Demand for differentiated products in varieties of rice and effects in retailers and manufacturers profits

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Abstract

Preferences for characteristics of rice products in the market equilibrium generate large effects on profits of retail distributors and manufacturers, in the context of a market with differentiated products due to rice varieties, origins, private-labels and *national brands* of recognized large manufacturers. A structural non-parametric random coefficients model using retail transactional data is estimated for demand. For supply, information on marginal costs for manufacturers and wholesale prices for retailers provide reliable information to estimate profits using a canonical Nash-Bertrand competition model. Heterogeneity in preferences for product attributes influences substitution patterns. Counterfactual market equilibrium scenarios analyzed by the model rationalize characteristics of this industry in Chile, such as the interest of manufacturers to provide incentives and sign contracts with farmers producing local varieties of rice, and the entry of retailers into the market for this product in recent years, with private-label brands in the segment that has the most preferred characteristics, although these are produced also by the *national brands* companies competing in that product category. Research findings question the use of prices of varieties of imported origin in a price index that manufacturing companies use to value the purchase of *paddy* rice from local farmers, since it is not related to the market premium due to demand preferences for local origin rice varieties developed in the country.

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1 Introduction

The objective of this work is analyze the effects on profits of commercialization of rice products in situations of supply and demand equilibrium, driven by heterogeneous preferences of consumers for differentiated products in the market for this product in Chile.

National production is carried out by two large manufacturers, and according to marketing reports, these companies own the brands with the most important identification and knowledge in consumers (Mintel, 2017). These firms – henceforth, *national brands* – are practically the exclusive suppliers of a specific variety of this cereal developed in Chile, which is cultivated in a limited area of the territory with temperate climate.

The variety cultivated in the country presents characteristics that suppose a high valuation from consumers for idiosyncratic reasons, as highlighted by Barrios Aguire (2009), and this work will put to test that argument. Likewise, *national brands* companies also actively participate in the imports of other product varieties and thus compete in all market segments. Downstream, retail supermarkets represents the main distribution channel for products in this industry.

Over the past twenty years, demand estimates have served as a key methodological foundation in industrial organization literature focused on market power, mergers, valuation of new products or brands and, in general, in the analysis of horizontal or vertical relationships between agents in industries with differentiated products. Examples of its most relevant applications are the works of S. T. Berry (1994) and S. Berry et al. (1995) in the automobile industry, Hausman (1996) in the valuation of new goods and its effect on welfare gains, Nevo (2000a, 2001) analyzing competition in prices and mergers in the breakfast cereal industry and Davis (2006) in the movies industry. In Chile, an application to the analysis of strategic vertical relationship between suppliers and retailers based on a structural demand model, can be found in Noton and Elberg (2014, 2018) on coffee products.

This work contributes with an application of a method for demand estimation based in non-parametric techniques applied to a setting of differentiated products, of recent development in the literature that represents an advance in this field, and which not require imposing a (non-testable) parametric distribution to the heterogeneous set of preferences (Fox et al., 2011, 2016).

The research have the advantage of using data on individual transactions from two supermarket brands of a large retail holding in Chile, along with a dataset of wholesale prices paid by the retailers to the producers (manufacturers), information which is hardly available in the market. The estimation of demand allows to know the importance of certain attributes and types of products, and analyze counterfactual scenarios of equilibrium assuming a supply model of competition. In this context, further work can be initiated to the strategies that retailers adopt to face the interaction with these suppliers, increasing its bargaining power through the entry of private-label brands, and their strategic association with any of the two largest manufacturers in the chilean rice industry.

Next, section 2, presents the background necessary to understand the organization of this industry in Chile. Section 3 describes the available data for this study, and decisions regarding the use of this information in the model. Section 4 presents the analytical framework for demand estimation and the supply model, along with a discussion of the literature to understand its suitability for this particular setting. Section 5 have the discussion of results, and Section 6 concludes.

2 Industry characterization

2.1 Primary production

Rice represents 20% of caloric intake worldwide (Smith, 1998), ranking as one of the main cereals in the human diet. A large proportion of rice produced globally corresponds to two varieties: *indica*, which is characterized by having long and thin grains, and *japonica*, with wider grains. Other specific varieties are added to these main varieties, such as the aromatic *basmati*, grown in Pakistan and northern India, or *javanica*, from regions of Indonesia and Madagascar.

Production is concentrated in Asia, with world trade being very low, with 8% to 9% of total availability (FAO, 2017).[1] As a plant of tropical origins, it must be adapted to cultivation during the summer season in temperate climates. While in tropical and subtropical zones several harvests can be obtained per year, in temperate zones it is only possible to obtain one, generally using irrigated cultivation systems and management techniques that, however, allow obtaining a better yield per hectare (Scarlato, 2000).

Rice is produced in Chile since 1925, however, it began to have commercial importance several decades later. The crop is established in the Maule and Biobio regions, mainly in areas with clayey soils, which are largely cultivated only with rice.[2]

Cultivation in Chile has had the support of a genetic improvement program developed by the *Instituto Nacional de Investigación Agropecuaria* (INIA), which in the sixties developed a variety of short-grain rice that in the following decade represented almost 100% of the sown area. As a result of this experience, germplasm of other varieties were introduced and evaluated, resulting in more recent years in varieties of *japonica* rice with long-wide type grains. Out of 8 varieties of certified rice seeds developed and promoted on the market by INIA since the beginning of this program, there are 6 varieties still present in national production (Paredes et al., 2015).

2.2 Manufacturing

Regarding the manufacture or elaboration of products, industrial processes are relatively simple, with innovations in grain classification systems according to their size, or in the cooking process used in parboiled rice, a particular type of product, which however is not produced by national firms.

Processes include the stages of collection, drying, processing, storage and distribution. The processing industry purchases paddy rice crops directly from local farmers without the involvement from other companies or intermediary agents.

The Ministry of Agriculture of Chile publishes weekly price indicators of alternative import costs based in international market value and price indexes for the main cereals

[1] India, Thailand and Vietnam are leaders in trade, with 26%, 19% and 19% of exports between 2012-2014, respectively, according to figures reported in FAO (2017). This trade is made up of low-quality products and lower prices, which represent surplus production destined for domestic markets of these countries

[2] According to Alvarado A. (2007), rice soils have a high clay content (16% to 42% in superficial stratum), low organic matter content and drainage problems that hinder the establishment of other crops. As indicated by Alvarado A. and Grau B. (1986) regarding the origins of rice cultivation in Chile, the introduction of this crop allowed a significant area of soils considered marginal – because they had no other alternative for agricultural use – to be used more intensively and became an economic option.

used by the food industry in the country. Indicators for durum wheat, bread wheat, corn and rice are available since 2009.

The imported rice cost weekly indicator is published since March 2009, and is constructed with actual imports information that chilean firms report about their own purchases of imported rice. An analysis of the consistency of this indicator, its ability to represent the marginal cost of the local industry and its relevance as a market signal for the purchase of *paddy* rice to local farmers, is presented in Espinoza and Farías (2017).

Their analysis indicate that the companies that acquire the local production use the information provided by the indicator to establish a basis for their purchasing policy. Coordination and purchases of farmers production each year is done mainly with an extensive use of contracts, and *spot* transactions are infrequent. In all, there is a long-term relationship between manufacturing companies and farmers. Accordingly, there are also efforts by the industry to maintain production locally, through participation together with INIA in research and development projects, adaptation of new varieties, and favoring the use of contracts and certified seeds.

A large proportion of sales in the market is concentrated in the *national brands* manufacturing companies according to market research reports (Mintel, 2017), and concentration in also a characteristic in distribution with a reduced presence of actors. Retailers are the main channel of distribution of production with nearly 65% to 70% of sales from manufacturers destined to that channel, according to market data and manufacturers and retailers managers's interviews analyzed in Espinoza and Farías (2017). The remaining fraction is destined to foodservice channel (hotels, restaurants), and a minor proportion to the traditional channel (distributors for small stores and markets). Likewise, the national manufacturing companies are also the main importers of rice products, an aspect that will be analyzed later.

2.3 Products

Unlike other grains, rice is mainly eaten as a whole grain, after elaboration processes that basically consist of totally or partially removing its shell and vegetable coverings, which allows the primary product to be an important part of the cost of the final product (Juliano & Bechtel, 1985).

Products available in chilean markets consider a main category of conventional white rice of the long-wide grain variety of national origin. A main culinary characteristic of these products is their great resistance to overcooking and, due to their high starch content, a creamy texture.

The second important group of white rice products is constituted by products of varieties with grains of the long-thin type, produced mainly in Argentina, Paraguay or in Asian countries such as Thailand or Vietnam. The preparation of this rice generates a more "grained" result, because the grains harden after cooking and have a more solid and dry texture.

Along with these, which constitute the most important segments, there is a smaller proportion of parboiled rice products – also called pre-grained or pre-cooked – that is totally imported.

A recent irruption in the product lines of each brand, has been the brown rice products, with grains that preserve part of the vegetable layers of high nutritional content, and which is mainly made with varieties of local origin.

Other processed products correspond to rice with ingredients in ready-to-eat preparations, which incorporate vegetables or other additional ingredients and are quick to prepare, since they are made with pre-grained rice. There are also more "niche" products on the market, with rice varieties of very specific origins, such as *basmati* or *carnaroli* rice.

The main quality attribute and standard used in Chile in the rice processing industry is whole grain yield (Cordero L. & Saavedra B., 2011; Hernaíz L. & Alvarado A., 2002). This is defined as the percentage of whole grains that is obtained after the elaboration process, and which is also a parameter used to value the purchase of production from farmers.

The norm Nch. 1359 of 2003, which constitutes the industrial standard used in Chile, classifies processed rice products in grade 1, when the content is up to 5% broken grains, and in grade 2, when the content is up to 20% of broken grains.[3]

The same standard also establishes a classification according to the dimensions of the grain which, as has been pointed out, is explained by its origin and variety and influences the culinary result obtained after its preparation.[4]

In short, it can be deduced that the rice products available to consumers in Chile present differentiation in terms of varieties, origins, characteristics, culinary uses and quality.

2.4 Distribution: retail and consumers

Per capita consumption of this cereal in Chile is between 10 and 11 kilos of rice per year, with a frequency of preparation of three to four times a week. This level of consumption is similar to that of countries in Europe and the United States – which average less than 10 kilos per person per year – and in South America region is below Colombia and Brazil, which register an annual per capita consumption of almost 50 kilos (Barrios Aguire, 2009).

Figure 1, with statistics from official sources, reflects that the volume of national production is always lower than imports, which in the last decade have represented close to 57% of the apparent availability for domestic consumption.[5]

The volumes of imports reported in Table 1 show that the companies purchase over 80% of the volume in processed rice products, which do not require additional industrial processes except those associated with packaging or distribution. The remaining percentage is attributed to imports of broken-grain rice, which are not intended for consumption as a final rice product.[6] It is noted that the local industry does not import *paddy* rice, which is the cereal in its raw input state prior to the elaboration process, nor does it acquire relevant volumes of brown rice in foreign markets.

A breakdown of the type of imported processed rice products, presented in Figure 2, reveals that in recent years about 65% of the volume corresponds to white rice products

[3]These standards are similar to those established in other countries and are consistent with the classification of products in international trade. For example, in the United States, the *Long Grain Milled US N°1* has a maximum content of 4% broken grains and also requires not presence of grains of another variety; unlike the *Long Grain Milled US N°5*, with a tolerance of 35% broken grains and 10% of other varieties (USDA, 2009).

[4]Norm Nch. 1359 of 2003 establishes that short-grain rice have a length to width ratio of less than 2, the long-wide type have a ratio above 2 and less than 3, and the long-thin type (also called fine or narrow) have a ratio greater than or equal to 3.

[5]Calculation of apparent availability of this product does not consider inventories, and is obtained by adding the volume of domestic production with imports and subtracting exports.

[6]Espinoza and Farías (2017) confirm that imports of this special type of rice product are done exclusively by companies in the brewing industry.

that contain between 5% to 15% broken grains, that is, they are considered in the grade 2 standard, while 19% of the volume of imports corresponds to the grade 1 standard. All this volume of rice of imported origin has grains of the long-thin type. An approximate proportion of 15% of the volume imported in that period corresponds to parboiled or pre-grained rice and other more specific varieties.

Espinoza and Farías (2017) indicate that in the last years there has been an irruption of companies dedicated to imports that are beginning to gain volume to the detriment of national manufacturers companies, which are the ones that have traditionally imported this product in Chile. Trade records analyzed indicate that retail companies practically do not participate in the direct import of rice products, which indicates that they prefer to purchase them from importer firms, or from national manufacturing companies that also have these products in their offer.

However, in more recent years, large retailers has entered the market through private-label products, in the segments of varieties of both national and imported origin. The analysis carried out by Lara T. (2017) show that entrance has generated significative effects on the assortment of products offered by retailers, to the detriment of products from importer companies or smaller local processors.

3 Data

The data comes from individual daily transactions, carried out in 64 different supermarkets in the Metropolitan Region of Santiago de Chile, in a period from October 2009 to July 2010, that is, 10 months.

These records belong to two different retail supermarket chains – which in this study will be called QUALITY and VALUE – owned by the same holding company. The two supermarket chains together have 28% of the total share of the retail market in Chile in the aforementioned period, measured by their sales, ranking second in this industry according to figures reported in TDLC (2012).[7]

The type of stores has more homogeneous characteristics in the QUALITY retailer, with 11 large stores – hypermarkets – located in municipalities with the largest population and highest relative level of income in the urban area of the Metropolitan Region of Santiago. In the VALUE retailer, the group is more heterogeneous, with 53 stores of different sizes, in accordance with the strategy and business model of this chain.

The records of daily purchases in each store are organized to have weekly data based on the individual combination or tuple $customer - product - store - week$. This implies consolidating records leaving an observation when this combination appears more than once, which occurs when a customer repeats the purchase of the same product item on another day of the same week in the same supermarket store. In these cases, a single purchase is considered for that product and the median of its price is taken.[8]

Transaction records have the identification number (in Chile called RUN) of the person who purchases the products when voluntarily delivers that information at the checkout

[7] According to Table 1 in TDLC (2012), the C-3 concentration index of the retail industry in Chile in 2010 was measured in 80%.

[8] It can be noted that if in the same week an individual buys different products, or buys the same product but in different stores, for the purposes of this database it will be considered as a different observation, since in these situations there is no repetition of the combination that defines the individual data in the tuple $customer - product - store - week$.

at the time of payment, in order to obtain benefits and/or discounts from the respective retailer. Although the database also records transactions from individuals who do not report their identification number (approximately one-third of the transactions), only records from consumers who disclosed their RUN will be used in this study.

It is the identification number that allows to recognize visits to stores by each customer, and determine the times when they go to the supermarket and do not purchase rice products. This fact is considered in the definition of the *outside good*, which for modeling purposes will correspond to the alternative of not buying rice by customer i.

The sale prices of the products correspond to prices observed by the buyer, therefore, they already include all the discounts that could have been promoted by the retailer at the level of each store. Regarding quantities purchased, all the units of product j that a customer i purchases in each store n in a week w are transformed into the variable:

$$y_{ijnw} = 1[q_{ijnw} > 0]$$

This is due to the fact that in this model the purchase decision is binomial, 1 or 0, for multiple products, or multinomial. The structure of the database allows the number of product options available in each store and week to vary. When a product is not for sale in any week and at any location, the probability of acquiring it is zero, which in the model to be estimated is considered in the multinomial logit formula, since the individual utility and the probability of purchase will be computed knowing the alternatives – or choice-set – that were effectively available in that $store - week$ for customer i (see Section 4).

Also for the purposes of modeling individual utility and subsequent estimation, the other products available in the choice-set and not purchased by customer i present a price that corresponds to their median weekly value, that is, the same criteria applies to the price of purchased or non-purchased items for customer i.

The number of products available at both retailers is approximately 200 different items per month. As it is transactional information, these are identified with a unique SKU number and the database includes a field with the description of brand and characteristics. Due to the large number of product types on the available offer, a ranking of the most important products according to sales is generated in both retailers, with the top 33 items in terms of revenue for each retail chain. At the QUALITY retailer, these 33 main SKUs represent 74% of the rice sales revenue, while at VALUE these represent 85%. The remaining group of minor sales SKU's are grouped as a #34 product in the choice-set offered by each retailer.

In the main products, there are items of long-wide rice grade 1 and grade 2, of national origin, imported long-thin rice grade 1 and grade 2, plus some parboiled and integral rice. Given that the criteria for inclusion in the *inside good* corresponds to that of sales in both retail chains, these products belong to the main *national brands* companies in the market, such as Carozzi (Miraflores, Rizzo) and Tucapel (Banquete), in addition to the brands owned by the retailer and also others from smaller producers. The rest of the products that are grouped as option #34, mainly consider ready-to-eat rice with special ingredients and varieties, with lower sales and market shares.

The market shares are presented in Table 2, both for a definition that consists of the share with respect to the total transactions of a random sample, and for that obtained by considering only rice purchases. For simplicity, prices of product groups are presented according to producer (or brand) and type. Adding shares of product groups shows that Carozzi and Tucapel are the most relevant manufacturers, with shares of 26% and 28%

respectively in QUALITY and 20% and 30% in VALUE, when measured over rice purchases. On the other hand, private-label brands, represent 7% of preferences in QUALITY and 8% in VALUE, respectively.

Regarding the participation of other brands, Table 2 reveals that in QUALITY this represent around 10% of total rice purchases, while in VALUE they add up to 25%. It is in QUALITY where the products of other types of special varieties, instant rice, parboiled from other manufacturers and the rest of the products have a greater preference, with almost 30% of the total, which reflects the differences in the alternatives and types of products offered. However, it is important to highlight that in a random sample of 100,000 transactions in each retailer, in QUALITY 16.5% of these register purchases of rice, while in VALUE this figure only reaches 9.5% of transactions.

Table 3 presents descriptive statistics of the prices of rice products sold by both retailers. The coefficient of variation of the sale prices denotes that these do not vary substantially in their weekly offer. However, when applying a contrast to the price averages, significant differences are observed in the vast majority of products. The products of national origin and better standard (long-wide grade 1) have higher prices in QUALITY, with the exception of those of their private-label brand.

Surprisingly, in products of national origin and lower standard (grade 2 long-wide), the contrast between retailers positions Tucapel and the private-label brand with higher prices in VALUE compared to QUALITY, without significant differences in Carozzi products.

In products of imported origin, long-thin grade 2 type, QUALITY has an offer at a 10% higher price in Carozzi brands, while those of Tucapel are 4% cheaper than in VALUE. Products from other brands have a 10% higher price in QUALITY compared to VALUE, while the group that represents the rest of special varieties and other types do not have a statistically different average price between retailers.

The price differences observed in the transaction samples of both retailers, and the different market shares registered for products of different variety or type, quality standard and manufacturer, account for heterogeneity of preferences that needs to be explored in the analysis of the demand for the products, an issue that is dealt with in Section 4 of this study.

Finally, it is necessary to point out that modeling this particular set of transactional data assumes that the weight of rice products is not very significant in the household food budget of consumers. If it were a large and significant amount, consumers would be willing to switch to another store or retailer when the product they are looking for is not available. This is because the data does not capture situations of change of purchase location explained by scenarios where the brands and types of products available to the consumer are altered in a specific $store - week$. To support this assumption, the weighting that rice has in the basket of goods and services of the consumer price index (CPI) in Chile is 0.2%, which corresponds to 1.2% of the food group items, according to what is established in the methodology for the CPI.[9]

In addition to the above, it should be noted that the way demand is modeled from these individual transaction data assumes that it will be static, that is, without accumulation of inventories or purchases with inter-temporal reasons. This implies that each transaction is considered independent through time. This assumption can be supported by the

[9]This value is distant from bread, with 2.1%, which represents 12.3% of the total food basket, or beef, which has a weight of 1.7% and is equivalent to 10.1% of the food group in the CPI.

verification that the prices of the main products do not present very high coefficients of variation (generally less than 10% and a maximum of 15%, see Table 3), which reflects that retailers do not have periods of price promotions of great magnitude or duration. The importance and frequency of consumption of this product (mentioned above), and the format and size of the packaging container commonly used in Chile (1 kg), allow to argue that purchases in this market are consistent with a demand with static characteristics.

4 Analytical framework

4.1 Demand

4.1.1 Homogeneous preferences: Logit

In this section, the linear utility model and the econometric approach used to estimate the parameters of "tastes" for the characteristics that products have are defined, as a first approximation based on homogeneous preferences that describe a single representative agent.

In the data available to this study, transaction records were observed individualized in $customer-product-store-week$ combination for each retail chain separately. A conditional logit model is then assumed in specific alternatives, which is based on the pioneering work of McFadden (1973), where the indirect utility of individuals $i = \{1,\ldots,I\}$ for products $j = \{1,\ldots,J\}$ in supermarket store $n = \{1,\ldots,N\}$ in week $w = \{1,\ldots,W\}$ is given by:

$$u_{ijnw} = \alpha(y_i - p_{jnw}) + \beta' x_j + \xi_{jnw} + \epsilon_{ijnw} \tag{1}$$

where y_i is the individual income, p_{jnw} is price of product j and x_j are binary variables (*dummies*) that identify brand and characteristics, which in this specific setting do not vary between weeks or stores.[10]

The term ξ_{jnw} groups factors that are not observable for the econometrician (but are perceived by the consumer), which can affect the demand for product j and are specific to store n and week w. As usual in this literature, it is assumed that the random term ϵ_{ijnw} is iid and has a Type I extreme value distribution function.

Regarding the parameters of the model, α captures the marginal utility of income, therefore, it reflects how much disutility is explained by a price that decreases disposable income, while β groups the coefficients of "tastes" by characteristics and brands of the products. Then, $\theta = (\alpha, \beta)$ is defined as the vector that contains all the parameters, which, as has been pointed out, do not vary between individuals in the logit model.

According to Nevo (2000b), the specification given by equation (1) leaves some elements implicit. First, this form of indirect utility can be derived from a quasilinear utility function, which is income-effect free. For some products, this assumption is reasonable, as this author exemplifies with breakfast cereals, an argument that can be extended to rice products; while for others, such as automobiles, it may not be plausible.[11]

A second aspect is that equation (1) models individuals who observe specific prices in the $store-week$ for that product, which, unlike a model with aggregated data, prevents the

[10] As mentioned in Section 3, the products in each week and store may be different, however, the dummies that denote their characteristics and brands remain invariant and are specific for each product j.

[11] It is for this reason that the model developed by S. Berry et al. (1995) to estimate demand for differentiated products in the automobile industry, is built on a Cobb-Douglas utility function, which derives an indirect utility as a function of $\log(y_i - p_{jt})$.

problem of bias due to measurement error that could be generated if using a list price or an average price instead. However, and even with this advantage of individual data, demand estimates must take account of the potential endogeneity problem that observed prices could have, if there is a correlation with the unobservable factors contained in ξ_{jnw}. In the defined setting, for this to happen the retailer in each *store – week* would have to set prices based on those factors not captured by the econometrician in the characteristics and brands of the products. It is in this situation where there could be a bias in the price parameter, and although as previously stated this would be less than if aggregated data were used, it is plausible to assume that the variation possibilities provided to this model by the individual data prevent that this effect could be systematic.

We now denote $y_{inw} = \{1, \ldots, J\}$ when individual i chooses product j in store n and week w. Thus, the probability of acquiring that product j will be the integral over the shocks ϵ that ensure that said product j maximizes utility given the choice-set of products available in that market. Using the distribution of ϵ, a closed form solution is obtained for the individual probability s_{ijnw} of acquiring product j.

Formally, this is equivalent to:

$$s_{ijnw}(\theta) \equiv \mathbb{P}(y_{inw} = j \mid \theta) = \mathbb{P}(u_{ijnw} > u_{iknw}, \forall k \neq j) = \frac{\exp(-\alpha p_{jnw} + \beta' x_j + \xi_{jnw})}{\sum_{h=1}^{J} \exp(-\alpha p_{hnw} + \beta' x_h + \xi_{hnw})} \tag{2}$$

The alternative of the *outside good* is denoted j_0, and as mentioned, represents the option of not acquiring the rice products in the transaction carried out by the individual customer i. The utility given by equation (1) for the *outside good* option is normalized in its random term, and then it is found that for this alternative its utility corresponds to $u_{ij_0nw} = \epsilon_{ij0nw}$, and subsequently $-\alpha p_{j_0nw} + \beta' x_{j_0} + \xi_{j_0nw} = 0$.[12]

The normalization of individual utilities is valid, since, as can be seen from equation (2), the probability of purchase results from a comparison of the utility of different products for the same consumer, and then what matters is the order of utility that determine their preference. For this same reason, explanatory variables that are not specific to the products, such as the individual's income given by y_i, or even fixed-effects that could be included for each store n, are subtracted from the comparison and do not have influence on the individual probability that decides the purchase.

The model is estimated using detailed information from a sample of transactions, limited to 100,000 observations at each retailer for computational reasons. The estimation is made via maximum likelihood (MLE), finding the parameters θ that solve:

$$\hat{\theta}_{MLE} = \arg\max_{\theta \in \Theta} \ln L(\theta) = \arg\max_{\theta \in \Theta} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{n=1}^{N} \sum_{w=1}^{W} y_{ijnw} \ln(s_{ijnw}(\theta)) \tag{3}$$

where the dummy y_{ijnw} is one if individual i chooses product j in store n in week w, and zero otherwise.

The popularity of the logit model is fundamentally due to the fact that it solves the dimensionality problem that the estimation of a system of demand equations for differentiated

[12] With this normalization for the *outside good* option, and considering that the individual faces a choice-set that depends on the availability of products in the *store – week*, which is denoted a_{jnw}, the expression for the individual probability of purchase to use is:
$s_{ijnw} = \frac{a_{jnw} \exp(-\alpha p_{jnw} + \beta' x_j + \xi_{jnw})}{1 + \sum_{h=1}^{J} a_{hnw} \exp(-\alpha p_{hnw} + \beta' x_h + \xi_{hnw})}$, $\forall h \neq j_0$.

products would present, with as many parameters to be estimated as the square of the number of products.[13] When projecting the products to a space of characteristics and attributes valued in utility, it is the size of this space that determines the parameters of interest. Although the assumptions allow obtaining a closed form for the integral of the purchase probabilities in equation (2), its simplicity has costs in terms of analytical capabilities.

Due to the way in which heterogeneity is restricted, substitution patterns between products are explained by their market shares and not by how similar they are. This unattractive property of the logit model is called Independence of Irrelevant Alternatives (IIA) and it is explained because the iid shocks occur not only between individuals and/or markets, but also between products, which could lead to questionable substitution predictions.[14]

Aware of this problem, methodological developments from the work of McFadden (1978) with the generalized extreme-value (GEV) and nested logit models induce a greater similarity between the available options, allowing ϵ to be correlated between products and not independently distributed. However, the a priori definition of groups, and the fact that the substitution patterns are not altered between them, means that the IIA problem continues to be present. Additionally, as Nevo (2000b) points out, this model does not solve the problem that own price elasticity continues to depend on the functional form.

It is from the contribution of S. T. Berry (1994) and mainly S. Berry et al. (1995) that it is possible to develop a more general model of indirect utility, which "liberates" the space of preferences to distributions of specific parameters for each individual, which may even depend on socio-demographic characteristics, and thus manages to generate the correlation between products similar as those preferred by individuals with similar tastes.

This model, which in its specific application to this thesis is described in the following section, has received a lot of attention in empirical industrial organization literature, as mentioned in Section 1. It has various names, the most common being the BLP model, discrete-choice random coefficients or mixed logit.

4.1.2 Heterogeneous preferences: Mixed Logit

As previously stated, the need for greater flexibility to realistically capture substitution patterns between products makes the mixed logit model appropriate for this purpose. As it is a structural model, it also manages to capture preferences that allow simulating hypothetical market situations, with product entry or exit. These counterfactual scenarios will be analyzed in detail with a supply model described in the next section, which as a condition requires previously estimating demand. Among other things, for example, it makes it possible to know the effect on demand when a supplier or a particular type of product exit the market, something that is not observed in the data for the period under analysis, and therefore it would not be possible to rationalize with reduced form estimates.

[13] A market with 20 products would imply estimating at least 400 parameters, divided into 20 equations, one for each product, with 20 prices on each.

[14] To see this, it can be noted that by deriving the market shares generated by equation (2) with respect to price, we obtain $\partial s_j/\partial p_j = -\alpha s_j(1-s_j)$ y $\partial s_j/\partial p_k = \alpha s_j s_k$. This implies that the own price elasticity of a product j will be given by the expression $\eta_j = -\alpha p_j(1-s_j)$, strictly increasing in price. This is unrealistic considering that those customers who purchase more expensive products may be less price sensitive. On the other hand, the cross-price elasticity between two products j and k will be given by $\eta_{jk} = \alpha p_k s_k$, which depends exclusively on the price and share of product k and not on the similarity it may have with product j.

This model is defined based on the following expression for individual utility, which considers for individual customer i, product j, store n and week w a value given by:

$$u_{ijnw} = \alpha_i(y_i - p_{jnw}) + \beta_i' x_j + \xi_{jnw} + \epsilon_{ijnw} \tag{4}$$

Unlike the traditional logit model, price sensitivity parameters given by α_i are specific for each individual, and similarly, the parameters associated with tastes for product characteristics or brands, contained in β_i.

These parameters can be decomposed in a constant (e.g. an average) and a random term, in the form:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \bar{\alpha} \\ \bar{\beta} \end{pmatrix} + \Gamma D_i + \Sigma v_i \ , \tag{5}$$

where D_i is a vector of demographic variables and v_i is a term that captures unobservable heterogeneity in individuals' tastes and price sensitivity. Demographic variables could have a known distribution and the main discussion of this model do not focus on them.[15] But in the unobservable variables this distribution is clearly unknown, and the mixed logit model requires establishing a parametric form on it or estimating it to find the market shares of each product.

Specifically, defining $\theta = (\alpha, \beta, \Gamma, \Sigma)$ as the vector containing all the parameters and omitting the store and week subscripts for simplicity, s_j is obtained by integrating over the mass of individuals who choose product $j(A_j)$, and which depends on random variables $\epsilon_{ij} = (\epsilon_{i0}, \ldots, \epsilon_{iJ})$ and an individual shock v_i. Formally,

$$s_j(x, p, \xi; \theta) = \int_{A_j} dF_\epsilon(\epsilon | v_i) d\Phi(v_i) = \int_{A_j} s_{ij} d\Phi(v_i) \tag{6}$$

As a logit model, ϵ is iid with a Type I extreme value distribution, and then the s_{ij} term will have a closed form similar to equation (2), except that here it contains individual parameters.[16] As Nevo (2000b) explains in detail, the model proposed by S. Berry et al. (1995) assume that the distribution $\Phi(v_i)$ is a standard multivariate normal, and it is the matrix Σ that allows each component v_i to influence the individual parameters with different variances and cause correlation in the characteristics preferred by i, necessary to find patterns of substitution that respond to the similarity of the products.

S. T. Berry (1994) and S. Berry et al. (1995) propose an iterative method to solve the definite integral in (6) through simulations. With this, they obtain market shares that are contrasted with the observed data, and thus find the parameters θ that minimize the term ξ_j, which in this model operates as a residual. Likewise, they propose instruments to solve the endogeneity that the price may present.

[15] As Nevo (2000b) points out, this may be a non-parametric distribution known from a source of demographic data, or a parametric distribution estimated in a separate model.

[16] Note that by replacing (α_i, β_i) in terms of the common parameters $(\alpha, \beta, \Gamma, \Sigma)$ and assuming for simplicity that $\Gamma = 0$ we will have: $-\alpha_i p_j + \beta_i' x_j + \xi_j = -\alpha p_j + \beta' x_j + \xi_j + [-p_j, x_j] \Sigma v_i$. In this model, this equation with terms that in the general case may be non-linear is the one that corresponds to be included in the closed form for the individual probability s_{ij} described by equation (2). It can be seen that this complicates obtaining an analytic value for the definite integral in equation (6).

In this thesis, instead, a non-parametric approach of recent development in the literature will be adopted, which, unlike the BLP model, does not establish a form for the distribution of v_i shocks that determine the heterogeneity of individual parameters.

4.1.3 Non-parametric estimation

This section is based on the work of Bajari et al. (2007), Fox et al. (2011) and Fox et al. (2016), who develop a non-parametric estimator of mixtures of joint distributions, applied to heterogeneous parameters in structural models. Previously, Kamakura (1991) had presented the use of a discrete grid to obtain histograms of "ideal points" for a predefined space, although in the context of preferences associated with psychophysical attributes in fields other than economics. The advantage of the approach is having greater flexibility in finding distributions that are not necessarily unimodal.

For simplicity in the notation it is assumed that the parameters containing the individual heterogeneity (α_i, β_i) will be contained in a single vector β. With this, the goal will be to estimate the distribution of these heterogeneous parameters, $F(\beta)$, in a model of the type:

$$P_j(x) = \int g_j(x, \beta) dF(\beta) \tag{7}$$

The similarity between this expression and equation (6) can be noted. In this context, j denotes the index of J finite values that an outcome can take, x is a vector of observed explanatory variables, and $g_j(x, \beta)$ is the probability that the jth outcome occurs for an observation with heterogeneous parameters β and variables x. With this structure, P_j is a probability of observing that outcome j in any cross-section when the explanatory variables are x.

In the logit model, the result corresponds to y_{ij}, which equals one when $y_i = j$ and zero otherwise, denoting the observed choice by i. Adding the variable y_{ij} to both sides of equation (7), and moving P_j to the right side, for observation i we will have the following expression:

$$y_{ij} = \int g_j(x, \beta) dF(\beta) + (y_{ij} - P_j(x)) \tag{8}$$

Fox et al. (2016) argue that this is a linear probability model that has in $F(\beta)$ a "parameter" of infinite dimension. They even indicate that it would be possible to work directly with this equation if it were computationally simple to estimate this infinite-dimensional parameter, restricting it to being a valid cumulative distribution function (CDF). Instead, they propose an empirical strategy based on a finite-dimensional space to make an approximation to F, exploiting the linear form as it enters into equation (8).

In particular, they define $R(N)$ as the total number of points in all dimensions, in a grid $\mathcal{B}_{R(N)} = (\beta^1, \ldots, \beta^{R(N)})$, where each point is a vector since β is a vector. The econometrician then must choose the set of points in $\mathcal{B}_{R(N)}$, and given that choice, estimate $\theta = (\theta^1, \ldots, \theta^{R(N)})$, which corresponds to the "weights" on each of the corresponding points of the chosen grid. With this approximation, equation (8) becomes:

$$y_{ij} \approx \sum_{r=1}^{R(N)} \theta^r g_j(x_i, \beta^r) + (y_{ij} - P_j(x)) \tag{9}$$

As each θ^r enters linearly in y_{ij}, estimation of $(\theta^1, \ldots, \theta^{R(N)})$ is performed using a regression on the linear probability model given by y_{ij} in the R "regressors" $z_{ij}^r = g_j(x_i, \beta^r)$. As the model requires that the distribution be a valid CDF, restrictions are imposed by $\theta^r \geq 0 \ \forall r = 1, \ldots, R(N)$ and $\sum_{r=1}^{R(N)} \theta^r = 1$. Subject to these restriction, the proposed estimator is defined by:

$$\hat{\theta}_{FKRB} = \arg\min_{\theta} \frac{1}{NJ} \sum_{i=1}^{N} \sum_{j=1}^{J} \left(y_{ij} - \textstyle\sum_{r=1}^{R(N)} \theta^r z_{ij}^r \right)^2 \tag{10}$$

It can be seen that there will be J "regression observations" of the linear probability model for each statistical observation (y_i, x_i). The minimization proposed by the *FKRB* estimator can be implemented as a quadratic minimization problem subject to inequality constraints.[17]

After estimation of parameters θ, the cumulative distribution function of the heterogeneous parameters β can be constructed based on:

$$\hat{F}_N(\beta) = \sum_{r=1}^{R(N)} \hat{\theta}^r 1[\beta^r \leq \beta] \tag{11}$$

Since it is a non-parametric approach, there will always be the disadvantage of choosing "starting points" when tuning the parameters. Fox et al. (2016) point out that in this case, the choice of a grid of points is a very broad dimension calibration, unlike other non-parametric approaches.

Fox et al. (2011) discuss the number of grid points, the support range of the points, and their values. In particular, this work adopts what is suggested in relation to the fact that the chosen points will correspond to values of a multiple of the confidence intervals of the parameters found in the estimations of the traditional logit model. Likewise, the number R will be bounded for computational reasons to a maximum of 200, given that up to 100,000 observations are considered for the estimation, and 6 explanatory variables in addition to price.[18] Fox et al. (2011) present results of Monte Carlo exercises that demonstrate excellent results in terms of estimator adjustment in small samples, and also confirm that this estimator has a significant advantage in terms of processing times.[19]

4.2 Supply

In order to model market equilibrium prices and estimate profits from the sale of products in different counterfactual scenarios, a supply model is estimated. This is developed from the analytical framework proposed in the works of Nevo (2000a, 2001), Sudhir (2001) and

[17] In this work, it is implemented with the routine *lsqlin* in Matlab. Fox et al. (2016) also define an estimator based on the maximum likelihood criterion following Train (2008). Likewise, they verify the convergence conditions to the true distribution for the logit model and for other applications.

[18] As explained by Fox et al. (2011), the estimator, like any other, has a bias-variance trade-off: choosing a higher R makes the grid more flexible and therefore reduces the bias, but implies a greater number of parameters to be estimated and increases the variance. This study presents estimates with different sizes for R, as well as different support ranges for the grid points.

[19] In these exercises, Fox et al. (2011) compare the estimator with a bivariate normal distribution and consider a number of $R \leq 100$ and $N \leq 10{,}000$, and between 2 to 6 mixtures of parameter distributions for a demand estimate of $J = 10$ products.

Villas-Boas (2007), and assumes the existence of firms – distributors and producers – that maximize profits and compete in a market for differentiated products, with equilibrium prices derived from strategies consistent with the Nash-Bertrand paradigm.

These articles are widely cited in the vertical relationship analysis literature, specifically in the determination of the value that is generated as a surplus of distributors and producers. Based on the estimation of structural demand models, they propose methods to identify price-cost margins of the vertical contract that best fit the data, implicitly assuming a model of competitive behavior of the agents and without bilateral negotiation.

Unlike what is commonly used in this literature, this work has the advantage of having effective wholesale prices for each product. Therefore, it is known the most relevant part of the marginal cost for the retailer: the negotiated wholesale price with the producer for each item. This implies that it is not necessary to establish assumptions or additional estimates on marginal cost components, to contrast with the prediction of the estimates of the structural model.

Likewise, in the case of producing companies upstream, the marginal cost of production of rice that will be used to calculate the profits of these agents will be based on the rice alternative imports cost indicator that the Ministry of Agriculture of Chile publishes weekly for purposes of market transparency in domestic markets of this cereal, a policy implemented to improve transparency in domestic agri-food markets also in other cereals (wheat and maize), and developed after public-private roundtables between Government, producers, manufacturers and industry representatives 6 months before the start of our data time-frame.

This cost indicator or index is based on the cost of imports of this product, therefore, on the international market price, and considers technical transformation coefficients of the cereal from its state of raw input to rice elaborated with different standards of quality (whole grain). As already indicated in previous sections, a complete analysis of the construction of this indicator and its ability to represent the cost of rice production in Chile can be found in the article of Espinoza and Farías (2017).

In this way, in the analysis it is not necessary to establish assumptions about the formation of the wholesale price, since this indicator of marginal cost publicly available will be used, as it is employed by manufacturers to purchase *paddy* rice to local producers in chilean rice farms.

This advantage in terms of available information make possible to simplify the focus of the analysis, evaluating the influence that on the generation of profits of retailers and producers is explained by demand and the characteristics of the products. Based on different counterfactual scenarios of the supply of products by the agents, the objective is to examine the economic outcome in hypothetical situations considering the behavior what is expected of them in a context of competition of differentiated products. The aforementioned literature, particularly Villas-Boas (2007), generates these equilibrium values through double marginalization models, both in retail distributors and in producers, and it will also be the focus of the supply model to be used in the following analysis.

Information on wholesale prices or negotiated prices reflects the result of a contractual agreement between private parties and, in general, it is data that is not available for research purposes. Similar to what happens with costs, it is information strategically sensitive for producers and distributors. However, in the last years, as the possibilities of transparency and availability of information in B2B transactions have expanded, elements have been identified that affect the observed result, which are generally defined and recognized as components of "bargaining power" of the agents involved in these transactions, a line of research that cannot be explored with the supply model developed here, and could be a follow-up of the present work.[20]

Below are the necessary definitions for the analysis of the revenue generated in retail sales and also those that correspond to the manufacturing companies, assuming a Nash-Bertrand competition behavior of the agents and without considering the bilateral negotiation approach. Although the model can be extended to behaviors not consistent with competition and also assuming a role of vertical integration of the producer-distributor, having effective information on negotiated prices and production cost indicators allow the robustness check not to be carried out between different models and assumptions, but rather against the price-cost margin data actually available.

We then define F retail chains that sell a set $\mathcal{J}$ of $j = 1,\ldots,J$ different types of product. The profit for the sale of these different items for the retailer f in the market t will be given by the expression:

$$\Pi_{ft} = \sum_{j\in\mathcal{J}} (p_{jt} - p^w_{jt}) T s_{jt}(p) - C_f \tag{12}$$

The dimension that defines the scalar T for the total size of the market, allows a quantification in terms of units, which is obtained from the respective market share $s_{jt}(p)$ of each product j in that market t. In the context of differentiated goods that compete for consumer preference, this market share is based on their own price, but also on the price of other products that are presented as options to choose from, which implies that each market share depends on all the prices that are grouped in the vector p. Sales revenue is explained by the differential between the offered price p_{jt} and the wholesale price p^w_{jt}, which corresponds to the value that the retailer pays to the manufacturing firm for each of the products $j \in \mathcal{J}$ that it sells. This wholesale price is equivalent to the cost for the retailer in unit terms for that product, while the C_f expression corresponds to a fixed marketing cost.

In the setting described here, the retailer f makes the supply decision and is the one who sets prices for each product to be sold. Assuming the existence of a Nash-Bertrand equilibrium of pure price strategies, and that these are strictly positive, the optimal price for product j, p_{jt}, must satisfy the following first-order condition:

$$s_{jt}(p) + \sum_{m\in\mathcal{J}} (p_{mt} - p^w_{mt}) \frac{\partial s_{mt}}{\partial p_{jt}} = 0 \quad \forall j \in \mathcal{J} \tag{13}$$

Then, O_f is defined as an "offer matrix" with the general element $O_f(i,j)$ equal to one when products i and j are sold by retailer f, and equal to zero otherwise. Along with this, Δ_{ft} is set as the "response matrix" of retailer f in market t, containing the partial derivatives of all product shares with respect to their prices, with the element $\Delta_{ft}(i,j) = \frac{\partial s_{jt}}{\partial p_{it}}$.

[20] This literature confronts the limitations that a double marginalization model has and captures elements such as risk aversion, impatience, and also the own negotiation skills of the parties that affect the determination of negotiated prices, in transactions of agents that interact in forms of vertical relationships in a supply chain. The works of Noton and Elberg (2014, 2018) incorporate bargaining models into the structural analysis.

It can be noted that the first order conditions given by equation (13) for the price of all products, can be stacked one by one forming column vectors with their respective terms. Using the notation described in the previous paragraph and rearranging elements, the following vector expression for price margins is obtained:

$$p_t - p_t^w = -(O_f * \Delta_{ft})^{-1} s_t(p) \tag{14}$$

In this way, it is found that the vector of price margins on the left side of this equation is based on the supply that the retailer has and demand variables in each market t on the right-hand side, where $O_f * \Delta_{ft}$ corresponds to the element-by-element multiplication of the two matrices. If the equilibrium is unique, this equation allows the retailer to find the optimal prices to sell the products and maximize their profits.

On the side of the manufacturing companies, each of these, defined w, will maximize their profits by choosing the wholesale prices p_j^w of the products they produce knowing that retailers behave optimally according to equation (14). Assuming that they set prices according to pure Nash-Bertrand equilibrium strategies, the first-order conditions for the wholesale prices that producers will present are expressed in vector form as follows:

$$p_t^w - c_t^w = -(O_w * \Delta_{wt})^{-1} s_t(p), \tag{15}$$

where c_t^w corresponds to the producer's marginal cost. In this expression, the matrix O_w is used, with the general element $O_w(i, j)$ which is equal to one when products i and j are manufactured by producer w and zero otherwise, which is why in this literature is called the "property matrix". On the other hand, the matrix Δ_{wt} in this equation also contains the response in the market shares of the products offered by firm w, but in this case, in the face of changes in wholesale prices that the producer establishes for its offer, that is, it contains a general element $\Delta_{wt}(i, j) = \frac{\partial s_{jt}}{\partial p_{it}^w}$.

As pointed out by Villas-Boas (2007), finding a closed expression for these derivatives is difficult even for the logit case. However, the author notes that $\Delta_{wt} = \Delta_{pt}{}'\Delta_{ft}$, therefore, knowing Δ_{ft} it is only necessary to obtain the elements that make up the matrix Δ_{pt} that represents the *pass-through* from wholesale prices to the prices of retailers, and for this, it proposes a derivation from the total differentiation of the first order conditions (14).[21]

With the data available for wholesale prices, and once the demand parameters have already been estimated using the structural model described in the previous section, the first-order conditions for retailers and producers make it possible to simulate counterfactual scenarios where a product is sold from a subset of the products available. In these cases, which are explained and described below, the supply of products is modified and the agents establish optimal prices based on equations (14) and (15). Consumers now choose within the available products, producing reactions in accordance with what both "response matrices" predict, which, by containing the derivatives of market share with respect to retail prices and wholesale prices, remains a function of demand parameters.

In the case of the retailer f, the utility obtained in the counterfactual scenario situation c, will be given by the following expression, where now the products sold are in a restricted

[21] The reference with examples and the definition of the expressions in an ideal way to program and obtain the elements of these matrices in the cases of the mixed logit model and also of the conventional logit, are presented in the online supplement of her paper (Villas-Boas, 2007).

subset $\mathcal{D}$ of available items, with prices and quantities for each product in the new setting c

$$\Pi_f^c = \sum_{j \in \{\mathcal{J} \cap \mathcal{D}\}} (p_j^c - p_j^{w^*}) q_j^c \tag{16}$$

Analogously for the producer firm w, the utility generated in the new scenario c is given by (17), which contains the prices and quantities that result from the new equilibrium $(p_j^c, p_j^{w^*}, q_j^c)$ and reflects the new "optimal vertical contract" between producer and retailer.

$$\Pi_w^c = \sum_{j \in \{\mathcal{J} \cap \mathcal{D}\}} (p_j^{w^*} - c_j^w) q_j^c \tag{17}$$

Given that the focus of this thesis is the analysis of the profits explained by the valuation of local variety rice products, it is necessary to point out that the counterfactual scenarios on which the new market equilibria are analyzed consider the possibility that the long-wide variety is not available on the market, and therefore must be replaced by substitute products, especially the long-thin variety of imported rice or by other available rice products. In this way, it will be studied whether the substitution explained by consumer preferences, and its effect on the size of the market, generate repercussions for the agents' profits in the face of these new situations, both for retailers and for producing companies.

Along with the above, and considering that there is knowledge of effective price-cost margins for both retail and the manufacturing industry, the simulation of a market equilibrium according to the Nash-Bertrand paradigm allows to check whether the current economic results are consistent with competitive behavior.

4.2.1 Scenario 1: Base

The base scenario corresponds to the computation of the profits of retailers and producers from the sale of the products, using equations (16) and (17) without restricting the supply of products, using the available data on sale prices, effective wholesale prices and marginal production costs of the period under analysis together with the market shares. Here it is important to note that there is no information on the fixed costs or other marketing costs of the retailer, nor on other costs of the producing firms other than their rice processing from its raw material state, therefore, these profits would correspond to gross margins.

4.2.2 Scenario 2: Excludes main long-wide variety rice products of domestic origin

In this scenario, prices are obtained at each retailer for rice products in a situation where they decide to exclude items of the main varieties of national origin from their shelves. Given that these products, long-wide variety rice of grades 1 and 2 standards, from the most important *national brands* and also from their private-label brands, have the largest market shares, it is assumed that this scenario exerts pressure on consumer demand, who based on their preferences, must choose between products that are not part of their usual purchases.

The utility parameters associated with the characteristics, attributes and brands of the products become relevant, since now many of these preferred items are not available and must be replaced by others. On this level, the utility-maximizing retailer can charge higher prices for products that are receiving a greater demand from consumers who choose them to replace items that are not available. Something similar should occur in the optimal response by the manufacturing firms.

This logic of interaction in supply and demand is what is also expected to be found in the rest of the scenarios to be analyzed, and it has consequences for the economic result that the sale of rice products generates for agents. However, since the products present differences based on their attributes, substitution will not be an alternative for many consumers and they will opt for the neutral option for their utility that represents the *outside good*, that is, not buying rice, and therefore, the size of the market will shrink and it will also affect profits.

4.2.3 Scenario 3: Excludes main long-wide variety rice products of domestic origin of standard grade 1, all brands including private-labels

In this case, those products of national origin, variety long-wide grade 1, which are in the highest value segment of each brand, are discarded from each retailer's offer. The objective is to analyze if the similarity that other products present in terms of the variety of rice they contain and their origin, is capable of solving the lack of items from the best segment with others that have a lower standard or degree of quality, considering the demand that the latter have in each retailer and using the substitution patterns generated by the structural model.

4.2.4 Scenario 4: Excludes main long-wide variety rice products of domestic origin of standard grade 1, only *national brands* excluding private-labels

The objective of this scenario is to analyze the result for the retailer of leaving only their own private-label brand products in the highest value segment, excluding from this the items of rice grade 1 long-wide manufactured by the two main national manufacturing companies, Carozzi and Tucapel.

4.2.5 Scenario 5: Excludes foreign origin varieties (imported) long-thin grade 2 rice products, all brands

Finally, this scenario allows to know what would happen in case of excluding long-thin grade 2 rice products, of imported origin, and which are positioned as the products in the lowest value segment in the market. It is important to point out that both Carozzi and Tucapel are relevant participants in this product segment, but not the private-label brands, which are concentrated in the local variety (see Table 2).

5 Results

5.1 Estimation logit model

The results of the estimation via maximum likelihood of the logit model are presented in Table 4 and Table 5, for each retailer respectively.

The product price sensitivity parameter is statistically significant in all specifications for both retailers and is also negative, as expected. Due to the homogeneity in preferences imposed by the logit model, this result is interpreted as a representative customer who experiences disutility compared to the price level of the products.

The estimates indicate that there are differences between retailers in the level of significance of the other explanatory variables in addition to price.

It is noted that in the clients of the retailer QUALITY (see Table 4), the parameters in the utility that correspond to dummy variables of the brand manufacturer are statistically significant in specifications that include them. This does not occur with the logit estimation for the VALUE retailer (see Table 5), which only presents statistically significant estimates in the parameter associated with price in all specifications. Regarding the parameters that capture the attributes of variety (type of rice) and quality, only in some cases in specifications of the QUALITY retailer are obtained statistically significant estimates.

The dummy variable for "seasonality", which identifies transactions carried out in the spring or summer months, and which was included to capture effects on demand attributable to specific time of the year, is not statistically significant. The same occurs with other dummy control variables included in specification (4) in both retailers. In this, utility was modeled with a variable that reflects whether the consumer repeats the purchase of a product of the same brand or type as in the immediately previous purchase, as a way of controlling "loyalty" of the consumer in its utility function. However, its associated parameter was not statistically significant in any of the retailers.

A similar result is observed for the dummy variable that identifies purchases made in establishments located in municipalities in the eastern sector of Santiago, to control for socioeconomic aspects and their association with the location of the supermarket in those municipalities with higher income households.

These results are indicative of a demand where, in addition to price, the brands of the products would play a role in the preferences of some consumers. Likewise, there would be differentiation in the target market that goes to the stores of each retailer, explained by different valuations in attribute variables obtained in the estimates. This heterogeneity of preferences in the market for rice products supplied by each retailer cannot be adequately captured with a representative consumer, and the mixed logit model advances towards this with more structure.

5.2 Estimation mixed logit model

5.2.1 Probability distribution of preferences

As pointed out in section 4, the estimation of the mixed logit model made possible to recognize the heterogeneity in consumer preferences for the characteristics of the products. In addition to this, the available information allows to identify different demand parameters in each retailer, which, as could be seen with the estimation of the traditional logit model, yielded different results for the demand in the markets supplied by their respective stores.

As the estimation approach used in this work is non-parametric, the probability distributions of these coefficients will be supported by the grid of β^r points of dimension R that are generated by simulation in the specifications that are defined.

Fox et al. (2011) highlight the importance of having a grid coverage in the relevant area of the parameter space, and recommend that the econometrician focus this search on the initial estimates of the logit model. They state that a Uniform distribution has superior convergence results than a random one, because in the presence of computational and data limitations ensures better coverage of points on the defined support.

For these reasons, support points used in the estimates are generated from a Uniform distribution, in the range given by multiples of the standard deviations of the logit estimates. The domain range of the coefficients is presented in detail for each retailer in Table 6. The specifications to be estimated consider the variables used in the traditional logit model in specification (3), without the dummy variables associated with seasonality, loyalty or location, since these were not reported to be statistically significant (as shown in Table 4 and Table 5).

Specifications used in the estimation consider samples of 50,000 and 100,000 observations and an R number of 30 to 200 simulations for each parameter. Since the coefficient α is essential for the calculation of price elasticity, it is necessary to analyze the sensitivity of the $FKRB$ estimator against different specifications. For this, Table 7 and Table 8 present the mean and standard deviation of the estimated parameter α with different sample sizes of transactions N, number of simulations R and different amplitude of the grid of points used in the estimation, in each retailer respectively.

The moments indicate that the non-parametric estimate is robust to the width of the grid, more so if a sufficient number of R points are available. As discussed by Fox et al. (2011), in the results obtained the bias-variance trade-off can be appreciated, because although a wide grid with sufficient density of points offers flexibility to find the population value, there is also a greater number of parameters to be estimated and increases the standard deviation of the estimator.

In the variables that identify brand characteristics and product variety, Table 9 and Table 10 present the mean and standard deviation of the coefficients. These are obtained for the different grids used, but only specifications (2) and (5) for N and R are chosen as they are considered to adequately balance the trade-off according to what was analyzed for the price sensitivity parameter. The moments of these coefficients confirm what was obtained in the traditional logit model for the QUALITY retailer, with variables associated with product manufacturers that have significant magnitudes on utility. In the VALUE retailer, on the other hand, the estimates of these coefficients present a higher variance, and therefore, this inference cannot be made.

By obtaining a value for the probability of the vector (α^r, β^r), the non-parametric estimation of the model allows to find a joint probability distribution. As the number of explanatory variables ($K = 7$) prevents the representation of this distribution, bivariate forms of this probability can be observed by plotting the coefficient of a characteristics' variable together with that of price (see Figure 3 and Figure 5), or simply in two dimensions when the probability distribution of each parameter is examined separately (see Figure 4 and Figure 6).

The results reveal heterogeneity in the distribution of demand parameters in both groups of consumers, although this is limited since a large number of sub-populations with very different preferences are not identified. However, it is noted that the probability densities are higher, that is, they have their mode, in values that do not necessarily correspond to the mean of the distributions. It can also be noted that the distributions in most cases are far from resembling a Normal distribution.

In particular for the price sensitivity parameters, α^r, it can be seen in the comparison of Figure 4 and Figure 6 that the density and groups with the highest probability are located in different areas in both retailers, even if the mean between them is similar (see Table 7 and Table 8). In the estimates for QUALITY, there are groups of consumers that present less sensitivity to price, while in the case of the group that purchases products in the

VALUE retailer, a mass of probability accumulates in high values of dislike for the price level.

5.2.2 Elasticities and substitution patterns

As indicated in Section 4, the estimation of a mixed logit model enriches the analysis of demand in a structural model, because the heterogeneous parameters are capable of generating the correlation in the attributes' space that is necessary to find substitution patterns according to the similarity of the products. The results of own-price and cross-price elasticity calculations are presented in Table 11 and Table 12, for each retailer respectively.

In these calculations, and to facilitate the presentation of results, a grouping of products was made according to their brand and type, identical to the one used to present the descriptive statistics of the data from the purchase transaction samples used (see Table 2). Obtaining elasticities is possible thanks to the closed formula of the logit model, and with the knowledge of the distribution of parameters that is the result of demand estimations. The reference is found in Nevo (2000b).

In relation to values of elasticities found in other studies of demand for food products marketed by retailers in Chile, the results are indicative of a lower own-price elasticity when compared to products such as coffee (Noton & Elberg, 2014), and quite similar to what is found in the kitchen oil market, in retailer supermarket chains that also have private-label brands (Bosch et al., 2001). In the rice market analyzed here, the result indicates that it is relatively lower (inelastic) in some product groups, particularly for the long-wide variety of national origin, which is more pronounced in consumers of the QUALITY retailer.[22]

The price elasticities between products – or "cross" – show an interesting pattern in the case of Carozzi brands grade 1 long-wide rice. In these products, they reveal that in case of price increases, consumers tend to replace them with others from the same manufacturer, which is observed in the demand in both retailers. This pattern of substitution does not occur with the same intensity in the case of the long-wide grade 1 product from Tucapel.

In the private-label brands, it is observed that in the retailer QUALITY they challenge Carozzi products to a moderate extent (cross elasticity of 0.24 in grade 1 long-wide rice), and to a greater extent in Tucapel products (up to 0.53 in long-wide rice grade 2). This trend is repeated in VALUE, with private-label brand products that tend to have higher cross-elasticity (up to 0.19 in the grade 2 long-wide rice segment) relative to Tucapel products than relative to Carozzi products.

When examining the products of long-thin grade 2 rice of imported origin, the cross elasticities are greater with products of the same segment (up to 0.13 in QUALITY and 0.12 in VALUE) than with respect to the rest of the products, which predicts that the price increases of these products would have a limited effect on the demand for the rest of varieties.

However, price increases in the leading segments of market share, made up of varieties of national origin, appear to be challenged by the segment with lower prices comprised by products of imported variety but from the same manufacturer, with cross-elasticities of up to 0.66 in the case of the products long-thin grade 2 of Carozzi with respect to

[22]These products have a 50.2% share of the rice market in the QUALITY retailer and 42.7% in the VALUE retailer (see Table 2), so they are undoubtedly the most relevant.

the long-wide grade 1 of the same manufacturer in QUALITY, and 0.20 in VALUE in the elasticity between those same varieties and manufacturer.

5.2.3 Counterfactual scenarios

With structural demand estimations, and based on the supply model defined in Section 4.2, the market shares and profits of retailers and manufacturing companies for the sale of rice products are simulated in counterfactual scenarios, based on of the expressions given by equations (16) and (17) defined.

By modifying the set of available products, the estimated preference parameters of demand for the products and the supply model allow to generate equilibrium prices in each new market situation.[23] New market equilibria imply new shares for the products, which are presented for each scenario in Table 13 and Table 14, for each retailer respectively.

In both retailers, the exclusion of products of national origin (scenario 2), and of the subgroup with the highest quality standard (scenarios 3 and 4, which only exclude grade 1 products), generates a shrinkage in the market. In the case of the VALUE retailer, the reduction is almost 45% in the scenario that does not have long-wide variety products (see last row of Table 14). Consumers, faced with the new offer available, make purchase choices substituting according to their preferences for products of other varieties, or opting for the *outside good* by not buying rice, and the results indicate that this last alternative is frequently chosen when national variety products are not available. Scenarios 3 and 4 also indicate that since the best quality products on the market cannot be found, they are replaced by others of the same national long-wide variety, but of lower standard grade 2. Private-lanel brands in scenario 4 indicate that they are only partially capable of coping with the absences of the most important *national brands* competitors in this market.

What is observed for the varieties of national origin is very different from what is produced with the exclusion of products of the imported variety of long-thin rice (scenario 5), according to what is reported in Table 13 and Table 14. It is shown that in the QUALITY retailer, consumers increase their consumption of the national variety when the long-thin rice products are not available, and thus the size of the market remains practically unchanged. In the case of VALUE, there is a diversion of demand towards other products, but this is not total and the size of the market experiences a reduction of 10%.

Regarding profits estimates, the knowledge of the sale price to the consumer and the wholesale price payed by the retailer, implies being certain of the most relevant part of the marginal cost that retailers incur to sell each product. However, since other components of the cost of retail distribution that also fall within the marginal cost, such as the expense of managing the retailer stores, these profits must be interpreted as the result of a direct accounting profit margin – gross – for the sale of the products. Similarly, for the profits of the manufacturing company, the marginal cost of rice production is derived exclusively from purchases of raw inputs for processing the cereal, and therefore does not include other components.

Bearing that disclaimer in mind, the estimates of the profits of each retailer and manufacturer companies in the optimal contract between them in the equilibrium of the counterfactual scenarios, are presented in Table 15 and Table 16, for the markets supplied by QUALITY and VALUE respectively.

[23] Obtaining the equilibrium prices implied by the first-order conditions of the new scenarios is performed on the same samples of transactions used in demand estimation.

In each Table, the first row is base of comparison for the actual situation reported by the available data, and which is contrasted with the total profits of the retailer and of the manufacturing companies in the simulated counterfactual scenarios and, in the last column, a scenario with the result of equilibrium with all the products of the current supply under the assumption of Nash-Bertrand competition – hereinafter, N-B scenario –. In the second row of each Table, the profits of the agents are compared, taking the profits that would be obtained in the N-B scenario with all the products as a contrast basis measure. In this comparison, the contrast basis is lower, since the N-B scenario manages to partially explain the profits obtained.

Indeed, for the QUALITY retailer, the N-B scenario is capable of explaining 49% of the actual profits of the distributor and 74% of the actual profits of the manufacturing companies. Counterfactual scenarios that alter the supply of products reveal significant reductions in profits for both types of agent. When looking at the last row in the Table 15, which presents the calculation of unitary-profits in each scenario, it is reflected that the absence of long-wide variety products puts downward pressure on the unit-margin that retailers and producers can obtain for the remaining products they sell left on the market. If we add to this that demand shrunk (see the last row of Table 13), it is possible to understand the reduction in total profits.

In the VALUE retailer, the ability to explain the profits with the Nash-Bertrand behavior is similar between both agents, with 66% of the actual profits obtained by the distributor and 64% of the actual profits of the manufacturing companies. As in the previous case, the counterfactual scenarios reveal significant losses for retailers and producers. However, and unlike the previous case, in VALUE there is no downward pressure on the unitary-profit margins for products that remain available for sale, and what explains the decrease in profits is the strong contraction in demand in the new scenarios (see last row of Table 14).

In sum, for both retailers and also for the manufacturing companies, the profits implied by the new scenarios denote the importance of the sale of certain products in this market, particularly those of a variety of national origin.

As Nevo (2000a) indicates, not knowing the marginal cost and imposing it based on a model of competitive behavior is part of the tradition of the new empirical industrial organization literature. In the market power analysis that this author presents regarding the breakfast cereal industry (Nevo, 2001), the Nash-Bertrand equilibrium was more consistent with accounting data than other non-collusive behavior models. On the other hand, in the market analyzed here, and noting that the known margin given by the difference between the sale price and the price paid to the producer represents an incomplete measure, the Nash-Bertrand paradigm offers a partial answer, especially in the QUALITY retailer, and motivates the search for other explanations about the way in which the retailer and the producer negotiate the wholesale price.

One explanation is offered by Villas-Boas (2007), who points out that examining the demand in a single product category can be restrictive, because manufacturers not only sell differentiated products in different segments of the same market, but also in other categories with different products. This is valid for the market analyzed here in the case of the producer Carozzi, which has a strong presence in a wide range of foods, not just rice. This fact would not only affect the decision on the price to be negotiated for that product, but would also improve its negotiating flexibility with the retailer. As this author indicates, retailers can also use a strategic way of setting sales prices in some product categories to boost trips to stores, thus increasing overall sales. From this point of view, an attractive price for more important products in the household consumption basket would generate a greater commercial signal, and would free up other products – such as rice – where the retailer margin may be higher and could act as compensation to the other categories.

The second explanation is more obvious, and involves recognizing that the part of the marginal cost that is not being considered in this dataset may have a significant magnitude, especially for the QUALITY retailer, considering that for VALUE the explanation of the gross margin reaches 66% and for manufacturing companies an equivalent or higher figure. Conditions of differentiation of stores such as their size, location and the inclusion in them of other services or their proximity to other department stores, malls and economies of scope in general that are offered to the consumer, imply costs for the QUALITY retailer that a more extended analysis of the multiple category margins that rationalize the market equilibrium must contemplate.

6 Conclusions

In Chile, rice is not a food with high levels of consumption in international comparisons, however, the results of the estimation of structural demand presented in this work indicate that in groups of the population the weekly purchase decision reveals more insensitive with respect to prices and manifests more accordingly to preferences for varieties and brands.

Using data from individual transactions of purchases in two important supermarket chains in Santiago de Chile, structural demand estimations and the supply model acting in competitive equilibrium reflect that there is a significant economic result for the retail distributor and also for the manufacturing companies producing rice. Likewise, they reveal consumer fidelity to the manufacturers of *national brands* and to the varieties of product from local origin long-wide grain. When reviewing the profits obtained by both distributors and manufacturers, these results suggest the existence of significant bargaining power over retailers by the manufacturing companies that have these local origin varieties in their offer.

This economic result is consistent with the interest of the chilean rice manufacturing industry in maintaining long-term relationships with farmers who produce the variety of national origin, and its links with public organizations that carry out research and development in this area, especially regarding certified seeds adapted to the temperate climate in the region of production. The result is also consistent with the entry of private-label retailer brands that occurred in the period under analysis and their interest in gaining positioning in the market. The supply model based on Nash-Bertrand strategies explains around 64%-74% of a gross estimate of margin data for manufacturing companies and 66% for the VALUE retailer. However, in QUALITY the explanation of the margin is close to 50%. Differentiating characteristics as a "hypermarket" type store and elements associated with the negotiation between this retailer and manufacturers, which cannot be addressed with the model developed here, motivate the search for other answers that complement the analysis of price-cost margins and profits.

The preferences for certain attributes revealed by the demand estimate also have "up-stream" implications in the supply chain of this product. The purchase of local variety rice from farmers by the processing industry, especially by the two companies that manufacture *national brands* with a strong presence in this market, is based on an indicator published by the Ministry of Agriculture to increase market transparency in domestic sourcing markets for the cereal, but is constructed based in alternative import cost prices index built with foreign trade records information, which from the perspective of demand seems questionable given the attributes and preference of consumers. This is because the locally produced variety has a higher price paid by consumers, and having these products in their offer generates significant profits in the agri-food value chain of rice.

Based on the structural estimation developed in this work, a scenario that excludes all local variety products from sale in each retailer generates a very limited shift in demand towards products of imported origin, and the response in the preferences of consumers would generate a reduction in the size of the market for this product. In addition, in the estimated scenarios for one of the retailers, it is evidenced that demand causes downward pressure on unit margins of the remaining products on offer, which is manifested both for the distributor and for the manufacturing companies. All these factors imply that a scenario where the national variety of long-wide rice is not available in the market would generate significant loss of profits for both types of agent.

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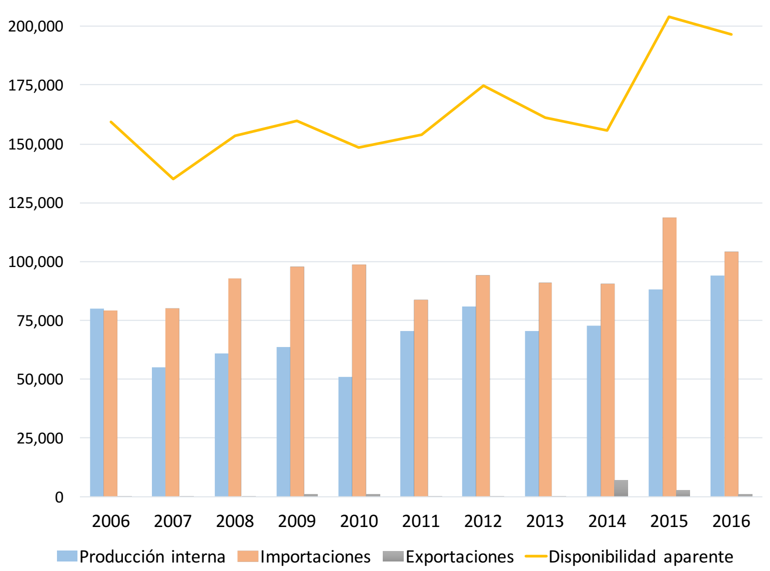
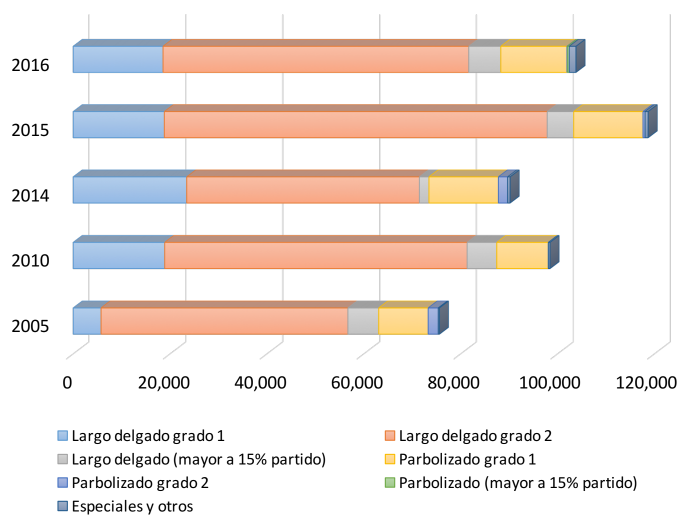
7 Figures and Tables

Figure 1: Producción interna, importaciones, exportaciones y disponibilidad aparente de arroz en Chile, 2006-2016 (toneladas).



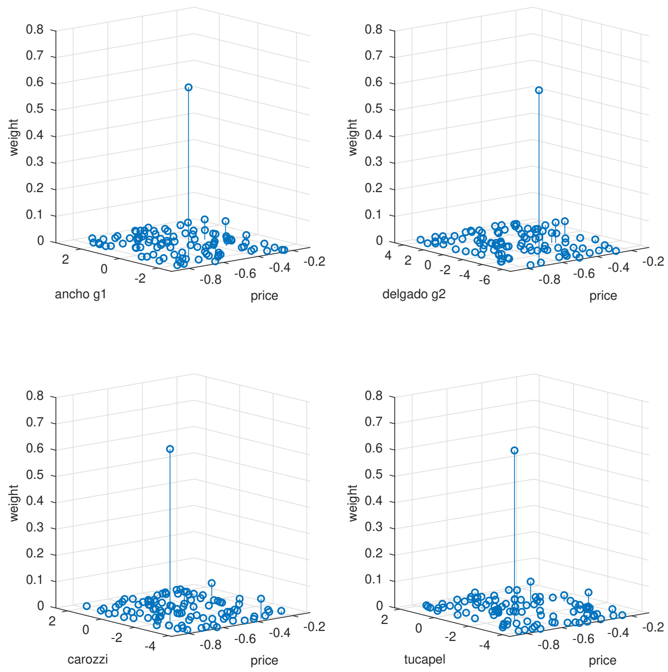
Fuente: Espinoza and Farías, 2017, con datos de INE, ODEPA y Servicio Nacional de Aduanas.

Figure 2: Importaciones de arroz elaborado, según tipo de producto: 2005, 2010 y 2014-2016 (toneladas).



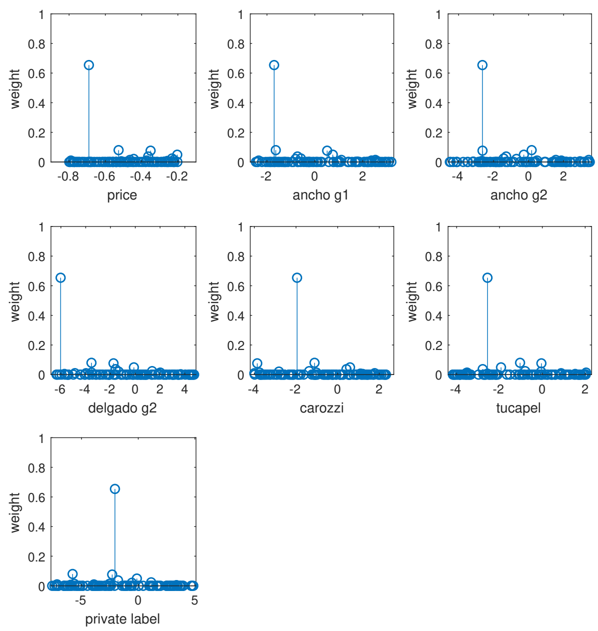
Fuente: Espinoza and Farías, 2017, con datos del Servicio Nacional de Aduanas.

Figure 3: Distribución conjunta en tuplas elegidas de $(\alpha^r, \beta^r, \hat{\theta}^r)$, retailer QUALITY



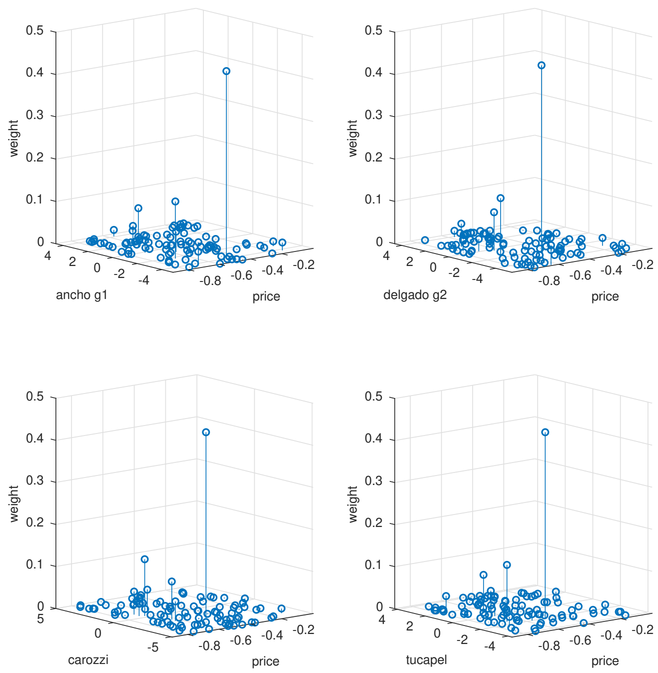
Nota: Especificación (5.c), con N=100,000 y R=100.

Figure 4: Plot en 2-D para la probabilidad $\hat{\theta}^r$ estimada para α^r y distintos β^r, retailer QUALITY



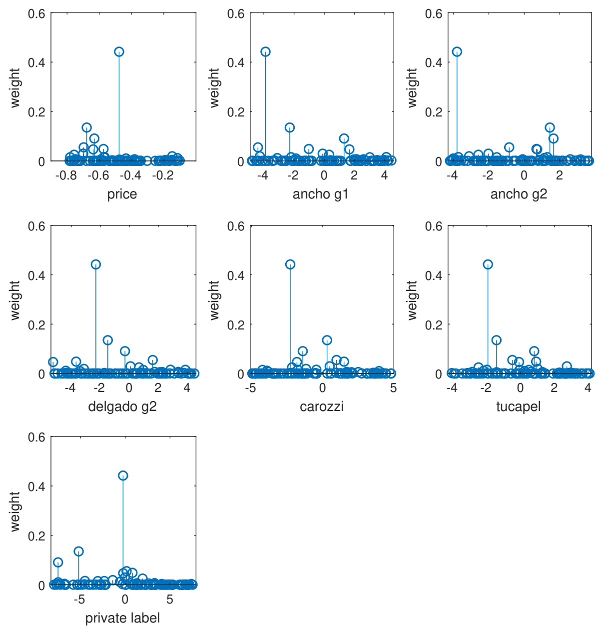
Nota: Especificación (5.c), con N=100,000 y R=100.

Figure 5: Distribución conjunta en tuplas elegidas de $(\alpha^r, \beta^r, \hat{\theta}^r)$, retailer VALUE



Nota: Especificación (5.c), con N=100,000 y R=100.

Figure 6: Plot en 2-D para la probabilidad $\hat{\theta}^r$ estimada para α^r y distintos β^r, retailer VALUE



Nota: Especificación (5.c), con N=100,000 y R=100.

Table 1: Importaciones de arroz según clasificación aduanera de Chile, 2005, 2010, 2014-2016 (toneladas)

Tipo de producto en clasificación aduanera	2005	2010	2014	2015	2016
Arroz con cáscara (*paddy*)	33	270	0	0	0
Arroz descascarillado (integral)	16	135	83	165	245
Arroz elaborado <5% grano partido	16,010	29,713	37,927	33,427	32,469
Arroz elaborado ≥5% y ≤15% grano partido	53,008	62,445	50,009	79,502	63,200
Arroz elaborado >15% grano partido	6,570	6,253	2,240	5,746	8,110
Arroz partido	17,589	25,106	19,488	23,404	25,158
Total	93,226	123,922	109,748	142,245	129,181

Fuente: Espinoza and Farías, 2017, con datos del Servicio Nacional de Aduanas.

Table 2: Participaciones de mercado para grupos de productos, sobre el total de transacciones o el total de compras de arroz en cada retailer

	Total de transacciones		Total de compras arroz	
Marca y tipo de producto	QUALITY	VALUE	QUALITY	VALUE
Carozzi ancho grado 1	3.1%	1.1%	19.1%	11.7%
Tucapel ancho grado 1	1.8%	0.7%	11.0%	7.9%
M. Propia ancho grado 1	0.7%	0.3%	4.2%	2.6%
Carozzi ancho grado 2	0.6%	0.5%	3.4%	4.8%
Tucapel ancho grado 2	1.8%	1.3%	10.8%	13.7%
M. Propia ancho grado 2	0.3%	0.2%	1.7%	2.0%
Carozzi delgado grado 2	0.2%	0.3%	1.2%	2.7%
Tucapel delgado grado 2	0.5%	0.6%	2.9%	6.3%
M. Propia delgado grado 2	n/d	0.2%	n/d	2.0%
Carozzi otro tipo	0.4%	0.1%	2.1%	1.1%
Tucapel otro tipo	0.5%	0.2%	2.8%	2.1%
M. Propia otro tipo	0.2%	0.1%	1.3%	1.0%
Otras marcas	1.6%	2.3%	9.6%	24.5%
Resto de otro tipo	4.9%	1.7%	29.8%	17.5%
Todos los productos	16.5%	9.5%	100%	100%

Nota: Muestra de N=100,000 transacciones de cada retailer. n/d: No disponible en la oferta.

Table 3: Estadísticas descriptivas de precios de productos de arroz en ambos retailers

Marca y tipo de producto	p10 ($)	p50 ($)	p90 ($)	Desv. Estd. ($)	Coef. Var. (%)	Precio medio QUALITY ($)	Precio medio VALUE ($)	Diferencia Q-V (%)	Test t
Carozzi ag1	769	849	899	68	7.9	850	845	0.59	**
Tucapel ag1	809	899	999	96	10.6	907	868	4.43	***
M. Propia ag1	695	799	890	73	9.2	785	800	-1.85	**
Carozzi ag2	579	779	899	102	13.2	771	761	1.31	
Tucapel ag2	633	749	929	115	14.8	765	775	-1.26	**
M. Propia ag2	665	749	799	55	7.5	725	746	-2.79	***
Carozzi dg2	679	799	799	72	9.7	784	705	10.68	***
Tucapel dg2	543	579	599	57	9.7	570	595	-4.20	***
M. Propia dg2	499	499	539	17	3.5	n/d	503	n/d	
Carozzi otro	867	909	1,139	99	10.5	928	981	-5.62	***
Tucapel otro	949	1,095	1,119	100	9.4	1,085	1,001	8.03	***
M. Propia otro	860	909	1,009	76	8.1	918	976	-6.06	***
Otras marcas	499	599	879	386	53.7	713	644	10.19	***
Resto otro tipo	679	999	2,851	1,210	80.6	1,221	1,238	-1.38	
Todos	589	835	1,199	705	72.2	915	804	12.92	***

Nota: Muestra de N=100,000 transacciones de cada retailer. En última columna se presenta el nivel de significancia del contraste de diferencia de medias ($H_0 = 0$) para muestras de distinta varianza, con Pr(|T| > |t|) menor al 1% (***), 5% (**) y 10% (*). n/d: No disponible en la oferta.

Table 4: Resultados estimación modelo logit, retailer QUALITY

Variables	(1)	(2)	(3)	(4)
Precio	-0.63	-0.70	-0.51	-0.61
	(0.02)	(0.03)	(0.02)	(0.03)
	[-28.00]	[-20.88]	[-22.90]	[-20.53]
Ancho grado 1		-0.33	0.28	0.27
		(0.27)	(0.24)	(0.26)
		[-1.24]	[1.16]	[1.02]
Ancho grado 2		-1.03	-0.50	-0.53
		(0.35)	(0.33)	(0.35)
		[-2.93]	[-1.50]	[-1.53]
Delgado grado 2		-1.13	-0.98	-1.01
		(0.49)	(0.48)	(0.49)
		[-2.29]	[-2.04]	[-2.07]
Estacionalidad		22.18		
		(1881.22)		
		[0.01]		
Carozzi			-0.77	-0.76
			(0.28)	(0.29)
			[-2.77]	[-2.61]
Tucapel			-1.05	-1.03
			(0.27)	(0.29)
			[-3.86]	[-3.60]
Marca propia			-1.29	-1.37
			(0.52)	(0.53)
			[-2.47]	[-2.60]
Repite tipo o marca				19.29
				(878.71)
				[0.02]
Comuna sector oriente				-0.16
				(0.27)
				[-0.58]

Nota: Especificaciones con N=100,000. Bajo cada parámetro se presenta el valor de su (desviación estándar) y su respectivo [estadígrafo t].

Table 5: Resultados estimación modelo logit, retailer VALUE

Variables	(1)	(2)	(3)	(4)
Precio	-0.53	-0.62	-0.49	-0.57
	(0.03)	(0.04)	(0.03)	(0.04)
	[-18.03]	[-14.17]	[-16.81]	[-15.59]
Ancho grado 1		-0.29	-0.17	-0.16
		(0.44)	(0.39)	(0.42)
		[-0.65]	[-0.43]	[-0.39]
Ancho grado 2		-0.35	-0.25	-0.28
		(0.39)	(0.33)	(0.36)
		[-0.92]	[-0.74]	[-0.79]
Delgado grado 2		-0.49	-0.41	-0.45
		(0.46)	(0.41)	(0.43)
		[-1.07]	[-0.99]	[-1.04]
Estacionalidad		17.27		
		(275.14)		
		[0.06]		
Carozzi			-0.04	-0.07
			(0.41)	(0.44)
			[-0.09]	[-0.16]
Tucapel			-0.05	-0.06
			(0.34)	(0.37)
			[-0.16]	[-0.17]
Marca propia			-0.21	-0.28
			(0.67)	(0.70)
			[-0.32]	[-0.40]
Repite tipo o marca				18.8
				(982.79)
				[0.02]
Comuna sector oriente				-0.06
				(0.58)
				[-0.11]

Nota: Especificaciones con N=100,000. Bajo cada parámetro se presenta el valor de su (desviación estándar) y su respectivo [estadígrafo t].

Table 6: Soporte de distribución Uniforme para grillas de (α^r, β^r) en estimaciones no paramétricas del modelo mixed logit para QUALITY y VALUE

	4 D.E. desde logit				8 D.E. desde logit				12 D.E. desde logit			
Coeficientes	QUALITY		VALUE		QUALITY		VALUE		QUALITY		VALUE	
(K=7)	*min*	*max*	*min*	*max*	*min*	*max*	*min*	*max*	*min*	*max*	*min*	*max*
Precio	-0.6	-0.4	-0.6	-0.4	-0.7	-0.3	-0.7	-0.3	-0.8	-0.2	-0.8	-0.1
Ancho grado 1	-0.7	1.3	-1.7	1.4	-1.7	2.2	-3.3	3.0	-2.6	3.2	-4.8	4.5
Ancho grado 2	-1.8	0.8	-1.6	1.1	-3.2	2.2	-2.9	2.4	-4.5	3.5	-4.2	3.7
Delgado grado 2	-2.9	0.9	-2.0	1.2	-4.8	2.9	-3.7	2.9	-6.7	4.8	-5.3	4.5
Carozzi	-1.9	0.3	-1.7	1.6	-3.0	1.5	-3.3	3.3	-4.1	2.6	-5.0	4.9
Tucapel	-2.1	0.0	-1.4	1.3	-3.2	1.1	-2.8	2.7	-4.3	2.2	-4.2	4.1
Marca propia	-3.4	0.8	-2.9	2.5	-5.5	2.9	-5.6	5.1	-7.6	5.0	-8.2	7.8

Nota: Soporte basado en múltiplos de desviaciones estándar de los coeficientes logit de especificación (3) en cada retailer, presentados en cuadros 4 y 5, respectivamente.

Table 7: Media y desviación estándar de estimador $FKRB$ para el coeficiente de sensibilidad al precio, bajo distintas especificaciones y grillas de α^r en retailer QUALITY

			(a) 4 D.E.		(b) 8 D.E.		(c) 12 D.E.	
Especificación	N	R	Media	D.E.	Media	D.E.	Media	D.E.
(1)	50,000	30	-0.49	0.06	-0.48	0.09	-0.60	0.20
(2)	50,000	50	-0.49	0.06	-0.51	0.10	-0.56	0.17
(3)	100,000	30	-0.53	0.04	-0.53	0.07	-0.60	0.16
(4)	100,000	50	-0.53	0.08	-0.58	0.12	-0.63	0.21
(5)	100,000	100	-0.53	0.06	-0.53	0.09	-0.58	0.17
(6)	100,000	200	-0.54	0.06	-0.58	0.17	-0.64	0.21

Nota: El número de variables explicativas es K=7 en todas las especificaciones.

Table 8: Media y desviación estándar de estimador $FKRB$ para el coeficiente de sensibilidad al precio, bajo distintas especificaciones y grillas de α^r en retailer VALUE

			(a) 4 D.E.		(b) 8 D.E.		(c) 12 D.E.	
Especificación	N	R	Media	D.E.	Media	D.E.	Media	D.E.
(1)	50,000	30	-0.45	0.02	-0.48	0.14	-0.61	0.24
(2)	50,000	50	-0.44	0.03	-0.46	0.14	-0.52	0.19
(3)	100,000	30	-0.53	0.08	-0.56	0.13	-0.58	0.14
(4)	100,000	50	-0.53	0.07	-0.55	0.10	-0.64	0.18
(5)	100,000	100	-0.51	0.06	-0.55	0.14	-0.55	0.13
(6)	100,000	200	-0.51	0.07	-0.55	0.14	-0.65	0.20

Nota: El número de variables explicativas es K=7 en todas las especificaciones.

Table 9: Media y desviación estándar de estimador $FKRB$ para coeficientes de características, bajo distintas grillas de β^r y especificaciones (2) y (5) en retailer QUALITY

	(a)		(b)		(c)	
	4 D.E.		8 D.E.		12 D.E.	
Variables	(5)	(2)	(5)	(2)	(5)	(2)
Ancho grado 1	-0.1	-0.1	-0.9	0.0	-1.1	-0.6
	(0.5)	(0.6)	(0.9)	(1.2)	(1.1)	(1.7)
Ancho grado 2	-1.0	-0.9	-1.7	-1.5	-1.9	-2.5
	(0.6)	(0.7)	(1.3)	(1.2)	(1.3)	(1.4)
Delgado grado 2	-2.1	-1.7	-3.0	-3.1	-4.5	-4.4
	(1.1)	(1.0)	(1.1)	(1.8)	(2.3)	(2.2)
Carozzi	-1.0	-1.2	-2.0	-1.4	-1.8	-2.5
	(0.6)	(0.7)	(1.3)	(1.2)	(1.3)	(1.4)
Tucapel	-1.3	-1.0	-2.1	-1.3	-2.0	-2.3
	(0.5)	(0.5)	(1.0)	(1.2)	(1.1)	(1.5)
Marca propia	-1.5	-1.1	-1.3	-3.8	-2.3	-4.0
	(0.5)	(1.2)	(1.0)	(1.8)	(1.5)	(2.6)

Nota: Desviación estándar entre paréntesis.

Table 10: Media y desviación estándar de estimador $FKRB$ para coeficientes de características, bajo distintas grillas de β^r y especificaciones (2) y (5) en retailer VALUE

	(a)		(b)		(c)	
	4 D.E.		8 D.E.		12 D.E.	
Variables	(5)	(2)	(5)	(2)	(5)	(2)
Ancho grado 1	-0.3	-0.1	-0.8	-0.3	-2.1	-0.9
	(0.5)	(0.9)	(0.9)	(1.7)	(2.4)	(1.5)
Ancho grado 2	-0.6	-0.3	-0.5	-1.0	-1.6	-2.2
	(0.7)	(0.6)	(0.8)	(1.3)	(2.4)	(2.1)
Delgado grado 2	-1.1	-0.4	-1.5	-1.2	-1.5	-2.4
	(1.0)	(0.9)	(1.6)	(1.2	(1.9)	(2.3)
Carozzi	-1.0	-0.2	-1.9	-1.1	-1.2	-1.6
	(0.7)	(0.6)	(0.8)	(1.3)	(2.4)	(2.1)
Tucapel	-0.3	-0.3	-0.9	-0.7	-1.0	-2.1
	(0.5)	(0.8)	(1.2)	(0.9)	(1.4)	(2.3)
Marca propia	-0.6	-1.0	-2.0	-2.8	-1.6	-4.5
	(1.1)	(1.9)	(1.7)	(2.3)	(2.9)	(3.2)

Nota: Desviación estándar entre paréntesis.

Table 11: Elasticidades modelo mixed logit, retailer QUALITY

	Carozzi ag1	Tucapel ag1	M. Propia ag1	Carozzi ag2	Tucapel ag2	M. Propia ag2	Carozzi dg2	Tucapel dg2	Carozzi otro	Tucapel otro	M. Propia otro	Otras marcas	Resto otro tipo
Carozzi ag1	-1.05	0.04	0.05	0.10	0.02	0.02	0.04	0.01	0.07	0.01	0.01	0.14	0.06
Tucapel a1	0.07	-2.23	0.03	0.02	0.18	0.02	0.01	0.05	0.01	0.09	0.01	0.19	0.12
M. Propia ag1	0.24	0.08	-1.63	0.07	0.10	0.09	0.03	0.03	0.05	0.03	0.04	0.21	0.08
Carozzi ag2	0.55	0.06	0.09	-2.45	0.22	0.09	0.03	0.01	0.08	0.02	0.02	0.17	0.09
Tucapel ag2	0.04	0.19	0.04	0.07	-1.75	0.08	0.01	0.11	0.01	0.04	0.01	0.14	0.03
M. Propia ag2	0.18	0.10	0.22	0.18	0.53	-2.03	0.02	0.02	0.03	0.03	0.05	0.16	0.05
Carozzi dg2	0.66	0.12	0.10	0.08	0.05	0.03	-2.30	0.12	0.09	0.02	0.04	0.30	0.10
Tucapel dg2	0.08	0.21	0.05	0.02	0.43	0.01	0.05	-1.59	0.01	0.04	0.03	0.23	0.06
Carozzi otro	0.65	0.06	0.09	0.13	0.04	0.03	0.05	0.02	-4.00	0.02	0.03	0.29	0.16
Tucapel otro	0.05	0.34	0.04	0.02	0.14	0.01	0.01	0.04	0.02	-3.47	0.02	0.23	0.14
M. Propia otro	0.19	0.10	0.14	0.06	0.08	0.07	0.04	0.07	0.05	0.05	-2.83	0.38	0.13
Otras marcas	0.27	0.23	0.09	0.06	0.16	0.03	0.04	0.07	0.07	0.07	0.05	-5.09	0.20
Resto otro tipo	0.04	0.04	0.01	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.06	-1.14

Nota: Cálculos basados en estimación de especificación (5.c).

Table 12: Elasticidades modelo mixed logit, retailer VALUE

	Carozzi ag1	Tucapel ag1	M. Propia ag1	Carozzi ag2	Tucapel ag2	M. Propia ag2	Carozzi dg2	Tucapel dg2	M. Propia dg2	Carozzi otro	Tucapel otro	M. Propia otro	Otras marcas	Resto otro tipo
Carozzi ag1	-2.27	0.08	0.01	0.08	0.06	0.00	0.04	0.06	0.01	0.02	0.01	0.00	0.16	0.06
Tucapel a1	0.12	-2.99	0.05	0.02	0.15	0.02	0.03	0.08	0.02	0.01	0.02	0.01	0.12	0.05
M. Propia ag1	0.05	0.16	-2.85	0.01	0.10	0.04	0.01	0.07	0.06	0.00	0.01	0.03	0.14	0.04
Carozzi ag2	0.20	0.04	0.00	-2.40	0.10	0.01	0.05	0.03	0.01	0.02	0.01	0.00	0.20	0.06
Tucapel ag2	0.05	0.09	0.02	0.03	-2.97	0.03	0.01	0.07	0.01	0.01	0.02	0.01	0.12	0.05
M. Propia ag2	0.02	0.08	0.06	0.02	0.19	-2.87	0.01	0.07	0.04	0.00	0.02	0.02	0.15	0.05
Carozzi dg2	0.20	0.08	0.01	0.08	0.08	0.01	-2.55	0.13	0.02	0.02	0.02	0.01	0.23	0.06
Tucapel dg2	0.11	0.11	0.03	0.03	0.15	0.02	0.06	-2.67	0.04	0.01	0.03	0.01	0.17	0.05
M. Propia dg2	0.04	0.09	0.09	0.02	0.11	0.04	0.02	0.12	-2.53	0.01	0.02	0.02	0.20	0.06
Carozzi otro	0.16	0.04	0.01	0.08	0.06	0.01	0.04	0.05	0.01	-2.55	0.01	0.01	0.13	0.06
Tucapel otro	0.06	0.08	0.02	0.02	0.16	0.02	0.02	0.07	0.02	0.01	-3.23	0.01	0.11	0.06
M. Propia otro	0.03	0.06	0.07	0.02	0.11	0.04	0.01	0.06	0.04	0.01	0.02	-2.77	0.13	0.06
Otras marcas	0.08	0.04	0.02	0.04	0.07	0.01	0.02	0.04	0.02	0.01	0.01	0.01	-2.84	0.06
Resto otro tipo	0.04	0.02	0.01	0.02	0.04	0.01	0.01	0.02	0.01	0.00	0.01	0.00	0.08	-2.59

Nota: Cálculos basados en estimación de especificación (5.c).

Table 13: Predicción de shares en escenarios contrafactuales, retailer QUALITY

Productos	Share efectivo base	Share modelo	Escenarios 2	3	4	5	Escenario N-B
Carozzi ag1	3.15%	3.25%				3.65%	3.30%
Tucapel ag1	1.82%	2.02%				2.32%	2.14%
M. Propia ag1	0.69%	0.69%			0.96%	0.86%	0.73%
Carozzi ag2	0.57%	0.69%		1.23%	1.16%	0.80%	0.74%
Tucapel ag2	1.78%	1.76%		2.03%	1.98%	1.93%	1.82%
M. Propia ag2	0.28%	0.28%		0.39%	0.35%	0.33%	0.30%
Carozzi dg2	0.20%	0.30%	0.60%	0.51%	0.48%		0.30%
Tucapel dg2	0.48%	0.43%	1.00%	0.54%	0.52%		0.44%
Carozzi otro	0.36%	0.66%	1.28%	1.07%	1.01%	0.31%	0.70%
Tucapel otro	0.46%	0.62%	0.98%	0.81%	0.79%	0.71%	0.66%
M. Propia otro	0.21%	0.30%	0.52%	0.41%	0.38%	0.39%	0.32%
Otras marcas	1.59%	3.52%	4.83%	5.01%	4.83%	3.32%	4.05%
Resto otro tipo	4.93%	1.94%	2.70%	2.20%	2.12%	1.92%	1.80%
Total *inside goods*	16.52%	16.46%	11.91%	14.20%	14.60%	16.53%	17.30%
Diferencia respecto a base (%)		-0.4%	-27.9%	-14.0%	-11.6%	0.0%	4.7%

Nota: Escenarios basados en estimación de especificación (5.c), en muestra de N=100,000 transacciones.

Table 14: Predicción de shares en escenarios contrafactuales, retailer VALUE

Productos	Share efectivo base	Share modelo	Escenarios 2	3	4	5	Escenario N-B
Carozzi ag1	1.11%	1.09%				1.24%	1.15%
Tucapel ag1	0.75%	0.77%				0.91%	0.86%
M. Propia ag1	0.25%	0.25%			0.28%	0.28%	0.26%
Carozzi ag2	0.45%	0.48%		0.58%	0.57%	0.54%	0.53%
Tucapel ag2	1.31%	1.31%		1.55%	1.54%	1.50%	1.43%
M. Propia ag2	0.19%	0.17%		0.20%	0.19%	0.20%	0.18%
Carozzi dg2	0.26%	0.26%	0.37%	0.34%	0.33%		0.28%
Tucapel dg2	0.60%	0.59%	0.77%	0.69%	0.68%		0.62%
M. Propia dg2	0.19%	0.20%	0.23%	0.22%	0.21%		0.20%
Carozzi otro	0.10%	0.10%	0.14%	0.12%	0.12%	0.11%	0.11%
Tucapel otro	0.20%	0.21%	0.27%	0.24%	0.24%	0.24%	0.23%
M. Propia otro	0.10%	0.12%	0.15%	0.14%	0.14%	0.14%	0.13%
Otras marcas	2.33%	2.44%	1.60%	2.72%	2.79%	1.76%	2.62%
Resto otro tipo	1.67%	1.43%	1.73%	1.61%	1.60%	1.60%	1.56%
Total *inside goods*	9.49%	9.44%	5.26%	8.41%	8.70%	8.51%	10.17%
Diferencia respecto a base (%)		-0.6%	-44.6%	-11.4%	-8.3%	-10.3%	7.1%

Nota: Escenarios basados en estimación de especificación (5.c), en muestra de N=100,000 transacciones.

Table 15: Ganancias por la venta de productos de arroz en escenarios contrafactuales, retailer QUALITY

Ganancias		Base efectiva	Escenarios (2)	(3)	(4)	(5)	Escenario N-B
Totales sobre base efectiva (en %)	Retailer Productores	100% 100%	26.3% 33.6%	34.7% 60.6%	34.9% 60.3%	47.3% 74.3%	49.3% 74.0%
Totales sobre escenario N-B (en %)	Retailer Productores	202.9% 135.2%	53.3% 45.4%	70.5% 82.0%	70.9% 81.5%	95.9% 100.4%	100% 100%
Unitarias ($/kg)	Retailer Productores	$256 $185	$93 $86	$104 $131	$101 $126	$121 $138	$121 $131

Nota: Cálculos basados en estimaciones de especificación (5.c).

Table 16: Ganancias por la venta de productos de arroz en escenarios contrafactuales, retailer VALUE

Ganancias		Base efectiva	Escenarios (2)	(3)	(4)	(5)	Escenario N-B
Totales sobre base efectiva (en %)	Retailer Productores	100% 100%	37.0% 35.4%	54.1% 50.9%	55.8% 52.3%	59.9% 58.7%	66.1% 64.2%
Totales sobre escenario N-B (en %)	Retailer Productores	151.2% 155.8%	55.9% 55.2%	81.8% 79.4%	84.4% 81.6%	90.5% 91.4%	100% 100%
Unitarias ($/kg)	Retailer Productores	$228 $226	$152 $144	$139 $130	$139 $129	$152 $148	$141 $135

Nota: Cálculos basados en estimaciones de especificación (5.c).