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Demand estimation and market definition in quality-differentiated products: The case of beer in Argentina

This paper analyzes the issue of demand estimation and market definition in industries where products differ according to their quality levels. An econometric methodology based on substitution elasticities is explained, and then applied to the Argentine beer industry, using data from the period 2011–2017. The results are compared to equivalent ones obtained using an alternative methodology, concluding that in Argentina we can identify two relevant markets inside the beer industry (corresponding to high/medium quality beers, and low quality beers).

Keywords: demand estimation; market definition; elasticity of substitution; beer; Argentina.
JEL classification: C33; L40; L66.

1. Introduction

Market definition implies the use of different procedures to infer if two or more products belonging to a certain industry are actually part of the same market. Those procedures can be of different nature, but in all cases they imply some kind of test about the degree of substitutability between the products under analysis. One of the main avenues to implement market definition has to do with econometric demand estimation. This is the approach that we use in this paper, and we will apply it to a case in which the analyzed products are vertically differentiated.

Vertical differentiation has the property that products can be ordered according to their qualities, and we can safely make the assumption that substitution is direct between products that are relatively similar in their qualities but that it is indirect between products whose qualities differ considerably. This allows assuming that the elasticity of substitution between two products will be positive if both products are "adjacent" in their position in the quality space, while it will be equal to zero if they are not adjacent.

Using that idea in the context of demand estimation, we will present a variation of the so-called "substitution elasticity demand system" (SEDS), applied to an industry in which products differ according to quality. That method will generate a set of coefficients that can be interpreted in terms of own-price demand elasticities and in terms of elasticities of substitution, and those coefficients will have values that relate to its possible inclusion in a certain "relevant market". The way to know if two products belong to the same market is to compare their respective own-price demand

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elasticities with a "critical elasticity", which can be calculated using a variation of the so-called "hypothetical monopolist test".

Market definition can also be performed using alternative techniques, which may imply the use of supply-and-demand models. In this paper, however, market definition will be performed exclusively using demand estimations, based on the idea that substitutability is basically a demand phenomenon, and due to the fact that the dataset used does not contain information about explicit supply variables (e.g., input prices, installed capacity, etc.).

The methodology proposed here will be applied to the case of the beer industry in Argentina, using data for the period 2011–2017. This is an industry in which product differentiation is basically seen in terms of quality, since the different beer brands are typically included in certain segments (superpremium, premium, medium, low end) that group products according to their respective price levels (and, therefore, to their implicit quality levels).

The structure of this paper will be the following. In section 2 we will describe the basic procedure to estimate demands under quality differentiation, using the substitution elasticity demand model. Then, in section 3, we will introduce the main figures of the Argentine beer industry during the analyzed period, and we will present the demand estimation for the four main segments that we identify in that industry. In section 4, in turn, we will apply critical elasticity to define if those segments are actually different markets, or if some of them must be included in the same market. In section 5 we will compare our results with the ones obtained using a different procedure, known as "LaFrance method". Finally, in section 6, we will present a few conclusions of the whole analysis.

2. Demand estimation under quality differentiation

Let us assume that there is an industry with N products which are vertically differentiated, so that product i has a lower quality than product h but a higher quality than product j. If product demands follow a logarithmic specification, then the whole system of demands can be represented by $N-2$ equations of the following form:

$$\ln(Q_{it}) = \alpha_i + \beta_{ih}\ln(P_{ht}) + \beta_{ii}\ln(P_{it}) + \beta_{ij}\ln(P_{jt}) + \beta_{iY}\ln(Y_t) + \rho\ln(Q_{i,t-1}), \qquad (1)$$

where Q_{it} is the quantity of product i; P_h is the price of product h; P_i is the price of product i; P_j is the price of product j; Y is consumers' income, and $Q_{i,t-1}$ is the quantity of product i bought in the previous period $t-1$[2]. Similarly, the system will also have an additional equation for product 1 (i.e., for the product of highest quality) with the following specification:

$$\ln(Q_{1t}) = \alpha_1 + \beta_{11}\ln(P_{1t}) + \beta_{12}\ln(P_{2t}) + \beta_{1Y}\ln(Y_t) + \rho\ln(Q_{1,t-1}), \qquad (2)$$

while there will also be another equation for product N (i.e., for the one of lowest quality) whose functional form will be:

$$\ln(Q_{Nt}) = \alpha_N + \beta_{N,N-1}\ln(P_{N-1,t}) + \beta_{NN}\ln(P_{Nt}) + \beta_{NY}\ln(Y_t) + \rho\ln(Q_{N,t-1}). \qquad (3)$$

[2] The implicit theory behind this approach is the one originally proposed by Sutton (1986). See also (Bonnisseau, Lahmandi, 2007) and (Hernández, Morganti, 2022).

Note that the logic implicit behind equations (1)–(3) is that, in this model, each product can be substituted by (at most) two additional products: the one whose quality is immediately higher and the one whose quality is immediately lower. This implies that direct substitution only occurs between "adjacent goods", i.e., between goods whose quality levels are relatively close. As this is a "Marshallian demand model", quantities are in all cases "consumed quantities". As the main application of this model will be with aggregate data (i.e., data corresponding to aggregate consumption in each period), then income refers to consumers' income in the market as a whole.

The coefficients of the demand functions in equations (1)–(3) have a direct economic interpretation, related to the concept of elasticity. Therefore, β_{ii} can be interpreted as the short-run own-price elasticity of product *i*, while β_{ih} and β_{ij} are short-run cross elasticities. Correspondingly, β_{iY} is the short-run income elasticity of demand for product *i*, while ρ is the coefficient of serial correlation between the quantities demanded in two consecutive periods of time, which we assume to be the same in all the equations.

The figures obtained can also be used to estimate long-run elasticities. By dividing the corresponding elasticity coefficients by $1-\rho$, it is possible to obtain estimates for the long-run own-price, cross and income elasticities of demand. The demand functions themselves, moreover, can also be modified to include the so-called "homogeneity restrictions", which imply that the sum of all price and income elasticities must add up to zero in each equation. In our case, this means writing the following function for equation (1):

$$\ln(Q_{it}) = \alpha_i + \beta_{ih}\ln(P_{ht}/Y_t) + \beta_{ii}\ln(P_{it}/Y_t) + \beta_{ij}\ln(P_{jt}/Y_t) + \rho\ln(Q_{i,t-1}) \quad (4)$$

and defining β_{iY} as equal to $-\beta_{ih} - \beta_{ii} - \beta_{ij}$ [3].

If all the equations are estimated simultaneously, it is also possible to include symmetry restrictions that relate cross elasticities between themselves. Those restrictions can be modelled using the concept of elasticity of substitution (σ_{ij}), by introducing that elasticity in two consecutive demand equations (e.g., the ones corresponding to products *i* and *j*) [4]. This implies that:

$$\ln(Q_{it}) = \alpha_i + \sigma_{hi}s_h\ln(P_{ht}/Y_t) + \beta_{ii}\ln(P_{it}/Y_t) + \sigma_{ij}s_j\ln(P_{jt}/Y_t) + \rho\ln(Q_{i,t-1}), \quad (5)$$

$$\ln(Q_{jt}) = \alpha_j + \sigma_{ij}s_i\ln(P_{it}/Y_t) + \beta_{jj}\ln(P_{jt}/Y_t) + \sigma_{jk}s_k\ln(P_{kt}/Y_t) + \rho\ln(Q_{j,t-1}), \quad (6)$$

where σ_{hi}, σ_{ij} and σ_{jk} are elasticities of substitution, and s_h, s_i, s_j and s_k are the revenue market shares of products *h*, *i*, *j* and *k*. Note that σ_{ij} is a parameter that appears in the two consecutive equations. Its relationship with the corresponding cross elasticities is the following:

$$\beta_{ij} = \sigma_{ij}s_j\,,\ \beta_{ji} = \sigma_{ij}s_i\,. \quad (7)$$

The symmetry of the elasticity of substitution has to do with the idea that it is a parameter that is embedded in the utility that consumers derive from two different goods. Actually, this concept is related to the relationship between the marginal utilities of the goods, which does not depend on the order in which the derivatives of the utility function are taken. The relationship between substitution elasticities and crossed elasticities, correspondingly, has to do with the interaction between

[3] For a more detailed explanation of this relationship, see (Alston et al., 2002).

[4] The inclusion of these restrictions can be made in different ways. For other alternatives applied to logarithmic demand models, see (Yang, Preckel, 2020).

the utility function and the consumers' budget constraints, and that is why each cross elasticity depends on the elasticity of substitution and the revenue share of each of the analyzed goods [5].

In order to estimate this substitution elasticity demand model, it is good to use a statistical procedure that takes into account the endogeneity that occurs under this specification. This is due to the fact that in equations (5) and (6) there are independent variables that include revenue shares, and those shares are calculated using the different products' quantities (which are the dependent variables of the whole system). To solve this endogeneity problem, it is necessary to use instrumental variables that replace the endogenous variables. In this case, it is possible to do that by using the set of original variables of the system as instruments (i. e., the logarithms of the ratios between prices and income). The most straightforward way to perform this task is by running a system of regressions using two-stage least squares.

3. Application to the Argentine beer industry

3.1. Description of the data

The database that we have to estimate the demand of beer in Argentina basically consists of series of monthly data about quantities and revenues for the different brands of beer for the period that goes from June 2011 to June 2017 [6]. By dividing the corresponding revenues and quantities, it is also possible to obtain average price series, which also have a monthly frequency. If we order the different brands according to their price levels, several segments can be formed, that group the corresponding brands into larger sets.

Traditionally, in the Argentine beer industry, firms and government agencies have grouped the beer brands in three quality segments: high-end, medium and low-end beers [7]. During recent years, however, it has been customary to subdivide the high-end segment into two subgroups, that can be labelled as "premium" and "superpremium" (see Table 1). This is because in that segment there exist several brands whose average prices are considerably higher than the ones charged for the other beers, and that characteristic might imply that those beers are actually in a different market.

From the figures of Table 1, we can see that the volume of the superpremium segment is by far the smallest, while the largest category is the one that represents the medium segment. Nevertheless, the superpremium segment is the one that increased its quantity at a higher rate (181% during the 2011/2017 period), while the medium segment is the only one whose volume has decreased during the period under analysis (−26%). The superpremium segment has always kept a price level which is at least 53% higher than the one that corresponds to the premium segment,

[5] For a more complete explanation of the theory behind this result, see (Coloma, 2009). See also (Greer, 2012, ch. 9), for more details about the differences between price elasticities and substitution elasticities.

[6] All the information concerning the Argentine beer industry that we use in this study comes from data sets elaborated by the Argentine branch of the international consulting firm A. C. Nielsen.

[7] This idea that quality is the main source of product differentiation in the beer industry is, of course, not the only possible one. Some authors have developed models of beer demand estimation assuming some kind of horizontal product differentiation. See, for example, (Rojas, Peterson, 2008) or (Toro et al., 2014).

Table 1. Argentine beer industry (2011/2017)

Concept / Year	2011/2012	2012/2013	2013/2014	2014/2015	2015/2016	2016/2017
Quantity (million liters)						
Superpremium	8.17	8.18	7.91	7.16	13.67	22.99
Premium	138.18	146.33	153.62	158.73	161.44	167.78
Medium	759.12	745.81	703.70	706.84	650.63	563.75
Low end	332.09	336.42	329.59	379.77	397.02	416.68
Total	1237.56	1236.74	1194.82	1252.50	1222.76	1171.21
Price (US dollars/liter)						
Superpremium	6.4758	7.6198	6.9757	7.7359	6.7498	6.2560
Premium	3.5796	4.1950	3.9024	4.1101	3.9678	4.0790
Medium	2.2839	2.6974	2.4603	2.5405	2.4669	2.5828
Low end	1.8780	2.1988	2.0649	2.1922	2.1969	2.1105
Total	2.3473	2.7715	2.5665	2.6635	2.6253	2.7012

Source: Own calculations based on data from A. C. Nielsen.

while the other three segments have had price levels that are much closer between themselves (see Figure 1).

Another characteristic of the beer industry related to the demand of their different products has to do with the existence of a strong seasonality. In Argentina, in general, beer sales have a peak in the month of December, in which the Southern Hemisphere Summer begins and there are also two important holidays (Christmas and New Year's Eve). After that, the demand for beer tends to decline until June, and then it begins to recover in order to reach another peak in the following December. This seems to be a general movement for all kinds of beer, as can be seen in Figure 2.

All major beer brands in Argentina are produced and marketed by only two firms: Anheuser-Busch InBev (ABI) and Compañía de Cervecerías Unidas (CCU). They are both international corporations, although ABI has a very large worldwide presence (North America, Europe, Africa, Asia) and CCU only sells beer in South American countries. Their respective revenue market shares are also very uneven, mainly because there is one beer brand (Quilmes, produced by ABI) whose market share has always been above 36% in Argentina, while other brands have less than 1%. On Table 2 we can see the evolution of the different brands' market shares during the period 2011–2017. Brands are classified according to the segment that they belong to, and also according to the firm that supplies them.

The matching between brands and firms informed on Table 2 corresponds to the end of the period 2011–2017. During that period, however, some brands were transferred from one firm to another. Budweiser and Corona, for example, used to be supplied by CCU, while Isenbeck used to be supplied by a third company (CASA) that left the market in 2017 [8]. Among the CCU premium brands, moreover, we include Warsteiner and Miller (previously supplied by CASA), while in the group of CCU medium brands we include Norte (previously supplied by ABI). The same occurs within the group of other CCU low-end brands, where we can find Baltica and Iguana (previously supplied by ABI) and Diosa (previously supplied by CASA).

[8] This was actually an effect of the worldwide acquisition of another international firm (SABMiller) by ABI, since CASA was an Argentine company that used to be controlled by SABMiller.

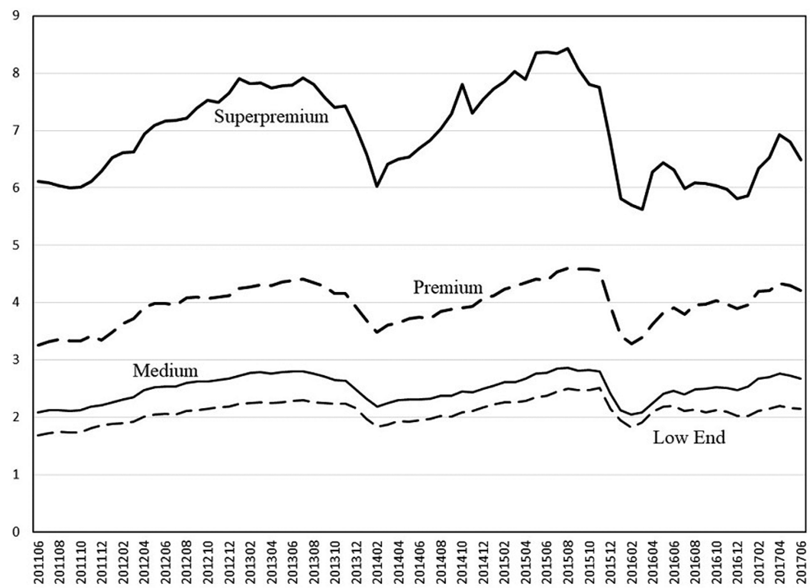

Fig. 1. Evolution of beer prices in Argentina (in US dollars/liter).
(*Source:* Own calculations based on data from A. C. Nielsen)

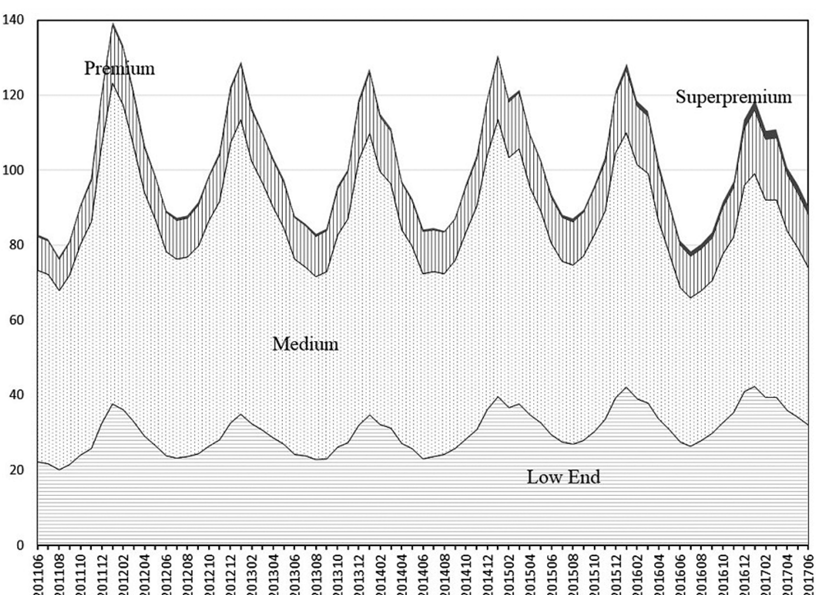

Fig. 2. Monthly quantity sold in Argentina (in million liters).
(*Source:* Own calculations based on data from A. C. Nielsen)

Table 2. Revenue market shares by brand (2011/2017), in %

Brand	Segment	Firm	2011/2013	2013/2015	2015/2017	Average
Corona	Superpremium	ABI	1.20	1.09	2.52	1.86
Other ABI brands	Superpremium	ABI	0.47	0.50	1.10	0.81
Other CCU brands	Superpremium	CCU	0.15	0.13	0.22	0.18
Stella Artois	Premium	ABI	11.09	12.18	11.55	11.66
Heineken	Premium	CCU	4.96	4.85	5.16	5.03
Other CCU brands	Premium	CCU	1.49	2.54	4.21	3.23
Quilmes	Medium	ABI	47.05	43.32	36.34	40.32
Budweiser	Medium	ABI	4.70	4.71	5.11	4.92
Isenbeck	Medium	CCU	2.23	2.26	2.39	2.32
Other ABI brands	Medium	ABI	2.59	2.49	2.27	2.39
Other CCU brands	Medium	CCU	2.52	2.11	1.53	1.88
Brahma	Low end	ABI	13.64	16.67	19.79	17.77
Schneider	Low end	CCU	3.19	3.02	3.54	3.32
Other CCU brands	Low end	CCU	4.72	4.13	4.27	4.31

Source: Own calculations based on data from A. C. Nielsen.

3.2. Beer demand estimation

In this section of the paper, we will estimate demand functions for the different segments of the Argentine beer industry. Due to the seasonality that beer demand seems to have in Argentina, we have run a series of regressions including that phenomenon through monthly dummy variables[9]. As we have already seen that the beer segments have evolved differently during the six years of our sample, we have also included a trend variable in the regression equations, to capture the different trends that those types of beer seem to have. As a consequence of all this, the logarithmic model of demand for our four product segments is in principle the following:

$$\begin{aligned}\ln(qsuper_t) = {} & c_1 + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ & + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{13} trend_t + \\ & + c_{14} \ln(psuper_t) + c_{15} \ln(ppremium_t) + c_{16} \ln(ynom_t) + c_{17} \ln(qsuper_{t-1}),\end{aligned} \tag{8}$$

$$\begin{aligned}\ln(qpremium_t) = {} & c_{21} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ & + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{23} trend_t + c_{24} \ln(psuper_t) + \\ & + c_{25} \ln(ppremium_t) + c_{26} \ln(pmedium_t) + c_{27} \ln(ynom_t) + c_{17} \ln(qpremium_{t-1}),\end{aligned} \tag{9}$$

$$\begin{aligned}\ln(qmedium_t) = {} & c_{31} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ & + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{33} trend_t + c_{35} \ln(ppremium_t) + \\ & + c_{36} \ln(pmedium_t) + c_{37} \ln(plowend_t) + c_{38} \ln(ynom_t) + c_{17} \ln(qpremium_{t-1}),\end{aligned} \tag{10}$$

[9] These regressions, like all the ones whose results are reported in this paper, were run using EViews 10.

$$\ln(qlowend_t) = c_{41} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{43} trend_t + \\ + c_{46} \ln(pmedium_t) + c_{47} \ln(plowend_t) + c_{48} \ln(ynom_t) + c_{17} \ln(qlowend_{t-1}), \quad (11)$$

where *qsuper, qpremium, qmedium* and *qlowend* are quantity variables (measured in liters), *psuper, ppremium, pmedium* and *plowend* are price variables (in Argentine pesos per liter), *ynom* is nominal income (measured through a monthly index that combines the evolution of average consumer prices and the evolution of Argentina's gross domestic product), *feb, mar, apr, may, jun, jul, aug, sep, oct, nov* and *dec* are monthly dummy variables, *trend* is the trend variable, and $t-1$ indicates that a variable has a one-period lag[10]. The coefficients c_1 to c_{48}, finally, are the ones to be estimated using a system of simultaneous-equation regressions.

If we include homogeneity restrictions in the estimations, the system formed by equations (8) to (11) is somehow transformed, because c_{16}, c_{27}, c_{38} and c_{48} disappear as autonomous coefficients, and the model becomes:

$$\ln(qsuper_t) = c_1 + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{13} trend_t + \\ + c_{14} \ln(psuper_t / ynom_t) + c_{15} \ln(ppremium_t / ynom_t) + c_{17} \ln(qsuper_{t-1}), \quad (12)$$

$$\ln(qpremium_t) = c_{21} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{23} trend_t + c_{24} \ln(psuper_t / ynom_t) + \\ + c_{25} \ln(ppremium_t / ynom_t) + c_{26} \ln(pmedium_t / ynom_t) + c_{17} \ln(qpremium_{t-1}), \quad (13)$$

$$\ln(qmedium_t) = c_{31} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{33} trend_t + c_{35} \ln(ppremium_t / ynom_t) + \\ + c_{36} \ln(pmedium_t / ynom_t) + c_{37} \ln(plowend_t / ynom_t) + c_{17} \ln(qpremium_{t-1}), \quad (14)$$

$$\ln(qlowend_t) = c_{41} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{43} trend_t + \\ + c_{46} \ln(pmedium_t / ynom_t) + c_{47} \ln(plowend_t / ynom_t) + c_{17} \ln(qlowend_{t-1}). \quad (15)$$

The last modification to be included in this model has to do with the symmetry restrictions given by the use of elasticities of substitution, and this implies that the system of equations is now the following:

$$\ln(qsuper_t) = c_1 + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{13} trend_t + \\ + c_{14} \ln(psuper_t / ynom_t) + c_{15} \ln(ppremium_t / ynom_t) \cdot spremium_t + c_{17} \ln(qsuper_{t-1}), \quad (16)$$

[10] Due to lack of information, we have not included other possible explanatory variables such as the prices of goods that can be either complements (e.g., food) or substitutes (e.g., other beverages) for beer.

$$\ln\left(qpremium_t\right)= c_{21}+c_2 feb_t+c_3 mar_t+c_4 apr_t+c_5 may_t+c_6 jun_t+c_7 jul_t+c_8 aug_t+ \\ +c_9 sep_t+c_{10} oct_t+c_{11} nov_t+c_{12} dec_t+c_{23} trend_t+c_{15}\ln\left(psuper_t/ynom_t\right)\cdot ssuper_t+ \\ +c_{25}\ln\left(ppremium_t/ynom_t\right)+c_{26}\ln\left(pmedium_t/ynom_t\right)\cdot smedium_t+c_{17}\ln\left(qpremium_{t-1}\right), \quad (17)$$

$$\ln\left(qmedium_t\right)= c_{31}+c_2 feb_t+c_3 mar_t+c_4 apr_t+c_5 may_t+c_6 jun_t+c_7 jul_t+c_8 aug_t+ \\ +c_9 sep_t+c_{10} oct_t+c_{11} nov_t+c_{12} dec_t+c_{33} trend_t+c_{26}\ln\left(ppremium_t/ynom_t\right)\cdot spremium_t+ \\ +c_{36}\ln\left(pmedium_t/ynom_t\right)+c_{37}\ln\left(plowend_t/ynom_t\right)\cdot slowend_t+c_{17}\ln\left(qpremium_{t-1}\right), \quad (18)$$

$$\ln\left(qlowend_t\right)= c_{41}+c_2 feb_t+c_3 mar_t+c_4 apr_t+c_5 may_t+c_6 jun_t+c_7 jul_t+ \\ +c_8 aug_t+c_9 sep_t+c_{10} oct_t+c_{11} nov_t+c_{12} dec_t+c_{43} trend_t+ \\ +c_{37}\ln\left(pmedium_t/ynom_t\right)\cdot smedium_t+c_{47}\ln\left(plowend_t/ynom_t\right)+c_{17}\ln\left(qlowend_{t-1}\right), \quad (19)$$

where *ssuper, spremium, smedium* and *slowend* are the revenue market shares of the different beer segments, and the coefficients c_{15}, c_{26} and c_{37} are now estimates for the elasticities of substitution between those segments.

While the estimations of equations (8) to (11) (Model 1) and equations (12) to (15) (Model 2) can be conducted using ordinary least squares (OLS), the system formed by equations (16) to (19) (Model 3) must be run using two-stage least squares (2SLS), in order to control for the endogeneity of revenue market shares. The main results of those estimations appear on Table 3. As we can see there, Model 1 has more estimated coefficients than Model 2 and Model 3, because those other models include several restrictions on the values of the coefficients (related to homogeneity and symmetry). The inclusion of these restrictions is good to improve the meaning and the significance of several coefficients, as occurs with c_{15}, c_{26} and c_{37}.

Note the use of 2SLS in this case is simply aimed at solving one possible endogeneity problem, which is the one related to the use of revenue market shares. As those market shares are functions of the different products' quantities, and those quantities are the dependent variables of the demand system, then that is the type of endogeneity that is intended to be corrected through the 2SLS procedure implemented. In a situation like this, however, other possible endogeneity problems could arise, related to prices and/or lagged variables [11]. These problems are not analyzed in this specification, assuming that they are less important than the one related to market shares.

In all our estimated systems, coefficients c_{14}, c_{25}, c_{36} and c_{48} can be interpreted as estimates for the different short-run own-price elasticities, and all those coefficients can be converted into long-run elasticities by dividing them by $1-c_{17}$. These figures can also be used to compute the whole set of long-run elasticities implied by each model, as seen on Table 4. That table shows that the results obtained in our estimations improve when we move from Model 1 to Model 2, and even more when we move to Model 3 (which is the one that includes both the homogeneity restrictions and the symmetry restrictions).

Note that these models assume that cross elasticities are zero if beer segments are not adjacent, and that is the case for the cross elasticities between superpremium beer with medium

[11] For a more complete explanation of this, see (Mitze, 2010).

Table 3. Main results for the alternative demand estimation regressions

Concept	Model 1 (OLS)		Model 2 (OLS)		Model 3 (2SLS)	
	Coefficient	Probability	Coefficient	Probability	Coefficient	Probability
c_{14}	–0.5315	0.0013	–0.5251	0.0008	–0.6849	0.0000
c_{15}	0.1874	0.4265	0.1120	0.5363	1.1452	0.0005
c_{16}	0.3538	0.0006				
c_{17}	0.9024	0.0000	0.9025	0.0000	0.8783	0.0000
c_{24}	0.0324	0.7745	0.0825	0.4357		
c_{25}	–0.8718	0.0441	–0.7022	0.0874	–0.4154	0.0002
c_{26}	0.4053	0.2503	0.4039	0.2500	0.3635	0.0398
c_{27}	0.1435	0.1662				
c_{35}	–0.2193	0.6215	0.1521	0.6975		
c_{36}	–0.1108	0.7309	–0.1933	0.5451	–0.2287	0.0178
c_{37}	–0.1109	0.5181	–0.1041	0.5422	0.0627	0.5991
c_{38}	0.0696	0.5009				
c_{46}	–0.1689	0.3701	–0.0759	0.6305		
c_{47}	–0.0912	0.5331	–0.0344	0.7966	–0.0883	0.2688
c_{48}	0.0355	0.7312				
R^2 Superpremium	0.9819		0.9819		0.9835	
R^2 Premium	0.9761		0.9744		0.9714	
R^2 Medium	0.9829		0.9811		0.9799	
R^2 Low end	0.9795		0.9793		0.9782	

Table 4. Estimated long-run demand elasticities for the different models

Concept	Psuper	Ppremium	Pmedium	Plowend	Ynom
		Model 1			
Superpremium	–5.4454	1.9198	0.0000	0.0000	3.6247
Premium	0.3322	–8.9314	4.1523	0.0000	1.4696
Medium	0.0000	–2.2463	–1.1354	–1.1361	0.7126
Low end	0.0000	0.0000	–1.7299	–0.9338	0.3640
		Model 2			
Superpremium	–5.3863	1.1492	0.0000	0.0000	4.2370
Premium	0.8463	–7.2035	4.1438	0.0000	2.2135
Medium	0.0000	1.5602	–1.9828	–1.0681	1.4907
Low end	0.0000	0.0000	–0.7781	–0.3523	1.1305
		Model 3			
Superpremium	–5.6297	1.8155	0.0000	0.0000	3.8142
Premium	0.2275	–3.4141	1.6158	0.0000	1.5708
Medium	0.0000	0.5763	–1.8796	0.1249	1.1785
Low end	0.0000	0.0000	0.2788	–0.7260	0.4472

and low-end beers, and between premium and low-end beers. This is one of the basic characteristics of this type of estimations when applied to quality-differentiated products.

4. Market definition and critical elasticity

The great advantage of having developed a model whose output consists of a set of long-run own-price elasticities is that those figures can be compared to a standard that defines if each segment must be considered as a separate market. That standard is called "critical elasticity". If a product's long-run own-price elasticity is smaller (in absolute value) than this critical elasticity, then we may say that such product must be considered as a market in itself. Conversely, if that long-run elasticity is larger than the critical elasticity, then that product is not a market in itself, and it has to be included in a larger market (together with other products).

The typical formula to calculate the critical elasticity (*Ec*) to be used in a particular industry is the following:

$$Ec = -\frac{1+r}{m+r}, \tag{20}$$

where *m* is the proportional margin between price and marginal cost, and *r* is a "small but significant and non-transitory increase in price" (which is generally set as equal to 10%) [12].

While the value of *r* is defined exogenously, the value of *m* has to do with the industry under analysis, which in our case is the Argentine beer industry. One way to calculate this margin is to assume that it has to be equal to the inverse of the long-run own-price elasticity of the "average firm" in that industry, and this elasticity can in turn be estimated by running a system of demand regressions similar to the one formed by equations (16) to (19). In order to do that, it is necessary to define which are the firms that operate in the industry under analysis, and try to estimate their corresponding demand functions [13].

As we have already mentioned, in Argentina all major beer brands are produced and marketed by two firms: ABI and CCU. In order to estimate the demand functions for those firms, we can run an additional system of regression equations based on the substitution elasticity demand model, and that system will have the following form:

$$\begin{aligned} \ln(qabi_t) = {} & c_1 + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ & + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{13} trend_t + \\ & + c_{14} \ln(pabi_t / ynom_t) + c_{15} \ln(pccu_t / ynom_t) \cdot sccu_t + c_{17} \ln(qabi_{t-1}), \end{aligned} \tag{21}$$

$$\begin{aligned} \ln(qccu_t) = {} & c_{21} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ & + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{23} trend_t + \\ & + c_{15} \ln(pabi_t / ynom_t) \cdot sabi_t + c_{25} \ln(pccu_t / ynom_t) + c_{17} \ln(qccu_{t-1}), \end{aligned} \tag{22}$$

[12] For an explanation of the logic behind this formula, see (Werden, 1998) or (Church, Ware, 2000, ch. 19).

[13] For a more complete explanation of this idea, see (Coloma, 2011).

where *qabi* and *qccu* are the quantity variables, *pabi* and *pccu* are the price variables, and *sabi* and *sccu* are the revenue market shares of the brands controlled by ABI and by CCU. Once we estimate the coefficients of this system using 2SLS, we can use the values of c_{14}, c_{15}, c_{17} and c_{25} [14], together with the average revenue market shares for both ABI (80.14%) and CCU (19.86%), to calculate the corresponding demand elasticities. Those elasticities are the ones that appear on Table 5.

Table 5. Estimated demand elasticities for the Argentine beer firms

Concept	Pabi	Pccu	Ynom
	Short-run elasticities		
ABI	–0.2515	0.0271	0.2244
CCU	0.1093	–0.3236	0.2143
	Long-run elasticities		
ABI	–1.6869	0.1817	1.5052
CCU	0.7334	–2.1709	1.4375

The long-run elasticities reported on Table 5 can, in turn, be used to compute the optimal price/cost margins that correspond to both ABI and CCU. These are the absolute values of the inverse of the long-run own-price elasticities, and in this case they are equal to $m_{ABI} = 59.28\%$ and $m_{CCU} = 46.06\%$. If we calculate the weighted average of those margins, we can estimate an average margin of 56.66%.

Assuming that $r = 10\%$ and $m = 56.66\%$, and applying the formula stated in equation (20), then our critical elasticity will be equal to –1.6502. This number can be compared with the actual elasticities of the different beer segments, to see if those segments can be considered as separate markets.

As the estimates for our long-run own-price elasticities reported on Table 4 for the most complete model are $\eta_S = -5.6297$ (superpremium), $\eta_P = -3.4141$ (premium), $\eta_M = -1.8796$ (medium) and $\eta_L = -0.7260$ (low end), we can conclude that the only segment that might be considered as a separate market is the one formed by the low-end beer brands. This is because that is the only group of products whose actual long-run price-elasticity is below 1.6502 in absolute value, and therefore a hypothetical monopolist who controls all the brands included in that segment can profitably increase prices by more than 10% (if he is currently operating with a price/cost margin of 56.66%).

All the other segments, conversely, fail to be considered as separate markets, because their corresponding own-price elasticities are above 1.6502 in absolute value, and therefore a hypothetical monopolist who controls all the brands included in one of those segments cannot profitably increase prices by 10%. In order to check if some of those segments can be part of another relevant market, we have to pool more products into a single category. One possibility is to check if superpremium and premium beers can be considered as a single segment (high-end beers). A further test is to group superpremium, premium and medium beers into a single segment (that we can call "high/medium quality beers"). When we carry out those tests, we end up with estimations of new long-run elasticities, which are the ones shown on Table 6.

[14] Those coefficients are $c_{14} = -0.2515$, $c_{15} = 0.1364$, $c_{17} = 0.8509$, and $c_{25} = -0.3236$.

Table 6. Estimated long-run demand elasticities for different market definitions

Concept	Phighend	Pmedium	Plowend	Ynom
		Three segments		
High end	–3.2565	1.4359	0.0000	1.8206
Medium	0.5763	–1.8796	0.1249	1.1785
Low end	0.0000	0.2788	–0.7260	0.4472
		Two segments		
High/Medium		–1.4515	0.0891	1.3624
Low end		0.2788	–0.7260	0.4472

As we can see on Table 6, when we combine the superpremium and premium beers into a single high-end segment, we find that the new own-price elasticity for that segment becomes $\eta_H = -3.2565$, but that figure is still above our critical elasticity of –1.6502. We therefore have to group those high-end beers together with the medium beers, in order to create a new segment (high/medium), whose own-price elasticity is $\eta_{HM} = -1.4515$. This number is now smaller than 1.6502 in absolute value, and therefore we can conclude that the high/medium quality segment is actually a market in itself, because now a hypothetical monopolist who controls all the brands included in that segment can profitably increase prices by more than 10%.

The calculations performed to find the elasticities of the newly-defined segments imply averaging the corresponding income and cross-price elasticities, and then calculating the own-price elasticities using the homogeneity restriction. For example, to calculate the income elasticity of high-end beers, we averaged the income elasticity of superpremium beers ($\eta_{SY} = 3.8142$) and the income elasticity of premium beers ($\eta_{PY} = 1.5708$), taking into account that the average share of superpremium beers is 2.42% and the average share of premium beers is 19.29%. This gives us a weighted average equal to 1.8206. Similarly, to calculate the cross elasticity of high-end beers with medium beers, we averaged the cross elasticity of superpremium beers with medium beers ($\eta_{SM} = 0.0000$) and the cross elasticity of premium beers with medium beers ($\eta_{PM} = 1.6158$), obtaining a number equal to 1.4359. The implicit own-price elasticity of high-end beers, therefore, has to be equal to –3.2568, because that number is the one that fulfils the homogeneity restriction under which the sum of the three elasticities has to be equal to zero.

The same situation occurs when we calculate elasticities for high/medium quality beers. As we can estimate that the income elasticity for that category is 1.3624 (provided that the average share of medium beers is 54.08%), and the cross elasticity between that segment and low-end beers is 0.0891, then the implicit long-run own-price elasticity for high/medium quality beers has to be equal to –1.4515. And as this is actually a number which is below the critical elasticity level, then we can conclude that high/medium quality beers in Argentina are a market in itself, which is separable from the market for low-end beers [15].

[15] Note that all the own-price elasticities reported on Table 6 are relatively high, especially if we compare them with most beer price elasticities reported elsewhere (see, for example, (Nelson, 2014)). This is basically because our estimates are long-run elasticities rather than short-run elasticities, and also because they refer to specific quality segments of the beer industry. If we wanted to calculate a short-run elasticity for the Argentine beer as a whole, consistent with our 2SLS system of equations (Model 3), that figure would be equal to –0.1388, while the corresponding long-run elasticity would be –1.1408.

5. Comparison with an alternative methodology

The results that we obtained for the demand of beer in Argentina, using a model of logarithmic demand and substitution elasticities, can be compared with the ones generated by other alternative methodologies. One that is suitable to use as a yardstick is the methodology proposed originally by LaFrance (1986), which also relies on a logarithmic demand specification with certain restrictions. The idea behind this method has to do with an implicit utility function for a representative consumer, that produces logarithmic demand functions that fulfil the homogeneity and symmetry restrictions in a different manner. In particular, LaFrance's model assumes that cross elasticities have a certain relationship with own-price elasticities, which can be written in the following way:

$$\beta_{ij} = 1 + \beta_{jj}, \quad \beta_{ji} = 1 + \beta_{ii} \quad \text{(if products } i \text{ and } j \text{ are adjacent)}, \tag{23}$$

$$\beta_{ij} = \beta_{ji} = 0 \quad \text{(if products } i \text{ and } j \text{ are not adjacent)}. \tag{24}$$

This way of introducing the homogeneity and symmetry restrictions implies estimating the following model for our four-segment beer demand system of equations:

$$\begin{aligned} \ln(qsuper_t) = {} & c_1 + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ & + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{13} trend_t + \\ & + c_{14} \ln(psuper_t / ynom_t) + (1 + c_{25}) \ln(ppremium_t / ynom_t) + c_{17} \ln(qsuper_{t-1}), \end{aligned} \tag{25}$$

$$\begin{aligned} \ln(qpremium_t) = {} & c_{21} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ & + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{23} trend_t + (1 + c_{14}) \ln(psuper_t / ynom_t) + \\ & + c_{25} \ln(ppremium_t / ynom_t) + (1 + c_{36}) \ln(pmedium_t / ynom_t) + c_{17} \ln(qpremium_{t-1}), \end{aligned} \tag{26}$$

$$\begin{aligned} \ln(qmedium_t) = {} & c_{31} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + c_8 aug_t \\ & + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{33} trend_t + (1 + c_{25}) \ln(ppremium_t / ynom_t) \\ & + c_{36} \ln(pmedium_t / ynom_t) + (1 + c_{47}) \ln(plowend_t / ynom_t) + c_{17} \ln(qpremium_{t-1}), \end{aligned} \tag{27}$$

$$\begin{aligned} \ln(qlowend_t) = {} & c_{41} + c_2 feb_t + c_3 mar_t + c_4 apr_t + c_5 may_t + c_6 jun_t + c_7 jul_t + \\ & + c_8 aug_t + c_9 sep_t + c_{10} oct_t + c_{11} nov_t + c_{12} dec_t + c_{43} trend_t + \\ & + (1 + c_{36}) \ln(pmedium_t / ynom_t) + c_{47} \ln(plowend_t / ynom_t) + c_{17} \ln(qlowend_{t-1}). \end{aligned} \tag{28}$$

As we see, this method estimates only four short-run elasticity coefficients (c_{14}, c_{25}, c_{36} and c_{47}) and one serial correlation coefficient (c_{17}), and all this can be used to calculate the whole set of long-run elasticities. Running our system while using OLS generates the following coefficients: $c_{14} = -0.7109$, $c_{17} = 0.8634$, $c_{25} = -0.8973$, $c_{36} = -0.6759$ and $c_{47} = -0.5696$. With those coefficients, the estimated long-run elasticities are the ones that appear on Table 7.

Table 7. Estimated long-run demand elasticities using LaFrance method

Concept	Psuper	Ppremium	Pmedium	Plowend	Ynom
Superpremium	–5.2019	0.7517	0.0000	0.0000	4.4501
Premium	2.1160	–6.5661	2.3716	0.0000	2.0785
Medium	0.0000	0.7517	–4.9462	3.1497	1.0448
Low end	0.0000	0.0000	2.3716	–4.1681	1.7965

This table shows that, for our dataset of the Argentine beer industry during the period 2011–2017, LaFrance method produces long-run own-price elasticities that are typically larger than the ones obtained using the substitution elasticity demand system. This is particularly clear for the premium, medium and low-end segments, whose long-run own-price elasticities are well above the critical elasticity that we calculated in the previous section of this paper. Applying the procedure for combining the different goods into larger segments, we can obtain estimates for the demands of those segments, like the ones shown on Table 8.

The results obtained using LaFrance method imply that the only relevant market in this case would be the one formed by the whole set of beer brands (total beer). This is because all the other alternative categories (high-end, high/medium, medium/low) have long-run own-price elasticities that are above the critical elasticity level (which is $Ec = -1.6502$), while the total demand for beer generates a long-run own-price elasticity that is equal to -1.5085.

Table 8. Estimated long-run elasticities for different market definitions

Concept	Phighend	Pmedium	Plowend	Ynom
		Three segments		
High end	–4.4501	2.1075	0.0000	2.3427
Medium	0.7517	–4.9462	3.1497	1.0448
Low end	0.0000	2.3716	–4.1681	1.7965
		Two segments (1)		
High/Medium		–3.6641	2.2477	1.4165
Low end		2.3716	–4.1681	1.7965
		Two segments (2)		
High end	–4.4501	2.1075		2.3427
Medium/Low	0.5192	–1.7965		1.2773
		One segment		
Total beer		–1.5085		1.5085

Note, however, that the estimated long-run elasticities reported on Tables 7 and 8 have some inconsistencies that do not appear in the figures calculated using our previous methodology. This is because some cross elasticities are larger or smaller than expected, as is the case of the elasticities between superpremium and premium beers, and the elasticities between medium and low-end beers. For the first of those cases, one expects that, as the quantity of premium beers is considerably larger than the quantity of superpremium beers, η_{SP} has to be larger than η_{PS} . This relationship is guaranteed if one estimates cross elasticities using substitution elasticity figures, but it does not hold under our LaFrance method estimation, since here it occurs that $\eta_{SP} = 0.7517$

and $\eta_{PS} = 2.1160$. At the same time, as the quantity of medium beers is larger than the quantity of low-end beers, it should also hold that $\eta_{ML} < \eta_{LM}$. But here we find that, according to our estimations, $\eta_{ML} = 3.1497$ and $\eta_{LM} = 2.3716$.

6. Concluding remarks

The analysis performed in the previous sections suggests that our econometric method based on the estimation of own-price elasticities and substitution elasticities is advantageous when applied to demand functions of quality-differentiated products. In particular, it seems to be suitable when those demand functions are used for market definition, in order to see if two or more products belong to the same market.

In this paper, we have applied this methodology to the estimation of beer demand in Argentina, using data from the period 2011–2017. Our results show that in such industry it is possible to distinguish two relevant markets: one of high/medium beers, that includes the different brands of beer belonging to the superpremium, premium and medium segments (which in Argentina are Corona, Stella Artois, Heineken, Quilmes, Budweiser, etc.), and another market that includes the brands of beer belonging to the low-end segment (Brahma, Schneider, etc.). The corresponding demands in those markets have estimated long-run own-price elasticities that are below the calculated critical elasticity ($Ec = -1.6502$), and that is essentially the reason why we believe that they are actually separate markets. On the contrary, when we evaluated more narrow market definitions (e. g., superpremim beers, premium beers, medium beers, high-end beers) we found relatively large own-price elasticities (i.e., numbers above the critical elasticity level), concluding that those segments were not relevant markets themselves.

The conclusions obtained using the proposed methodology were contrasted with the ones gotten using an alternative estimation method (LaFrance method), which is also based on logarithmic demand functions. Although the ranking of elasticities was relatively similar using both methodologies, the absolute value of those elasticities was in general higher using LaFrance method, and the conclusion of that method is that all Argentine beers belong to the same relevant market. This result, however, is based on estimations that are not as good as the ones generated by our proposed methodology, especially because some cross elasticities become abnormally high or abnormally low. We can therefore conclude that, for industries where product differentiation is basically defined by a quality space, our methodology based on logarithmic demands and substitution elasticities is better than other similar alternative econometric methods.

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