Redmond, WA) to be fit for data wrangling in R. We used the R language (version 4.2.1) with RStudio (Build 494) as the integrated development environment to analyze the data.

We conducted an Analysis of Variance (ANOVA) to examine the influence of factors such as milk type, shelf life, and week effect (static vs dynamic pricing) on sales volume and revenue. Post hoc testing with estimated marginal means further explored significant differences in consumer behavior.

Results

Impact of the study the overall consumer purchasing behavior

We performed a 2-week study in a medium-sized traditional retail grocery store where we observed the change in consumer behavior when the classical static pricing model of fluid milk (Week 1) was replaced with a dynamic pricing model (Week 2). Preliminary analysis comparing study data with two additional sets of data were performed to confirm the 2-week study design did not influence consumers overall purchase behavior; (i) sold units recorded one year prior to the study capturing the same time duration and time period in the year (Appendix C, Table 1), and (ii) units sold recorded two weeks prior to the study capturing the same time duration (Appendix C, Table 2). Analysis of variance showed no significant difference in units sold between the year when the study was conducted and the same period 1 year prior ($p = 0.375$). Similar results were also obtained when units sold during the 2 weeks of the study were compared to units sold during 2 weeks prior ($p = 0.293$).

Impact of dynamic pricing on the overall consumer purchasing behavior

During the two weeks of the study, there were no significant differences found (p=0.456-Table 6) in number of milk units sold during Week 1 (static pricing model) compared to Week 2 (dynamic pricing model); there were 50.14 and 54.29 total units per day sold (including all milk types and shelf lives) during Week 1 and 2, respectively. This is an 8.2% increase in the number of units sold per day. Transition from static to dynamic pricing model resulted in a significant increase in overall sales (p=0.0084); the average sales of $ 129.87 per day in Week 1 was increased to $153.79 per day in Week 2 (Figure 7B). This difference of $23.92 per day represents an increase of 18.4% increase in revenue per day.

Impact of dynamic pricing on the shelf-life based pricing

During Week 1 when the static pricing model was used, the highest number of units sold across all three fat levels was milk with the highest remaining shelf-life (i.e., High, 21-8 days). On average there were 38.00 units of milk with this shelf-life sold every day during Week 1 (Figure 7A). The lowest average number of units sold (3.00 per day) was represented by milk with the lowest shelf-life left (i.e., Low 3-0 days) while milk with medium shelf-life left (i.e., Medium 7-4 days) sold on average 9.14 units per day. While consumers preference for milk with the highest shelf-life remained in Week 2 when dynamic pricing model was implemented, the number of units sold per day during this period was significantly reduced (27.86 units per day; p=0.0001). This partial shift in consumer preference resulted in a significant increase (p=0.002) in units of milk with medium and low shelf-life that were sold; 18.86 and 7.57 units per day, respectively. This supports the notion that switching static pricing model for a dynamic one would result in higher sales of product that has lower shelf-life left and is more likely to be wasted.

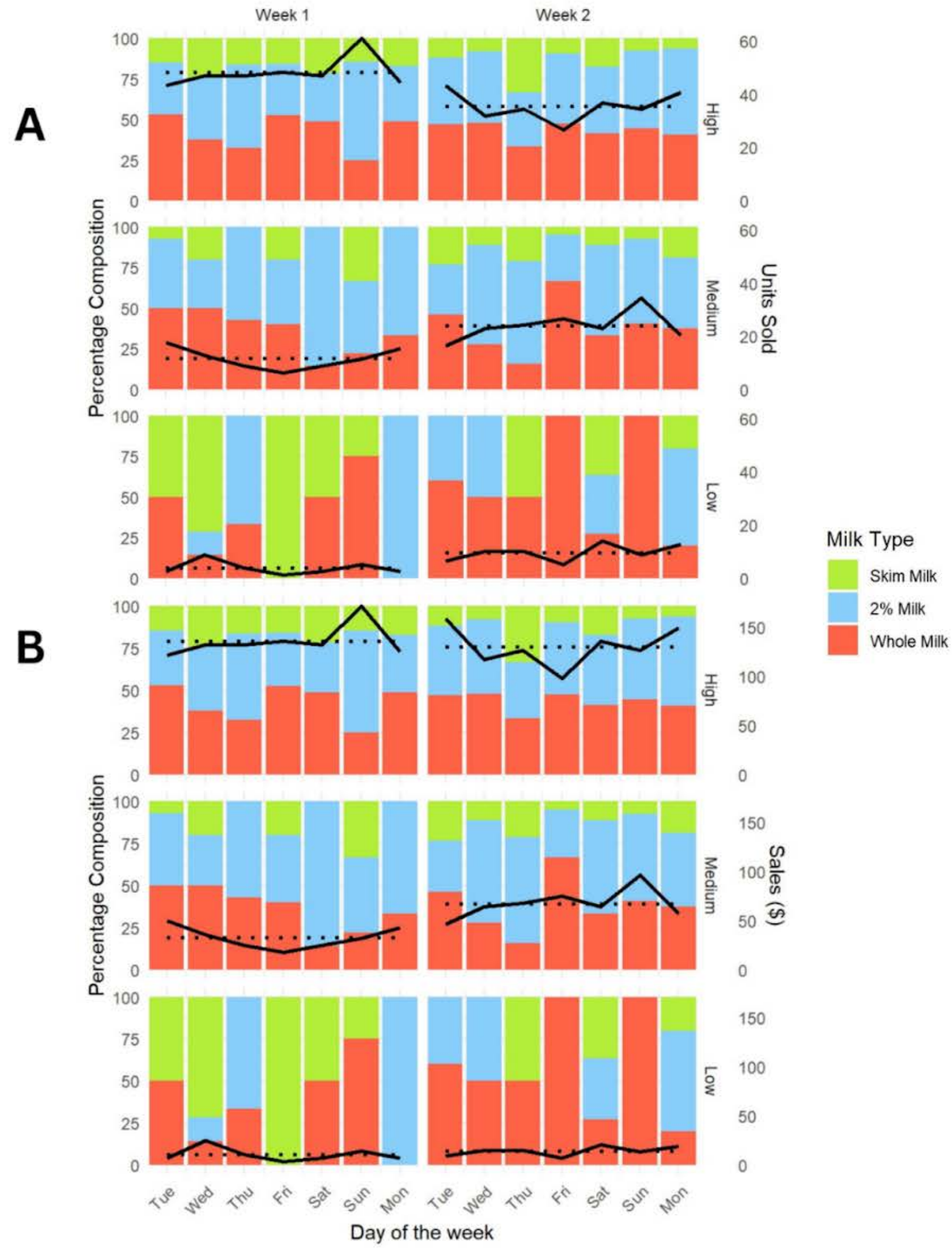


Figure 7: Fluid milk sales over 2-week study separated by number of units sold, sales, shelf-life category, and milk fat level. Red bars represent whole milk, blue bar reduced 2% milk, and green bars represent skim milk (primary y-axis). Black solid line represents the total amount and the dotted line the average amount (secondary y-axis).

Impact of dynamic pricing on the milk type choice

During both weeks of the study, fat-free milk represented the milk type with the lowest number of units sold and on average represented 17.9% and 13.95% of all units sold, respectively during Week 1 and Week 2 (Figure 7A). Reduced-fat milk represented the milk type with the highest number of units sold during both weeks, and it was comparable to units of whole-fat milk sold; reduced-fat milk represented 41.59% and 43.42% of total units sold and whole-fat milk 40.45% and 42.63%, respectively during Week 1 and Week 2.

These percentages can be quantified as the fat-free milk was sold by an average of 3.00 units per day during Week 1 and then saw a decrease to 2.52 units sold per day during Week 2. The milk sold the highest, reduced fat milk was sold by an average of 6.95 units per day during Week 1 and then saw an increase to 7.86 units sold per day during Week 2. Comparably, whole fat milk was sold on an average of 6.76 units per day during Week 1 and then saw an increase to 7.71 units sold per day during Week 2. (Appendix B, Figure 2)

While there was an increase in units sold generally in the dynamic pricing week, we also observed an overall increase in daily sales across the milk types.

The average sales of fat-free milk were 7.77 $ per day during Week 1 and then saw a decrease to 6.95 $ per day during week 2. The milk sold the highest reduced fat milk had the sales of an average of $ 18.00 per day during Week 1 and then saw an increase to 22.67 $ per day during Week 2. Comparably, whole fat milk had the sales of 17.51 $ per day during Week 1 and then saw an increase to 21.64 $ per day during Week 2. (Appendix B, Figure 2)

The increase in daily sales during Week 2 (dynamic pricing week) was used to calculate the average revenue obtained per each unit sold during the experiment. Averaging over the prices per unit of high, medium and low shelf-life milks, we saw an increase of $0.29, $0.25, and 0.21

per unit was identified for reduced-fat, whole-fat, and fat-free milk, respectively (Appendix B, Figure 3).

Factors affecting the sales of fluid milk during the study

To determine the factors that significantly contributed to the number of milk units sold and corresponding sales, we performed an analysis of variance test (Table 6). The result of the test indicates that both milk-fat level and shelf-life of the product are significantly impacting the number of milk units sold and the sales that are resulting from it ($p<0.0001$). Although variations in the number of units sold from day to day can be observed, overall, the association between day of the week and units sold or sales is not significant ($p<0.800$). Similarly, the pricing model used (i.e. static, dynamic) was also found to not be significantly associated with the milk units sold ($p=0.864$) or sales ($p=0.0982$). This supports the notion that switching static pricing model for a dynamic one would revenue-neutral switch and have no negative impact on the retailer.

Table 6: Association between units of milk sold or sales and the product characteristics (i.e., milk fat level, shelf life, pricing model applied, day of the week, and relevant interactions)

Variable	Df[9]	Sum Sq[10]	Mean Sq[11]	F-statistic[12]	P-value[13]
Units[1]					
Milk Type[3]	2	582.7	291.3	29.38	<0.0001***
Shelf Life[4]	2	1864.1	932.1	93.99	<0.0001***
Pricing Model[5]	1	6.7	6.7	0.673	0.414
Day[6]	6	30.1	5.0	0.506	0.803
Pricing Model x Shelf Life[7]	2	247.8	123.9	12.50	<0.001***
Pricing Model x Shelf Life x Milk Type[8]	4	18.2	4.5	0.615	0.653
Residuals	112	1110.7	9.9		
Sales[2]					
Milk Type[3]	2	4454	2227	29.03	<0.0001***
Shelf Life[4]	2	18625	9312	121.4	<0.0001***
Pricing Model[5]	1	223	223	2.904	0.0911
Day[6]	6	207	35	0.451	0.8431
Pricing Model x Shelf Life[7]	2	543	272	3.542	0.0323*
Pricing Model x Shelf Life x Milk Type[8]	4	26	6	0.125	0.9733
Residuals	112	8589	77		

[1]Number of half-gallon milk units sold (Dependent Variable)
[2]Sales in $ generated from units sold (Dependent Variable)
[3] Milk fat level (Whole, Reduced 2% and Skim)
[4] Shelf-life of milk (High 21-8 days, Medium 7-4 days, and Low 3-0 days)
[5] Pricing model applied (Static, Dynamic pricing model)
[6] Day of the week
[7] Interaction between the pricing model and shelf life of the milk
[8] The Interaction between the pricing model, shelf life, and the milk type of the milk
[9] Degrees of freedom
[10] Explanatory Variable Sums of Squares/Residual Sum of Squares
[11] Explanatory Variable Mean Sums of Squares/Residual Mean Sum of Squares
[12] F-statistic for ratio of variances.
[13] P-value for ratio of variances (* P<0.05, ** P<0.001, *** P<0.0001).

Impact of dynamic pricing on the overall number of units sold and sales

We conducted an estimated marginal means test, based on the analysis of variance results to understand how the three shelf-life groups were associated with the number units sold under different pricing models (Appendix C, Table 3).

We found that there was a significant decrease in the number of units of milk with high shelf-life when switching from static to dynamic pricing ($p = 0.0001$). The number of units sold increased for both milk with medium and low shelf-life left. There was a significant increase in the number of units sold for medium shelf-life ($p=0.0002$) while the increase for low shelf-life was not found to be significant ($p = 0.072$). To quantify these shifts, we saw a 26.7% decrease in units sold of high shelf-life milk and observed an 117.5% increase in units sold of medium and low shelf-life milks. (Figure 7A)

Similarly, we found that there was a non-significant decrease ($p = 0.57$) in the sales of milk with high shelf-life and a significant increase in milk with medium shelf-life left ($p=0.0006$) when dynamic pricing model was introduced. The sales of medium-shelf-life milk from week 1 to week 2. ($p = 0.0006$), and there was an increase in sales of low-shelf-life milk from week 1 to week 2 but was not significant ($p = 0.69$). To quantify these shifts, we saw a 4% decrease in sales of high shelf-life milk and observed an 88% increase in sales of medium and low shelf-life milks. **(**Figure 7B)

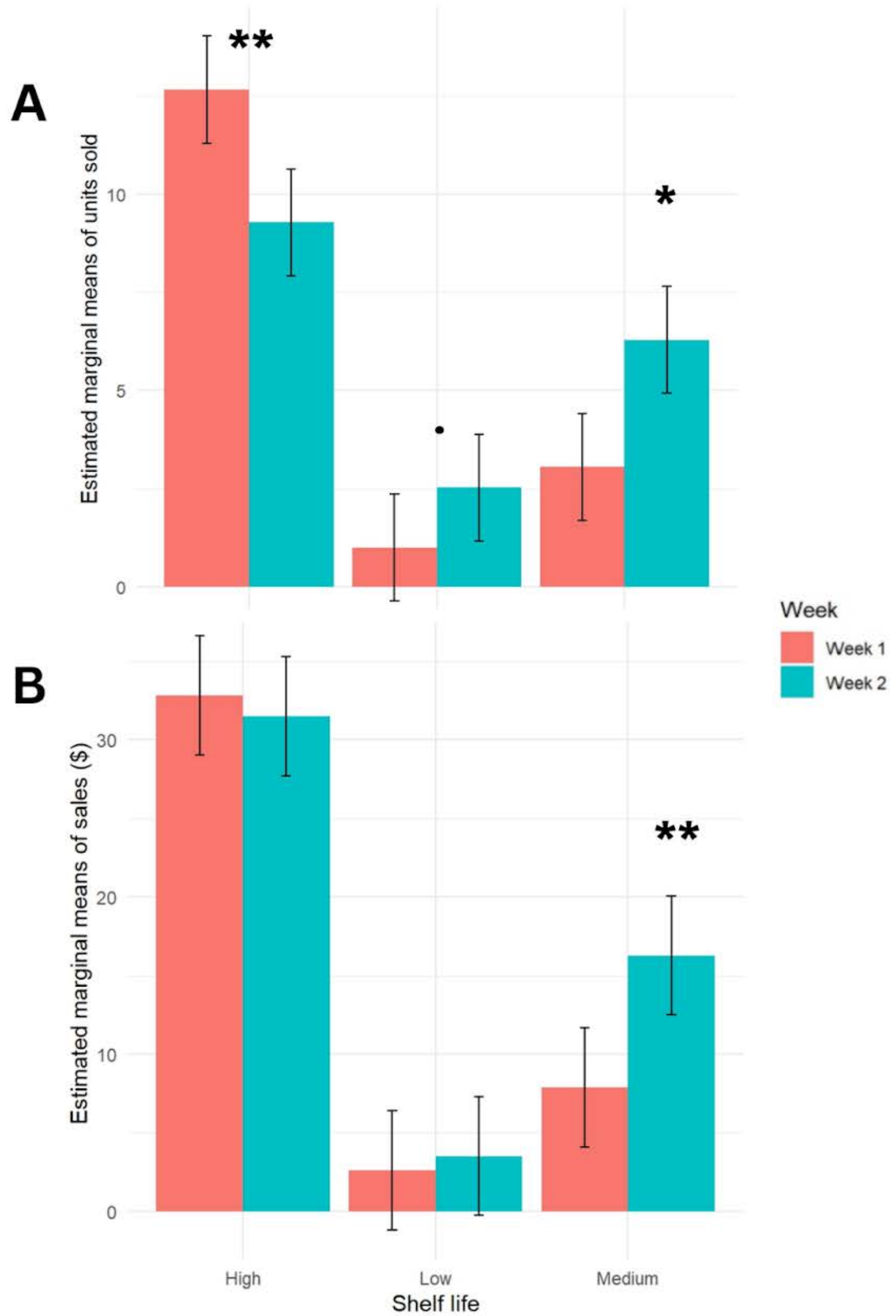


Figure 8: The estimated marginal means table's graphical visualization of units sold and sales for the three types of shelf lives based on the week with static pricing (week 1) vs dynamic pricing (week 2). The level of significance is shown on the graph, where P-value for ratio of variances (**.** P<0.1, * P<0.05, ** P<0.001, *** P<0.0001).

Discussion

The dynamic pricing model explored in this study demonstrates significant potential to influence consumer purchasing behaviors while maintaining robust overall sales. These findings suggest shifts across various consumer preferences and economic outcomes, highlighting the complexity and effectiveness of dynamic pricing strategies.

The implementation of shelf-life based dynamic pricing does not affect overall consumer demand for fluid milk and the factors that govern consumer preferences.

We observed that there was no significant difference observed in milk units sold (p=0.864) or sales (p=0.0982) between static and dynamic pricing models. This indicates that while dynamic pricing did alter the distribution of sales across different shelf lives, it did not impact the overall volume of milk purchased. This neutrality in demand response suggests that consumers may be relatively insensitive to price changes within the range tested, or that other factors such as product visibility or consumer loyalty to certain types may override price considerations.

Moreover, despite a partial shift in consumer preference from milk with higher shelf-life to those with medium or lower shelf-lives, high shelf-life milk remained the most preferred. This aligns with findings by P. Endara et al. (2023), who noted that milk purchase decisions are strongly influenced by shelf-life, with consumers consistently favoring fresher milk despite price variations. While dynamic pricing did not significantly alter the overall volume of milk purchased, it effectively guided consumer preferences in a positive direction. This suggests that dynamic pricing, when strategically implemented, can enhance consumer responsiveness to price variations, particularly with perishable products. The subtle yet positive shift towards lower shelf-life products underscores the potential of dynamic pricing not only as a tool for adjusting consumer buying patterns but also to promote sustainability.

Implementing dynamic pricing model partially but uniformly shifts consumers preference from milk with highest shelf-life to the milk with lower shelf-life.

In this study we observed that there was a significant decrease in the number of units of milk with high shelf-life when switching from static to dynamic pricing ($p = 0.0001$). The number of units sold increased for both milk with medium and low shelf-life left. There was a significant increase in the number of units sold for medium shelf-life ($p=0.0002$) while there was a weak increase for low shelf milk products ($p = 0.072$). To quantify these shifts, we saw a 26.7% decrease in units sold of high shelf-life milk and observed an 117.5% increase in units sold of medium and low shelf-life milks. We saw a uniform shifting of milk purchase across milk types as we shifted from static to dynamic pricing across the shelf life. types ($p = 0.653$). This means that there were less consumers that switched/ gravitated towards one particular milk type due to dynamic pricing and shelf-life categorization.

Consistent with our observations of increased purchases of milk with lower shelf lives, studies in behavioral economics suggest that consumers are often driven by perceived savings and urgency, which dynamic pricing can effectively create. This reaction is particularly pronounced in perishable goods, where the imminent risk of product spoilage adds a time-sensitive component to purchasing decisions. For example, Ellickson and Misra (2008) found that consumers are more likely to purchase perishable items at discounted rates as the expiration date approaches, which they attribute to the incentive of cost savings and minimizing waste.

The substantial increase in purchases of milk with medium and low shelf lives not only demonstrates a successful shift in consumer behavior but also sets the stage for evaluating the economic impact of dynamic pricing. The observed flexibility in consumer purchasing preferences, as they respond to price adjustments, suggests that dynamic pricing strategies can be effectively leveraged not just for reducing waste but also for enhancing retailer revenue streams. This adjustment in consumer behavior, which aligns with our strategic price reductions, inherently supports a more sustainable consumption pattern and highlights the dual benefit of dynamic pricing—reducing waste while enhancing economic returns.

Implementing dynamic pricing model weakly improves retailer revenue from fluid milk sales.

During our study we observed an increase in units sold which corresponded to an average of 8.2% and resulted in an 18.42% increase in average sales. The changes in units sold during the experiment were also reflected in the overall sales. Transition from static to dynamic pricing model resulted in a significant increase in overall sales ($p=0.0084$); the average sales of $ 129.87 per day in Week 1 was increased to $153.79 per day in Week 2 (Figure 7B). This difference of $23.92 per day represents an increase of 18.4% in overall sales of milk. The sales of medium-shelf-life milk from week 1 to week 2. ($p = 0.0006$), and there was an increase in sales of low-shelf-life milk from week 1 to week 2 but was not significant ($p = 0.69$). To quantify these shifts, we saw a 4% decrease in sales of high shelf-life milk and observed an 88% increase in sales of medium and low shelf-life milks. (Figure 7B) This aligns with findings from a study on perishable food, specifically strawberries, where dynamic pricing significantly impacted sales and waste reduction (Scholz & Kulko, 2022). The study demonstrated that food waste could be reduced by up to 53.6%, and revenue could be increased by up to 10% when shifting from static to dynamic pricing strategies. This suggests that dynamic pricing not only increases retailer revenue but also contributes to food waste reduction and more sustainable business practices by partially shifting the sales from product with higher shelf-life to product with less shelf-life left.

GENERAL DISCUSSION

Study 1 provides insights on the effect of providing industry-wide information or individual-related information about food waste on consumer WTP for fluid milk products. In the general information treatment, subjects are informed of overall food waste situation in the US, as well as its contribution to environmental damage, financial loss, and ethical problems at a national level. In the personal information treatment, subjects are provided with information on average household milk waste per year and the damages that causes. The positive coefficients we estimate for the both treatments imply that information on food waste shifts consumer WTP, and the larger coefficient for the personal information treatment suggests that individual-related information has a greater impact on consumer demand. Lastly, we also test whether providing information on food waste affects consumer WTP for remaining shelf-life and find not significant relationship.

Our findings have important implications for industry and also suggest several opportunities for future research. Given that consumers do place more value on fluid milk with longer remaining shelf-life, retailers could consider a premium price for milk with long remaining shelf-life and a discount on milk nearing its label date, rather than using the same static price for fluid milk regardless of remaining shelf life. In addition, the decreasing marginal effect of remaining shelf-life points to some nuances that such a pricing model might need to address. Implementing shelf-life based pricing in fluid milk industry may contribute to increased profits for retailers and a better match between milk products and consumer demand. Accordingly, further research is needed to explore shelf-life based pricing under two constraints: (1) retailer profits should not decrease; and (2) Consumer-level milk waste should not increase.

With regards to Study 2, investigating the long-term impacts of dynamic pricing on sales, consumer behavior, and waste reduction would provide deeper insights into its sustainability as a business practice. Long-term studies could assess whether dynamic pricing leads to significant changes in consumer purchase patterns over time and how it affects retailer profitability in the long run. To ensure that reduced waste at the retail level does not simply translate to increased waste at the consumer level, future studies should track what happens to products with shorter shelf lives once purchased. This research could involve follow-ups with consumers to determine how much of the perishable goods they buy are actually consumed versus thrown away. This would help verify the true effectiveness of dynamic pricing in reducing overall food waste. Expanding research to include different product categories beyond dairy, such as produce or baked goods, and different retail settings, from small local stores to large supermarkets, could help determine the versatility and adaptability of dynamic pricing models. This could also include testing in various geographic and economic contexts to see how socio-economic factors influence the effectiveness of dynamic pricing.

Future research could explore the integration of advanced digital price tags that automatically adjust prices based on the shelf-life of products. This would require advancements in point-of-sale (POS) systems to seamlessly manage these adjustments. Such technology could enable real-time pricing updates, making the dynamic pricing model more responsive and easier to manage at the retail level. There can also be adjustments in packaging at the dairy processing level, such as integrating smart barcodes or RFID (Radio Frequency Identification) tags that reflect the shelf-life status, could significantly facilitate the implementation of dynamic pricing. These innovations would allow retailers to automatically adjust prices based on the information encoded in the packaging, reducing manual input, and enhancing accuracy in pricing perishable products. With the rise of AR (Augmented Reality) technology, there is potential to use AR glasses in retail environments to display dynamic pricing information directly to consumers as they shop. This could include not only price but also detailed product information like shelf-life and nutritional content. AR integration could enhance the shopping experience, making it more interactive and informative, which may encourage consumers to make more conscious purchasing decisions aligned with sustainability goals.

Study Limitations

There are several limitations of Study 1 that also provide opportunities for future work. First, the econometric analysis only introduces a quadratic term for shelf-life, which may not optimally characterize the relationship between consumer WTP and remaining shelf-life. Second, in this study subjects were financially compensated to make bid decisions about a retail food product in controlled lab conditions, which does not mimic a traditional retail setting. It is possible that some subjects may care more about the monetary benefits and fail to carefully consider the information we provided, thereby leading biased results from inefficiency in information delivery.

Similarly, Study 1 limitations include constrained sample size, duration, and geographic specificity. The research was conducted within a limited timeframe at a singular retail location, which may not adequately represent broader consumer behavior patterns that evolve over extended periods or across different seasons. Short-duration studies often fail to capture longitudinal trends and seasonal variations that significantly influence purchasing behaviors. Moreover, the geographic restriction to one retail setting limits the generalizability of our findings. Consumer behaviors and preferences can vary widely across different regions due to cultural, economic, and demographic factors. Consequently, the applicability of our conclusions might be limited to similar contexts and may not extend to other settings without further validation. Future research could address these limitations by incorporating a larger sample size, extending the study duration, and diversifying the geographic locations involved. This would improve the reliability and applicability of the data, providing a more comprehensive analysis of dynamic pricing's effectiveness across varied retail environments

REFERENCES

Becerra, P., Mula, J. and Sanchis, R., 2021. Green supply chain quantitative models for sustainable inventory management: A review. *Journal of Cleaner Production*, 328, pp.1-16.

Bernard, J. and Bernard, D., 2009. What Is It About Organic Milk? An Experimental Analysis, American *Journal of Agricultural Economics*, 91(3), pp.826-836.

Berry, J., Fischer, G. and Guiteras, R., 2020. Eliciting and Utilizing Willingness to Pay: Evidence from Field Trials in Northern Ghana. *Journal of Political Economy*, 128(4), pp.1436-1473.

Blackburn, J. and Scudder, G., 2009. Supply Chain Strategies for Perishable Products: The Case of Fresh Produce, *Production and Operations Management*, 18(2), pp.129-137.

Bohm, P., Lindén, J. and Sonnegård, J., 1997. Eliciting Reservation Prices: Becker–DEGroot–Marschak Mechanisms *vs.* Markets. *The Economic Journal*, 107(443), pp.1079-1089.

Buzby, J., Farah-Wells, H. and Hyman, J., 2014. The Estimated Amount, Value, and Calories of Postharvest Food Losses at the Retail and Consumer Levels in the United States, *USDA-ERS Economic information Bulletin*, 121.

Campbell, C. and Feldpausch, G., 2022. Invited review: The consumer and dairy food waste: An individual plus policy, systems, and environmental perspective, *Journal of Dairy Science*, 105(5), pp.3736-3745.

Canning, P., Charles, A., Huang, S., Polenske, K. and Waters, A., 2010. Energy use in the US food system, *USDA Economic Research Report*, 94.

CEC. 2017. Characterization and management of food loss and waste in North America, 289. Montreal, Canada: Commission for Environmental Cooperation.Cecchi, F., P. Traverso, P. Pavan, D. Bolzonella, and L. Innocenti. 2002. Characteristics of the OFMSW and behavior of the anaerobic digestion process. ChemInform 34. doi:10.1002/chin.200313272.JOURNAL OF THE AIR & WASTE MANAGEMENT ASSOCIATION629

Collart, A. and Interis, M., 2018. Consumer Imperfect Information in the Market for Expired and Nearly Expired Foods and Implications for Reducing Food Waste. *Sustainability*, 10(11), pp.1-17.

D'Amato, A., Goeschl, T., Lorè, L. and Zoli, M., 2023. True to type? EU-style date marking and the valuation of perishable food, *Food Policy,* 114, pp.1-15.

Entrup, M., 2005. Advanced Planning in Fresh Food Industries: Integrating Shelf Life into Production Planning, 1 edn, Springer, Dordrecht.

Fauza, G., Amer, Y., Lee, S. and Prasetyo, H., 2015. A Vendor-Buyer Inventory Model for Food Products Based on Shelf-Life Pricing, *OSCM Publications*, 8(2), pp.68-73.

Gao, D., 2019. Food Loss and Waste; Building on Existing Federal Efforts Could Help to Achieve National Reduction Goal, GAO-19-391 United States Government Accountability Office: Washington, DC, USA, 2019; pp. 1–47.

Gao, Z., Amer and Schroeder, T., 2009. Effects of Label Information on Consumer Willingness-to-Pay for Food Attributes. *American Journal of Agricultural Economics*, 91(3), pp.795-809.

Gerini, F., Alfnes, F. and Schjøll, A., 2016. Organic- and Animal Welfare-labelled Eggs: Competing for the Same Consumers? *Journal of Agricultural Economics*, 67(2), pp.471-490.

Godfray, H., Beddington, J., Crute, I., Haddad, L., Lawrence, D., Muir, J., Pretty, J., Robinson, S., Thomas, S. and Toulmin, C., 2010. Food Security: The Challenge of Feeding 9 Billion People. *Science*, 327(5967), pp.812-818.

Gunders, D. and Bloon, J., 2017, Wasted: How America Is Losing Up to 40 Percent of Its Food from Farm to Fork to Landfill. [online] NRDC ISSUE PAPER. Available at < https://www.ccrrc.org/wp-content/uploads/sites/24/2014/03/wasted-food-IP.pdf>.

Hall, K., Guo, J., Dore, M. and Chow, C., 2003. The Progressive Increase of Food Waste in America and Its Environmental Impact, *PLoS ONE*, 4(11), pp.1-6.

Levis, J., Barlaz, M., Themelis, N. and Ulloa, 2010. Assessment of the state of food waste treatment in the United States and Canada, *Waste Management*, 30(8-9), pp.1486-1494.

Li, T., Messer, K. and Kaiser, H., 2020. The impact of expiration dates labels on hedonic markets for perishable products, *Food Policy,* 93, pp.1-12.

Nahmias, S., 2011. Perishable Inventory Systems, vol. 160, Springer, US (2011).

Noussair, C., Robin, S. and Ruffieux, B., 2003. Revealing consumers' willingness-to-pay: A comparison of the BDM mechanism and the Vickrey auction, *Journal of Economic Psychology*, 25(6), pp.725-741.

Macías-López, A., Cárdenas-Barrón, L., Peimbert-García, R. and Mandal, B., 2021. An Inventory Model for Perishable Items with Price-, Stock-, and Time-Dependent Demand Rate considering Shelf-Life and Nonlinear Holding Costs. *Mathematical Problems in Engineering*, 2021, pp.1-36.

Mcfadden, J. and Huffman, W., 2017. Willingness-to-pay for natural, organic, and conventional foods: The effects of information and meaningful labels. *Food policy*, 68, pp.214-232.

Qi, D. and Roe, B., 2016. Household Food Waste: Multivariate Regression and Principal Components Analyses of Awareness and Attitudes among U.S. Consumers, *PLoS ONE*, 11(7), pp.1-19.

Risius, A. and Hamm, U., 2017. The effect of information on beef husbandry systems on consumers' preferences and willingness to pay, *Meat Science*, 124, pp.9-14.

Risius, A. and Hamm, U., 2017. The effect of information on beef husbandry systems on consumers' preferences and willingness to pay, *Meat Science*, 124, pp.9-14.

Thyberg, K., Tonjes, D. and Gurevitch, J., 2009. Quantification of Food Waste Disposal in the United States: A Meta-Analysis. *Environmental Science and Technology*, 49(24), pp.13946-13953.

USDA, 2021. [online]usda.gov. Available at < https://www.ers.usda.gov/topics/food-nutrition-assistance/food-security-in-the-u-s/key-statistics-graphics/#:~:text=In%202021%3A,with%20adults%2C%20were%20food%20insecure>

Venkat, K., 2011. The Climate Change and Economic Impacts of Food Waste in the United States, International *Journal on Food System Dynamics*, 2(4), pp.431-446.

Vicchio, R., Loo, E. and Annunziata, A., 2016. Consumers' willingness to pay for conventional, organic and functional yogurt: evidence from experimental auctions, *International Journal of Consumer Studies*, 40(3), pp.368-378.

Zossou, E., Fiamohe, R., Vedouhe, S. and Demont, M., 2022. Experimental auctions with exogenous and endogenous information treatment: Willingness to pay for improved parboiled rice in Benin, *Journal of Agricultural Economics*, 73(3), pp.806-825

Hall, K., Guo, J., Dore, M. and Chow, C., 2003. The Progressive Increase of Food Waste in America and Its Environmental Impact, *PLoS ONE*, 4(11), pp.1-6.

Hanks, A. S., Just, D. R., & Wansink, B. (2012). Trigger Foods: The Influence of 'Irresistible' Foods on Overeating and Obesity. *American Journal of Agricultural Economics*, 94(2), 638-643.

IDFA. (2021). 2021 Economic Impact Study of the Dairy Products Industry Summary Results : In International Dairy Foods Association (Issue May).

Endara P, Wiedmann M, Adalja A. Consumer willingness to pay for shelf life of high-temperature, short-time-pasteurized fluid milk: Implications for smart labeling and food waste reduction. J Dairy Sci. 2023 Sep

Scholz, K., & Kulko, T. (2022). Dynamic Pricing Strategies and Their Impact on Retail Revenue: A Case Study of Perishable Products. *Journal of Business Research*, 125, 389-402.

Technical platform on the measurement and reduction of food loss and waste: Food and Agriculture Organization of the United Nations. FoodLossWaste. (n.d.). https://www.fao.org/platform-food-loss-waste/en/

Online Supplementary Material

The carbon footprint impact of adopting a plant-based menu: A case study in a U.S. fine dining establishment

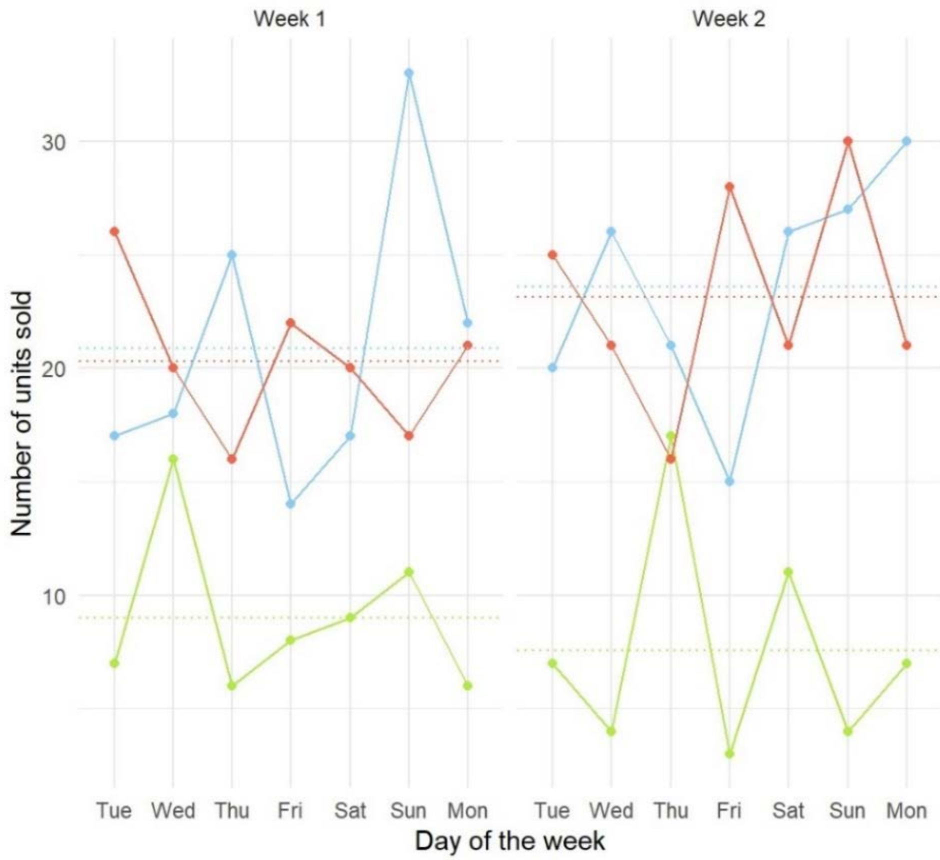
May 2024

List of Appendices:

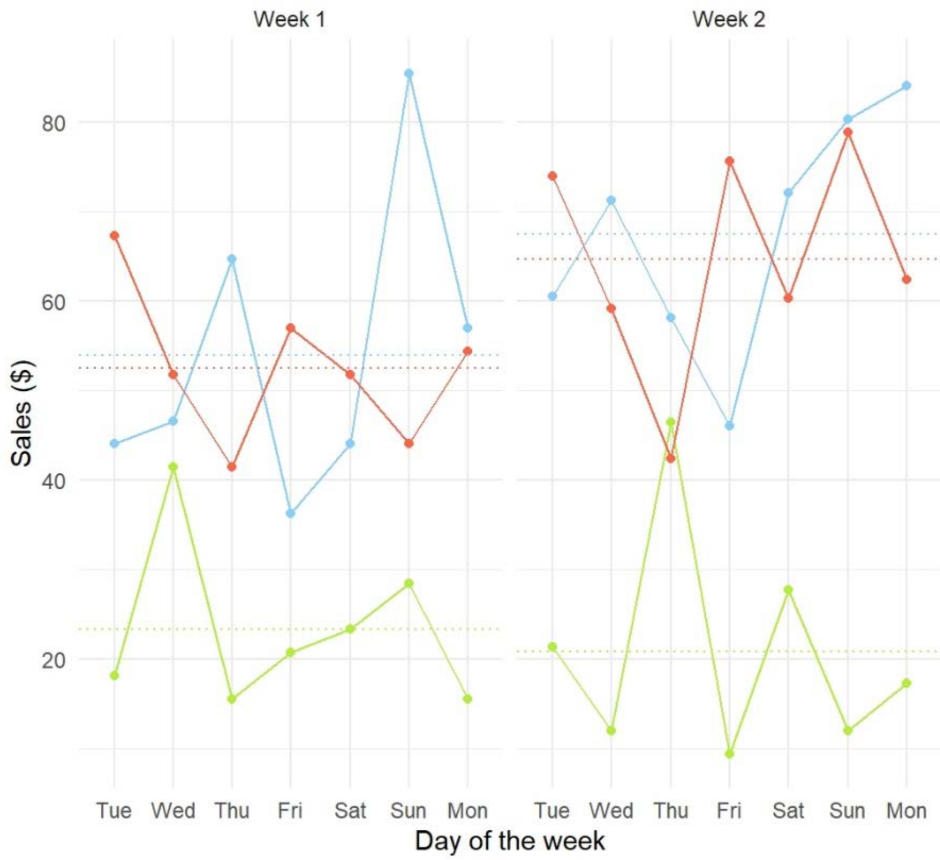
Appendix A: Overview of Study 1 survey and experiment design

Appendix B: Study 2 supplementary figures

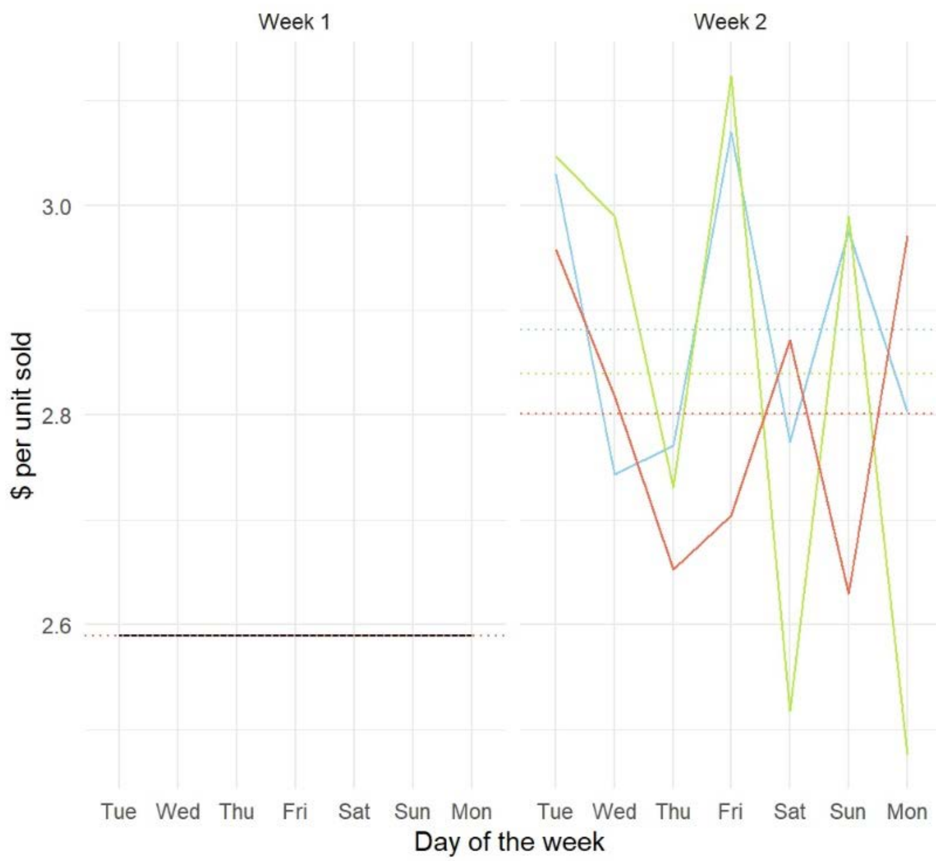
Supplement Figure 1: Study execution at the grocery store during the dynamic pricing week (week 2)



Supplement Figure 2: The number of units sold of fluid milk over a 2-week study. Red solid line represents whole milk, blue solid line represents reduced 2% milk, and green solid line represents skim milk. The corresponding-colored dotted lines represent the average amount of units sold.



Supplement Figure 3: The sales of fluid milk over a 2-week study in US dollars. Red solid line represents whole milk, blue solid line represents reduced 2% milk, and green solid line represents skim milk. The corresponding-colored dotted lines represent the average amount of sales.



Supplement Figure 4: The price per unit for fluid milk over 2-week study. Red solid line represents whole milk, blue solid line represents reduced 2% milk, and green solid line represents skim milk. The corresponding-colored dotted lines represent the average price per unit.

Appendix C: Study 2 supplementary tables

Supplement Table 1: Association between units of milk sold or sales and the product characteristics (i.e., milk fat level, year that it was sold, and day of the week)

Variable	Df[6]	Sum Sq[7]	Mean Sq[8]	F-statistic[9]	P-value[10]
Units[1]					
Milk Type[3]	2	7718	3859	163.759	<0.0001***
Year[4]	1	19	19	0.792	0.3748
Day[5]	6	577	96	4.078	0.000786***
Sales[2]					
Milk Type[3]	2	53337	26668	161.516	<0.0001***
Year[4]	1	19	19	0.118	0.7321
Day[5]	6	3870	645	3.907	0.00115**

[1]Number of half-gallon milk units sold (Dependent Variable)
[2]Sales in $ generated from units sold (Dependent Variable)
[3]Milk fat level (Whole, Reduced 2% and Skim)
[4] The year of observation (2022 vs 2023)
[5]Day of the week
[6]Degrees of freedom
[7] Explanatory Variable Sums of Squares/Residual Sum of Squares
[8] Explanatory Variable Mean Sums of Squares/Residual Mean Sum of Squares
[9] F-statistic for ratio of variances.
[10] P-value for ratio of variances (* P<0.01, ** P<0.001, *** P<0.001).

Supplement Table 2: Association between units of milk sold or sales and the product characteristics (i.e., milk fat level, effect of study intervention, and day of the week)

Variable	Df[6]	Sum Sq[7]	Mean Sq[8]	F-statistic[9]	P-value[10]
Units[1]					
Milk Type[3]	2	3280	1639.9	59.474	<0.0001***
Study Intervention[4]	1	31	31	1.123	0.293
Day[5]	6	114	19.1	0.692	0.657
Sales[2]					
Milk Type[3]	2	23411	11705	59.489	<0.0001***
Study Intervention[4]	1	574	576	2.918	0.0918
Day[5]	6	812	135	0.687	0.6603

[1]Number of half-gallon milk units sold (Dependent Variable)
[2]Sales in $ generated from units sold (Dependent Variable)
[3]Milk fat level (Whole, Reduced 2% and Skim)
[4] The effect of study intervention (Week -2 and Week -1 vs Week 1 and Week 2)
[5]Day of the week
[6]Degrees of freedom
[7] Explanatory Variable Sums of Squares/Residual Sum of Squares
[8] Explanatory Variable Mean Sums of Squares/Residual Mean Sum of Squares
[9] F-statistic for ratio of variances.
[10] P-value for ratio of variances (* P<0.01, ** P<0.001, *** P<0.001).

Supplement Table 3: Estimated means contrast table of units sold and sales per day of the three types of shelf lives averaging over milk types in week 1 (static pricing) and week 2 (dynamic pricing).

Variable	**Shelf life**[3]	**Week 1** [4]	**Week 2**[7]	**Difference**[8]	**P value**[9]
Units[1]	High	12.7 [11.31 to 14.03]	9.29 [7.92 to 10.65]	-3.38	0.0007
	Medium	3.05 [1.69 to 4.41]	6.29 [4.92 to 7.65]	+3.24	0.0012
	Low	1.00 [-0.36 to 2.36]	2.52 [1.16 to 3.89]	+1.52	0.1197
Sales[2]	High	32.8 [29.02 to 36.59]	31.5 [28.19 to 34.76]	-1.33	0.5704
	Medium	7.89 [4.11 to 11.68]	16.3 [12.99 to 19.56]	+8.39	0.0006
	Low	2.59 [-0.69 to 5.87]	3.51 [0.23 to 6.79]	+0.92	0.6947

[1]Number of half-gallon milk units sold per day
[2]Sales in $ generated per day from units sold
[3]Shelf-life of milk (High 21-8 days, Medium 7-4 days, and Low 3-0 days)[4]Estimated means during Week 1 (static pricing model)

[4]Estimated marginal means with 95% confidence interval during Week 1 (static pricing model)

[5]Lower confidence level

[6]Upper confidence level

[7]Estimated marginal means during Week 2 (dynamic pricing model)

[8]Difference between Week 1 and Week 2. (Transition from static to dynamic pricing model)

[9] P-value for ratio of variances (* P<0.05, ** P<0.001, *** P<0.0001).

Supplement Table 4: Detailed Association between units of milk sold or sales and the product characteristics (i.e., milk fat level, effect of study intervention, and day of the week) using Linear Model.

	units	sales
	(1)	(2)
WeekWeek 2	-3.381^{***}	-1.328
	(0.972)	(2.703)
Shelf.LifeLow	-11.667^{***}	-30.217^{***}
	(0.972)	(2.703)
Shelf.LifeMedium	-9.619^{***}	-24.913^{***}
	(0.972)	(2.703)
Milk.TypeSkim Milk	-4.643^{***}	-12.977^{***}
	(0.687)	(1.911)
Milk.TypeWhole Milk	-0.167	-0.765
	(0.687)	(1.911)
WeekWeek 2:Shelf.LifeLow	4.905^{***}	2.246
	(1.374)	(3.822)
WeekWeek 2:Shelf.LifeMedium	6.619^{***}	9.715^{**}
	(1.374)	(3.822)
Constant	13.468^{***}	35.245^{***}
	(1.050)	(2.919)
Observations	126	126
R^2	0.711	0.737
Adjusted R^2	0.677	0.706
Residual Std. Error (df = 112)	3.149	8.757
F Statistic (df = 13; 112)	21.188^{***}	24.125^{***}
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Supplement Table 5: The total amount of units sold in week 1 and week 2 categorized in terms of shelf life and type of milk sold.

Total Units Sold	**Week 1**			**Week 2**		
	High SL	**Medium SL**	**Low SL**	**High SL**	**Medium SL**	**Low SL**
Whole Milk	111	24	7	84	51	27
Reduced Milk	108	33	5	85	64	16
Skim Milk	47	7	9	26	17	10

Supplement Table 6+7+8: Analysis of variance and Estimated Marginal Means + Contrasts table for the Shelf Life and Milk type interactions.

```
> aov_units<- aov(sales~ Day + Week + Shelf.Life + Milk.Type + Shelf.Life*Milk.Type, data = data)
> summary(aov_units)
                      Df Sum Sq Mean Sq F value   Pr(>F)    
Day                    6    207      35   0.629   0.7068    
Week                   1    223     223   4.052   0.0466 *  
Shelf.Life             2  18625    9312 169.436  < 2e-16 ***
Milk.Type              2   4454    2227  40.519 6.53e-14 ***
Shelf.Life:Milk.Type   4   3087     772  14.040 2.75e-09 ***
Residuals            110   6046      55                     
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> emmeans(aov_units, pairwise~Shelf.Life*Milk.Type)
$emmeans
 Shelf.Life Milk.Type  emmean   SE  df lower.CL upper.CL
 High       2% Milk     40.56 1.98 110  36.6355    44.49
 Low        2% Milk      2.51 1.98 110  -1.4130     6.44
 Medium     2% Milk     17.95 1.98 110  14.0184    21.87
 High       Skim Milk   14.99 1.98 110  11.0641    18.92
 Low        Skim Milk    2.66 1.98 110  -1.2688     6.58
 Medium     Skim Milk    4.44 1.98 110   0.5134     8.37
 High       Whole Milk  40.88 1.98 110  36.9484    44.80
 Low        Whole Milk   3.98 1.98 110   0.0491     7.90
 Medium     Whole Milk  13.88 1.98 110   9.9484    17.80

Results are averaged over the levels of: Day, Week 
Confidence level used: 0.95 
```

```
$contrasts
 contrast                             estimate  SE  df t.ratio p.value
 High 2% Milk - Low 2% Milk             38.049 2.8 110  13.579  <.0001
 High 2% Milk - Medium 2% Milk          22.617 2.8 110   8.072  <.0001
 High 2% Milk - High Skim Milk          25.571 2.8 110   9.126  <.0001
 High 2% Milk - Low Skim Milk           37.904 2.8 110  13.527  <.0001
 High 2% Milk - Medium Skim Milk        36.122 2.8 110  12.891  <.0001
 High 2% Milk - High Whole Milk         -0.313 2.8 110  -0.112  1.0000
 High 2% Milk - Low Whole Milk          36.586 2.8 110  13.057  <.0001
 High 2% Milk - Medium Whole Milk       26.687 2.8 110   9.524  <.0001
 Low 2% Milk - Medium 2% Milk          -15.431 2.8 110  -5.507  <.0001
 Low 2% Milk - High Skim Milk          -12.477 2.8 110  -4.453  0.0007
 Low 2% Milk - Low Skim Milk            -0.144 2.8 110  -0.051  1.0000
 Low 2% Milk - Medium Skim Milk         -1.926 2.8 110  -0.687  0.9989
 Low 2% Milk - High Whole Milk         -38.361 2.8 110 -13.690  <.0001
 Low 2% Milk - Low Whole Milk           -1.462 2.8 110  -0.522  0.9999
 Low 2% Milk - Medium Whole Milk       -11.361 2.8 110  -4.055  0.0029
 Medium 2% Milk - High Skim Milk         2.954 2.8 110   1.054  0.9793
 Medium 2% Milk - Low Skim Milk         15.287 2.8 110   5.456  <.0001
 Medium 2% Milk - Medium Skim Milk      13.505 2.8 110   4.820  0.0002
 Medium 2% Milk - High Whole Milk      -22.930 2.8 110  -8.183  <.0001
 Medium 2% Milk - Low Whole Milk        13.969 2.8 110   4.985  0.0001
 Medium 2% Milk - Medium Whole Milk      4.070 2.8 110   1.452  0.8744
 High Skim Milk - Low Skim Milk         12.333 2.8 110   4.401  0.0008
 High Skim Milk - Medium Skim Milk      10.551 2.8 110   3.765  0.0080
 High Skim Milk - High Whole Milk      -25.884 2.8 110  -9.238  <.0001
 High Skim Milk - Low Whole Milk        11.015 2.8 110   3.931  0.0045
 High Skim Milk - Medium Whole Milk      1.116 2.8 110   0.398  1.0000
 Low Skim Milk - Medium Skim Milk       -1.782 2.8 110  -0.636  0.9994
 Low Skim Milk - High Whole Milk       -38.217 2.8 110 -13.639  <.0001
 Low Skim Milk - Low Whole Milk         -1.318 2.8 110  -0.470  0.9999
 Low Skim Milk - Medium Whole Milk     -11.217 2.8 110  -4.003  0.0035
 Medium Skim Milk - High Whole Milk    -36.435 2.8 110 -13.003  <.0001
 Medium Skim Milk - Low Whole Milk       0.464 2.8 110   0.166  1.0000
 Medium Skim Milk - Medium Whole Milk   -9.435 2.8 110  -3.367  0.0280
 High Whole Milk - Low Whole Milk       36.899 2.8 110  13.169  <.0001
 High Whole Milk - Medium Whole Milk    27.000 2.8 110   9.636  <.0001
 Low Whole Milk - Medium Whole Milk     -9.899 2.8 110  -3.533  0.0169

Results are averaged over the levels of: Day, Week
P value adjustment: tukey method for comparing a family of 9 estimates
```