Understanding consumer behavior for perishable products attributes

Mariana Silva Sousa

Master's Dissertation

Supervisors FEUP: Maria João Santos and Pedro Sanches Amorim
Supervisor INESC TEC: Sara Baltazar Martins

U.PORTO
FEUP FACULDADE DE ENGENHARIA UNIVERSIDADE DO PORTO

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Abstract

Food waste is a widespread concern around the world. Throughout the supply chain, from production facilities to the final consumer, issues related to refrigeration, transportation, processing, aesthetic standards, and the approximation or misinterpretation of expiration dates have been causing billions of tons of food to be wasted every year (Quested et al., 2021). Although many campaigns are currently underway to raise awareness about this matter, individuals' conscience and common sense have proven insufficient to generate a unified grassroots movement.

Nonetheless, for profit-oriented entities, particularly retailers, an increased interest in reducing waste has been seen, as it represents monetary losses worth a typical net income each year (Phenix, 2022). Actually, the depreciation (in-store) of food products such as vegetables, fruits, and bakery supplies or the transgression of the expiration date of dairy and canned products have been the source of many spoiled feeds, which have yielded substantial losses in sales.

As a result, great efforts have been made to implement policies that encourage the purchase of perishable products before they reach a deteriorated state or are likely to create consumer distrust. However, there is still a gap in understanding consumer behavior when considering perishable products with different remaining shelf life. Generally, the policies implemented have been indiscriminate, neglecting characteristics that determine different percentage variations in utility and manifesting constraints in achieving the intended goal.

In the foresight of this knowledge void, this study aims to demystify the link between consumers' revealed preferences and the dichotomy between remaining shelf life versus the price of perishable goods. To this end, we introduce econometric models based on sales data from the yogurt portfolio of a large European retailer. In order to achieve this, we present the development of panel regressions for the perceived inequality of relevance of item attributes from the consumer's point of view. We also apply discrete choice models to discern consumers' preferences between products with or without a discount label due to reduced shelf life. Finally, we gauge the developed models to formulate unified conclusions about consumer behavior as well as to determine the consumer's willingness to pay for a product with one more day of shelf life.

Based on the insights of this dissertation, the goal is to incorporate the knowledge gained into future policies, namely in the realms of pricing and inventory management, to tackle retailer waste and losses effectively.

Resumo

O desperdício alimentar constitui uma preocupação generalizada em todo o mundo. No decurso de toda a cadeia de abastecimento, desde as unidades de produção até ao consumidor final, questões relacionadas com a refrigeração, transporte, processamento, normas estéticas e a aproximação ou má interpretação das datas de validade têm causado o desperdício de milhares de milhões de toneladas de alimentos por ano (Quested et al., 2021). Embora estejam atualmente em curso muitas campanhas de sensibilização para esta realidade, a autoconsciência e sensatez dos indivíduos tem-se revelado insuficiente para gerar o movimento coletivo unificado necessário.

Ainda assim, para as entidades com fins lucrativos, particularmente os retalhistas, tem-se assistido a uma maior preocupação em reduzir o desperdício, uma vez que este implica perdas monetárias anuais equiparáveis a um rendimento líquido habitual (Phenix, 2022). De facto, a depreciação (em loja) de bens alimentares como legumes, frutas e produtos de padaria, ou a transposição da data de validade de lacticínios e conservas tem estado na origem de muitos alimentos estragados, dos quais advêm perdas substanciais de vendas.

Por este motivo, têm sido feitos grandes esforços com vista à implementação de políticas capazes de impulsionar a compra de produtos perecíveis, antes que estes atinjam um estado deteriorado, ou que sejam suscetíveis de criar desconfiança nos consumidores. Não obstante, denota-se a subsistência de uma lacuna na compreensão do comportamento do consumidor aquando da escolha de produtos com diferentes prazos de expiração. Em geral, as políticas aplicadas têm sido indiscriminadas, negligenciando caraterísticas determinantes para diferentes variações da utilidade e provocando claros constrangimentos na consecução do objectivo proposto.

Visando colmatar esta lacuna, este estudo procura desmistificar a relação entre as preferências reveladas pelos consumidores e a dicotomia entre o prazo de validade restante versus o preço dos bens perecíveis. Para este efeito, introduzimos modelos econométricos baseados em dados de vendas do portfólio dos iogurtes de um grande retalhista Europeu. Em particular, apresentamos o desenvolvimento de regressões de painel para que se perceba a desigual relevância dos atributos dos artigos sob o ponto de vista do consumidor. Aplicamos também modelos de escolha discreta para discernir a preferência dos consumidores entre produtos com ou sem etiqueta de desconto, devido ao reduzido prazo de validade. Finalmente, aferimos os modelos desenvolvidos para se formularem conclusões unificadas sobre o comportamento do consumidor, bem como para se determinar a disponibilidade de um consumidor genérico para pagar por um produto com mais um dia de prazo de validade.

Com base nos conhecimentos adquiridos com esta dissertação, o objetivo é impulsionar políticas relacionadas com gestão de preços e de inventário que possam combater eficazmente o desperdício e perdas dos retalhistas.

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To all, I extend my warmest gratitude.

Contents

Acronyms and Symbols

AIC	Akaike Information Criterion
ASC	Alternative Specific Constant
BIC	Bayesian Information Criterion
CI	Confidence Interval
IIA	Independence of Irrelevant Alternatives
MIXL	Mixed Logit model
MNL	Multinomial Logit model
NL	Nested Logit model
OLS	Ordinary Least Squares
RSL	Remaining Shelf Life
SKU	Stock Keeping Unit
WTP	Willingness To Pay

List of Figures

List of Tables

Chapter 1

Introduction

The scarcity of affordable resources, exacerbated by the unequal distribution of wealth, has been creating severe deprivation for a substantial part of the world population. As noted by the Food and Agriculture Organization of the United Nations (2021), about one-third of the population did not have access to sufficient food supplies in 2020. Notwithstanding, it is also known that about 1.3 billion tons of food are thrown away every year and, as recently as 2021, about 8 to 10% of global daily greenhouse gas emissions were associated with wasted products in households, food services, and retailers (Quested et al., 2021).

As a response to this, an active effort of sensitization for this problem has risen, which has led to the emergence of many studies focused on providing knowledge to support decisions consistent with the food waste minimization goal (Luo et al., 2021; Ilyuk, 2018; Akkaş and Gaur, 2021; d'Amato et al., 2020; Chung, 2019). Moreover, the United Nations leaders have committed to achieving several Sustainable Development Goals, among which the following stand out: "By 2030, halve per capita global food waste at the retail and consumer levels and reduce food losses along production and supply chains, including post-harvest losses" (SDG, 2020).

The current project is, therefore, in line with this intention, as it proposes to understand consumer behavior that should help prevent food waste and that, ultimately, contribute to reducing world hunger levels.

For a better overview of the work undertaken, Section 1.1 provides a brief description of the large project into which this study is integrated. Subsequently, Section 1.2 introduces in detail the current practices developed in grocery retailers. The goals and their phased planning are outlined in Section 1.3 and finally, the structure of this work is detailed in Section 1.4.

1.1 Project background

This study is fostered by a larger project called *BeFresh: Integrating Consumer Behavior to Improve Food Value Chains*. Committed to the progressive shifting toward a more sustainable society, namely in terms of food production and consumption and economic growth that does not jeopardize future generations, this proposal includes four tasks.

The first task is explored in this thesis in partnership with a European grocery retailer, which reported significant losses of unsold items close to their expiration dates. The company provided aggregate data of customer choices for the yogurt portfolio at the time of purchase, which enabled the study of general consumer behavior towards perishable products over the whole display time.

The subsequent tasks will then be designed to assess the impact of the consumer-related knowledge on production and discounting planning, which was acquired earlier. In addition, it will be intended to quantify the gains from potential collaboration between retailers and producers, mainly to arrive at the most favorable Minimum Life On Receipt of the groceries for both parties.

1.2 Problem scope

Retailers are responsible for 13% of global food waste on their own. Simultaneously, by operating at the center of the supply chain, they can interact with and influence both the consumers and the food producers to switch to more sustainable practices (ReFED, 2022). Consequently, their impact on waste reduction is critical, so the proper mechanisms must be implemented.

Nevertheless, the reality that these grocery retailers are confronted with is highly challenging. According to Ferguson and Ketzenberg (2006), a remarkable 15% of perishable products are lost due to spoilage or damage. The uncertain nature of consumer behavior, exacerbated by the quest for a wider variety of products, makes it difficult to predict demand for each Stock Keeping Unit (SKU) (Mena et al., 2011; Buisman et al., 2019). In addition, the short life cycle of many food products (so-called perishables) and consumers' undisputed freshness standards are often the causes for the accumulation of (increasingly) older items. As the stock is replenished, consumers consistently prefer the newer products, often ending up with unsold older stocks (Buttlar et al., 2021).

But by far the most worrying issue is the consumers' lack of knowledge or misinterpretation of food expiration labels since it accounts for nearly 50% of retailers' food waste (ReFED, 2022). Products with an approaching expiration date (i.e., with low remaining shelf life) are inevitably unappealing to consumers, even if such items are still edible. According to A. C. Nielson Company (Karakaya and Harcar, 2005), 88% of the consumers always or almost always check expiration dates. Moreover, among these individuals, most of them feel insecure about purchasing articles close to their expiration date, either because they associate them with a higher risk of not being consumed in time or because they consider them to be of inferior quality (Chung and Li, 2017; Chung, 2019). That conviction of poorer quality can only be overcome by the application of educational efforts, which implies a reform of the mindset that is a long-term social project. However, regarding the association of higher risk, it is believed that economic incentives can counterbalance the perceived risk.

So, retailers have begun to introduce discounts on products with low remaining shelf life (RSL) to offset the risks associated with consumers with lower prices. By doing so, they are persuading consumers to buy these products, thus reducing the loss of resources (Chung, 2019). In fact, food products that flow through the supply chain but do not reach the final consumer cause significant investments that are not rewarded and, consequently, represent heavy profit losses. Many studies have supported such policies based on dynamic pricing and inventory models, linear programming, and analytical solution methods (Tsiros and Heilman, 2018). However, while some of the retailers' losses have been minimized and consumers have experienced some gains, such initiatives have not achieved the extent of their intended effects.

For this reason, pursuing the desire to change this paradigm and to grasp better the factors and respective intensity that govern consumer behavior, this project undertakes the development of econometric models, notably panel regressions and discrete choice models. Considering the growing popularity that econometric analysis has recently been experiencing, thanks to its ability to help understand what drives people's choices, it is hoped that their utilization supports the design of policies that promote the reduction of food waste. In particular, one expects to understand what might lead a generic customer to buy yogurts close to their expiration date. Nonetheless, it should be noted that it is expected that the same method could also be applied to any other perishable product with a stated expiration date, and therefore, equivalent information on such products could be derived.

Whit this in mind, despite all the previous works carried out in this area, this research stands out as being unprecedented, firstly because it approaches this issue from the consumer demands' point of view and not just the retailers' cost/revenue balance; secondly, because it is based on aggregate, revealed preference data, rather than individual choices and stated preferences (supported by controlled and fictitious scenarios); thirdly, because it aims at understanding customers' perception of the risk associated with the discount label for low RSL, by itself; and finally, because of the use of a Mixed Logit model to arrive at the willingness to pay (WTP) of perishable products with different RSLs.

1.3 Problem statement

Bearing in mind the above-mentioned context, the main objective of this research is to model consumer behavior towards perishable products with stated expiration dates. More specifically, the goal is to establish statistical models capable of indicating the sources of variability that determine how much a consumer is willing to pay for an additional day of shelf life for different types of yogurts (and even desserts).

Since the ultimate goal is to integrate the results of this study into policies that leverage more assertive pricing and inventory management decisions, a holistic and unified perception is sought-off. That is, we are interested in generic consumer behavior, ignoring the inherent variability between consumers (preference heterogeneity), particularly in relation to their sociodemographic conditions.

In this regard, the following research questions were raised:

- What are the specific attributes of SKUs that have the greatest impact on the consumer's choice?

- Is the importance given to each SKU-related attributes the same when comparing labeled and unlabeled products?
- What is the effect of placing discount labels due to low RSL?
- How does the WTP for an extra day of RSL vary according to distinct product attributes?

We believe that the combination of external incentives and the desire to combat the sales losses due to outdated groceries make the prospective answer to these issues especially attractive to retailers. Moreover, as the integration of knowledge about the most valued attributes by consumers as well as their WTP for an extra day of RSL provides an opportunity for sustained policy implementation, it is thought that this will bring a massive advantage to retailers.

Lastly, it is also pertinent to highlight the relevance of this project to society, as a whole, because of the impact it is expected to have on fighting food waste and hunger.

1.4 Dissertation structure

The remainder of the thesis is as follows. In chapter 2, a summary of the most relevant econometric models is presented, as well as a review of their applications, emphasizing the most relevant contributions to this work. In the following chapter, a brief overview of the company's existing policies and the data used in this study is detailed. Furthermore, chapter 4 provides the framework for selecting and developing the panel regressions and the results of the linear econometric models. The exact sequence of analysis is also done for the non-linear econometric models in chapter 5. Lastly, the final chapter presents the main conclusions and alludes to the work plan intended to follow this study.

Chapter 2

Theoretical framework

This chapter first analyzes the econometric models deemed most relevant to unravel interrelationships between inherent product characteristics and their marketability (or not).

Thus, we present a summary of the assumptions made by each model, ways to evaluate their performance, and a compilation of examples that illustrate their potential.

Finally, some of the methodologies previously used to determine willingness to pay (WTP) and adjusted prices for items with different remaining shelf life (RSL) are also explained.

2.1 The econometric models

Econometric models assume a fundamental role in interpreting the behavior of economic agents and, thus, predicting the outcome of their future actions. Based on economic data and theories, together with statistical inference techniques, they emerged to test hypotheses and allow the deduction of causal relationships between a response variable - dependent variable - and a set of explanatory variables - independent variables - (Jefrey, 2010).

An econometric model comprises a set of equations that includes observed variables, their errors, and sometimes even random variables (disturbances assumed to follow a given distribution), used to simplify a complex phenomenon. The unknown parameters are estimated based on gauging the fit of the observed versus the expected data, using different statistical formulations.

According Greene (2003), depending on the assumptions and specifications undertaken, a wide diversity of models emerge, allowing for two distinct types: linear models (in which all the estimators obtained have a closed form) and non-linear models (wherein some of the estimators do not have a closed form).

In order to support the analysis performed here, the models used are outlined, as well as some of their successful applications.

2.1.1 Linear econometric models

Within econometric linear estimation models, the panel data models constitute the one that has triggered the greatest interest and potential for this study.

As reported by Greene (2003), panel data consist in observing repeated measurements of a given event related to the same agents (which can be individuals or collectivities) over time. The potential of models based on this type of data is tremendous compared to those built on cross-sectional data. By accounting for correlation over time due to handling the same entities, while imposing independence from one another, such models better capture inherently fixed effects, thus allowing better insight into variables that change over time (Wu et al., 2021). In addition, panel models can more accurately manage the omission of unobservable factors that affect the dependent variable, even assuming that the independent variables are not stochastic and multicollinear.

That said, in general, panel models undertake a regression of the shape:

$$Y_{it} = \beta * X_{it} + \alpha * z_i + \varepsilon_{it} \tag{2.1}$$

Where β stands for the estimated coefficients of the observable attributes; X_{it} denotes the explanatory variables of entity i at time t; and $\alpha * z_i$ is the entity effect, in which z_i can be composed of a constant and variables specific to each observed entity.

One can arrive at different regressions depending on the assumptions made for z_i.

The simplest model is the Pooled OLS regression, where z_i is assumed to be constant for each entity i, therefore ignoring the fact that the data is panel and making it reliable to be estimated with the OLS estimator. As stated by Greene (2003), it is necessary to ensure independence across observations and a zero expected value and constant variance for the error ε_{it}. Furthermore, the independent variables must be assumed not to depend on the explanatory variable, such that the error term is uncorrelated with any dependent variable (strict exogeneity).

Another widely used model is the fixed effects regression, which is based on the premise that changes in the constant term can apprehend differences between individuals. Thus, it starts by offsetting the fixed effect to make the coefficient estimates of the time-varying characteristics. It assumes that the characteristics of the entities observed over time - z_i - are correlated with the dependent variables considered - X_{it} - (Wu et al., 2021).

Finally, the random effects regression is also of note, which assumes that the entity attributes are uncorrelated with the explanatory variables. Within this model, an entity-specific term is assumed to be a random element (Greene, 2003).

Each model provides different information, as they have divergent abilities to incorporate variability in their respective estimates. The assumptions made by each one may not always be adequate to shape the observed events accurately. For this reason, several tests guide the diagnosis of appropriateness.

Among those is the Breusch-Pagan Lagrange Multiplier test, which allows testing whether there are significant differences between entities. That is, it checks for evidence pointing to serial correlation and heteroscedasticity between entities. Similarly, the Pasaran CD test verifies if there is a correlation between entities. These tests then help determine whether or not a Pooled OLS regression is appropriate (Jefrey, 2010).

To distinguish between a random and fixed effects regression, the Hausman test is usually performed, analyzing the existence (or not) of correlation between the entities' errors and the regressors (Stock and Watson, 2014).

That said, there has been growing interest in the research community concerning the use of panel regressions. Consequently, a couple of promising applications of such models, which served as the basis for the analysis conducted here, are now highlighted.

First, the work done by Landry et al. (2018) should be reported due to its proximity to the subject under analysis - food waste. Based on data from food retailers and demographic data of the target populations, these authors use the three types of regression described above to study the relationship between food retail density and municipal solid waste. In the same sense, Cerciello et al. (2019) also address the problem of food waste, this time to understand its relationship with sociodemographic and economic factors. To do so, they use a fixed effects regression, accounting for the effects of the province and the time horizon.

Still, it is possible to point to other works carried out with an analysis similar to the one intended to be done. In particular, one can mention the work undertaken by Araya et al. (2018) which, like the present study, also study the impact of food labels on consumers' eyes using linear econometric models. However, instead of these being related to RSL, in this case, they address the nutrition labels of cereals, chocolates, and cookies. Finally, of note is also the research conducted by Wu et al. (2021), intending to examine the impact of the ecological footprint on people's quality of life. They use a fixed effects regression, as they found multicollinearity and endogeneity in the data.

The first part of the analysis is close to the methodologies used in the studies mentioned above. Similarly, we also performed a simple Pooled OLS regression and panel regression models to assess compliance with the assumptions made when performing each regression and conclude on the reliability of the results. However, the goals and scope of the current project are completely different from those cited, as no study has ever been conducted focusing on our topic. The purpose behind this research's linear models differs in that it is not so much about predicting the dependent variable but more about determining the extent to which different inherent product attributes impact consumer choices.

2.1.2 Non-linear econometric models

Now, concerning the group of non-linear econometric models, discrete choice models stand out. The theory around these models emerged from the pioneering work of McFadden, based on the utility theory and inspired by the principle that "An object can have no value unless it has utility" - (Haney, 1912).

Generically, the utility is a theoretical measure that associates a relative degree of satisfaction with the acquisition/use of each good (Train, 2009). For an individual j, the utility of an alternative i (U_{ij}) can be divided into two components: a systematic part, which is usually denoted as V_{ij}; and an error term, referenced as ε_{ij}:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{2.2}$$

On one hand, the deterministic part is usually a linear function of the characteristics (X) of the alternatives and the decision-maker – $V_{ij} = \beta_{ij} * X_{ij}$ (with β_{ij} being a vector of parameters, which are then to be estimated statistically). On the other hand, the error term reflects the component that the analyst cannot capture from the attributes of the alternatives and the individuals and allows for a heterogeneous stochastic taste (Train, 2009). In order to obtain a zero expected value for this component, a particular constant is usually added to the deterministic part of the utility of each alternative, called the alternative specific constant (ASC_i).

From stated preferences (through hypothetical scenarios or surveys) or revealed preferences (real scenarios, observation of past choices), discrete choice models enable to understand of the causal process that guides the decision-maker's behavior in choosing one of a set of several mutually exclusive, exhaustive, and finite alternatives (Train, 2009).

Therefore, the probability that an individual j selects alternative i instead of any other alternative n is given by:

$$P_{ij} = Prob(\varepsilon_{nj} - \varepsilon_{ij} < V_{ij} - V_{nj} \forall n \neq i) \tag{2.3}$$

Then, an underlying rational behaviour is assumed, claiming that decision-makers choose the alternative that provides them with the highest utility (regardless of its absolute value, as long as it is positive). The parameters are estimated by maximizing the probability of generation of the sample considered by resorting to the Maximum Likelihood Method. That is, as displayed in Equation 2.4, they are estimated by attempting to maximize the probability that each decision-maker chooses the alternative that was actually recorded while assuming the choices of different individuals to be independent.

$$\mathscr{L}(\beta) = \sum_{j=1}^{J} \sum_{i=1}^{I} y_{ij} * ln(P_{ij}) \tag{2.4}$$

After obtaining the parameters, and if the discrete choice model specification includes price among the attributes expressed in the deterministic utility, it is possible to obtain the monetary propensity to pay against each of the other observed attributes (Gillespie and Bennett, 2022; Gallardo et al., 2015). I.e., it is possible to understand the marginal rate that a consumer is willing to pay for a unit variation of an attribute of the considered alternative, as shown in Equation 2.5.

$$WTP_{attribute} = -\frac{\beta_{attribute}}{\beta_{cost}} \tag{2.5}$$

Where $\beta_{attribute}$ is the coefficient of the non-monetary attribute and β_{cost} is the coefficient for price.

Based on the preceding, different models can be derived by making different assumptions about the density of the error term.

One of the most well-known families of discrete choice models is the Logit models, comprising the binary Logit model (used when the choice is made from a set of two alternatives) and the Multinomial Logit model (when there are three or more alternatives). When considering these models, the probability of choosing an alternative i is established on the logistic function. The errors are assumed to be independent and identically distributed, following a Gumbel (also known as Type I extreme value) distribution. These underlying assumptions lead to very narrow applicability conditions: there must be error term independence between time horizons and between alternatives, and therefore, changes in a given alternative do not affect the ratio of any other two alternatives (problem of the independence of irrelevant alternatives - IIA). Since these conditions are often inconsistent with the particularities of the behaviors under analysis, these models may not always be able to perform the modeling of the decisions made.

Other models have subsequently been derived to accommodate scenarios for which the highlighted assumptions cannot be made.

Notably, it is worth mentioning the Nested Logit model (NL), which groups the alternatives into nests and allows correlation between choices in the same nest (but maintains independence between choices in different nests); the Probit Model, which allows correlation between error terms, since they are presumed to follow a multivariate normal distribution; and, the Mixed Logit Model, which besides including in the error term an independent and identically distributed component, also considers one (or more) additional random component, which can follow the distribution chosen by the analyst (Train, 2009). That way, it can accommodate the presence of correlation and different variances of the error terms (due to unobserved decision-makers heterogeneity). The latter two models have been increasingly used because of the flexibility they allow. However, the estimation of the probability of choosing each alternative, addressed in Equation 2.3, leads to the need to calculate an integral that does not have a closed form. Such a situation requires simulation, a technique in which the results of multiple draws are averaged. For each random error component draw, the product over the probability of each choice set alternatives for each individual is calculated (Scarpa and Alberini, 2005).

Finally, it is further important to point out the existence of Latent Class models, which consider that the population could be divided into a finite and discrete number of groups, among which there are distinct preferences, but within each, there are similar preferences (Greene and Hensher, 2003).

The indicators usually used to compare the performance of all these models are the likelihood ratio, the Cox test, the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

The likelihood ratio is founded upon testing the hypothesis that two models are equivalent: unrestricted and restricted models. The first model is the one in which one is interested in being aware of performance. The second is a reference model and can be defined in many ways as long as only linear restrictions are enforced. That is, if one wants to directly compare whether a model with a logarithmic relationship performs better than a model with linear specification, this test cannot be applied. Instead, one usual approach is to consider this restricted model as one that assigns to all alternatives equal susceptibility to be chosen, i.e., assuming that all parameters of the deterministic part of the utility are zero. Equation 2.6 then illustrates how this indicator is calculated.

$$-2(\mathscr{L}(0)-\mathscr{L}(\hat{\beta}))\sim\chi_k^2 \tag{2.6}$$

Where k is the number of degrees of freedom given by the difference between the number of parameters of the constrained model (which has 0 parameters) and the number of parameters of the unconstrained model (which has k parameters).

The Cox test arises to compare non-nested hypotheses, that is, models that cannot be obtained from each other with non-linear relationships. This test is based on the likelihood ratio but requires the formulation of a model that includes all variables and their parameters from two non-linearly related models. Then, comparing the composite model with each of the models of interest allows one to see whether any (or even both) models are better than the composite model, using the likelihood ratio. In case only one of the models is better than the composite model, selecting the best model is trivial. If both models are better than the composite model, this test does not allow any conclusions to be drawn. Finally, suppose the two models of interest are worse than the original hypothetical model. In that case, a model better suited to the situation at hand needs to be formulated.

In turn, the AIC and BIC are widely used tools to select the model that best fits the data from which it was obtained, among several candidate models, while penalizing their complexity. To do this, they take into account the number of parameters used by the models (k) and their maximum log-likelihood ($\mathscr{L}$), and the BIC also takes the sample size (n), being obtained by performing:

$$AIC=2*k-2*ln(\mathscr{L}) \tag{2.7}$$

$$BIC=k*ln(n)-2*ln(\mathscr{L}) \tag{2.8}$$

As can be seen, these indicators differ only with respect to the penalty terms. One can verify that the two indicators show significant differences for larger samples. In general, it is expected that the AIC penalizes models with a larger number of parameters and, therefore, biases in favor of models with higher predictive ability. Conversely, the BIC tends toward models with better descriptive ability (Cavanaugh and Neath, 2019). Regardless of the metric, the lower its value, the better the model is expected to be.

Although the discrete choice models outlined are a fairly recent statistical and quantitative mathematical application, their ability to explain consumer choices has been quickly realized effectively. Since they provide an essential basis for understanding the target audience of organizations and thus making more reliable decisions, their practical use has been widely explored.

Hence, a summary of some of the more standardized work in this area is now presented, followed by a description of some of the more innovative works, both dealing with the same particularities addressed in this review.

The study conducted by Bucklin and Gupta (1992) is one of the pioneers to show the potential of these models, namely, providing insight on the impact of price changes and promotions appraisal on consumers' perceived utility. Using a Multinomial Logit Model (MNL) and a Nested Logit model (NL), they managed to arrive at a causal model that allowed them to group consumers within the liquid laundry detergent market into several segments. Drawing on products' price sensitivity, these researchers aimed to prevent consumers from switching brands and product categories. In turn, Cherchi and Cirillo (2008) illustrate the need to apply a Mixed Logit model (MIXL) when significant variability in preferences for different alternatives is perceived. They aimed to model the sequence of travel mode choices between two fixed locations over six weeks for a given group of respondents. After performing it with an MNL, significantly better results were achieved by including systematic and random heterogeneity in tastes and correlation between individuals' choices over time. Moreover, Cui and Wang (2010) also examine the impact of pricing and discounts on consumers' choice of an SKU in an online supermarket while considering brand loyalty and product quantity. This paper is distinguishable from previous ones because the authors use a latent class model to incorporate consumer heterogeneity. It is also distinctive in that it incorporates the price at which products are sold into two variables: base price per liter of product and discount, as a binary variable.

That said, one could also cite a few papers that used discrete choice models to perceive the WTP for different products and/or services. Khachatryan et al. (2021) grasp the WTP for fruit plants with and without eco-labels as a means to understand the impact of such labels according to the consumer's view. Likewise, Danne et al. (2021) has sought to gain knowledge about the WTP by green electricity tariff attributes in pursuit of the same goal as this study: assisting in implementing policies that encourage consumers to more sustainable consumption.

So far, all the above examples rely on stated preference data since they result from information collected through surveys that consider specific cases and variability within individuals in (a small interviewed part of) the population. Furthermore, they are all regarded as individual consumer behavior, which allowed for the inclusion of demographic characteristics of the individuals surveyed in the deterministic component of utility.

Still, it is often desirable to model aggregate consumer behavior (i.e., for the whole population under analysis), and from revealed preference data - that is precisely what we do. However, practical applications of data-driven models with such characteristics are rarer in the literature because they are computationally very demanding. But also because, when conclusions are to be drawn at the aggregate level, it is more convenient to develop models on individual choices and only then specify the global view for the market. The analysis conducted by Berry (1994) is an example of this. The choice of each individual, faced with a set of differentiated products, is determined by considering the product characteristics and the random tastes of each consumer. From this, the aggregate market demand is obtained by considering the probability of a particular consumer being part of the group that chose a particular alternative.

Nevertheless, it is worth highlighting some works belonging to the small set of articles that simultaneously accommodate the two mentioned particularities and stand out for their innovative methodologies.

First, Bentz and Merunka (2000) introduce a novel combination of artificial intelligence with discrete choice models to then model the choice between chocolate brands. A feedforward neural network is used along with a MNL to assist the analyst in defining the utility. On the one hand, this procedure made it possible to determine whether the linear utility specification was appropriate for the situation under analysis. On the other hand, it enabled the ascertainment of the existence (or not) of deterministic aspects that could be incorporated but that the analyst had not accounted for. Moreover, the work undertaken by Mariuzzo et al. (2010), being based on scanner data and therefore on aggregate and revealed preference data, is the one that comes closest to the analysis carried out in the current research. Relying on bimonthly sales data for all carbonated refrigerator products spread across 12,000 Irish retail stores, they derive the utility that a given consumer obtains from each product and store in each period. In this way, the authors made the specification of the store coverage and, considering their actual values, estimate the utility parameters, which made it possible to obtain the price elasticity and welfare indicators. Despite that, between this article and the current thesis, there are still some crucial differences concerning the development of discrete choice models. First, we only consider two alternatives for each yogurt in each store (further explained in section 3.2), while the cited study has a vast set, causing it to consider an external good. Furthermore, due to the great interest in understanding the unobserved component of utility, our final procedure differed from the above.

2.2 Willingness to pay for products with different remaining shelf life

As stated by Gillespie and Bennett (2022), willingness to pay is the willingness of a consumer to pay an additional amount for a unit variation of an attribute.

Most retailers strive to be aware of this monetary disposition toward different RSLs, or more broadly, the price sensitivity of their customers to more or less aged products. Indeed, this is a very relevant indicator for organizations, especially to better guide pricing decisions for perishable products. In this regard, such estimation has been subject to extensive analysis to minimize waste and encourage and enhance consumer welfare.

Notably, many papers used dynamic pricing models and addressed inventory holding strategies for perishable products that depreciate over time while accounting for inventory replenishment frequency and profit maximization from the retailers' perspective. Chung and Li (2017) investigate the unequal impact of applying single-period, two-period or multi-period pricing policies using simulation. They concluded that the latter approach allows the maximization of the firm's profit and thus the minimization of food waste. In turn, Chung (2019) simultaneously simulate two disjoint scenarios - one in which only products with longer shelf life appear displayed in-store (while the rest stay in storage) and another in which updated discounts are realized as the RSL decreases. The author warns of the potential for combining these two approaches in that one does not always work better than the other. Finally, Herbon (2013), based on a single perishable product periodic replenishment and a two-level piecewise-constant price function, suggest that, at the monetary level, it is not worth gathering information on consumers' purchases for a successful implementation of a pricing policy. Hence, the current dissertation attempts to complement this view insofar as it is expected that the knowledge extracted from the preferences revealed by consumers allows the implementation of discounts on products with a low shelf life that reduces food waste and losses.

Additionally, it should be noted that the vast majority of the cited works have in view the perspective of making dynamic pricing that allows the maximization of the retailers' profit. However, in this case, while aiming to minimize sales losses, one hopes to achieve this by taking into consideration the requirements of those who have the decision to buy what they prefer. So, it is sought to incorporate the consumers' perception, maximizing their utility, hopefully urging them to consume the older products first.

Following this requirement, it is worth spotlighting differentiated approaches that attempt to act on clients' feelings of insecurity about the approaching expiration date of perishable foods. Buisman et al. (2019) combine the research on the impact of discount placement contingent on the expiration date on waste and monetary losses. They rely on an approach called Dynamic Shelf Life, which consists in updating the expiration dates depending on the quality of the food at any given moment. The results of this study indicate that the effectiveness of applying the two approaches in parallel, compared to using them individually, is greater. It should be noticed, however, that these authors recommend consumer behavior research, as is the intention of the present study since the literature usually assumes that demand increases when prices decrease. Indeed, this is not always the case, as there are substitution effects (from LEFO - Last Expiration First Out - to FEFO - First Expiration First Out) which are generally neglected but may influence the analysis.

On the grounds of this, the closest contribution to what is intended here coincides with the study conducted by Tsiros and Heilman (2018), who starts from the stated preferences through a survey to model precisely the consumers' WTP for a perishable product over its shelf life. Still, this analysis is only done with products with 7, 4, or 1 day to go, so it is expected that it is not able to capture the expected variability of WTP for the large spectrum of products with a much longer shelf life. In addition, the study on which the author based the analysis is applied to a small portion of consumers, which may not be fully representative of the population. In that way, they were even able to take into account some demographic characteristics to model the issue.

In contrast, the current study stands out by claiming to grasp the generic behavior of consumers so that broad actions could be introduced to promote, at large extent, less waste. Moreover, the actual research distinguishes itself from the others by focusing on the effect of placing low expiration date labels, which alone are deemed to have a significant effect on customers' perception of risk. That is, it is intended to test the hypothesis that, during the aging of perishable products, the presence of a label simultaneously signaling discount and low RSL causes an exacerbated effect of the risk acknowledged by consumers. This premise was supported by the study of Li et al. (2020), in which it is found that the presence of expiration dates already influences how consumers devalue perishable products when their age increases. Lastly, the analysis undertaken in this dissertation differs further in that it is based on revealed preferences, which certainly afford a more authentic interpretation of consumer behavior, to the extent that stated preferences do not always embody the actions individuals would perform.

Chapter 3

Empirical context

This section describes the product portfolio chosen for analysis and some internal company policies relevant to the study. In addition, it outlines statistics on the data collected and the process carried out to process it, namely cleaning, integration, reduction, and transformation, to make the data readable and fit for use.

3.1 Corporate environment

This study is undertaken in collaboration with a large European grocery retailer, which has a substantial part of its sales linked to perishable products such as vegetables, fruits, cooked meals, meat, fish and yogurts. As this particular set of products is the one that deteriorates the fastest, the amount of monetary losses incurred by this company has been considerable, making it the perfect partner to conduct this analysis.

With several stores around the country, differentiated by size and typology, there is varying availability of items within them. That is, some products can be found in all stores, while others are limited to the larger ones.

Regarding pricing management practices, each store has standard prices and occasional temporary discounts on specific product groups. In addition, discount coupons also exist for loyal consumers, which can be combined with any other in-store promotions.

Aiming to encourage consumers to buy items closer to the end of their useful life and, therefore, to maximize profitability, this company has also taken the initiative to implement a depreciation system for perishable products close to obsolescence. That is, for perishable products that are near to reaching their expiration date, discounts of fluctuating value are granted. In order to communicate this to customers, labels are then placed on the products stating the discount that has been implemented.

In 2020, this price depreciation system was accountable for only 0.4% of total sales and allowed 58% of the critical stock to be sold. Given this evidence, the need to revise the current policy becomes clear to enable a more effective reduction of losses.

Considering the huge variety of perishable products sold by this retailer, it is deemed necessary to opt for the examination of a single portfolio. So, in order to support such a decision, we resort to the data obtained from ReFED (2022) on the distribution of surplus food in the United States of America, during the year of 2019:

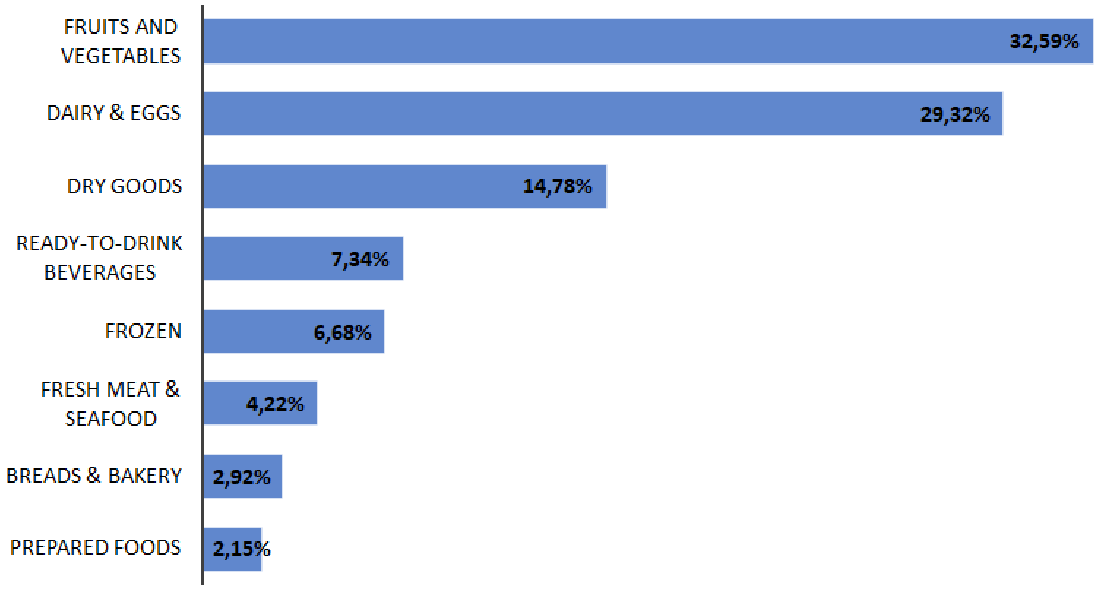

Figure 3.1: Source ReFED (2022) - Distribution of food waste by food categories

The goal is to select the group of products with the most significant impact to promote the greatest waste minimization. At first glance, the choice would fall on vegetables and fruits. However, given the subjectivity of such an analysis and considering that there are no expiration labels for this group of products, the second most striking group is preferred. Then, combining this desire with our partner's needs and its insight into the product group that brings them the most losses, we decide to study the yogurt and dessert portfolio (which ended up including products from the 2^{nd} and 4^{th} groups where the most waste occurs, according to ReFED (2022)).

The differentiation of this range of products in the market is remarkable, from flavors to textures, made available by several brands. For this reason, to facilitate the management of the different articles, this company chooses to group them according to classes and subclasses (see Appendix A).

Independently of the item within the yogurt portfolio, a discount of up to 50% of the potential yogurt price (to which a temporary discount or discount coupon can also be attached) is applied when they only have around 4 days left until expiration. Conversely, when a yogurt is about to expire, it is removed from the shelf, automatically representing an unsaleable product. Notice that, due to human error or the store manager's decision, sometimes the label placement and/or the removal of the product from the shelf deviates from the predetermined timing.

3.2 Data collection and preprocessing

For the sake of apprehending consumer preference between products considered riskier but at a lower price (labeled products) versus products considered safer but at a higher price (unlabeled products), the company provided data for the period from December 1, 2021, to March 14, 2022, for the yogurt portfolio, particularly on the following realms:

- the articles - with the description of each SKU, the class and subclass it belongs to, the average number of shelf life days from when it reaches the stores, the brand, the weight and whether it is a component or pack;
- sales - containing the revenue obtained by the products sold with or without any promotion, in each store and each day;
- daily inventory - inventory on hand of each product in each store and day;
- stock receipts - receipt of batches, indicating quantity, expiration and arrival dates;
- issuance and daily sales of the aforementioned labels - containing the product's expiration date and its price both before being put on the label and at which it was sold, on a given day and store, for the SKUs involved.

Consequently, although accurate data on the RSL and price of labels issued and sold per day were available, this information was not detailed for unlabeled items. In this sense, to estimate their RSL, we combine the data on stock entries and stock on hand each day to determine which batch the products sold belonged to. In turn, for the cases where the price of the unlabeled products was missing, we assume that the price expressed would be the same as the price before the labeling in the label's dataset.

Hence, once the missing values were input and some outliers were corrected, the integration of the labels' data with the sales data was performed.

Next, to select only the group of observations in which, for a given day within a given store and a given SKU, both labeled and unlabeled items were displayed, we add a variable concerning the number of labels exhibited.

Thus, after all the preprocessing steps described, we obtain a set of data regarding the sale of 62,104 labeled and 118,679 unlabeled units, referring to 373 distinct items (from 42 different brands), distributed by 291 stores and 104 days of analysis, in which at one store there is available both the labeled and unlabeled product. Yet, it should be highlighted that the data do not include all 373 products for each of the 291 stores and 104 days, because not all stores were open from the first day of the analysis; and, among those open, not all sell all products; and even among those that do, the labeled and unlabeled alternatives were not always available, for the same item. As a result, we get unbalanced data, i.e., with a very different number of observations per panel effect. To minimize potential problems, we selected only SKU store combinations (which constitute the panel entity) with at least five distinct day observations.

With this stated, the information in the data described above was structured in three ways to meet the specificities of the different software used. For instance, the primary dataset obtained consisted of 36,137 observations. Each row had the sales and characteristics of the labeled and unlabeled products existing on a given day and store (wide format). Notwithstanding, given the need to have the data from each set of sales in a single row for the intended regressions, each original row of the first dataset was subdivided into two (one accounting for the label option and the other for the unlabeled one), obtaining 72,274 observations. Finally, since most available tools for running discrete choice models require the input of disaggregated data, each unit sold was also placed in a different row, symbolizing the preference given by the consumer. Thus, we achieve a long format dataset consisting of 180,783 observations.

Accordingly, Table 3.1 presents summary statistics for the variables of interest, and B adds further details regarding the inherent product characteristics.

Table 3.1: Statistical summary of the main interest variables

Alternative	Variable	Mean	1^{st} Q.	2^{nd} Q.	3^{rd} Q.	Minimum	Maximum	Std Dev.
Labeled	Price	1.33	0.87	1.34	1.72	0.23	5.75	0.63
	RSL	1.09	0	1	2	0	4	0.88
	Quantity sold/day	1.84	0	1	2	0	64	3.06
Unlabeled	Price	2.09	1.30	2.00	2.69	0.33	6.99	0.89
	RSL	22.80	16	21	25	0	388	17.66
	Quantity sold/day	3.51	1	2	4	0	96	4.77

Note: Observations 36,137.

The statistics provided demonstrate some expected patterns. First, it turns out that, on average, heavier products have higher prices and have fewer sales when they have a close expiration date (i.e. when a label has been attached). Additionally, it can be observed that name brands are usually linked to higher prices, fewer sales and higher RSLs (with regard to this last attribute, only when unlabeled). Finally, it should also be noted that among all the units sold covered by the data used, labeled products accounted for 34.4%, whereby more than half (around 52.7%) of the labeled products have remained unsold.

On top of that, it is also valuable to know the proportion of yogurts and desserts included in the portfolio by the respective categories designed by the company, and even to check the average discount practiced in each of them. Besides, it is useful to see each class's quantities sold, prices, and RSL. For this purpose, one can scan the Appendix C. There, it can be seen that the most representative classes in the dataset (i.e., the classes with the greatest diversity of products included) are those related to Greek yogurts, protein yogurts and desserts. On the other hand, it can be observed that organic yogurts have the most pronounced discounts, followed by liquid and lactose-free yogurts, while protein yogurts account for the highest number of units sold, functional yogurts have the highest average price, and plant-based yogurts have the highest RSL, on average.

Chapter 4

Analysis of linear econometric models

As mentioned earlier, one of the objectives of this project is to develop econometric models that provide insight into the impact of the inherent characteristics of the products in the yogurt and dessert portfolio on consumer behavior, as well as their potential unequal contribution if dealing with labeled or unlabeled products.

A description of the methodology followed and the results obtained with the linear econometric models chosen to accomplish the proposed goals are now provided.

4.1 Methodology

Seeking to clarify how the impact of time-invariant attributes differ, we use sales and display data for labeled and unlabeled products and execute two linear estimation models: a Pooled OLS regression and a random effects regression. By performing both of these models, we seek to understand whether or not independence between observations can be assumed, even given the panel structure (an important finding for the design of the non-linear models).

Subsequently, we run two fixed effects regressions separately for labeled and unlabeled products so that the influence of the presence or absence of the label could be included as a fixed effect and thus, the impact of time-varying attributes could be compared. This partitioning of the data was necessary because of the inability of this regression type to account for effects that remain unchanged over time. That is, if the regression was conducted on the entire dataset, the between-effects would be absorbed when compensating for the panel effect (Bell and Jones, 2014), and it would then not be possible to realize the effect of the label.

That said, irrespectively of the regression, we include all variables that vary over time as independent variables, namely the price (*Price*), the remaining shelf life (*RSL*) and the number of labels available for purchase (N_{labels}). Yet, in addition, for the Pooled OLS and the random effects regressions, all available variables related to the fixed characteristics of the items are also introduced, namely dummies for the category ($Class_i$, with i belonging between 1 and 15 except 10), the weight (*Weight*), the type of brand (generic or name brands - *BrandType*), and a binary variable, which assumed the value 1 in the case of a product with a label or 0, otherwise (D_{label}).

Further, the natural logarithm of the sales (*ln(Sales+1)*) is the dependent variable adopted for all regressions, instead of just the sales (*Sales*). This choice was motivated, firstly, by the non-normality of the error residuals initially detected using only the variable of interest without any transformation. Indeed, using the logarithmic relationship allow the highly skewed dependent variable to come close to a normal distribution. Moreover, since sales only take integer values and the output of the regressions is continuous, this is also a way to improve the model fit and to make the analysis more reliable. Finally, it is worth noting that the results obtained in this manner are easier to interpret since we can now see the relationship between the independent variables and the dependent variable as a percent change.

To enable greater certainty in the results obtained, we decided to use two softwares: *Statsmodels* library in Python; and *Plm* in R Studio.

In summary, we perform the following regressions:

Pooled OLS

$$\begin{aligned} ln(Sales+1) = \sum_{n=1}^{15} \beta_n * Class_n + \beta_{Weight} * Weight + \beta_{BrandType} * BrandType \\ + \beta_{Price} * Price + \beta_{RSL} * RSL + \beta_{N_{labels}} * N_{labels} + \beta_{label} * D_{label} + \varepsilon \end{aligned} \tag{4.1}$$

- ε is the residual error term, which joins the effect of the average unobservable entity heterogeneity and the average unobservable time heterogeneity.

Random effects

$$\begin{aligned} ln(Sales+1) = \sum_{n=1}^{15} \beta_n * Class_n + \beta_{Weight} * Weight + \beta_{BrandType} * BrandType \\ + \beta_{Price} * Price + \beta_{RSL} * RSL + \beta_{N_labels} * N_{labels} + (\beta_{label} * D_{label}) + \alpha + u_i + \varepsilon_{it} \end{aligned} \tag{4.2}$$

- α is the general intercept, which catches the average of all entity effects;
- u_i is the variability introduced by the specific effect of entity i (between-entity error);
- ε_{it} is the error term that includes all other sources of variability for entity i over time period t (within-entity error).

Fixed effects

$$ln(Sales+1) = \beta_{Price} * Price + \beta_{RSL} * RSL + \beta_{N_{labels}} * D_{N_{labels}} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{4.3}$$

- α_i is the SKU, store specific effects, which allows to account for characteristics that do not vary over time;
- α_t is the time effects;
- ε_{it} is the error term for unit i at time t.

Once the regressions are obtained, a comparison of the results of the coefficients, their significance (using a 95% confidence level), and the final indicators achieved is performed. In addition, amongst the Pooled OLS and random effects regressions, different factors are weighed to conclude the most appropriate type of model to deal with the particular characteristics of the data. Namely, the residual error distribution is evaluated, including tests for homoskedasticity, and the correlation between these and the independent variable.

4.2 Results

As described in Section 4.1, one of the reasons we decided to use the natural logarithm for the dependent variable was that this allowed the residuals of the Pooled OLS regressions conducted to be closer to a normal distribution. Thus, the following graphs are now presented to exemplify this statement.

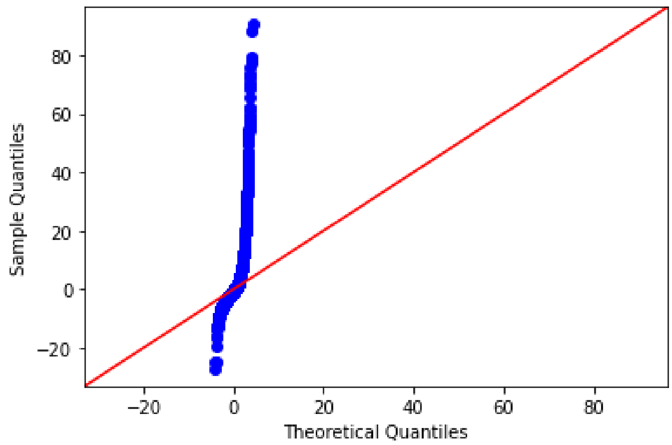

Figure 4.1: Q-Q plot of the residual errors of the Pooled OLS model without the natural logarithm

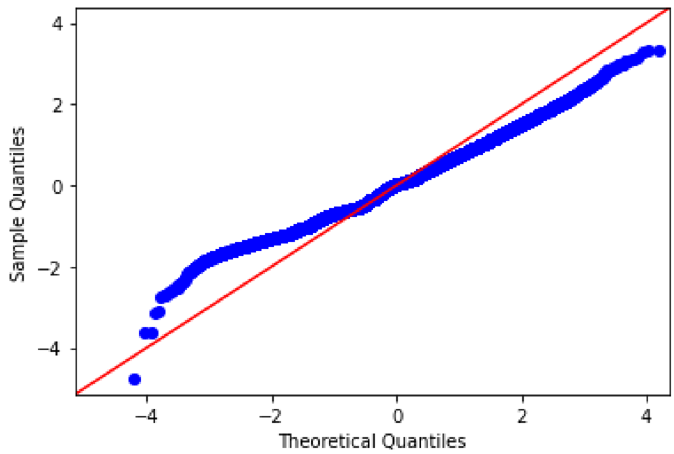

Figure 4.2: Q-Q plot of the residual errors of the Pooled OLS model using the natural logarithm

Therefore, after corroborating the importance of performing the transformation of the dependent variable, the results of the regressions conducted in the complete dataset are shown in Table 4.1. Note that these were obtained by including the impact of Class 1 in the constant term.

Table 4.1: Parameters estimates of the regression models

	Pooled OLS	Random effects
Constant	1.4234*** (0.0344)	1.4097*** (0.0209)
RSL	0.0019*** (0.0003)	0.0020*** (0.0002)
Label(1)	-0.4494*** (0.0150)	-0.4469*** (0.0086)
Price	-0.0786*** (0.0092)	-0.0784*** (0.0068)
Number of labels	0.0109*** (0.0012)	0.0097*** (0.0003)
Weight	-0.0942** (0.0289)	-0.0844*** (0.0210)
Brand Type	-0.1257*** (0.0148)	-0.1369*** (0.0104)
Class 2	-0.1366*** (0.0317)	-0.1176*** (0.0267)
Class 3	-0.0457* (0.0276)	-0.0255 (0.0173)
Class 4	-0.0710** (0.0347)	-0.0765*** (0.0228)
Class 5	-0.1567*** (0.0288)	-0.1314*** (0.0185)
Class 6	-0.1964*** (0.0262)	-0.1754*** (0.0201)
Class 7	-0.1014*** (0.0273)	-0.0724*** (0.0177)
Class 8	-0.1144*** (0.0294)	-0.0926*** (0.0227)
Class 9	-0.0279 (0.0309)	0.0065 (0.0187)
Class 11	-0.0427 (0.0330)	-0.0267 (0.0204)
Class 12	-0.0201 (0.0810)	-0.0345 (0.0412)
Class 13	0.0468 (0.0457)	0.0655* (0.0357)
Class 14	-0.0979*** (0.0342)	-0.0792*** (0.0278)
Class 15	-0.0956** (0.0389)	-0.0651* (0.0341)
R-squared	0.1331	0.1340
R-squared (Between)	0.1916	0.1912
R-squared (Within)	0.1013	0.1021
R-squared (Overall)	0.1331	0.1329
Log-likelihood	-7.895e4	-7.705e4

Note: Observations 72,274. Entities (different combinations of SKUs stores) 8,748. Base class 1.

$^{*}p < 0.1$, $^{**}\ p < 0.05$, $^{***}p < 0.01$

Although we expected that the Pooled OLS regression would have a less successful performance when compared with the random effects regression, by not being able to account for the effect of analyzing the same entities over time, a clear similarity between the coefficient estimates and the explanatory power of the two models can be observed. In fact, the signals and magnitudes of the parameters obtained are concordant for both models, except for the signals for the dummy of class 9 - protein yogurt. Still, this is irrelevant since these coefficients are not significant, exhibiting a confidence interval that includes the null value. As for the significance of the coefficients obtained, taking into account a confidence level of 95%, a general consistency is also noted, except for the coefficient related to class 15 - plant-based yogurts. For this type of yogurts, it is not possible to conclude the similarity or dissimilarity with the base class - solid yogurts. As such, an attempt should be made to determine this matter in further analysis.

That said, by separately analyzing the values obtained for the significant coefficients at a 95% confidence level, it can be seen that both the coefficients for RSL and the number of labeled items available are positive, corroborating the expected positive impact of these factors on the purchase decision. Similarly, the coefficients for price and weight also show the predicted effect, in this case, negative. Actually, since a decrease in sales usually accompanies a price increase, we anticipate a negative parameter. As for weight (linked to the quantity per package and the number of containers per yogurt), once our analysis is based on perishable products, we foresee a preference for products with a smaller quantity at a time. In this way, customers may feel more secure as they are more likely to be able to consume the whole good by its expiration date. In turn, the influence of variables such as brand type (name or generic brands), and especially whether the product has a label attached or not, have led to the need for more careful analysis when looking at the collected results. Regarding brand typology, the results point to a preference for generic brands, suggesting that there is no perception of different quality between these and name brands, which means that there is no significant brand equity influence. Regarding the influence of labeling on products, there is an apparent negative impact on demand, which may question the effectiveness of these types of policies. However, while at first, we thought it to be possible to measure the impact of the presence of the label on yogurt, after obtaining the results and attempting to understand this negative relationship, we suspect that it may not be reliable to assess such an effect. As a matter of fact, despite considering only the days when labeled products were available for the input data, there are still significantly more unlabeled products compared to the labeled ones. Thus, a penalizing perception of the presence of the label may be induced, as the model perceives that fewer sales occurred when a label was in place. In that way, it can be seen that the underlying supposition portrayed by the model may be misconceived since having fewer sales may have very little to do with the label's impact on consumer perception. Consequently, the conclusions about the exclusive impact of the label are revised in the following models.

Thereafter, in their turn, considering the non-significance of the Greek (class 3), protein (class 9), special (class 12) and organic (class 13) yogurts, as well as desserts (Class 11), one can infer that they exhibit a similar demand pattern when compared to the base class. Conversely, the remaining classes - chunks, liquid, infantile, Bifidus, low-fat, functional, and lactose-free - point to a demand pattern significantly different from solid yogurts.

After gaining an overview of the coefficients obtained, we regard it essential to assess the models' reliability by performing the Breusch-Pagan Lagrange Multiplier test on the residuals of the Pooled OLS regression. Corroborating what Figure 4.3 shows, the null hypothesis, which states that the residuals are homoskedastic, was rejected (with a p-value below 2.2e-16).

Indeed, it can be observed that the dispersion of the observations is very significant, given the differences found between the actual and predicted values. As a result, it seems evident that the variance is not the same across all data and that the OLS estimator is likely inefficient, potentially leading to inaccurate standard errors and parameters' confidence intervals.

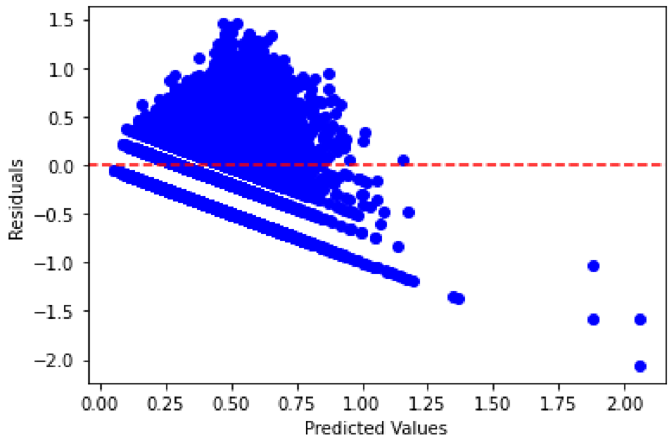

Figure 4.3: Homoskedasticity Test

Additionally, we also perform a Durbin-Watson Test to grasp how strong the correlation between the produced residuals is. The computed statistic was 2.318, which is significantly close to 2 (the value for which autocorrelation is assumed not to be present). Henceforward, it can be concluded that the serial correlation observed in the data due to the panel effect is not very meaningful and insufficient to reject the null hypothesis that the error terms are independent. As a matter of fact, such a result was predictable thanks to the highly unbalanced data being used. Since most SKU-store combinations have no more than 5 observations, it might be challenging to detect the panel effect.

Finally, the degree of correlation within the dependent variable versus the residual errors is even scrutinized with Figure 4.4.

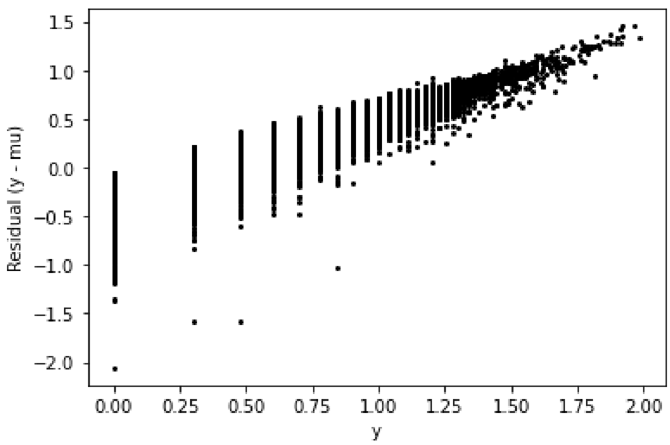

Figure 4.4: Pooled OLS residuals versus ln(Sales+1)

As a strong relationship between the dependent variable and the residuals seems to exist, one can conclude that there is a high correlation between both. Thus, one can suspect that the value of sales is only partially explained by the dependent variables, suggesting that it would be relevant, in the future, to strive to obtain additional explanatory variables.

In short, given the tests performed, it is believed that the parameters obtained from the Pooled OLS regression and the random effects regression are robust enough to discern the positive or negative impact of attributes on consumer perception. While the Pooled OLS regression may reveal inaccuracies regarding the standard errors and the confidence intervals of the parameters, the random effects model supports the results of its average parameters.

With all that stated, the results gathered for the two fixed effects regressions undertaken are now displayed in Table 4.2.

Table 4.2: Parameters estimates of the fixed effects regressions

	Labeled products dataset	Unlabeled products dataset
Constant	1.0507***	1.8930***
	(0.0272)	(0.1545)
RSL	0.0206***	0.0022***
	(0.0043)	(0.0003)
Price	-0.3908***	-0.0174***
	(0.0201)	(0.0005)
Number of labels	0.0296***	-0.3295***
	(0.0005)	(0.0730)
R-squared	0.1315	0.0449
R-squared (Between)	0.2873	-0.1081
R-squared (Within)	0.1359	0.0446
R-squared (Overall)	0.2459	-0.0576
Log-likelihood	-2.608e4	-2.777e4

Note: Observations 36,137. Entities (different combinations of SKUs stores) 8,748.
*$p < 0.1$, ** $p < 0.05$, ***$p < 0.01$

When estimating the coefficients of the fixed effects models, an offset of between-entity variability is performed, and thus a clearer perception of the influence of time-varying attributes (RSL, number of labels available, and price) on demand for labeled and unlabeled products is possible. However, it should only be noted that since these models were run on different datasets, it is not possible to directly compare the magnitude of the coefficients obtained (only ratios between them), although it is possible to compare signals.

In this sense, a first ascertainment of the results emphasises a differential effect of the number of available labels on the demand for unlabeled and labeled products. This was expected because, on the one hand, greater availability of labeled products is likely to lead to higher consumption of these products; and, on the other hand, increased consumption of labeled products is inevitably linked to lower consumption of unlabeled products, as consumers may substitute the unlabeled product for the labeled one. Beyond this, one can denote that the impact of price and RSL on sales is heading in the same direction in both models and that price causes a more considerable percentage change than RSL in the sales of the respective product alternative. Nevertheless, it turns out that the RSL of the unlabeled products appears to have a larger relative impact than the RSL of the labeled products when comparing the relative magnitude of the corresponding parameters under each model.

Lastly, contemplating the heterogeneity that the models could capture, the most relevant R-squared to evaluate is that of within-entities. Looking at it in the regression that focuses on the data for labeled products, one can see that the considered variables were able to explain a significant part of the variability. However, the same cannot be claimed for the regression performed on unlabeled products. In fact, recalling the statistics presented in Table 3.1 and Figure 4.4, one can see that there is much greater variability in the sales of unlabeled products and that it is imminent that there are non-fixed factors that vary over time that the model does not take into account, respectively, such as changing customer tastes, the substitution of yogurt for another product, among others.

Chapter 5

Analysis of non-linear econometric models

After obtaining the linear models described in Chapter 4, we gauge both the relative importance of each observable characteristic of the yogurt/dessert under analysis and the impact that the label, on its own, has on consumer purchasing tendencies. However, while this insight is relevant to distinguish the discount management policies to be applied to this entire product portfolio, it still does not allow us to understand what motivates the choice between a given labeled or unlabeled SKU. That is, the panel regressions do not allow us to find out what motivates the choice between yogurts with a longer or a shorter RSL when a customer arrives at a grocery store and already knows which specific item (s)he wants to buy. In this sense, the goal of assessing the potential of the labeling policy used to combat waste has not yet been achieved, leading to the need to complement the analysis by developing non-linear econometric models, specifically, discrete choice models.

5.1 Methodology

This time, the software tool used was Python with the library *Biogeme*, given the perceived greater flexibility to adapt the calculation of the various estimates to the particularities of the data.

That said, to select the most appropriate model to address the unanswered research questions, some specificities of the data are determinant and caused a detachment from some models reviewed in the literature.

The first particularity has to do with the fact that, in addition to the data including choices made at a given time (cross-sectional data), it also covers the time sequence of the decisions made (time series) - resulting in a typical representation of panel data. The second peculiarity is that, in each observation course, the data do not show individual choices but rather the choices of a group of individuals who went to a particular store and chose a specific SKU. That is, each choice encompasses decisions made by several individuals, who may or may not be the same over time, and about whom no knowledge exists. Therefore, it is not possible to include characteristics related to the socio-economic conditions of individuals in the constructed models.

Then, it became clear that it is imperative to choose a model capable of capturing the heterogeneity resulting from observing the same entities (SKU, store) over time. Given the exemption from making too many assumptions, we consider that the MIXL is the most appropriate model, considering that fewer complex models within the diversity of existing models, such as Logit and Probit models, require too restrictive assumptions. In light of this, we deem it unacceptable to assume that the unobserved factors have no correlation between alternatives or even to accept the non-existence of serial correlation, i.e. no correlation between time horizons. Since the data collected is sales data on different days for the same stores and items, it is inevitable to expect a pattern of choices over time for the same entity. That is, factors that are not directly captured are expected to persist over this period because, regardless of the alternative selected, the specific characteristics of each SKU (namely its class, subclass, brand, and weight) remain the same.

Despite all this, given the immense time it takes to run a MIXL, we decide to study the most appropriate way to model this situation using the most straightforward and fastest model: the Logit model. It is believed that even if this model does not fit the specifics of the data, it can still guide the election of specifications (Wasi and Keane, 2012; Cherchi and Cirillo, 2008).

Thus, having defined the models to be used, the next step in the consumer behavior modeling process is clearly defining the set of alternatives to be addressed. We assume that it is beyond our scope to determine the consumer's desired SKU, in that a consumer would not be expected to trade one specific SKU for another just because one or the other has a low shelf life discount label attached. Instead, we suppose that the consumer knows which SKU (s)he wants and that the customer makes the choice under scrutiny if it is available with a longer or shorter RSL.

As such, to examine this generic consumer decision, two alternatives were carefully defined:

- unlabeled yogurt: article without discount and therefore with a long RSL (usually, more than 4 days before expiration)
- labeled yogurt: article with a discount due to the upcoming expiration date (usually, less than or equal to 4 days before expiration).

Once the set of choices is defined, we check whether it fulfils the preconditions for applying discrete choice models. In this respect, a representative basket of consumers was briefly studied to verify that this set of alternatives could also be considered mutually exclusive besides being finite and exhaustive.

Moreover, consumers typically only choose to buy the labeled or unlabeled SKU one at a time; thus, it is clear that a discrete choice model could be applied.

During the second phase, it is necessary to decide which variables to include in the models and how to relate them to the deterministic part of the utility. For the sake of streamlining the models created, shortening their running time, and considering that only the differences between the utility of the two alternatives are valuable and that the previous models already allowed understanding the impact of other variables, only attributes that differ between the alternatives and over time were included: price, and RSL. Thus, variables such as brand, class, and subclass were discarded as they are specific to SKUs that are the same in each observation, regardless of the alternative and period.

Regarding the parameters to be estimated, depending on whether the effects on utility of each of the alternatives are considered similar or not, we decide to use generic or non-generic parameters, respectively.

For the price, since we expect to have a different relevance depending on whether or not the product is close to its expiration date, specific alternative parameters were assigned. For RSL, we also consider it desirable to stipulate specific parameters for each alternative. Despite that, further doubts arise about the suitability of a linear relationship to model consumers' perceived utility because of the vast range of values this variable can take on. That is, consider changing the RSL of the same product from 8 days to 4 days, or from 30 days to 26 days. It seems evident that the former should have a substantially greater impact on the utility that a consumer can obtain from the good than the latter, so it is inaccurate to expect a similar variation in utility across the entire RSL of the unlabeled items spectrum.

As a result, we decide to divide the range into smaller and more meaningful intervals. Considering the period generally covered in the literature (Chung, 2019; Tsiros and Heilman, 2018) and, at the same time, the pursued intention to have at least 1% of the data in each category, we consider 8 days as the first breaking point. Subsequently, to maintain the same interval in the following categories, 17 and 26 days are also considered breakpoints. Further, we choose to have one class for products with more than 26 days of RSL since purchases of this type of product do not have such a long time horizon in sight (Bijwaard, 2005).

Figure 5.1 provides an overview of the distribution of the RSL of the unlabeled yogurts over the discretization intervals.

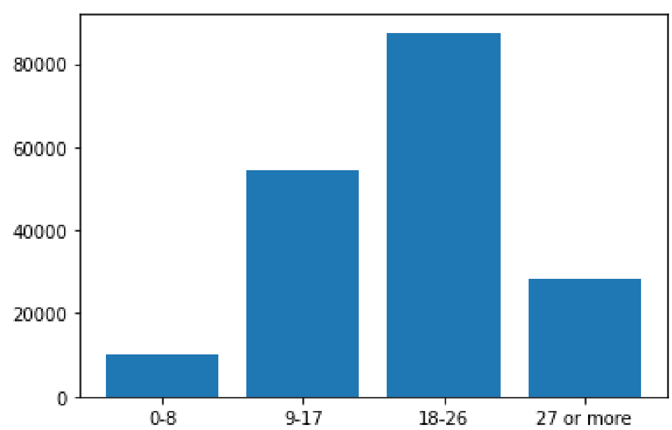

Figure 5.1: Number of unlabeled yogurt samples per discrete interval of remaining shelf days

When performing the Logit models, we test four alternative ways of quantifying deterministic utility, thus declaring different parameters. The first is retained as the benchmark, assuming a linear relationship between the utility and the RSL (model 1). Nevertheless, a piecewise specification is also generated to create a non-linear relationship between the utility retained by consumers when buying an unlabeled yogurt and the RSL (model 2). For that purpose, four variables are created for each of the categories listed above, each assuming the corresponding number of days of RSL if it is within the range of the category it refers to or a null value otherwise (see Appendix D). In such a way, each of the variables derived is linked to distinct parameters capable of demonstrating different effects on utility. On the other hand, the expected non-linearity between the utility of the unlabeled item and the RSL is also shaped by considering dummies (see Appendix E) associated with the classes created (model 3). Finally, the feasibility of the relationship between the utility and the RSL being logarithmic is examined (model 4). This forth specification implies that the fewer days left to expire, the more significant the impact on consumers' perception of utility.

On top of that, to capture the average effect of the unobserved factors, an alternative specific constant (ASC) is included in each of the two alternatives (independently of the specification used). The one for the unlabeled items is normalized to 0 so that the parameter values obtained can be compared, regardless of the specification used.

Taking all this into account, the deterministic utility of each of the two alternatives resulted in a base specification and three possible competing specifications (models 2-4). Let us present the base specification for a given SKU:

Model 1 - Linear relation

$$V_{unlabeled} = ASC_{unlabeled} + RSL_{unlabeled} * \beta_{RSL_{unlabeled}} + Price_{unlabeled} * \beta_{Price_{unlabeled}} \tag{5.1}$$

$$V_{labeled} = ASC_{labeled} + RSL_{labeled} * \beta_{RSL_{labeled}} + Price_{labeled} * \beta_{Price_{labeled}} \tag{5.2}$$

Model 2 and 3 - Piecewise and Classes

$$\begin{aligned} V_{unlabeled} = ASC_{unlabeled} + RSL1^{*}_{unlabeled} * \beta_{RSL1_{unlabeled}} \\ + RSL2^{*}_{unlabeled} * \beta_{RSL2_{unlabeled}} + RSL3^{*}_{unlabeled} * \beta_{RSL3_{unlabeled}} \\ + RSL4^{*}_{unlabeled} * \beta_{RSL4_{unlabeled}} + Price_{unlabeled} * \beta_{Price_{unlabeled}} \end{aligned} \tag{5.3}$$

$$V_{labeled} = ASC_{labeled} + RSL_{labeled} * \beta_{RSL_{labeled}} + Price_{labeled} * \beta_{Price_{labeled}} \tag{5.4}$$

* *Despite having the same name, these variables are different for the two models. See Appendixes D and E respectively.*

Model 4 - Logarithmic relation

$$V_{unlabeled} = ASC_{unlabeled} + log(RSL_{unlabeled} + 1) * \beta_{RSL_{unlabeled}} + Price_{unlabeled} * \beta_{Price_{unlabeled}} \tag{5.5}$$

$$V_{labeled} = ASC_{labeled} + RSL_{labeled} * \beta_{RSL_{labeled}} + Price_{labeled} * \beta_{Price_{labeled}} \tag{5.6}$$

Each of the above models is conducted by considering an error term independent over time - ε_{ij} - as specified in Equation 2.2, and the parameter estimation performed according to Equation 2.4 using the Maximum Likelihood method.

From this point on, the specification that best fits the data is chosen by comparing the BIC obtained. In this case, we use BIC instead of the most commonly used indicator - the AIC - because the main objective of the models to be developed is to describe the most critical aspects of consumer behavior, and not to predict its choices.

Having then decided on the most appropriate specification for deterministic utility, the final model - the MIXL - is finally carried out. For its development, it is only necessary to modify the error term utilized in the Logit model so that it could then take into account the aforementioned correlations:

$$U_{ij} = x_{ijt}\beta + \alpha_{ij} + \varepsilon_{ijt} \tag{5.7}$$

where x_{ijt} represents observable attributes of the alternative i, at time t, for the combination j of SKU and store; β, α_{ij} and ε_{ijt} are unobserved stochastic influences, where the former is relative to parameters to be computed and the latter two correspond to the error component: $\alpha_{ij} \sim N(\mu, \sigma)$ and $\varepsilon_{ijt} \sim$ EV(0, σ').

Regarding the error component, α_{ij} is inserted to capture the heterogeneity stemming from factors that remain over time - panel effect. That is, as mentioned above, since the data include observations for the same SKU in the same store over time, one would expect the utility to show similar patterns regardless of the instant of analysis. We then define this parameter as a random variable, following a normal distribution (random effect). Otherwise, if one considers this as an unknown parameter (fixed effect), the model could be biased in that the number of observations for each SKU and store is often small.

Moreover, the ε_{ijt} was assumed to be independently and identically distributed over time, according to a Gumbel distribution, capturing, namely, seasonal variability. We also admit that this component is independent of the correlated component over time α_{ij}.

Finally, let us denote how the estimates are performed throughout the MIXL realization. As for the unconditional probability, to include the quantities sold trajectory(derived from the choices made by several individuals) over the days for each combination of store and SKU, we rely on the Equation 5.8.

$$P_{ij} = \int_{\alpha} \prod_{t=1}^{T} \frac{e^{V_{ijt}+\alpha_{ij}}}{\sum_{k=0}^{1} e^{V_{kjt}+\alpha_{kj}}} f(\alpha) d\alpha \tag{5.8}$$

Where *f(α)* is the density function of the random effect.

Pointing out that the integral within the unconditional choice probability does not have a closed form, its calculation requires an approximation, performed using simulation, as shown in Equation 5.9.

$$P_{ij} \approx \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \frac{e^{V_{ijt}+\alpha_{ij}}}{\sum_{k=0}^{1} e^{V_{kjt}+\alpha_{kj}}} f(\alpha) d\alpha \tag{5.9}$$

Where R is the number of draws.

The number of draws greatly impacts the accuracy of the estimates obtained. However, there is a high computational trade-off in that a larger number of draws is associated with substantially more time expenditure. For this reason, we use 400 draws (Hensher and Greene, 2011; Lerche and Mudford, 2005).

Thereafter, by accounting for the number of customers who purchased each alternative at each moment, the log-likelihood estimate is attained according to Equation 5.10.

$$\mathscr{L} = sold_{unlabeled} * \sum_{j} log(P_{unlabeled\,j}) + sold_{labeled} * \sum_{j} log(P_{labeled\,j}) \tag{5.10}$$

Where, for the attempts performed with the aggregated dataset, $sold_{unlabeled}$ corresponds to the sales value of the option without label for a given day, store, and product, and $sold_{labeled}$ corresponds to the sales value of the labeled option, under the same conditions; and, in turn, for the attempts with the disaggregated dataset, if the product without label has been chosen, $sold_{unlabeled}$ takes the value of 1 and $sold_{labeled}$ the value of 0, and if the product with label has been chosen, both variables take the values 0 and 1, respectively.

Once the model is completed, we diagnose the estimated parameters to assess the reliability or unreliability of the conclusions to be drawn. As a final step, we estimate each alternative's expected WTP for one more day of RSL.

5.2 Results

In Section 3.2, the consolidation of the data into an aggregated and disaggregated format was reported, as this allowed flexibility to experiment different ways of specifying the models in different libraries. At this point, it should be noticed that the results presented were achieved using the data while using the disaggregated dataset.

That said, as a means of obtaining an initial grounding, and as mentioned before, four Logit models were conducted, to then select the most suitable specification. Accounting for the fact that the constant of the unlabeled alternative was set to 0, the results obtained are presented in Table 5.1.

Regardless of the model considered, it is clear that the utility of the two alternatives is diminished by the increase in price, as expected.

Table 5.1: Parameters estimates of the Logit Models

	1 - Base	2 - Piecewise	3 - Classes	4 - Log
$Constant_{labeled}$	0.412***	0.252**	0.295***	-0.130*
	(0.078)	(0.1120)	(0.95)	(0.077)
$Price_{labeled}$	-1***	-0.986***	-0.682***	-7.080***
	(0.089)	(0.0901)	(0.068)	(0.919)
$Price_{unlabeled}$	-0.284***	-0.327**	-0.114***	-3.170***
	(0.060)	(0.0604)	(0.043)	(0.623)
$RSL_{labeled}$	-0.054*	-0.039	-0.0348	1.640***
	(0.030)	(0.0305)	(0.031)	(0.309)
$RSL_{unlabeled}$	0.0003	-	-	0.763***
	(0.001)			(0.056)
$RSL1_{unlabeled}$	-	-0.212***	-1.250***	-
		(0.0305)	(0.139)	
$RSL2_{unlabeled}$	-	-0.0147**	-0.252***	-
		(0.0063)	(0.074)	
$RSL3_{unlabeled}$	-	0.009**	0.164**	-
		(0.0039)	(0.066)	
$RSL4_{unlabeled}$	-	-0.0017	-ʾ	-
		(0.0013)		
$\mathscr{L}(\hat{\beta}))$	-4626.455	-4561.82	-4558.413	-4221.822
AIC	9262.911	9139.641	9130.825	8453.644
BIC	9297.183	9194.476	9178.806	8487.916

Note: Observations 180,783. ʾ set to 0.

$*p < 0.1$, $**\ p < 0.05$, $***p < 0.01$

For the RSL, the results are diverging. For the baseline model, we find that the RSL coefficients are not significant at a 95% confidence level, showing this model's inability to quantify the existing variability in the data. Similarly, the coefficients related to the RSL of the labeled products within the piecewise and the class specifications show non-significant. In turn, concerning the unlabeled products RSL coefficients of these models, we observe that consumers attribute a negative impact to the items with an RSL of 0 to 8 days. This finding was predictable given that this range of values includes products potentially not labeled due to misstatements. Considering that they have a low RSL but a regular price, it is understandable that customers would not value them. Moreover, a decrease in utility for products with RSLs of 9 to 17 days is still denoted when compared to products with longer RSLs. In contrast, we verify that products with RSLs of 18 to 26 days are more valued than products with more than 27 days. However, for the piecewise specification model, this is not meant as we find that consumer utility is not significantly affected by the RSL of products with more than 27 days of RSL. Notwithstanding, the higher valuation of the parameter related to *RSL3* may be related to its being estimated predominantly with different products set from those covered by the parameter related to *RSL4*. That is, perhaps the differences obtained are due to the estimates of one and the other coefficients being based on different sets of products, resulting in variability owed to unobservable characteristics of the products and not owed to the RSL discrepancy. Finally, the model with the logarithmic relationship shows both coefficients' significance and a positive impact of the RSL coefficients on the utility.

In relation to the difference between the alternative specific constants, the model with a logarithmic relationship is the only one that shows a negative signal. In contrast, all the other models predict a positive association between the label and the utility. Even so, we verify that the model's constant in the model 4 is not significant, while all the others are at the significance level adopted so far - 95%.

Then, when trying to discern the best performing model, it is relevant to recognize that they all started from the same initial log-likelihood (-4,855.496) and that the number of parameters of the base and logarithmic models is equal to and less than those of the other two models. Thus, comparing the final log-likelihood of each model is enough to make it evident that the model specified with the logarithmic relationship is arguably a more fitting specification than the others. In fact, since the increase in the number of parameters in models 2 and 3 is not accompanied by any improvement in the log-likelihood, no further testing is necessary. Still, when considering the BIC indicator, one can even corroborate the above, considering that a gain of about 9% occurred upon comparing the standard model with the logarithmic model. This specification is so the basis for the MIXL.

With the importance of considering serial correlation using the constant contained in the labeled alternative already stated, the need to account for heterogeneity within entities is not clear. For this reason, to find a parsimonious model that enables the computation of the requested WTP range, the following alternative models are explored: model A is the simplest, including only mean parameters, except for the constant, for which it assumes a normal distribution; model B only including a mean parameter for the price, and assuming that both the constant and the RSL follow a normal distribution; model C, taking a mean parameter for the RSL, and normal distributions for the constant and the price; finally, model D, assuming that both the constant and the two attributes are normally distributed.

The results for these four models are presented in Table 5.2.

Overall, one can notice that the values of the average parameters are quite stable across models, and even their signals are consistent with the Logit model using the logarithmic specification. The only discrepancy that emerges is in the sign of the average expected value of the constant for labeled products, which had already shown inconsistencies in the previous models. Although, this time, one should realize that for the model where the label has, on average, a negative effect on utility, the estimated coefficient is non-significant. Furthermore, we also observe that for the two models where the parameter is significant (models B and D), the expected value for the standard deviation is more than seven times larger than the average value, suggesting a substantial amount of heterogeneity. That is, presumably depending on the product and the store (which is to say, the consumers who revealed their preferences in that store), the impact of viewing a label placed on a product is highly variable. Therefore, whilst the average results seem to point to a positive effect, the standard deviation leads to conclude that there are many cases where the outcome is reversed.

Table 5.2: Parameters estimates of the Mixed Logit Models

	Model A	Model B	Model C	Model D
$\mu_{Constant}$ (Labeled)	-0.035	0.181***	0.023	0.156***
	(0.037)	(0.041)	(0.039)	(0.042)
$\sigma_{Constant}$ (Labeled)	1.12***	1.050***	1.07***	1.060***
	(0.014)	(0.017)	(0.017)	(0.024)
μ_{Price} (Unlabeled)	-2.240***	-2.040***	-2.100***	-2.050***
	(0.219)	(0.251)	(0.230)	(0.276)
σ_{Price} (Unlabeled)	-	-	0.147	0.001
			(0.235)	(0.459)
μ_{Price} (Labeled)	-8.700***	-8.190***	-9***	-8.160***
	(0.294)	(0.333)	(0.315)	(0.350)
σ_{Price} (Labeled)	-	-	3.170***	1.910***
			(0.287)	(0.466)
μ_{RSL} (Unlabeled)	0.492***	0.968***	0.493***	0.947***
	(0.015)	(0.028)	(0.015)	(0.029)
σ_{RSL} (Unlabeled)	-	1.100***	-	1.050***
		(0.022)		(0.026)
μ_{RSL} (Labeled)	2.040***	2.180***	2.040***	2.240***
	(0.073)	(0.117)	(0.073)	(0.121)
σ_{RSL} (Labeled)	-	5.560***	-	5.720***
		(0.118)		(0.140)
$\mathscr{L}(\hat{\beta})$	-100117.2	-97389.21	-100102	-97394.42
AIC	200246.4	194794.4	200220	194808.8
BIC	200287.5	194849.3	200274.9	194877.4

Note: Observations 180,783. Number of draws 400.

$^{*}p < 0.1$, $^{**}\ p < 0.05$, $^{***}p < 0.01$

For the remaining parameters, one encounters very similar values over all models. That said, the results match the projections for the price-related parameters since the higher the price, the lower the expected utility for customers. Moreover, for the labeled products, the price impact is expected to be higher when compared to the unlabeled products price, given the need to counterbalance the higher perceived risk for the former case. Concerning the RSL parameters, the outcomes are also in line with what was expected. On average, a one-day increment in the RSL for a labeled product is estimated to be much higher than the same increment for an unlabeled product. In other words, and as mentioned earlier, the impact on the utility of a variation from 4 to 2 days of RSL should be higher than the impact from 20 to 18 days. Yet, it is even found that the RSL of the labeled products shows considerable heterogeneity across entities. This means that among different types of products, there may be different importance given to RSL. For example, think of fresh cheese or chocolate mousses. The shelf life of the former product is certainly expected to be more critical. On top of that, among consumers, there may again exist varying sensitivities, and even considering the same product and consumer, it should be noted that at different time horizons, fluctuations in consumers' perceived utility can be found. Namely, in warmer weather, consumers certainly perceive a greater risk that products with a shorter RSL may be spoiled.

The model that seems to best explains the variability found is model B. Besides presenting the lowest log-likelihood, BIC and AIC values, it delivers all the calculated parameters with significance.

Nonetheless, model D draws attention to the proximity of the performance indicators obtained and for having proven the existence of heterogeneity at the level of the labeled products' price. Despite the perceived lack of variability in the price of unlabeled products, it leads to specifying a model that accounts for all parameters as following a normal distribution, except for the price of unlabeled products.

Thus, model E emerged, whose results are presented in Table 5.3 (together with the results from model B, for ease of comparison).

Table 5.3: Parameters estimates of the final Mixed Logit model (model E) versus model B

	Model E	Model B
$\mu_{Constant}$ (Labeled)	0.132***	0.181***
	(0.050)	(0.041)
$\sigma_{Constant}$ (Labeled)	0.970***	1.050***
	(0.021)	(0.017)
μ_{Price} (Unlabeled)	-3.080***	-2.040***
	(0.301)	(0.251)
μ_{Price} (Labeled)	-9.880***	-8.190***
	(0.413)	(0.333)
σ_{Price} (Labeled)	3.270***	-
	(0.225)	
μ_{RSL} (Unlabeled)	0.973***	0.968***
	(0.030)	(0.028)
σ_{RSL} (Unlabeled)	1.100***	1.100***
	(0.025)	(0.022)
μ_{RSL} (Labeled)	2.270***	2.180***
	(0.123)	(0.117)
σ_{RSL} (Labeled)	5.520***	5.560***
	(0.118)	(0.118)
$\mathscr{L}(\hat{\beta})$	-97355.29	-97389.21
AIC	194728.6	194794.4
BIC	194790.3.1	194849.3

Note: Observations 180,783. Number of draws 400.
$*p < 0.1$, $**\ p < 0.05$, $***p < 0.01$

Analyzing the results obtained for this final model, we observe that all coefficients are significant, present numerical similarity and complete consistency with the model B signals, and the performance indicators are the most favorable (taking into account their lower values). From this comparison, we infer significant heterogeneity in the RSL and the price of labeled products. Indeed, any variability in the price of unlabeled products is due to the intrinsic characteristics of the

SKUs and, as such, is included in the constant term. Additionally, the positive average effect of the label indicated by the previous discrete choice models is confirmed, although again with extreme variability, demonstrated by the value of the standard deviation. Similarly, we notice an adverse effect on the price and a positive impact of the RSL at consumers' perceived utility level.

That said, no further concerns remained, and model E is selected to make the WTP estimates.

5.2.1 Willingness to pay for one extra day of shelf life

Estimating the WTP for one more day of shelf life is not straightforward, since the deterministic utility of the unlabeled alternative includes a logarithmic relationship for the RSL, and, as such, for this alternative, it is not sufficient to just divide the two parameters as described in the Section 2.1.2. For this reason, it is required to calculate it using the same software as for the discrete choice models, through a Monte Carlo simulation of the ratio between the derivatives of the RSL and the price. Moreover, taking advantage of the estimates obtained in this way, it is also possible to obtain, apart from the average absolute value of the WTP for an additional day of validity, the corresponding average value of the WTP in respect to the percentage of the total product's price. In these circumstances, the WTP estimates are then exhibited in the Table 5.4.

Table 5.4: WTP Estimates

	$\mu_{WTP_{unlabeled}}$	$CI_{WTP_{unlabeled}}$	$\mu_{WTP_{labeled}}$	$CI_{WTP_{labeled}}$
Absolute values	0.172	[0.130, 0.273]	0.280	[0.083, 0.708]
Percentage (%)	13.14	[9.91, 20.89]	32.66	[10.09, 84.13]

First, for a more explicit interpretation of the results obtained, it is important to explain the underlying line of thought. Note that a higher WTP for an extra day of RSL can be seen conversely as the need for a higher discount so that the consumer is willing to pay for a product with one less day of RSL. So, when looking at the results achieved, one finds a higher average WTP for an extra day of RSL for labeled products than for unlabeled products. In other words, it suggests that the average discount needed for the consumer to be willing to pay for a labeled product with one-day validity left should be higher than the average discount for the unlabeled product with one-day validity left. Still, we verify that the confidence interval for the WTP for labeled products has a much larger range than for the unlabeled products. It was predictable given the significant variation in the parameters corresponding to price and RSL for labeled products.

For a concrete view of the impact that an RSL one-day variation is likely to have on the WTP depending on some product characteristics, one can glance at F. There we observe a significant difference in WTP between classes and, within each, a large discrepancy between labeled and unlabeled products. Nevertheless, there is also a large discrepancy between the WTP of unlabeled and labeled products referring to brand typology. Note that while for products with a longer shelf life, the WTP per extra day of RSL is higher for generic brands, for products with a shorter shelf life, the WTP is higher for private brands, albeit the difference is less significant. This can be explained by the prospect of greater confidence in name brands' products, leading to greater preference for them when the RSL is low. Concerning products with more or less weight, when the products are not labeled, there is less appreciation of an extra day of RSL for heavier products. In contrast, the extra day of shelf life already receives a higher appreciation when they are labeled.

That said, generically, we obtain that, on average, a consumer is willing to pay 28 cents more for a labeled yogurt with one more day of RSL and only 17 cents more for an unlabeled yogurt with one more day of RSL. Alternatively, a consumer is willing to pay 33% less for a product labeled one day less off, or 13% less for an unlabeled product one day shorter off. Thereafter, since for unlabeled products, the RSL range under consideration is very high, and since 13% less for a high RSL product (for example, with more than 27 days of RSL) seems unreasonable, it was deemed important to calculate the average WTP of the products encompassed in the categories constructed for models 2 and 3. The results obtained are presented in Table 5.5.

Table 5.5: WTP, in percentage of sold price, for one more day of RSL by categories

RSL $\in$	[0, 8]	[9, 17]	[18, 26]	[27, 388]
WTP (€)	0.68	0.20	0.13	0.08
WTP (%)	66.09	16.57	8.03	4.58

As can be observed, from the first to the second class, there is an abrupt drop in WTP, which is followed by a more gradual fall. As a result, we suspect the potential advantage of introducing discount policies earlier, i.e., more than 4 days before the expiration date, and even the possibility of scaling prices down progressively. As a complement to this discussion, Figure 5.2 is also provided, showing the absolute WTP for one more day of RSL for unlabeled products.

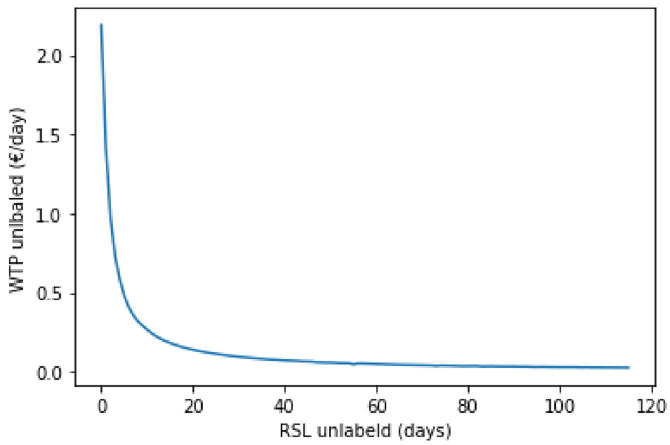

Figure 5.2: WTP for days of RSL of unlabeled products

By examining the graph, one can only add to the above the possibility of delimiting the target of future depreciation policies to a maximum of 18 RSL days since, from that point on, consumers no longer value one more day of RSL (as shown by the proximity of the WTP to 0).

5.2.2 Discount rate change simulation

Prompted by the substantial differences in the WTPs obtained, it is interesting to evaluate changes in the current depreciation policy. Since changing the day on which labels are attached to products cannot be assessed using Monte Carlo simulation, an analysis of the potential application of higher discounts is performed. For this purpose, the probability that each consumer, responsible for the choice in each observation, chooses one or another alternative is first calculated, using 1000 draws (Lerche and Mudford, 2005; Hensher and Greene, 2011). Then, after computing a curve showing the trade-off between the threshold for choosing one alternative and the accuracy of the predicted choice using this threshold, the expected choice is considered to be the one that is reached more than 500 times within 1000. That said, the labeled option price is then changed to a minimum of 30, 40, or 50 percent discount from the unlabeled option price, and the same process is repeated to forecast which choices in each of these cases would be predicted by the model. The number of observations in which the predicted choice changed from unlabeled to labeled yogurt is thus calculated, as this can give insight into the impact on minimizing wasted resources and lost sales.

Notwithstanding, one must underline that we are referring to minimum discounts since the discounts observed in reality often amount to more than 50 percent. In this sense, it is deemed incorrect to impute lower discounts than the ones that occurred since this could lead to the consumer becoming unwilling to buy such a product and therefore refusing to choose any of the alternatives. Only those prices where the discount applied is lower than those simulated have been changed.

The number of individuals expected to switch from an unlabeled to a labeled product and the percentage to which this number of individuals corresponds, compared to the number of observations affected when increasing the observed discount, are presented in Table 5.6.

Looking at the percentage of the number of individuals willing to trade depending on the minimum discount implemented, one can denote a quite different effect across classes. This is essentially related to how different the discount applied is from the ones now enforced. However, the outcomes are certainly also associated with higher or lower price appreciation depending on the product category. That said, there is a greater influence of the potential change in policy for classes 7, 9 and 13 (all with a change of more than 4%, considering any of the implemented discounts). Still, it is also worth mentioning classes 3 and 5, for which, whilst the percentage change is not so significant, as they are products with relatively high demand, a low percentage equates to potentially several products not being wasted.

Furthermore, at first glance, an unexpected phenomenon occurs in classes 13 and 14. It seems that as the discount increases, even if the number of consumers increases, the percentage to which they correspond decreases. At this point, we can see the notorious heterogeneity among consumers, emphasizing that a lower price for yogurt with a short RSL will not encourage some of them to change their decision. In their view, no price drop can compensate for the risks of products with a low RSL.

Ultimately, we note that the findings point to the fact that discounts do not need to be much higher for most consumers to be willing to pay for products. In contrast, we predict interest in

Table 5.6: Number of consumers that change the choice to a labeled product according the minimum discount of them

Discount	30%	40%	50%
Class 1	23 (0.41%)	41 (0.61%)	61 (0.75%)
Class 2	1 (0.11%)	3 (0.23%)	7 (0.40%)
Class 3	88 (1.41%)	196 (1.47%)	378 (2.03%)
Class 4	16 (2.16%)	26 (2.75%)	54 (3.09%)
Class 5	85 (0.82%)	160 (1.18%)	523 (3.02%)
Class 6	8 (0.60%)	15 (0.69%)	61 (2.43%)
Class 7	301 (4.34%)	536 (4.48%)	932 (6.95%)
Class 8	15 (1.44%)	38 (1.70%)	57 (1.85%)
Class 9	686 (4.86%)	1296 (4.98%)	2106 (6.76%)
Class 11	152 (3.31%)	242 (3.35%)	545 (5.79%)
Class 12	4 (2.54%)	12 (2.45%)	17 (2.81%)
Class 13	37 (19.17%)	48 (16.55%)	79 (15.31%)
Class 14	19 (7.42%)	31 (4.98%)	48 (3.31%)
Class 15	6 (1.52%)	12 (2.11%)	26 (3.15%)

applying discount labels to products earlier and then set out for a two-period pricing policy (as indicated by Chung and Li (2017)). We believe that implementing higher discounts for the last days of RSL and lower discounts for the remaining days of a policy that extends the discounted product period may minimize situations with a direct association of risk to the label. Thereby, retailers can improve their profits by having less product waste.

Chapter 6

Discussion and conclusion

Food waste can be described to be one of the biggest atrocities consciously and openly committed in the 21^{st} century. Aggravated by the unequal distribution of commodities produced around the world, wars, natural disasters and poverty, it is leading to the starvation of billions of people every year (hunger hilfe, 2022). The urgency to act is therefore recognized by all.

But while for households - the entity with the greatest responsibility for the waste that occurs worldwide (Quested et al., 2021) - the minimization of wastage is mostly achievable with will and purpose, for large organizations, such as retailers, the task is more complex. From problems of operational and inventory control, collaboration and refrigeration conditions, to inadequate demand forecasts and misinterpretation of expiration labels (de Moraes et al., 2020), the need for theoretical and analytical support, which should be guided by empirical evidence, is evident.

Being aware of this urge, this study sheds light on consumer behavior towards perishable products and thus contributes to policies that prompt consumers to buy products before they become obsolete. Based on sales data of labeled and unlabeled yogurts, an innovative methodology was conceived, including developing discrete choice models suitable to explain the revealed preferences. Among the conducted models were panel regressions, used to provide information about the most important variables, and discrete choice models employed to give insight into the choice level process and the WTP for one more day of validity.

The results obtained allowed the consolidation of knowledge, essential for future decision-making.

Considering only the linear models, the first two research questions were addressed. As for the first, it was found that the attributes that have the greatest influence on consumer consumption tendency, in order of importance, are the presence or not of a label (in a prominent way), the product category (perceived by the class to which it belongs), the brand type (generic or name brands), the weight, the price and, lastly, the RSL. Additionally, it was ascertained that there are significant differences within categories, for instance, between solid, Greek, protein, specialty, and organic yogurts, and even desserts, when compared to chunk, liquid, infantile, bifidus, low-fat, functional, and lactose-free yogurts. Finally, it was found that consumers generally prefer yogurts with more RSL days, at a lower price, and that are from generic brands. This last factor may be linked to the perceived quality of name brands not being enough to make up for their higher price, leading consumers to view no purpose in preferring them over generic brands. Moving on to the second research question, it should be noted that the fixed effects regressions only allowed us to determine the differential effect between labeled and unlabeled products for RSL and price. In fact, all other attributes, being invariant over time, were absorbed by the perceived heterogeneity between entities, and thus cannot be quantified separately. Still, regarding RSL, it was found that its effect seems higher for unlabeled products, given its higher proportion in relation to price, when compared to the same proportion of the same attributes in unlabeled products. Similarly, the average impact of price on the demand for labeled products appears to be higher when compared to unlabeled products.

Turning to the discrete choice models, it was found that there is huge heterogeneity with respect to the price and RSL of the labeled items. Furthermore, it was possible to address the last two research questions. Accordingly, it was demonstrated that different entities report different receptivity to the attached label, showing enormous variability in this respect. In fact, even if the average effect is positive, depending on the product and its characteristics, a differentiated variation in the utility is to be expected. That is, even for the same products, one might induce heterogeneity of preferences for different consumers, which should try to be filled while adjusting the current depreciation policy. Regarding the WTP for one more day of RSL, it was found that there is a greater readiness to pay for labeled products, or conversely, there is a significant need for a greater discount for labeled products. Since longer shelf life is more highly valued for these products, which typically have a shorter shelf life, people are willing to pay an extra amount to have their perceived risk diminished. In addition, differential WTPs were also observed according to product type, brand type, and product weight, giving scope for further research on adapting prices in the light of such findings.

Actually, all the inferences gained, notably, through the class-differentiated WTP obtained for the RSL of unlabeled products, and also through the Logit models (which, despite not being completely accurate because of not capturing the inherent effects of observing the same stores and SKUs over time, allow for broader conclusions), lead to a clear need to revise the discount policy. One can see that for products between 0 and 8 days of RSL, the consumer experiences a greater need for price reduction thanks to the huge loss of utility suffered. Given that very few products in the dataset have less than 4 days of RSL (essentially cases where there was human error in label placement), it is revised that the large decrease in utility exhibited in these models is primarily based on products that have between 4 and 8 days of shelf life. And so this leaves room to speculate about the potential advantage of earlier labeling. Nevertheless, the discrete choice models did not allow the simulation of an early label application, unfortunately, as it would have been necessary to include a new alternative (making it impossible to use the established parameters) or to consider, in some cases, a choice between two alternatives with a label (which also makes it impossible to fit the utility equations obtained). Still, it was possible to simulate the feasibility of changing the depreciation policy for products with a low RSL, whereby a change in the discount percentage was mocked so as to understand the expected impact on customer preferences. So based on the results obtained, and albeit the models were not able to demonstrate the impact they would have had on profit increase and expected waste decrease, it is considered that it may support the prospect of retailers making some changes to their current policy.

With this in mind, we ideally foresee interest in experimenting with the implementation of discount labels 5, 6, 7, or 8 days before the expiration date, although we consider that the executed discounts do not need to exceed 30% for classes 1, 2, 4, 8, 13, and 14. On the other hand, we think that for classes 3, 5, 6, 7, 9, 11, 12, and 15, the best approach would be to use at least a two-period pricing policy (as indicated by Chung and Li (2017)), implementing a 50% discount for the last RSL days and a lower discount (e.g. 30%) for the other days of the adjusted policy. In this way, it is thought that the number of situations where there is a direct association of risk to the label would be minimized, and the retailer could even improve its profits by having less product waste.

On second thought, some points that may be a source of noise in the models obtained should lastly be mentioned. Firstly, although the number of labeled yogurts displayed on a given day was calculated, it was not possible to know precisely how many individuals actually had the choice between the two alternatives, out of all those who bought an unlabeled product. If all exhibited labeled products were sold, and there were sales of unlabeled products, it is not clear whether the individuals who bought the unlabeled products actually chose between the two possibilities or if, when they arrived at the store, there were no longer labeled products available. Furthermore, a doubt may also arise about whether consumers were aware of the availability of the labeled products, and also in case a given category or brand of yogurt is on general promotion in the store, whether they were aware that such promotions were cumulative with the promotion due to low RSL. These questions would need further investigation to be rigorously answered.

Conversely, as a way to be able to accurately guide new policies, it would be interesting to try to get more information about the level of awareness that consumers have when making their yogurt purchases. For example, as we enter the age of big data, it would be important for all retailers to take a step forward and collect instant data to know exactly what products are displayed and what have been purchased at any given time. This would enable better quality and more ready-to-use data. In addition, it would also be relevant to run MIXLs on subsets of the data with unlabeled products for which the RSL fits into each category that was elaborated (less than 8 days, 9 to 17, 19 to 27, and more than 27), to then compare the results. Beyond that, it could be interesting to check the agreement with the conclusions drawn from the linear models and gain more understanding of the implication of the inherent products' attributes on the consumers willingness to pay within 3 more divisions of the data: name brand versus generic brand products; classes 1, 3, 9, 11, 12 and 13 versus the remaining classes; and also products with more than a half of a kilo versus products with less than of a half a kilo. Finally, it would also be beneficial to try to include more product characteristics as well as store characteristics, in order to enhance a better explanatory and predictive capacity of the models.

On a final note, it is intended to make the results of this research a kick-start for the reform of price management systems that used to be merely focused on retailers and their interests. As the actions of consumers are the focus of this study, it is strongly believed that examining their behavior is the most appropriate way to achieve the proposed goals. Not only monetary benefits for retailers are at stake, but also, and more importantly, the mitigation of food waste and world hunger. So, it is hoped that, like the project in which this thesis is integrated, other similar projects will arise, so that organizations can be encouraged to face a common affliction, that is especially aggravated by climate change and wars that are currently being fought. It is the duty of the self and all Man to take care of our peers and of the world we share with all the other living beings.

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Appendix A

Description of some SKU's attributes

Table A.1: Overview of the classes and subclasses belonging to the yogurt portfolio

Class	Subclass
1	1 - Traditional Natural Solids 2 - Traditional Sweetened Natural Solids 3 - Traditional flavors Solids
2	1 - Chunks 2 - Pulps 3 - Other Chunks/Pulps 4 - Two components
3	1 - Natural greek 2 - Greek with flavors 3 - Greek with chunks 5 - Light greek 5 - Other greeks
4	1 - Traditional Liquid
5	2 - Infantile with flavors 3 - Petit suisse
6	3 - Low-fat
7	1 - Bifidus Natural or with flavors 3 - Bifidus with pulp
8	1 - Functionals - active defenses 3 - Other functionals
9	1 - Protein
11	1 - Mousses, puddings and gelatins
12	1 - Specials (Kefir, goat and sheep)
13	1 - Biologics
14	1 - Lactose-free
15	1 - Plant-based

Appendix B

Statistical summary of the item-related variables

We analyze the statistics based on weight and brand type due to the desire to discriminate future policies considering these attributes. We consider the half kilogram division to separate products that carry more or less quantity and therefore may translate into the perception of more or less risk.

	Variable	Mean	Minimum	Maximum	Std. Dev.
	$Price_{unlabeled}$	1.933	0.326	3.060	0.736
Weight $\leq$ 0.5Kg	$RSL_{unlabeled}$	22.180	0	388	17.952
	$Sales/day_{unlabeled}$	7.586	0	96	9.887
	$Price_{labeled}$	1.242	0.230	2.860	0.542
(61% of the products)	$RSL_{labeled}$	1.089	0	4	0.860
	$Sales/day_{labeled}$	4.017	0	64	6.053
	$Price_{unlabeled}$	2.582	0.890	6.990	1.127
Weight $>$ 0.5Kg	$RSL_{unlabeled}$	22.714	0	181	13.132
	$Sales/day_{unlabeled}$	8.720	0	82	13.249
	$Price_{labeled}$	1.599	0.440	5.750	0.779
(39% of the products)	$RSL_{labeled}$	1.080	0	4	0.866
	$Sales/day_{labeled}$	2.379	0	53	4.449
	$Price_{unlabeled}$	1.131	0.590	2.390	0.483
Generic brand	$RSL_{unlabeled}$	18.985	0	388	14.818
	$Sales/day_{unlabeled}$	10.453	0	96	14.201
	$Price_{labeled}$	0.673	0.290	1.930	0.313
(22% of the products)	$RSL_{labeled}$	1.103	0	4	0.876
	$Sales/day_{labeled}$	5.514	0	53	6.998
	$Price_{unlabeled}$	2.335	0.326	6.990	0.806
Name brand	$RSL_{unlabeled}$	23.662	0	236	17.684
	$Sales/day_{unlabeled}$	6.748	0	92	8.649
	$Price_{labeled}$	1.495	0.230	5.750	0.577
(78% of the products)	$RSL_{labeled}$	1.081	0	4	0.855
	$Sales/day_{labeled}$	2.900	0	64	5.006

Note: Observations 36,137.

Appendix C

Statistics by classes

Table C.1: Statistics surrounding product classes

Class	1	2	3	4	5	6	7	8	9	11	12	13	14	15
Proportion(%)	5.9	3.5	14.7	4.3	9.4	7.2	5.6	4.8	12.3	12.3	1.6	7.0	5.4	5.9
Average discount(%)	36.1	33.7	40.1	44.9	29.9	35.3	35.8	36.5	38.5	39.7	40.1	69.7	42.0	39.7

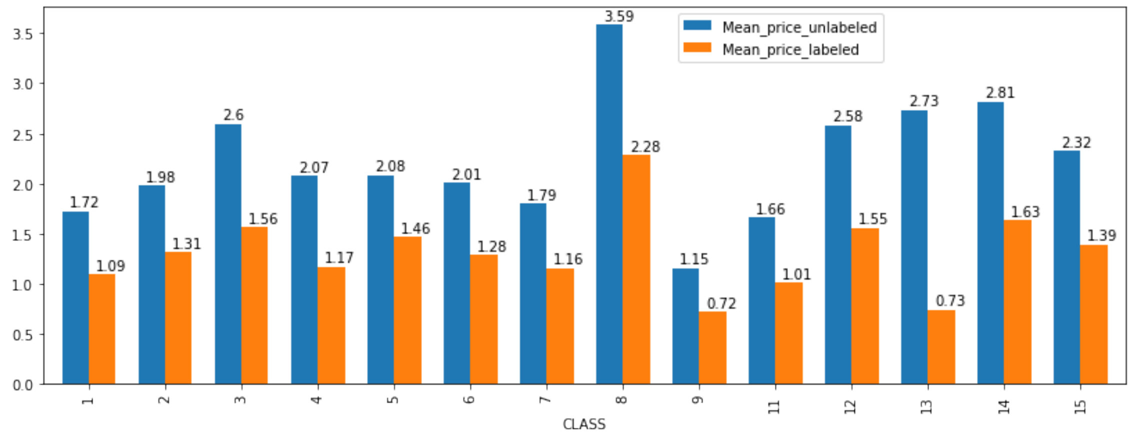

Figure C.1: Mean price by classes

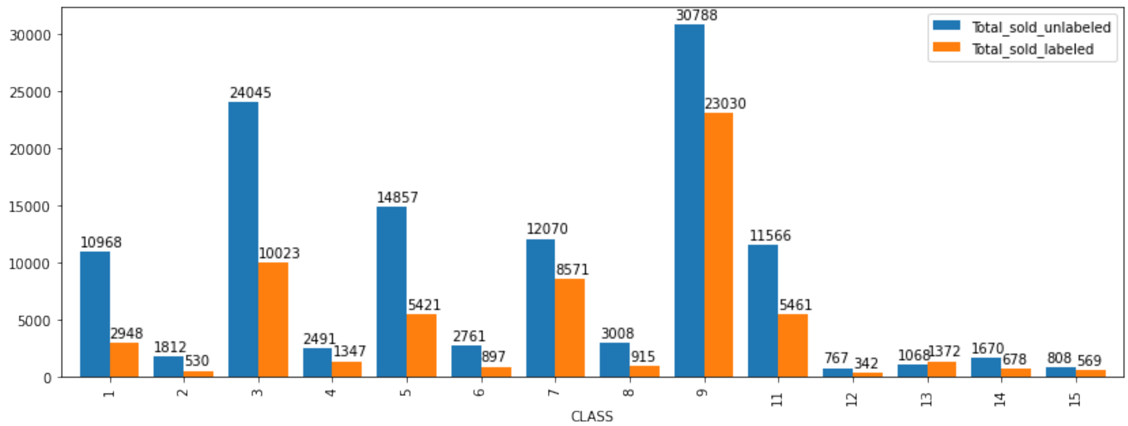

Figure C.2: Total sales by classes

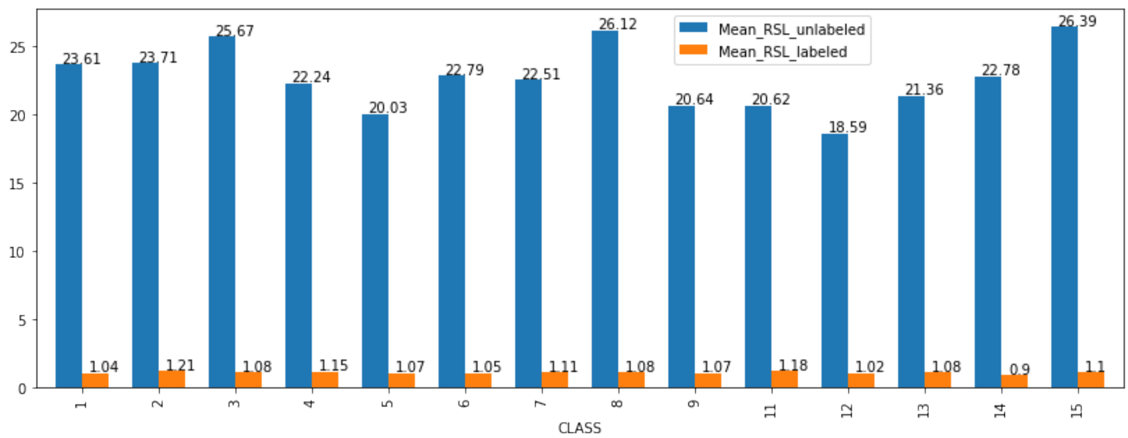

Figure C.3: Mean RSL by classes

Appendix D

Piecewise specification

$$RSL_1(x) = \begin{cases} x & \text{if } x \leq 8 \\ 0 & \text{if } x > 8 \end{cases} \tag{D.1}$$

$$RSL_2(x) = \begin{cases} x & \text{if } x \in [9, 17] \\ 0 & \text{if } x \notin [9, 17] \end{cases} \tag{D.2}$$

$$RSL_3(x) = \begin{cases} x & \text{if } x \in [18, 26] \\ 0 & \text{if } x \notin [18, 26] \end{cases} \tag{D.3}$$

$$RSL_4(x) = \begin{cases} x & \text{if } x \geq 27 \\ 0 & \text{if } x < 27 \end{cases} \tag{D.4}$$

Appendix E

Classes specification

$$RSL1(x) = \begin{cases} 1 & \text{if } x \leq 8 \\ 0 & \text{if } x > 8 \end{cases} \tag{E.1}$$

$$RSL2(x) = \begin{cases} 1 & \text{if } x \in [9, 17] \\ 0 & \text{if } x \notin [9, 17] \end{cases} \tag{E.2}$$

$$RSL3(x) = \begin{cases} 1 & \text{if } x \in [18, 26] \\ 0 & \text{if } x \notin [18, 26] \end{cases} \tag{E.3}$$

$$RSL4(x) = \begin{cases} 1 & \text{if } x \geq 27 \\ 0 & \text{if } x < 27 \end{cases} \tag{E.4}$$

Appendix F

WTP for one more day of RSL

Table F.1: Average WTP for one more day of RSL by subsets

	$WTP_{unlabeled}$	$WTP_{labeled}$
Class 1	0.131	0.285
Class 2	0.130	0.267
Class 3	0.149	0.258
Class 4	0.156	0.316
Class 5	0.173	0.329
Class 6	0.146	0.261
Class 7	0.178	0.285
Class 8	0.130	0.261
Class 9	0.203	0.270
Class 11	0.162	0.294
Class 12	0.162	0.287
Class 13	0.216	0.268
Class 14	0.189	0.281
Class 15	0.147	0.215
Name brand	0.154	0.282
Generic brand	0.215	0.275
Heavier products	0.159	0.286
Lighter products	0.176	0.278