Evaluating the performance of merger simulation using different demand systems:

Evidence from the Argentinian beer market

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Abstract

This research arises in a context of strong debate on the effectiveness of merger control and how competition authorities assess the potential anticompetitive effects of mergers. In order to contribute to the discussion, we apply merger simulation —the most sophisticated and often used tool to assess unilateral effects— to predict the post-merger prices of the AB InBev / SAB-Miller merger in Argentina.

The basic idea of merger simulation is to simulate post-merger equilibrium from estimated structural parameters of the demand and supply equations. Assuming that firms compete *à la* Bertrand, we use different discrete choice demand systems —Logit, Nested Logit and Random Coefficients Logit models— in order to test how sensible the predictions are to changes in demand specification. Then, to get a measure of the precision of the method we compare these predictions with actual post-merger prices.

Finally, to conclude, we point out the importance of post-merger evaluation of merger simulation methods applied in complex cases, as well as the advantages and limitations of using these type of demand models.

Keywords: unilateral effects; discrete choice models; merger simulation; post-merger evaluation
JEL Classification: C51; C63; G34; L13; L41; L66

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1 Introduction

Currently there is a lot of debate on whether antitrust agencies have been too lenient or too strict regarding merger control. The debate is well illustrated by several significant mergers in the digital economy such as Facebook/WhatsApp (M.8228) or by the Siemens/Alstom (M.8677) case.

An appropriate assessment on the potential anticompetitive effects of a merger is a key issue for competition practitioners from both public and private sector.

Merger simulation has been the most sophisticated and often used tool in controversial merger cases to assess unilateral effects. However, the sensitivity of the predictions of this technique to demand specification are a relevant though not fully understood issue yet. In order to contribute to the discussion, we evaluate the forecasts of the merger simulation technique for the potential anticompetitive effects of a merger case from Argentina. So as to get a measure of the precision we compare the predictions of different discrete choice demand systems with actual post-merger prices.

The basic idea of merger simulation is to simulate post-merger equilibrium from estimated structural parameters of the demand and supply equations. With the estimated elasticities and the supply equation we can recover the marginal costs and predict the price effects.

The first step in merger simulation is to estimate demand. It is not only a crucial step as it largely determines the outcome but also the most difficult one (Nevo, 2000b). In demand estimation, the challenge is that in a multiproduct environment people can choose among numerous different products. The most used demand estimation models in this setting are Logit, Nested Logit, and Random Coefficients Logit models, which have different properties that results in different predictions. One of the most important property, the independence of irrelevant alternatives (IIA) (Berry, 1994) has a profound effect on the cross-price elasticities. Under the IIA assumption, we mean that the substitution patterns across products are not determined by how closely the products are related but based on largely on the prevailing market shares of the product. As we proceed with the different demand estimation techniques, we analyze how their particular properties affect the price predictions.

We build our thesis at Leandro Benítez's merger simulation work at the Argentinian Competition Authority (Comisión Nacional de Defensa de la Competencia, CNDC) on the analysis of the Anheuser-Busch InBev and SAB-Miller's merger in Argentina (approved with remedies in 03.2018). The work employed a Nested Logit demand system and estimated the first-round effects of the merger. We develop Leandro's work further in three areas. First, we run Logit, Nested Logit, and Random Coefficients Logit demand systems to analyze the properties of each estimation methods. Based on the literature there is a reasonable presumption that the Random Coefficients Logit models can produce more robust results than the Logit and Nested Logit models (Grigolon & Verboven, 2014). Second, by iteration we want to simulate the full effects of the merger, not only the first-round predictions. Third, using post-merger data we want to analyze the performance of our simulation models.

The performance of merger simulation models was analyzed by Peters (2006), Whinston (2006), Weinberg and Hosken (2013), Björnerstedt and Verboven (2016), and Doi and Ohashi (2019). They all checked how closely the post-merger prices match the predicted prices. The authors had mixed finding regarding to performance of the simulations and suggest that more work needs to be done on this field.

Peters (2006) analyses mergers in the airline industry. He examined 5 mergers following the consolidation wave in the 80's in the United States. He compared simulated price increase with actual price increase. The results suggest that simulation does a reasonable job at predicting price effects, and large faction of the unexplained change in prices comes from supply-side effects such as marginal costs and change in firm conduct.

Weinberg and Hosken (2013) analyzed car motor oil and breakfast syrup markets. The models predicted well some of the price effects, but overall, underpredicted price effects in case of the oil merger and overpredicted effects in case of the breakfast syrup merger.

Björnerstedt and Verboven (2016) analyzed the performance of merger simulation in painkiller market in Sweden. During the investigation the merger raised competition concerns as the merging firms were the only one in producing paracetamol, which constituted as the largest market segment. The merger simulation predicted large price increase such as +34% under Bertrand competition. The merger was cleared in April 2009 following the optimistic standpoint of the Swedish competition authority that coming deregulation of the industry would encourage new entry and competition. The authors did post-merger evaluation 2 years after merger to contrast predictions of the simulation to actual price increase. The results show that actual prices increased similarly to predicted prices. +42% in absolute terms. Interestingly, the price increase happened almost immediately, one month after the merger and has remained high for the 2 years.

Doi and Ohashi (2019) studied a Japanese airline merger from 2002. Japan airlines (JAL) merged with Japan Air Systems (JAS) with the parties having 50% market share. The paper ties to quantitatively assess the nonprice response of the firms to the merger by allowing firms not only choose prices but also flight frequency. For the assessment of the merger the authors used merger simulation to create counterfactual scenario in which the merge did not take place. The authors considered the merger as exogenous to the development of the Japanese airline market because, as the authors claim, the merger was triggered by the September 11 terror attacks, which were unanticipated.

The paper is organized as follows. Section 2 discusses the industry background. Section 3 develops the framework for merger simulation. Section 4 discusses the dataset and details of estimation. Section 5 provides the empirical results for the demand model and merger simulations. Finally, section 6 discusses the ex post evaluation of merger simulation.

2 The Argentinian beer market

2.1 A brief history of the market

The Argentinian beer industry has had a significant development in the last decades. Although it was always characterized by a high degree of concentration, in the 1990s there was a sequence of entry and acquisitions that significantly modified its structure. As part of this process, the largest company in the market, Cervecería y Maltería Quilmes (CMQ), acquired several smaller companies, while CCU Argentina from the Chilean group CCU, CASA Isenbeck of the German group Warsteiner, and Brahma of Brazilian origin started their activities in the market.

In the 2000s, the structure of the market changed again by the merger between Quilmes and Brahma, then controlled by the company AmBev. The merger was authorized by the National Commission on the condition that the new group divested one of its plants and three of its brands. This split was carried out in 2006, and the new company that was formed took the name of Inversora Cervecera (ICSA). This company lasted for a short time as an independent company, since at the beginning of 2008 it was acquired by CCU. In 2010, SAB-Miller, a group of South African origin, made its entry to Argentina by acquiring CASA Isenbeck.

In October 2015, AB InBev, the product of the acquisition of the American brewer Anheuser-Busch by the then Belgian-Brazilian company InBev, expressed its interest in acquiring SAB-Miller worldwide. This announcement had an impact in several countries, including Argentina, given the amount of obstacles that this operation had to overcome to be approved by the world's competition agencies.

The merger was notified in Argentina in October 2016, and after a rigorous scrutiny by the competition authority, the operation was approved subject to conditions in March 2018. We will talk about the conditions in more detail in Section 5.

The data on the Argentinian beer market corresponds to the period January 2011 to August 2017, and is summarized in Table 1 below:

Table 1: Argentinian beer market, 2011 - August 2017

Concept	2011	2012	2013	2014	2015	2016	2017
Total Qty (Hlt)	12,002,571	12,804,576	12,531,442	12,381,045	12,641,237	11,976,920	8,361,336
ABI (Hlt)	9,274,093	10,000,858	9,892,156	9,705,930	9,691,053	9,078,807	6,283,210
CCU (Hlt)	2,374,324	2,396,543	2,241,335	2,234,149	2,450,039	2,390,295	1,698,447
SAB (Hlt)	351,303	399,712	387,223	429,555	488,551	499,893	375,449
Avg Price ($/lt)	8.69	11.69	15.19	19.86	26.30	36.22	45.06
ABI ($/lt)	8.82	11.83	15.33	20.03	26.54	36.44	45.44
CCU ($/lt)	8.15	10.95	14.39	18.89	24.73	34.59	42.63
SAB ($/lt)	8.78	11.69	15.45	20.58	28.67	39.29	48.96
Share ABI (%)	77.3	78.1	78.9	78.4	76.7	75.8	75.1
Share CCU (%)	19.8	18.7	17.9	18.0	19.4	20.0	20.3
Share SAB (%)	2.9	3.1	3.1	3.5	3.9	4.2	4.5
HHI	6,370	6,460	6,561	6,483	6,268	6,162	6,080

This table shows that the total beer consumed in the country is around 12.3 million hectoliters per year. In terms of market shares, the market is led by AB InBev, which has 75.1% of the market with the brands Quilmes, Brahma, Stella Artois, Norte, and Andes. It is followed by CCU, with 20.3%, due to its ownership of Heineken, Schneider, Imperial, and Budweise. In third place, with the remaining 4.5% is SAB-Miller, with Isenbeck, Warsteiner, Miller and Grolsch. Although the latter's share in the Argentinian beer market is not as large as that of the other players, it is worth noting that its market share increased by approximately 53% between 2011 and 2017, from 2.9% to 4.5%.

With an HHI of 6,080 points, the beer market in Argentina prior to the merger is highly concentrated. If the antitrust authority would have cleared the operation subject to no conditions, the HHI would be increased to 6,755 points. This represents an increase of 675 points.

Following the criteria established by the traditional concentration based approach, this operation raised significant competitive concerns and were analyzed in more depth. The reason is that it was very likely to strengthen the market power of the undertakings involved. Nevertheless, the use of this approach was not suitable to analyze the effects of this operation. This is due to the fact that the beer market is a typical example of Bertrand price competition with differentiated products: firms compete offering different brands, with different characteristics and packagings. Therefore, the analysis of the operation in the market with these characteristics must consider the intensity of the competition between brands, including those that are owned by the same company.

According to Argentinian[1] and international[2] jurisprudence, the market can be divided into different segments according to the quality of the beer (among other characteristics). For the purposes of this work, we similarly considering factors such as the price levels and image of the brands, therefore the following nests have been used: low-end, standard and premium beer. Tables 11, 12 and 13 in the annex summarizes the brands according to segments, as well as other relevant data referring to the characteristics of the products.

3 The empirical framework

The merger simulation can be described as a four-step process: First, a functional form of demand, such as Logit, Nested Logit, and Random Coefficients Logit, that matches consumer behaviour in the best possible

[1] AmBev/Quilmes (2003), Res. 5/03, SDC; CICSA/ICSA (2008), Res. 45/08, SCI; y AB InBev/Grupo Modelo (2017), Res. 257/17, SDC.

[2] U.S. Department of Justice (2013), or EC decision M.7881.

way has to be chosen. Based on the assumed demand function, cross-price and own-price elasticities can be simulated.

Second, the demand systems should be calibrated, meaning that the parameters are specified in a way that the calculated elasticities yield the prices and market shares actually observed in the pre-merger market.

Third, the supply side is modelled by assuming an oligopoly model that most closely describes the competition between firms in the market. In most of the cases, multiproduct Bertrand competition is chosen, because it allows to infer marginal costs from the first-order conditions of profit maximization. Using the information on marginal costs an empirical model of the pre-merger market can be calibrated.

Fourth, the new equilibrium after the merger can be simulated using the model that was calibrated with pre-merger empirical data, but adjusted to the post-merger situation.

By following the above steps, we implicitly assumes that all firms behave non-cooperatively and that the form of competition, the demand system and the functional form of marginal cost do not change due to the merger. The only change that is implemented concerns the merging parties the competition between them is internalized. In case of merger related efficiency gains, updated marginal costs can be used for the estimation.

3.1 Demand specification

For the first step, we implement discrete choice models. These type have gained considerable importance in empirical work. The reason is that they treat products as bundles of characteristics, thereby, contrary to standard and representative consumer models, they offer the possibility of uncovering rich substitution patterns with a limited number of parameters. Berry (1994) developed a framework to estimate a class of discrete choice models with unobserved consumer heterogeneity based on aggregate sales data. His framework includes the Logit model, the Nested Logit model, and the Random Coefficients Logit model of Berry, Levinsohn, and Pakes (1995).

According to Grigolon and Verboven (2014) the Logit and Nested Logit models have been popular because of their computational simplicity, since they can be transformed to simple linear regressions of market shares on product characteristics. At the same time, the Logit models yield substitution patterns that are fairly restrictive. The Logit model assumes that consumer preferences are uncorrelated across all products, implying symmetric cross-price elasticities.

The Nested Logit model allows preferences to be correlated across products within the same nest. It thus entails a coefficients on group dummy variables (Grigolon & Verboven, 2014). It allows products of the same group to be closer substitutes than products of different groups. However, the aggregate substitution patterns still remain restrictive. The cross-price elasticities within the same nest are symmetric, and substitution outside a nest is symmetric to all other nests.

The BLP's Random Coefficients Logit model incorporates random coefficients for product characteristics. This creates a more flexible substitution patterns. The products, which have similar characteristics, tend to be closer substitutes. However, the random coefficients model is computationally more demanding, and several recent papers have studied a variety of problems relating to its numerical performance (Knittel & Metaxoglou, 2014).

3.1.1 Logit

Individual i's conditional indirect utility function for alternative j is

$$u_{ij} = \delta_j + \varepsilon_{ij},$$

where $\delta_j = x_j\beta - \alpha p_j - \xi_j$ is the mean utility common to all consumers. The mean utility for the outside good is normalized to 0. In our model, the outside good includes brands outside the sample (e.g. craft beers), beer sold outside supermarkets, and non-beer beverages such as wine. ε_{ij} is an individual-specific component of utility, which is unobserved for the econometrician, and is modeled as an i.i.d. random variable with an extreme value distribution.

We can rearrange (see details in the Appendix) the market share equation to have $\delta_j = \ln s_j - \ln s_0$, in order to estimate the following linear equation (Berry, 1994):

$$\ln\left(s_j/s_0\right) = X_j\beta - \alpha p_j + \xi_j$$

where X_j is a vector of observed characteristics, p_j is price, ξ_j is a vector of unobserved characteristic for product j which will be the econometric error term.

The linear form of the traditional Logit model is very useful, because we can now instrument for prices using standard IV procedures. However, this model has restrictive implications for own and cross-elasticities.

- Own elasticity $-\eta_{jj} = \frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = -\alpha(1-s_j)p_j$ is increasing in price, which is to some extent unrealistic (we would think people who buy expensive products are less sensitive to prices).
- Cross elasticity $\eta_{jk} = \frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k} = \alpha s_j p_j$ depends only on market shares and prices but not on similarities between goods.

The cross price elasticity is restricted by the IIA property. Thus, the valuations are uncorrelated across products and the cross-price elasticities are driven by the market shares. This would have an effect on the price changes predicted by a merger simulation, making it less reliable as the predictions by Nested Logit and Random Coefficients Logit model.

The extensions of the Logit model try to resolve the restrictive nature of it.

3.1.2 Nested Logit

The basic idea of the Nested Logit model is to partially relax IIA by grouping the products. Within each group we have the standard Logit form (with all the issues discussed before), but not across nests.

For the Nested Logit model, the indirect utility is given by:

$$u_{ij} = \delta_j + \zeta_{ig}(\sigma) + (1-\sigma)\varepsilon_{ij}$$

with ζ_{ig} being common to all products in group g, and follows a distribution that makes the remaining part extreme value.

As σ goes to zero, we are back to the standard Logit, whereas as σ goes to one, products within the same segments are perfect substitutes.

The linear equation to estimate (Berry, 1994) (for details see Appendix):

$$\ln\left(s_j/s_0\right) = X_j\beta - \alpha p_j + \sigma \ln\left(s_{j|g}\right) + \xi_j$$

which allow us to instrument for prices and $s_{j|g}$ and slightly relaxes the Logit assumption, allowing to different substitution patterns. Now, own and cross elasticities will be given by:

- Own-price elasticity: $\eta_{jj} = -\frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = -\alpha\left(\frac{1}{1-\sigma} - \frac{\sigma}{1-\sigma}s_{j|g} - s_j\right)p_j$
- Cross-price elasticity:
  - $\eta_{jk} = \frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k} = \alpha\left(\frac{\sigma}{1-\sigma}s_{j|g} + s_j\right)p_j$, if j and k are in group g
  - $\eta_{jk} = \frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k} = \alpha s_j p_j$, otherwise.

A caveat of the Nested Logit model is that it needs a priori classification of the products, however this segmentation can affect significantly the estimation results.

The Random Coefficients Logit model provides a more general treatment for demand estimation.

3.1.3 Random Coefficients Logit

The Random Coefficients Logit model is a version of the Logit model which includes consumer heterogeneity. The consumers differ not only in the Logit error ε_{ij}, but also in their valuation of the product characteristics and price. This method was used first in Berry, Levinsohn, and Pakes (1995).

The model is:

$$u_{ij} = X_j\beta_i - \alpha_i p_j + \xi_j + \varepsilon_{ij}$$

with $\beta_i = \beta + \sigma_\beta \nu_{\beta i}$ and $\alpha_i = \alpha + \sigma_\alpha \nu_{\alpha i}$. Hence, we can write $u_{ij} = \delta_j + \mu_{ij}$ such that $\delta_j = X_j\beta - \alpha p_j + \xi_j$ and $\mu_{ij} = \sigma_\beta \nu_{\beta i} - \sigma_\alpha \nu_{\alpha i} + \varepsilon_{ij}$.

Now it is easy to see the difference from the basic Logit model: the idiosyncratic error term μ_{ij} is not i.i.d but depends on the product characteristics, so consumers who like a certain product are more likely to choose similar products.

As seen in the Appendix, inverting the system to obtain the market shares computationally more demanding. In the previous models, this inversion was carried out analytically. In the random coefficient model, we can invert numerically, conditional on the non-linear parameters of the model, i.e. σ_β and σ_α (Grigolon & Verboven, 2014). This can be done by a contraction mapping algorithm, allowing us to obtain:

$$s_j^{-1}(s) = x_j\beta - \alpha p_j + \xi_j$$

Elasticities will be:

- Own elasticity $\eta_{jj} = -\frac{\partial s_j}{\partial p_j}\frac{p_j}{s_j} = -\frac{p_j}{s_j}\int_\mu \alpha s_j(1-s_j)f(\mu)d\mu$
- Cross elasticity $\eta_{jk} = \frac{\partial s_k}{\partial p_j}\frac{p_j}{s_k} = \frac{p_j}{s_k}\int_\mu \alpha s_j s_k f(\mu)d\mu$

These results imply that substitution depends on the characteristics of the products.

3.2 Oligopoly model

Suppose the marginal cost is constant and equal to c_j and each firm f owns a subset of products F_f and chooses the prices of its own products $j \in F_f$ to maximize:

$$\Pi_f(\mathbf{p}) = \sum_{j \in F_f} (p_j - c_j) \cdot s_j(\mathbf{p})L \tag{1}$$

A Bertrand-Nash equilibrium is defined by the following system of first-order conditions (Björnerstedt & Verboven, 2013):

$$s_j(\mathbf{p}) + \sum_{k \in F_f} (p_k - c_k)\frac{\partial s_k(\mathbf{p})}{\partial p_j} = 0, \qquad j = 1, ..., J \tag{2}$$

Following Björnerstedt & Verboven (2013), let θ be a $J \times J$ product-ownership matrix, with $\theta(j,k) = 1$ if products j and k are produced by the same firm and 0 otherwise. Then, θ becomes the usual block diagonal matrix; if in addition there are no multiproduct firms, θ becomes the identity matrix. Furthermore, let $\mathbf{s}(\mathbf{p})$ be the $J \times 1$ market shares vector, $\boldsymbol{\Delta}(\mathbf{p}) \equiv \partial\mathbf{q}(\mathbf{p})/\partial\mathbf{p}'$ the $J \times J$ Jacobian of first derivatives, and c is the $J \times 1$ marginal cost vector. We can then write equation (2) in vector notation as

$$\mathbf{s}(\mathbf{p}) + (\boldsymbol{\theta} \odot \boldsymbol{\Delta}(\mathbf{p}))(\mathbf{p} - \mathbf{c}) = 0$$

This can be inverted to write price as the sum of marginal cost and a markup, where the markup term (inversely) depends on the price elasticities and on the product-ownership matrix:

$$\mathbf{p} = \mathbf{c} - (\boldsymbol{\theta} \odot \boldsymbol{\Delta}(\mathbf{p}))^{-1}\mathbf{s}(\mathbf{p}) \tag{3}$$

In the case of single-product firms, the markup term is simply price divided by the own-price elasticity of demand. With multiproduct-firms, the cross-price elasticities also matter and this increases the markup term (if products are substitutes) (Björnerstedt & Verboven, 2013).

Equation (3) is used in the third step of the merger simulation, since it can be rewritten to uncover the pre-merger marginal cost vector c based on the pre-merger prices and estimated price elasticities of demand such as

$$\mathbf{c}^{pre} = \mathbf{p}^{pre} + (\boldsymbol{\theta}^{pre} \odot \boldsymbol{\Delta}(\mathbf{p}^{pre}))^{-1}\mathbf{s}(\mathbf{p}^{pre})$$

Moreover, (3) is used to predict the post-merger equilibrium. The merger involves changes in the product ownership matrix from $\boldsymbol{\theta}^{pre}$ to $\boldsymbol{\theta}^{post}$ (if there are efficiencies, changes in the marginal costs as well).

4 Data and estimation

4.1 The data

We have a Nielsen supermarket scanner dataset which has 80 periods of monthly observation from January 2011 to August 2017. The data contains total volume of sales and quantities sold per brands. The average price per liter is calculated from the two and then deflated using the San Luis CPI Index from Argentina (January 2011 = 100). The dataset contains 55 brands which cover more than 99% of the Argentinian beer market in terms of quantities sold. 5 from these 55 brands were discontinued and not sold during the time of the merger allowing us to use BLP instruments. The industry is highly concentrated, since the 50 brand belongs to only 3 firms from which two merged in March 2018.

We have data on the following product characteristics: alcohol by volume and dummies on whether the beer is black, red, or special (wheat, fruit, etc.) and data on the number of packaging of beers. The database includes the calculated size of potential market for the demand estimation models. Moreover, we have data on hops prices as we will use them as instrumental variables.

We estimated the potential market size by using census data on the population of adult Argentinians in drinking age and on the average per capita alcohol consumption, measured in marketing study, for the relevant time periods. The methodology applied for estimating this potential market is discussed in more detail in Appendix B.

Post-merger data was obtained by web-scrapping beer prices from supermarkets' web pages for the month of May 2019.

4.2 Estimation

The demand models' main identification assumption is that the products' characteristics other than price are uncorrelated with the error term. However, prices may be correlated so that the ordinary least square regression would lead to a biased estimate of α towards zero or might have a wrong sign. The solution for this problem is to use instruments for prices.

As in our models the quantities and prices are endogenous, we will use instrumental variables for correctly identify and estimate the parameters. The candidate for IVs is hop prices (cost shifter) and BLP instruments (markup shifters) (Berry, Levinsohn, & Pakes, 1995).

The hop is one of the main ingredient of a beer, thereby its prices is relevant for the cost of production. It is a world widely traded commodity, exclusively imported to Argentina, thus the exclusion restriction likely to be fulfilled. Any changes in the hop prices should not be related to the demand of the beers. Because it is solely imported even through macroeconomic channels the link should be weak in this case.

In the BLP instruments one of the characteristics is the count of products with certain characteristics, and $\sum_{k\neq j,k\in F_f} x_k$ and $\sum_{k\neq F_f} x_k$. For the BLP instrument, we not only used the sums of characteristics but also the averages (Berry, Levinsohn, & Pakes, 1995). The reason why we can use them is that there are entry and exit in the product space which creates the necessary variation in the data. The changes in the product space and the related movement in prices should ensure that these instruments are relevant. The fulfillment of exclusion restriction is arguable not perfect in the case BLP instruments. This is related to their construction, since it is likely that firms react to other firms product offerings and their characteristics. Nevertheless, these instruments are often used in the academia (Björnerstedt & Verboven 2013).

In contrary to the OLS/2SLS estimation method used in the Logit and Nested Logit model, the RCL approach derives a generalized method of moments estimator from the random draws. Further details of the estimation and derivation of the demand models can be found in the Appendix.

In case of the merger simulation the new equilibrium is derived by newton method by using Björnerstedt and Verboven (2013) command. The command inserts an initial guess for the price vector and continue iterating until convergence is reached.

Moreover, for the merger simulation we assumed Bertrand differentiated multiproduct competition meaning that there is no collusion among the firms. However, based on Miller and Weinberg (2017) this might be an inaccurate assumption. The authors documented abrupt retail beer price increase following MillerCoors joint venture for MillerCoors and its competitor, Anheuser-Busch. This price increase based on the authors' model cannot be solely explained by moving from one to another Nash-Bertrand equilibrium, but by a partial coordination too.

5 Results

5.1 Demand models

Table 2 presents the results of the demand estimation. All regressions include not only the discussed instruments but also firm and time fixed effects to aid identification of the price coefficient. For simplicity we report the full tables in the annex.

The demand systems are identified from the variation in products' shares and in the composition of characteristics available (Berry, 1994).

As a starting point, we run the Logit specification. The results are presented in the first column of table 2. The price coefficient is estimated statistically significantly at 1% level and has the expected sign. The coefficients of the number of packagings suggest, ceteris paribus, that larger number of available options are preferred by consumers, as expected.

The second column of table 2 provides the results for the Nested Logit model. Compared to the Logit model, now the characteristic dark also estimated statistically significantly. The price coefficient is estimated statistically significantly at 1% level and again has the expected sign. The nesting parameter is in the expected range ($0 < \sigma < 1$). $\sigma = 0.853$ suggests that products within the same segments are close to perfect substitutes. The coefficients of the number of packagings similarly suggest that larger number of options are preferred by consumers.

The Random Coefficients Logit model results are presented in the last column of table 2. This model allow for consumer heterogeneity through random coefficients which randomness generated from a normal distribution to capture sources of consumer heterogeneity (Berry, Levinsohn, & Pakes 1995)

Again, the null hypothesis that the coefficients on price are zero is unable to be rejected at any reasonable significance level. In magnitude this price coefficient increased compared to the Logit specification similarly as observed by Grigolon and Verboven (2014). Their reasoning is that since we expect that in a differentiated market demand is elastic, taking into account distribution matters.

Table 2 shows only the coefficient of mean utility for the Random Coefficients Logit model. The full regression results can be found in the appendix. There the sigmas shows how the random coefficients interact with mean utility. Small values and insignificance of σ, as shown in the table in appendix, mean small heterogeneity in the valuation of the beer characteristics. E. g. this is likely following from that a price increase for a dark beer (or with high alcohol by volume) implies minimal substitution to other dark beers (with high alcohol by volume). Since we only used random draws and not income the interpretation of coefficients of interaction is less meaningful in our case.

The betas in table 2 in the last column shows the mean valuations of the product characteristics as estimated by the Random Coefficients Logit model. Most of the characteristics are statistically significantly identified at 1% level.

The large values for mean valuation for alcohol by volume is likely driven by the fact that in our dataset there is small differences among products in ABV (less than 1 since most of them has ABV around 5%). Moreover, the difference between the ABV coefficient in case of the Logit/Random Coefficients Logit model and Nested Logit model is probably related to the fact that no nesting parameter is added. The nesting parameter and ABV is likely to correlated since alcohol by volume is more similar among products in the same nest. Same reasoning related to the nesting parameter can be the applied behind the differences in the coefficient of dark among models.

Table 2: Estimation results : Logit, Nested Logit, and Random Coefficients Logit demand

Variable	Logit (1) $\ln(s_j/s_0)$	N. Logit (2) $\ln(s_j/s_0)$	RCL (3) $s_j^{-1}(s)$
Price	-0.503**	-0.081**	-1.600**
	(0.094)	(0.007)	(0.403)
Nesting parameter		0.853**	
		(0.018)	
Dark	0.238	0.591**	-2.973*
	(0.509)	(0.100)	(1.179)
Red	-2.212**	0.553**	-15.391**
	(0.721)	(0.156)	(1.061)
Special	-1.328†	0.322†	-2.487**
	(0.759)	(0.166)	(0.787)
Packs	0.521**	0.101**	0.093
	(0.046)	(0.013)	(0.244)
ABV	-14.490	0.142	31.282†
	(23.331)	(4.979)	(16.885)
Intercept	0.099	-0.598*	9.937**
	(1.476)	(0.274)	(3.798)
N	3,776	3,776	3,776

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

As expected, based on the first stage regression results of the Logit and Nested Logit model, our instruments are relevant. The F-statistics is above 10, for Logit 18.63 and 42.05 for Nested Logit. However, for the Random Coefficients Logit model the weak identification test (Cragg-Donald Wald F statistic) shows that our model suffers from weak identification problem, since the F-value is below 10. This weak identification will likely cause that the estimates of the endogenous variable, coefficient of price, is likely to be underestimated. One reason while we have weak identification problem in the Random Coefficients Logit model is that because of collinearity the model dropped from the estimation more BLP instrument than the Nested Logit and Logit model.

Table 3 shows the pre-merger weighted averages for the prices and marginal costs per firm for the month of August 2017 for the three demand models.

For CCU and SAB, the Logit and Nested Logit model give us approximately the same marginal cost estimates. However, for ABI, the estimated marginal costs are significantly different. In our view, it is driven by the fact that ABI has a strong, dominant position in the standard segment and thereby ABI has larger markups and Lerner index. The RCL pre-merger marginal costs are more similar to the results of Logit model.

At the brand level in case of all demand specifications, all the marginal cost estimates are positive except 1 brand for the Nested Logit model. Detailed data on marginal costs and pre-merger prices are in Appendix D.

Table 3: Pre-merger averages of prices and marginal costs

Firm	Prices	Marginal costs			Lerner Index		
		Logit	N. Logit	RCL	Logit	N. Logit	RCL
ABI	8.92	5.59	2.65	6.47	0.3733	0.7025	0.2746
CCU	8.30	6.07	6.04	7.49	0.2686	0.2722	0.0985
SAB	9.47	7.43	7.54	8.77	0.2154	0.2039	0.0739
Average	8.82	5.77	3.56	6.78	0.3455	0.5958	0.2311

Weighted averages for August 2017

Table 4 shows the firms' unweighted average elasticities per demand specification.

Table 4: Own and cross price elasticities. Unweighted averages.

Brands	**Own-price:** η_{jj}			**Cross-price:** η_{jk}			
	Logit	N. Logit	RCL	Logit	N. Logit		RCL
					$j,k =$ nest	$j,k \neq$ nest	
ABI	-5.3791	-5.5925	-13.5413	0.0820	0.3996	0.0133	0.1853
CCU	-5.4815	-5.9110	-12.5544	0.0215	0.1469	0.0035	0.1967
SAB	-4.6628	-5.0380	-15.0549	0.0170	0.1141	0.0027	0.1933
Average	-5.3218	-5.6486	-13.3387	0.0475	0.2535	0.0077	0.1912

Elasticities for August 2017.

The IIA restriction can be seen by observing the homogeneity that exists within the cross-price elasticities from table 20 in the Appendix. A further property of the Logit model that the own-price elasticities tend to be higher for more expensive products. The brand level cross-price elasticities show that products of the same segment are strong substitutes in the Nested Logit model, but not in the Logit and Random Coefficients Logit model.

The fact that there is no IIA property in Random Coefficients Logit model can be observed by the heterogeneity of the cross-price elasticities. Table 21 - 25 in the Appendix provides an elasticity matrix along cross-price elasticities. From it we can see which products are closer substitutes to each other.

The own-price elasticities at the product level increase almost proportionally with price in the Logit and Nested Logit models, however less proportionally in the Random Coefficients Logit model. The reason behind this is that Random Coefficients Logit model allows heterogeneity in the price parameter.

Recently two major articles employed Random Coefficients Logit model to estimate demand in the beer market. Asker (2016) and Miller and Weinberg (2017) both focused on the US beer market, thereby for comparison they are far from perfect however they can still serve as a benchmark and check for our demand estimation results. Both of the studies used not BLP, but different, Hausman type of instruments (Hausman et al, 1994).

Asker (2016) runs Logit and Random Coefficients Logit model as well. He similarly uses servings (packaging) and alcohol by volume as product characteristics. The author did not found considerable difference between the prediction of the models. In case of the Logit model an overall price elasticity for beer was estimated around -3.4. The estimated price coefficient for the Random Coefficients Logit model using random draws was $\alpha = -5.966$. Probably weak identification is the reason why our estimate of α is smaller than in Asker. Interestingly for our study, Asker had data on the promotion activities of the firms, and he found that the effect of it is limited on consumer demand.

Miller and Weinberg (2017) employed a Nested Logit and a Random Coefficient Nested Logit model. They also use alcohol by volume as characteristics and package size, but also calories. The price and nesting parameter coefficients are similar in sign and size to the results of our studies (N. Logit results: $\alpha = -0.1312$ and $\sigma = 0.6299$, and RCNL results: $\alpha = -0.0887$ and $\sigma = 0.8299$ while for us the N. Logit $\alpha = -0.081$ and $\sigma = 0.853$). They had a median own-price elasticity of -3.81 for the Nested Logit model -4.74- -6.10 for the Random Coefficient Nested Logit depending on the different specifications. Following a similar pattern, however in magnitude considerably larger, our median estimates of own-price elasticity for Logit -4.36, for Nested Logit -4.8, and for Random Coefficients Logit -11,87. The larger median own-price elasticities in Argentina are expected ex-ante because of the different economic condition of the two countries.

Contrary to Asker (2016), Miller and Weinberg (2017) found much lower market price elasticities. The authors list a set of other beer market demand estimation studies and found that the estimated own-price elasticities are in similar in range to their results (see Pinske & Slade, 2004, Hellerstein, 2008, and Romeo, 2016).

5.2 Merger simulation

5.2.1 Conditions of the merger

The merger between AB InBev and SAB-Miller was approved subject to conditions in March 2018. The main problem related to the effect of the merger were not solely the brands of SAB-Miller but the Budweiser brand. In Argentina CCU had the license to produce Budweiser until 2025. This was the result of a condition of a previous merger. This turned out to be a significant factor in the assessment of the merger since Budweiser was one of the most important brands on the market. To assess the effects of the merger the National Commission had to take into account the conditions prevailing in the market in the mid-term, thereby as a result of negotiations, a complex remedy was agreed on. CCU received all the brands of SAB-Miller, but gave the brand Budweiser to AB InBev after the merger was approved. Moreover AB InBev gave three/five additional brands (Iguana —with Iguana Summer—, Norte —with Norte Porter—, and Báltica) to CCU.

We simulated the effects of the merger in case of (a) a hypothetical unconditional approval (including the swap of Budweiser back to ABI's portfolio) and in case of (b) the conditional approval based on the above described conditions.

5.2.2 Simulation results

Tables 5 and 6 show the merger simulation main results for the predicted post-merger price increase at brand level for scenarios (a) and (b) respectively. The post-merger prices are averages weighted by the post-merger market share of each brand. In addition, tables 7 and 8 present the post-merger market shares as well as the HHI and its respective variation for scenarios (a) and (b) respectively. Detailed results per brand can be found in Appendix D.

Table 5: Price increase: Scenario (a)

Firm	Δ % Price		
	Logit	N Logit	RCL
ABI	1.9%	9.4%	5.0%
CCU	4.5%	4.7%	7.6%
Average	2.2%	8.1%	5.1%

Table 6: Price increase: Scenario (b)

Firm	Δ % Price		
	Logit	N Logit	RCL
ABI	1.0%	7.2%	3.9%
CCU	-2.5%	15.3%	-3.5%
Average	-0.5%	8.4%	1.0%

Table 7: Market Shares and HHI: Scenario (a)

Firm	Market Shares (%)		
	Logit	N Logit	RCL
ABI	83.46	78.66	77.60
CCU	16.55	21.34	22.40
ΔHHI	1,161	565	446

Table 8: Market Shares and HHI: Scenario (b)

Firm	Market shares (%)		
	Logit	N Logit	RCL
ABI	75.15	76.96	71.15
CCU	24.85	23.04	28.85
ΔHHI	188	376	-183

The merger simulation with the Logit demand predicts an average price increase of 2.2% and a ΔHHI of $1,162$ points in Scenario (a) with respect to the pre-merger situation. According to this specification, the conditions imposed to the merger are effective to countervail the potential unilateral effects of the operation, as in Scenario (b) the average price is practically unaffected —it decreases by -0.5%— and the ΔHHI is of 188 points.

Conversely, the results are considerably different when using a Nested Logit demand. The average price increase is 8.1% and the ΔHHI of 565 points in Scenario (a). According to the Scenario (b) results, the remedies imposed seem more suitable to curb concentration issues as the average price increase is 8.4% —practically the same as in (a)— whereas the ΔHHI is 376.

This difference between the Logit and the Nested Logit results is motivated by two factors. Firstly, when considering nests, after the merger both AB InBev and CCU have a position close to monopoly in the standard and low-end segments respectively. Secondly, the nesting parameter shows that products in the same segment are close substitutes, enhancing potential price increase predictions.

Another issue to point out is that, according to the Nested Logit specification, the relative relevance of the Budweiser brand is larger than all the brands of SAB-Miller and the three brands of AB InBev involved in the swap combined.

For the Random Coefficients Logit specification the predicted price increase in Scenario (a) is 5.1%, with a ΔHHI of 446 points. For Scenario (b), the remedies applied seem effective to tackle the potential unilateral effects of the merger regarding prices and concentration, given that the average price increase is 1.0%— and the ΔHHI is of -183 points.

6 Ex post merger simulation evaluation

6.1 Post-merger data

We collected post merger prices by web scraping the largest supermarket chains' online platforms (Coto, Jumbo, Día, Walmart). The average price per liter was calculated by weighting the prices of the different types of packaging (bottles, cans, etc.)[3]. Again, prices were deflated by using the San Luis CPI Index of Argentina (January 2011 = 100).

The data collecting process has some limitations regarding the smaller brands. Prices for these brands were not available to scrap given that the big supermarket chains usually do not sell them. Due to these limitations, for the sake of the analysis we focus on the largest and most important brands. The 11 brands covered account for 80% of the total beer market.

The underlying assumption behind our method is that approximately one year after the merger the firms have already set the new profit maximizing prices. Furthermore, no other major source should have affected the prices outside inflation (and the merger) in the last year.

6.2 Model comparison

Table 9 shows the pre- and post-merger prices, as well as the difference of the predicted prices per demand specification with respect to the latter.

Table 9: Post-merger evaluation: prices corrected by inflation.

Brand	Prices		Δ% Predicted vs Post Merger		
	Pre-	Post-	Logit	N. Logit	RCL
Brahma Chopp	7.41	7.23	2.4%	10.0%	2.5%
Budweiser	7.19	8.45	-1.9%	43.9%	-14.9%
Corona	20.56	17.77	15.6%	17.1%	14.9%
Heineken	12.03	10.92	10.7%	13.1%	10.1%
Iguana	5.53	5.71	-21.3%	138.9%	-3.1%
Imperial Lager	9.67	8.03	21.3%	21.0%	21.7%
Isenbeck Blanca	7.57	6.62	18.2%	19.8%	14.4%
Palermo	5.63	6.12	-7.0%	154.5%	-8.0%
Quilmes Cristal	8.41	7.06	19.0%	26.7%	19.1%
Schneider	7.05	7.41	-4.0%	-4.2%	-4.9%
Stella Artois	14.29	10.69	33.6%	36.0%	33.6%
Average	6.97	6.30	11.5%	23.3%	10.6%

It is interesting to point out that, contrary to expectations, the average price of the brands selected goes down post-merger. This has a serious impact on the post-merger merger simulation evaluation, as the predicted prices are upward biased for all demand specifications. In average both the Logit and the RCL specifications had similar predictions (11.5% and 10.6%, respectively), with the RCL performing slightly better. The Nested Logit underperformed with respect to the other models (23.3%). However for this particular model, the price predictions could be mostly determined by the nesting parameter. Therefore, the price effects will be stronger when considering that both AB InBev and CCU have a position close to monopoly in the standard and low-end segments respectively post-merger.

Given that the parties did not claim efficiencies in Argentina and did not do substantial product repositioning, the reasons for the price reduction are likely exogenous to the nature of the merger —and therefore to the model—. A feasible hypothesis might be the influence of the current macroeconomic conditions of Argentina. The economic stagflation reduced consumers' purchasing power over the last 2 years. As a result, the supermarket retail sector has been experiencing a significant drop in sales that forced chains to apply a more aggressive pricing behaviour. Hence, the potential unilateral effects might have been counterweighted by the discount strategies of the supermarkets.

[3]Information regarding market shares per packaging was available for October 2017. We assumed that these share remained constant by May 2019.

In order to take into account the macroeconomic context, we propose a solution based on correcting prices not only by inflation, but also by economic activity. By using an index for the activity level of the retail sector[4], we adjust the post-merger prices to address the economic downturn over the period (August 2017 = 100). Table 10 shows the same information as Table 9, but with the correction in activity level.

Table 10: Post-merger evaluation: prices corrected by inflation and activity level.

Brand	Prices		Δ% Predicted vs Post Merger		
	Pre-	Post-	Logit	N. Logit	RCL
Brahma Chopp	7.41	8.22	-9,85%	-3,21%	-9,78%
Budweiser	7.19	9.60	-13,67%	26,66%	-25,07%
Corona	20.56	20.20	1,76%	3,04%	1,11%
Heineken	12.03	12.41	-2,59%	-0,49%	-3,10%
Iguana	5.53	6.49	-30,70%	110,24%	-14,73%
Imperial Lager	9.67	9.13	6,73%	6,51%	7,06%
Isenbeck Blanca	7.57	7.52	4,05%	5,44%	0,68%
Palermo	5.63	6.96	-18,16%	123,93%	-19,07%
Quilmes Cristal	8.41	8.03	4,74%	11,54%	4,81%
Schneider	7.05	8.42	-15,55%	-15,72%	-16,30%
Stella Artois	14.29	12.15	17,53%	19,66%	17,58%
Average	6.97	7.16	-1,85%	8,53%	-2,65%

Once we correct by activity level, we can evaluate the performance of the models by analyzing the difference between the predicted prices and the adjusted post-merger prices. Given that all prices were adjusted with the same index, again the predictions for the Logit and the RCL specifications were similar (-1.85% and -2.65%, respectively), with the Logit performing slightly better. However, now both specifications underestimate the price effects in a small degree. The Nested Logit model still overestimates post-merger prices, but in a lesser extent (8.53%).

7 Conclusions

Merger simulations yield mixed conclusions on the use of different demand models. The Logit model is ex-ante considered inappropriate because of its restrictive pattern of substitution, however it performed better than expected. Its predictions on average were close to the predictions of the Random Coefficients Logit model, which should yield the most realistic and precise estimates. Conversely, the Nested Logit model largely overestimated the post-merger prices. However, the poor performance is mainly motivated by the nests configuration: the swap of brands generates almost two close to monopoly positions in the standard and low-end segment for AB InBev and CCU, respectively. This issue, added to the high correlation of preferences for products in the same nest, generates enhanced price effects.

Regarding the substitution patterns, the Logit, Nested Logit and Random Coefficients Logit models yielded different results. The own-price elasticities are similar for the Logit and Nested Logit model, however for the Random Coefficients Logit model they are more almost tripled. This is likely driven by the estimated larger price coefficient as well as the standard deviations of the product characteristics. As expected, by construction the Random Coefficients Logit model yielded the most realistic cross-price elasticities.

Our question on how does the different discrete choice demand models affects merger simulation —and, by extension, their policy implications— is hard to be answered. For the AB InBev / SAB-Miller merger the

[4]Estimador Mensual de Actividad Económica (EMAE), item "G", from the National Institute of Statistics and Census (INDEC) of Argentina. For the period under post-merger analysis the economic activity contracted by -9.5%.

Logit and Random Coefficients Logit model predict almost zero changes in prices. Conversely, according to the Nested Logit, both scenarios were equally harmful to consumers in terms of their unilateral effects. However, as mentioned above, given the particular post-merger nests configuration, evaluating this model solely by the precision of its predictions might be misleading. We cannot discard to have better predictions under different conditions.

As a concluding remark, we must acknowledge the virtues and limitations of merger simulation. Merger simulation is a useful tool for competition policy as it gives us the possibility to analyze different types of hypothetical scenarios —like approving the merger, or imposing conditions or directly blocking the operation—. However, we must take into account that it is still a static analysis framework. By focusing only on the current pre-merger market information, merger simulation does not consider dynamic factors such as product repositioning, entry and exit, or other external shocks.

8 Appendix A: Methodology for Logit, Nested Logit and RCL

8.1 Logit

Individual i's conditional indirect utility function for alternative j is:

$$u_{ij} = x_j\beta - \alpha p_j - \xi_j + \varepsilon_{ij},$$

δ_j is the mean utility common to all consumers and for the outside good it is normalized to 0.

ε_{ij} from the indirect utility is modeled as an i.i.d. random variable with an extreme value distribution:

$$F(\delta_0, ...\delta_J) = exp(-exp(-I)),$$

where I is an inclusive value defined as:

$$I = ln\sum_{k=0}^{J} exp(\delta_k)$$

I can be interpreted as the expected value of the maximum over all utilities. In the model individuals choose the product out of the $J+1$ products that maximizes their utility. The probability that i chooses product j takes the standard Logit form (McFadden, 1978):

$$s_j = \frac{exp(\delta_j)}{1 + \sum_{k=1}^{J} exp(\delta_k)},$$

where $exp(\delta_0) = 1$.

There are L consumers and they all buy one unit, thus the observed market share is $s_j = \frac{q_j}{L}$, which be interpreted relative to the potential market. To invert the market share system, we simply have to divide the shares of $j = 1...J$ by the market share of the outside good, and take logs to obtain:

$$\ln\frac{q_j}{L - \sum_{j=1}^{J} q_j} = x_j\beta - \alpha p_j + \xi_j, \text{ (Björnerstedt \& Verboven, 2013)}$$

where q_j are the units sold of product j, $j = 1, ..., J$, L is the potential market size, p_j is price, and x_j is the set of product characteristics, the number of presentations that each product has (bottles and cans), alcohol by volume, as well as monthly, yearly and firm fixed effects.

8.2 Nested Logit

In case of the Nested Logit, the inclusive value I in the extreme value distribution is defined as:

$$I_g = (1-\sigma_g)ln\sum_{j=1}^{J_g} exp(\delta_j/(1-\sigma_g))I = ln\sum_{g=1}^{G} exp(I_g)$$

Thus, the probability that i chooses product j:

$$s_j = s_{j|g}s_g = \frac{exp(\delta_j/(1-\sigma_g))}{exp(I_g/(1-\sigma_g))}\frac{exp(I_g)}{exp(I)} \text{ and } s_0 = \frac{1}{exp(I)}$$

Thereby, based on Björnerstedt and Verboven (2013):

$$\ln\frac{q_j}{L - \sum_{j=1}^{J} q_j} = x_j\beta - \alpha p_j + \sigma\ln\frac{q_j}{\sum_{j\in g}^{J} q_j} + \xi_j,$$

where $s_{j|g}$ market share of product j in the segment g. In this case both p_j and $s_{j|g}$ are endogenous correlated with the error term, ξ_j.

The Nested Logit model decrease the restriction following from the IIA property. Now the independence of irrelevant alternatives only valid within and between segment.

8.3 Random Coefficients Logit

In the Random Coefficients Logit model the consumers differ not only in the Logit error ε_{ij}, but also in their valuation of the product characteristics and price. This method was used first in Berry, Levinsohn, and Pakes (1995).

Individual i's conditional indirect utility for alternative j:

$$u_{ij} = x_j\beta - \alpha p_j + \xi_j + \varepsilon_{ij},$$

where α_i and β_i are modeled as random coefficients:

$$\beta_i = \beta + \sigma_\beta \nu_{\beta i} \text{ and } \alpha_i = \alpha + \sigma_\alpha \nu_{\alpha i}$$

Now it is easy to see the difference from the basic Logit model: the idiosyncratic error term is not i.i.d but depends on the product characteristics, so consumers who like a certain product are more likely to like similar products.

The aggregate market share function is the average over the choice probabilities (Berry, Levinsohn, & Pakes 1995):

$$s_j(\delta) = \int_\mu \frac{exp(\delta_j + \mu_{ij})}{1 + \sum_{k=1}^J exp(\delta_k + \mu_{ij})} f(\mu) d\mu$$

For the estimation of the above equation we have to work out the aggregate market shares conditional on mean utility δ. By taking R draws over ν_i we simulate (Berry, Levinsohn, & Pakes, 1995):

$$s_j(\delta) = \frac{1}{R} \sum_{i=1}^R \frac{exp(\delta_j + \mu_{ij})}{1 + \sum_{k=1}^J exp(\delta_k + \mu_{ij})} \quad \text{for} \quad j = 1...J,$$

where $\mu_{ij} = x_j \sigma_\beta \nu_{\beta i} - \sigma_\alpha \nu_{\alpha i} p_j$

Then we have to invert the above $J \times 1$ system numerically to obtain $s^{-1}(s) = \delta$, so we get $s_j^{-1}(s) = x_j\beta - \alpha p_j + \xi_j$, which can be done by a contraction mapping algorithm.

8.4 Supply

On the supply side, the firms maximize their profits over their set of products in every time period. The first order condition of the firm's profit function based on the multiproduct Bertrand equilibrium is:

$$s_j(p) + \sum_{k \in F_f} (p_k - c_k) \frac{\partial q_k(p)}{\partial p_j} = 0, \; j = 1, ..., J$$

Due to the merger F_f^{post} will change.

The above equation is the following when we isolate prices:

$$p_j^{post} = c_j - \left(s_j(p) + \sum_{k \in F_f^{post}, k \neq j} (p_k - c_k) \frac{\partial q_k(p)}{\partial p_j} \right) \left(\frac{\partial q_j(p)}{\partial p_j} \right)^{-1}$$

Thus, markup depends on the price derivatives and the ownership matrix

This equation in the Logit case:

$$p_j = c_j + \frac{1}{\alpha}\frac{1}{1 - s_f}$$

and in the Nested Logit case:

$$p_j = c_j + \frac{1}{\alpha}\frac{1}{1 - \sigma \sum_{k \in F_f^{post}} s_{k|g}(p) - (1-\sigma) \sum_{k \in F_f^{post}} s_k(p)},$$

where $s_{f|g} = \sum_{k \in F_f} s_{k|g}$ and $s_f = \sum_{k \in F_f} s_k$.

9 Appendix B: Potential Market size

A key task is to define the potential market size for the differentiated products. In the common unit demand specification of the Nested Logit, consumers have inelastic conditional demands: they either buy a single unit of their most preferred product $j = 1, ..., J$, or they buy the outside good $j = 0$. The potential market size is then the potential number of consumers I, for example an assumed fraction of the observed population in the market, $I = \gamma L$. An alternative is the constant expenditures specification, where consumers have unit elastic conditional demand: they buy a constant expenditure of their most preferred product or the outside good. In this case the potential market size is the potential total budget B, for example an assumed fraction γ of total GDP in the market, $B = \gamma Y$. For the beer market it is sensible to adopt a unit demand specification, since consumers choose to buy or not a unit of the product —instead of allocating a constant proportion of their monthly income to alcoholic beverages.

The potential market for the year k, $k = 2011, ..., 2017$, will be defined as

$$I_k = \gamma \cdot L_k \cdot \omega$$

Where γ is the share of the population over 15 years of age, L_k is the total population of year k and ω is the annual consumption in liters per capita of alcoholic beverages in Argentina, which will be assumed constant for the period under analysis: $k = 2011, ..., 2017$. To calculate γ and L_k data from The National Institute of Statistics and Censuses (INDEC) of Argentina were used[5]. For ω, however, information from newspaper articles was used[6]: considering that the annual per capita beer consumption in Argentina is 41 liters per person, and that its consumption represents 60% of the total of alcoholic beverages, it can be estimated that $\omega = 68$.

Once I_k has been calculated, the average monthly liters for each year k of the outside good q_0 —which, as it can be seen, will be assumed constant monthly but variable from year to year— can be calculated as,

$$q_{0t|k} = \frac{I_k - Q_{J|k}}{12}$$

Where $Q_{J|k}$ is the total amount of liters of beer for the year k. Finally, the monthly potential market will be

$$I_t = \sum_{j=1}^{55} q_{jt} + q_{0t|k}$$

[5] "Censo Nacional de Población, Hogares y Viviendas 2010" for γ and "Estimaciones y proyecciones de población. Total del país. 2010-2040" for L_k.

[6] "Las bebidas de los argentinos". *Clarín*, January 26th 2014. Retrieved from https://www.clarin.com/. "Argentina, el país con mayor consumo de alcohol de América Latina". *Infobae*, May 18th 2017. Retrieved from https://www.infobae.com/.

10 Appendix C: Brand characteristics

Table 11: Low-end beer segment. August 2017.

Brand	Firm	Type	Avg. Price (ARS)	ABV (%)	Packs	Market Share (%)		
						Beer	Potential	Segment
Iguana	ABI	Lager	30.23	5.0%	3	2.56%	1.37%	60.86%
Palermo	CCU	Lager	30.79	4.9%	2	1.58%	0.84%	37.44%
Bieckert	CCU	Lager	32.66	4.9%	1	0.04%	0.02%	0.86%
Báltica	ABI	Lager	26.67	4.9%	1	0.03%	0.02%	0.67%
Diosa	SAB	Lager	23.66	4.4%	1	0.01%	0.00%	0.17%
Total						**4.21%**	**2.25%**	**100.00%**
HHI Low-end segment							**5,252**	

Table 12: Premium beer segment. August 2017.

Brand	Firm	Type	Avg. Price (ARS)	ABV (%)	Packs	Market Share (%)		
						Beer	Potential	Segment
Stella Artois	ABI	Lager	78.11	5.0%	3	7.07%	3.78%	43.94%
Heineken	CCU	Lager	65.75	5.0%	7	3.82%	2.05%	23.77%
Corona	ABI	Lager	112.40	4.6%	2	1.23%	0.66%	7.68%
Miller	SAB	Lager	62.82	4.7%	6	0.76%	0.41%	4.71%
Stella Artois Noire	ABI	Dark	75.98	5.4%	2	0.72%	0.39%	4.49%
Warsteiner	SAB	Lager	68.02	4.8%	6	0.68%	0.36%	4.22%
Patagonia	ABI	Lager	102.50	5.5%	2	0.66%	0.35%	4.10%
Grolsch	SAB	Lager	67.80	5.0%	5	0.52%	0.28%	3.23%
Patagonia Küné	ABI	Special	94.84	5.0%	1	0.23%	0.12%	1.44%
Amstel	CCU	Lager	51.79	4.7%	3	0.23%	0.12%	1.41%
Sol	CCU	Lager	97.05	4.5%	2	0.14%	0.08%	0.88%
Kunstman	CCU	Lager	133.53	4.9%	1	0.01%	0.01%	0.09%
Negra Modelo	ABI	Dark	138.51	5.3%	1	0.01%	0.00%	0.05%
Guinness	CCU	Dark	230.06	4.2%	1	0.00%	0.00%	0.00%
Miller Lite	SAB	Lager	35.14	4.2%	1	0.00%	0.00%	0.00%
Total						**16.08%**	**8.61%**	**100.00%**
HHI Premium segment							**4,638**	

Table 13: Standard beer segment. August 2017.

Brand	**Firm**	**Type**	**Avg. Price (ARS)**	**ABV (%)**	**Packs**	**Market Share (%)**		
						Beer	**Potential**	**Segment**
Brahma Chopp	ABI	Lager	40.52	4.8%	6	27.00%	14.46%	33.88%
Quilmes Cristal	ABI	Lager	45.99	4.8%	8	24.72%	13.24%	31.02%
Budweiser	CCU	Lager	39.31	5.0%	6	5.65%	3.02%	7.08%
Schneider	CCU	Lager	38.53	5.5%	5	4.22%	2.26%	5.29%
Quilmes Bajo Cero	ABI	Lager	37.28	4.5%	4	2.81%	1.50%	3.52%
Isenbeck Blanca	SAB	Lager	41.40	4.6%	7	2.67%	1.43%	3.34%
Quilmes Stout	ABI	Dark	55.20	5.1%	2	2.64%	1.41%	3.31%
Andes Blanca	ABI	Lager	44.50	4.7%	5	1.59%	0.85%	2.00%
Imperial Lager	CCU	Lager	52.89	5.5%	4	1.42%	0.76%	1.78%
Quilmes 1890	ABI	Lager	52.42	5.4%	2	1.10%	0.59%	1.37%
Quilmes Bock	ABI	Dark	57.26	6.1%	2	1.01%	0.54%	1.27%
Santa Fe Frost	CCU	Lager	35.78	4.8%	1	1.00%	0.53%	1.25%
Norte	ABI	Lager	38.59	4.7%	2	0.80%	0.43%	1.00%
Salta Rubia	CCU	Lager	39.70	4.7%	3	0.51%	0.27%	0.64%
Iguana Summer	ABI	Lager	62.14	5.2%	1	0.49%	0.26%	0.62%
Córdoba	CCU	Lager	35.05	4.7%	2	0.47%	0.25%	0.59%
Imperial Cream Stout	CCU	Dark	56.46	3.9%	3	0.39%	0.21%	0.49%
Quilmes Lieber	ABI	Special	40.50	0.4%	3	0.32%	0.17%	0.40%
Salta Negra	CCU	Dark	46.87	3.9%	1	0.21%	0.11%	0.26%
Imperial Red Lager	CCU	Red	50.14	5.5%	2	0.17%	0.09%	0.21%
Andes Porter	ABI	Dark	47.91	5.6%	1	0.16%	0.08%	0.20%
Imperial Scotch Ale	CCU	Red	50.71	6.5%	2	0.11%	0.06%	0.14%
Santa Fe Lager	CCU	Lager	39.27	4.7%	3	0.08%	0.04%	0.10%
Imperial Weissbier	CCU	Special	49.97	5.3%	2	0.08%	0.04%	0.10%
Santa Fe Stout	CCU	Dark	40.85	4.8%	1	0.07%	0.04%	0.08%
Isenbeck Dark	SAB	Dark	57.39	4.6%	1	0.03%	0.02%	0.04%
Quilmes Night	ABI	Lager	46.88	6.9%	2	0.01%	0.00%	0.01%
Schneider Negra	CCU	Dark	39.47	3.8%	1	0.01%	0.00%	0.01%
Andes Red Lager	ABI	Red	42.05	4.9%	1	0.00%	0.00%	0.00%
Norte Porter	ABI	Lager	35.99	5.6%	1	0.00%	0.00%	0.00%
Total						**79.71%**	**42.70%**	**100.00%**
HHI Standard segment							**6,513**	

11 Appendix D: Full tables of regressions, elasticity matrixes, and merger simulation results

Table 14: OLS estimation: Logit demand

Variable	Coefficient	(Std. Err.)
Price	0.005	(0.010)
Dark	-1.164**	(0.384)
Red	-1.198*	(0.609)
Special	-1.325*	(0.663)
Packs	0.655**	(0.030)
ABV	-33.029	(20.195)
2.month	-0.054	(0.072)
3.month	-0.042	(0.072)
4.month	-0.140†	(0.072)
5.month	-0.228**	(0.072)
6.month	-0.359**	(0.072)
7.month	-0.384**	(0.072)
8.month	-0.346**	(0.072)
9.month	-0.380**	(0.075)
10.month	-0.298**	(0.075)
11.month	-0.220**	(0.075)
12.month	-0.142†	(0.075)
2012.year	-0.184**	(0.061)
2013.year	-0.312**	(0.060)
2014.year	-0.302**	(0.060)
2015.year	-0.318**	(0.060)
2016.year	-0.847**	(0.060)
2017.year	-0.849**	(0.067)
2.CCU	-0.893**	(0.334)
3.SAB	-1.905**	(0.503)
Intercept	-4.257**	(1.078)
N	3776	
Log-likelihood	.	
$\chi^2_{(25)}$	797.96	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 15: IV estimation: Logit demand

Variable	Coefficient	(Std. Err.)
Price	-0.503**	(0.094)
Dark	0.238	(0.509)
Red	-2.212**	(0.721)
Special	-1.328†	(0.759)
Packs	0.521**	(0.046)
ABV	-14.490	(23.331)
2.month	-0.048	(0.092)
3.month	-0.085	(0.093)
4.month	-0.166†	(0.093)
5.month	-0.243**	(0.093)
6.month	-0.414**	(0.093)
7.month	-0.434**	(0.093)
8.month	-0.329**	(0.092)
9.month	-0.357**	(0.096)
10.month	-0.296**	(0.096)
11.month	-0.222*	(0.096)
12.month	-0.120	(0.096)
2012.year	0.269*	(0.114)
2013.year	0.263*	(0.131)
2014.year	-0.184*	(0.079)
2015.year	0.141	(0.114)
2016.year	-0.495**	(0.101)
2017.year	-0.450**	(0.113)
2.CCU	-0.996**	(0.383)
3.SAB	-2.017**	(0.575)
Intercept	0.099	(1.476)
N	3776	
Log-likelihood	.	
$\chi^2_{(25)}$	532.20	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 16: OLS estimation: N. logit demand

Variable	**Coefficient**	**(Std. Err.)**
Price	-0.002†	(0.001)
Nest. Par.	1.003**	(0.002)
Dark	0.626*	(0.246)
Red	1.034**	(0.392)
Special	0.587	(0.425)
Packs	0.013**	(0.003)
ABV	2.429	(12.999)
2.month	-0.071**	(0.007)
3.month	-0.105**	(0.007)
4.month	-0.216**	(0.007)
5.month	-0.275**	(0.007)
6.month	-0.373**	(0.007)
7.month	-0.395**	(0.007)
8.month	-0.403**	(0.007)
9.month	-0.387**	(0.007)
10.month	-0.298**	(0.007)
11.month	-0.236**	(0.007)
12.month	-0.073**	(0.007)
2012.year	0.118**	(0.006)
2013.year	0.033**	(0.006)
2014.year	-0.027**	(0.006)
2015.year	-0.009†	(0.006)
2016.year	-0.142**	(0.006)
2017.year	-0.027**	(0.006)
2.CCU	-0.146	(0.216)
3.SAB	-0.635*	(0.324)
Intercept	-0.722	(0.688)
N	3776	
Log-likelihood	.	
$\chi^2_{(26)}$	499659.45	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 17: IV estimation: N. logit demand

Variable	**Coefficient**	**(Std. Err.)**
Price	-0.081**	(0.007)
Nest. Par.	0.853**	(0.018)
Dark	0.591**	(0.100)
Red	0.553**	(0.156)
Special	0.322†	(0.166)
Packs	0.101**	(0.013)
ABV	0.142	(4.979)
2.month	-0.068**	(0.016)
3.month	-0.103**	(0.016)
4.month	-0.209**	(0.016)
5.month	-0.271**	(0.016)
6.month	-0.380**	(0.016)
7.month	-0.401**	(0.016)
8.month	-0.392**	(0.016)
9.month	-0.383**	(0.017)
10.month	-0.299**	(0.017)
11.month	-0.234**	(0.016)
12.month	-0.080**	(0.017)
2012.year	0.145**	(0.016)
2013.year	0.073**	(0.016)
2014.year	-0.049**	(0.014)
2015.year	0.018	(0.016)
2016.year	-0.195**	(0.019)
2017.year	-0.091**	(0.021)
2.CCU	-0.274**	(0.083)
3.SAB	-0.842**	(0.125)
Intercept	-0.596*	(0.265)
N	3776	
Log-likelihood	.	
$\chi^2_{(26)}$	17749.25	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 18: OLS estimation: RCL demand

Variable	**Coefficient**	**(Std. Err.)**
Sigmas		
Price	0.276	.
Dark	0.121	.
Red	0.121	.
Special	0.120	.
Packs	0.132	.
ABV	0.147	.
Price	-0.607**	(0.004)
Dark	-0.250**	(0.064)
Red	-1.065**	(0.102)
Special	-0.630**	(0.140)
Packs	0.984**	(0.015)
ABV	15.408**	(3.444)
2.month	-0.029	(0.116)
3.month	-0.076	(0.117)
4.month	-0.230*	(0.117)
5.month	-0.370**	(0.116)
6.month	-0.551**	(0.116)
7.month	-0.626**	(0.116)
8.month	-0.525**	(0.116)
9.month	-0.536**	(0.121)
10.month	-0.397**	(0.121)
11.month	-0.275*	(0.121)
12.month	-0.066	(0.121)
2012.year	0.372**	(0.096)
2013.year	0.455**	(0.095)
2014.year	047	(0.095)
2015.year	0.414**	(0.094)
2016.year	-0.464	(0.094)
2017.year	-0.225*	(0.105)
2.CCU	-1.464**	(0.054)
3.SAB	-1.719**	(0.079)
Intercept	-2.219**	(0.215)
N	3776	
Significance levels :	† : 10% * : 5%	** : 1%

Table 19: IV estimation: RCL demand

Variable	**Coefficient**	**(Std. Err.)**
Sigmas		
Price	0.219	(5.596)
Dark	0.001	.
Red	5.889	(13623.37)
Special	0.002	.
Packs	2.133	(218.184)
ABV	0.221	.
Endogenous		
Price	-1.600**	(0.404)
Exogenous		
Dark	2.973*	(1.179)
Red	-15.392**	(1.061)
Special	-2.488**	(0.788)
Packs	0.093	(0.244)
ABV	31.283†	(16.886)
2.month	-0.143	(0.411)
3.month	-0.344	(0.412)
4.month	-0.703†	(0.412)
5.month	-0.966*	(0.412)
6.month	-1.472**	(0.412)
7.month	-1.634**	(0.412)
8.month	-1.442**	(0.410)
9.month	-1.307**	(0.431)
10.month	-1.024*	(0.429)
11.month	-0.809†	(0.428)
12.month	-0.191	(0.429)
2012.year	2.123**	(0.702)
2013.year	2.182**	(0.773)
2014.year	0.735	(0.458)
2015.year	1.824**	(0.702)
2016.year	0.702	(0.691)
2017.year	1.224	(0.766)
2.CCU	-1.268**	(0.191)
3.SAB	-2.455**	(0.332)
Intercept	9.938**	(3.798)
N	3776	
Significance levels :	† : 10% * : 5%	** : 1%

Table 20: Own and cross price elasticities

Brands	**Code**	**Own-price: η_{jj}**			**Cross-price: η_{jk}**			
		Logit	N. Logit	RCL	Logit	N. Logit $j,k=$ nest	N. Logit $j,k \neq$ nest	RCL
Amstel	AMS	-4.7569	-5.1848	-12.2933	0.0058	0.0623	0.0009	0.2071
Andes Blanca	ANB	-4.0573	-4.4275	-12.4268	0.0349	0.0711	0.0057	0.2427
Andes Porter	ANP	-4.4021	-4.8468	-22.3689	0.0037	0.0076	0.0006	0.1943
Andes Red Lager	ANR	-3.8669	-4.2616	-18.2630	0.0001	0.0001	0.0000	0.2053
Báltica	BAL	-2.4526	-2.6879	-12.9613	0.0004	0.0153	0.0001	0.2101
Bieckert	BIE	-3.0029	-3.2857	-13.2295	0.0006	0.0242	0.0001	0.1955
Brahma Chopp	BRA	-3.1874	-2.8328	-13.8875	0.5390	1.0994	0.0873	0.1787
Budweiser	BUD	-3.5060	-3.7260	-16.1948	0.1094	0.2231	0.0177	0.1611
Córdoba	CDB	-3.2155	-3.5336	-13.6249	0.0081	0.0165	0.0013	0.2279
Corona	COR	-10.2684	-10.6351	-17.2001	0.0683	0.7349	0.0111	0.2359
Diosa	DIO	-2.1755	-2.3941	-10.2555	0.0001	0.0035	0.0000	0.1575
Grolsch	GRO	-6.2178	-6.6797	-22.3205	0.0173	0.1864	0.0028	0.2073
Guinness	GUI	-21.1566	-23.3160	-8.7818	0.0001	0.0006	0.0000	0.1416
Heineken	HEI	-5.9224	-5.2926	-10.5664	0.1238	1.3307	0.0201	0.2370
Iguana	IGU	-2.7423	-1.4674	-11.9524	0.0381	1.5845	0.0062	0.1701
Iguana Summer	IGS	-5.6992	-6.2622	-11.3969	0.0150	0.0306	0.0024	0.2058
Imperial Cream Stout	IMC	-5.1818	-5.6972	-9.5534	0.0108	0.0221	0.0018	0.1815
Imperial Lager	IML	-4.8267	-5.2728	-26.7866	0.0370	0.0754	0.0060	0.2563
Imperial Red Lager	IMR	-4.6071	-5.0723	-15.6262	0.0041	0.0083	0.0007	0.2141
Imperial Scotch Ale	IMS	-4.6607	-5.1330	-14.6420	0.0028	0.0057	0.0005	0.2294
Imperial Weissbier	IMW	-4.5930	-5.0595	-13.8189	0.0019	0.0039	0.0003	0.2308
Isenbeck Blanca	ISB	-3.7526	-4.0672	-6.6859	0.0543	0.1109	0.0088	0.1158
Isenbeck Dark	ISD	-5.2763	-5.8139	-17.3628	0.0009	0.0018	0.0001	0.2387
Kunstmann	KUN	-12.2783	-13.5221	-10.5843	0.0010	0.0105	0.0002	0.1632
Miller	MIL	-5.7532	-6.1071	-11.6285	0.0234	0.2517	0.0038	0.1831
Miller Lite	MLL	-3.2319	-3.5619	-25.3350	0.0000	0.0000	0.0000	0.1954
Negra Modelo	NEG	-12.7366	-14.0315	-7.4119	0.0005	0.0058	0.0001	0.1248
Norte	NOR	-3.5337	-3.8754	-6.5464	0.0151	0.0309	0.0025	0.1483
Norte Porter	NOP	-3.3100	-3.6480	-21.5972	0.0000	0.0001	0.0000	0.1622
Palermo	PAL	-2.8073	-2.1199	-16.3364	0.0239	0.9926	0.0039	0.2399
Patagonia	PAT	-9.3929	-10.0200	-8.3309	0.0333	0.3578	0.0054	0.1810
Patagonia Küné	PAK	-8.7109	-9.4921	-14.5272	0.0108	0.1166	0.0018	0.1746
Quilmes 1890	Q90	-4.7923	-5.2459	-25.9165	0.0283	0.0577	0.0046	0.2024
Quilmes Bajo Cero	QBC	-3.3771	-3.6569	-10.2833	0.0515	0.1051	0.0083	0.1890
Quilmes Bock	QBO	-5.2372	-5.7361	-9.5155	0.0284	0.0580	0.0046	0.1499
Quilmes Cristal	QCR	-3.6688	-3.3368	-20.1061	0.5600	1.1423	0.0907	0.1698
Quilmes Lieber	QLI	-3.7177	-4.0892	-13.1762	0.0064	0.0131	0.0010	0.2054
Quilmes Night	QNI	-4.3108	-4.7507	-10.2499	0.0002	0.0004	0.0000	0.2176
Quilmes Stout	QST	-5.0043	-5.4248	-14.2395	0.0717	0.1463	0.0116	0.2076
Salta Negra	SAN	-4.3056	-4.7390	-9.3316	0.0048	0.0099	0.0008	0.1479
Salta Rubia	SAR	-3.6411	-4.0003	-8.4270	0.0100	0.0203	0.0016	0.1661
Santa Fe Frost	SFF	-3.2729	-3.5849	-11.7287	0.0176	0.0358	0.0028	0.1685
Santa Fe Lager	SFL	-3.6096	-3.9761	-10.7924	0.0016	0.0033	0.0003	0.2097
Santa Fe Stout	SFS	-3.7553	-4.1370	-9.3262	0.0014	0.0028	0.0002	0.1465
Schneider	SCH	-3.4637	-3.7163	-10.7859	0.0800	0.1633	0.0130	0.2107
Schneider Negra	SCN	-3.6295	-3.9999	-10.5335	0.0001	0.0003	0.0000	0.1599
Sol	SOL	-8.9181	-9.7615	-10.6785	0.0067	0.0723	0.0011	0.2358
Stella Artois	STE	-6.9109	-4.9051	-4.5370	0.2718	2.9230	0.0440	0.0895
Stella Artois Noire	STN	-6.9605	-7.4016	-11.0148	0.0270	0.2906	0.0044	0.2121
Warsteiner	WAR	-6.2325	-6.6423	-11.7961	0.0227	0.2442	0.0037	0.2553

Elasticities for August 2017. The cross-price elasticities are unweighted averages.

Table 21: RCL: Own and cross price elasticities (1)

Code	AMS	ANB	ANP	ANR	BAL	BIE	BRA	BUD	CDB	COR
AMS	-12.2933	0.1432	0.2985	0.3184	0.0231	0.8793	0.0084	3.4509	0.0727	0.0368
ANB	0.0009	-12.4268	0.0592	0.0915	0.0079	0.2939	0.0017	1.3494	0.0303	0.1551
ANP	0.0019	0.0621	-22.3689	0.4172	0.0183	0.7528	0.0159	2.6684	0.0370	0.0203
ANR	0.0024	0.1181	0.5136	-18.2629	0.0234	0.9111	0.0130	3.0886	0.0627	0.0305
BAL	0.0025	0.1439	0.3170	0.3287	-12.9612	0.8992	0.0089	3.4784	0.0734	0.0369
BIE	0.0025	0.1429	0.3493	0.3434	0.0241	-13.2294	0.0097	3.4736	0.0734	0.0365
BRA	0.0020	0.0667	0.5978	0.3974	0.0193	0.7869	-13.8874	2.3402	0.0407	0.0160
BUD	0.0026	0.1731	0.3266	0.3071	0.0246	0.9163	0.0076	-16.1947	0.0801	0.0651
CDB	0.0026	0.1822	0.2126	0.2923	0.0244	0.9085	0.0062	3.7542	-13.6249	0.0571
COR	0.0003	0.2381	0.0298	0.0362	0.0031	0.1152	0.0006	0.7797	0.0146	-17.2001
DIO	0.0018	0.0778	0.4013	0.3086	0.0173	0.6862	0.0110	2.3294	0.0435	0.0191
GRO	0.0020	0.0739	0.7939	0.4133	0.0197	0.7966	0.0157	2.6889	0.0425	0.0221
GUI	0.0016	0.0759	0.3215	0.2618	0.0155	0.6081	0.0089	2.1499	0.0411	0.0185
HEI	0.0002	0.2726	0.0147	0.0219	0.0020	0.0717	0.0004	0.4022	0.0102	0.1631
IGU	0.0019	0.0751	0.4977	0.3570	0.0187	0.7520	0.0135	2.4046	0.0437	0.0183
IGS	0.0013	0.0845	0.1476	0.1206	0.0111	0.3832	0.0023	1.6604	0.0373	0.0159
IMC	0.0021	0.1316	0.2267	0.2637	0.0199	0.7502	0.0063	3.0811	0.0645	0.0337
IML	0.0000	0.0003	1.0369	0.0555	0.0003	0.0174	0.0037	0.2918	0.0003	0.0009
IMR	0.0001	0.2057	0.0106	0.0102	0.0008	0.0291	0.0001	0.3821	0.0061	0.2871
IMS	0.0027	0.1839	0.2242	0.2992	0.0250	0.9308	0.0065	3.7943	0.0846	0.0586
IMW	0.0021	0.2099	0.1467	0.2231	0.0194	0.7198	0.0044	3.0629	0.0684	0.1047
ISB	0.0013	0.0689	0.2213	0.1942	0.0126	0.4811	0.0062	1.7605	0.0351	0.0160
ISD	0.0011	0.2295	0.0843	0.1151	0.0103	0.3798	0.0022	1.7706	0.0385	0.2517
KUN	0.0013	0.0833	0.2089	0.1514	0.0113	0.4056	0.0024	2.1573	0.0387	0.0191
MIL	0.0013	0.0831	0.2140	0.1539	0.0113	0.4072	0.0024	2.1950	0.0388	0.0194
MLL	0.0008	0.0036	1.0949	0.3176	0.0080	0.3704	0.0237	1.1671	0.0072	0.0027
NEG	0.0014	0.0716	0.2536	0.2170	0.0136	0.5254	0.0071	1.9067	0.0374	0.0170
NOR	0.0002	0.2716	0.0154	0.0229	0.0021	0.0748	0.0004	0.4208	0.0105	0.1684
NOP	0.0016	0.0429	1.0771	0.4175	0.0156	0.6610	0.0157	2.7617	0.0281	0.0180
PAL	0.0003	0.2455	0.0274	0.0358	0.0031	0.1147	0.0006	0.7333	0.0145	0.2947
PAT	0.0019	0.1542	0.1452	0.2082	0.0173	0.6420	0.0041	2.7839	0.0599	0.0448
PAK	0.0020	0.0611	0.6441	0.4126	0.0193	0.7917	0.0172	2.2706	0.0383	0.0145
Q90	0.0007	0.0030	1.1105	0.2974	0.0071	0.3294	0.0234	1.1182	0.0062	0.0028
QBC	0.0022	0.1365	0.2486	0.2827	0.0211	0.7978	0.0070	3.2391	0.0679	0.0351
QBO	0.0017	0.0772	0.3605	0.2854	0.0165	0.6489	0.0099	2.2516	0.0426	0.0190
QCR	0.0015	0.0217	0.8992	0.4374	0.0158	0.6839	0.0226	1.6609	0.0199	0.0052
QLI	0.0025	0.1437	0.3320	0.3360	0.0239	0.9113	0.0093	3.4835	0.0736	0.0368
QNI	0.0016	0.2055	0.1147	0.1749	0.0149	0.5512	0.0033	2.4178	0.0529	0.0846
QST	0.0026	0.1418	0.3626	0.3485	0.0242	0.9269	0.0101	3.4568	0.0731	0.0362
SAN	0.0017	0.0770	0.3505	0.2795	0.0162	0.6390	0.0096	2.2282	0.0422	0.0189
SAR	0.0020	0.1242	0.1996	0.2377	0.0182	0.6837	0.0056	2.8379	0.0596	0.0314
SFF	0.0019	0.0757	0.4861	0.3517	0.0186	0.7458	0.0132	2.4033	0.0438	0.0185
SFL	0.0023	0.1702	0.1800	0.2569	0.0213	0.7927	0.0052	3.3848	0.0731	0.0517
SFS	0.0017	0.0772	0.3580	0.2840	0.0164	0.6465	0.0098	2.2459	0.0425	0.0189
SCH	0.0023	0.1696	0.1786	0.2550	0.0211	0.7869	0.0051	3.3632	0.0726	0.0514
SCN	0.0018	0.0777	0.4174	0.3173	0.0176	0.6994	0.0114	2.3524	0.0438	0.0191
SOL	0.0007	0.2541	0.0502	0.0772	0.0067	0.2463	0.0014	1.1366	0.0259	0.1364
STE	0.0000	0.0896	0.0012	0.0012	0.0001	0.0042	0.0000	0.0630	0.0016	0.0764
STN	0.0023	0.1713	0.1825	0.2601	0.0215	0.8031	0.0053	3.4228	0.0740	0.0521
WAR	0.0001	0.2295	0.0044	0.0057	0.0006	0.0198	0.0001	0.1754	0.0049	0.1517

Elasticities for August 2017.

Table 22: RCL: Own and cross price elasticities (2)

Code	DIO	GRO	GUI	HEI	IGU	IGS	IMC	IML	IMR	IMS
AMS	0.0012	0.0652	0.0046	0.1133	0.0343	0.0004	0.0827	0.0000	0.0504	0.1391
ANB	0.0003	0.0143	0.0013	0.8548	0.0080	0.0001	0.0306	0.0000	0.7301	0.0570
ANP	0.0017	0.1605	0.0056	0.0484	0.0554	0.0003	0.0552	0.0018	0.0396	0.0729
ANR	0.0016	0.1029	0.0057	0.0886	0.0490	0.0003	0.0790	0.0001	0.0465	0.1197
BAL	0.0013	0.0688	0.0047	0.1122	0.0361	0.0003	0.0838	0.0000	0.0505	0.1404
BIE	0.0014	0.0747	0.0049	0.1094	0.0389	0.0003	0.0848	0.0000	0.0502	0.1404
BRA	0.0018	0.1190	0.0058	0.0470	0.0564	0.0002	0.0579	0.0002	0.0176	0.0796
BUD	0.0012	0.0666	0.0046	0.1618	0.0328	0.0004	0.0918	0.0001	0.1740	0.1509
CDB	0.0011	0.0493	0.0041	0.1919	0.0279	0.0004	0.0902	0.0000	0.1299	0.1578
COR	0.0001	0.0066	0.0005	0.7854	0.0030	0.0000	0.0120	0.0000	1.5641	0.0279
DIO	-10.2555	0.0822	0.0047	0.0564	0.0406	0.0002	0.0574	0.0000	0.0211	0.0845
GRO	0.0017	-22.3205	0.0058	0.0569	0.0554	0.0003	0.0611	0.0010	0.0412	0.0826
GUI	0.0012	0.0666	-8.7817	0.0568	0.0337	0.0003	0.0549	0.0000	0.0206	0.0793
HEI	0.0001	0.0035	0.0003	-10.5664	0.0018	0.0000	0.0085	0.0000	0.8366	0.0183
IGU	0.0016	0.1005	0.0053	0.0534	-11.9524	0.0002	0.0588	0.0001	0.0201	0.0851
IGS	0.0006	0.0301	0.0027	0.0664	0.0123	-11.3968	0.0586	0.0000	0.0163	0.0668
IMC	0.0010	0.0507	0.0040	0.1151	0.0269	0.0004	-9.5533	0.0000	0.0479	0.1234
IML	0.0001	0.1224	0.0002	0.0001	0.0065	0.0000	0.0003	-26.7865	0.0007	0.0010
IMR	0.0000	0.0022	0.0001	0.7392	0.0006	0.0000	0.0031	0.0000	-15.6262	0.0117
IMS	0.0011	0.0514	0.0043	0.1852	0.0292	0.0004	0.0924	0.0000	0.1343	-14.6420
IMW	0.0008	0.0349	0.0031	0.3960	0.0203	0.0003	0.0728	0.0000	0.3908	0.1298
ISB	0.0009	0.0466	0.0036	0.0556	0.0249	0.0003	0.0507	0.0000	0.0183	0.0668
ISD	0.0004	0.0190	0.0017	0.6121	0.0105	0.0001	0.0394	0.0000	1.1319	0.0730
KUN	0.0005	0.0420	0.0025	0.0636	0.0120	0.0413	0.0544	0.0000	0.0194	0.0720
MIL	0.0005	0.0429	0.0025	0.0633	0.0120	0.0420	0.0541	0.0000	0.0196	0.0724
MLL	0.0015	0.1805	0.0043	0.0022	0.0627	0.0000	0.0170	0.1377	0.0029	0.0164
NEG	0.0010	0.0531	0.0038	0.0561	0.0277	0.0003	0.0521	0.0000	0.0192	0.0716
NOR	0.0001	0.0037	0.0003	1.1167	0.0019	0.0000	0.0088	0.0000	0.8603	0.0189
NOP	0.0016	0.1871	0.0052	0.0342	0.0531	0.0002	0.0441	0.0044	0.0363	0.0572
PAL	0.0001	0.0062	0.0005	0.8423	0.0030	0.0000	0.0120	0.0000	1.4117	0.0275
PAT	0.0008	0.0344	0.0032	0.2469	0.0189	0.0005	0.0705	0.0000	0.1150	0.1137
PAK	0.0018	0.1272	0.0060	0.0430	0.0597	0.0001	0.0565	0.0004	0.0160	0.0753
Q90	0.0014	0.1800	0.0040	0.0017	0.0604	0.0000	0.0146	0.1907	0.0029	0.0145
QBC	0.0011	0.0553	0.0041	0.1149	0.0292	0.0004	0.0781	0.0000	0.0491	0.1299
QBO	0.0012	0.0743	0.0045	0.0568	0.0371	0.0003	0.0562	0.0000	0.0210	0.0824
QCR	0.0020	0.1668	0.0063	0.0153	0.0715	0.0001	0.0398	0.0066	0.0063	0.0410
QLI	0.0013	0.0716	0.0048	0.1110	0.0374	0.0003	0.0844	0.0000	0.0504	0.1407
QNI	0.0006	0.0276	0.0025	0.5247	0.0154	0.0003	0.0578	0.0000	0.3336	0.1004
QST	0.0014	0.0771	0.0050	0.1080	0.0399	0.0003	0.0849	0.0000	0.0499	0.1396
SAN	0.0012	0.0723	0.0044	0.0568	0.0363	0.0003	0.0559	0.0000	0.0209	0.0817
SAR	0.0009	0.0450	0.0037	0.1154	0.0240	0.0004	0.0719	0.0000	0.0459	0.1136
SFF	0.0015	0.0984	0.0052	0.0539	0.0477	0.0002	0.0587	0.0001	0.0203	0.0853
SFL	0.0009	0.0425	0.0037	0.2163	0.0235	0.0004	0.0807	0.0000	0.1217	0.1394
SFS	0.0012	0.0738	0.0045	0.0568	0.0369	0.0003	0.0561	0.0000	0.0210	0.0822
SCH	0.0009	0.0422	0.0036	0.2175	0.0233	0.0004	0.0803	0.0000	0.1214	0.1385
SCN	0.0014	0.0853	0.0048	0.0561	0.0420	0.0002	0.0578	0.0001	0.0210	0.0850
SOL	0.0003	0.0121	0.0011	0.9377	0.0067	0.0001	0.0264	0.0000	0.6561	0.0484
STE	0.0000	0.0003	0.0000	0.4257	0.0001	0.0000	0.0007	0.0000	0.7609	0.0028
STN	0.0009	0.0430	0.0037	0.2143	0.0238	0.0004	0.0815	0.0000	0.1222	0.1412
WAR	0.0000	0.0010	0.0001	0.9839	0.0004	0.0000	0.0029	0.0000	0.8736	0.0085

Elasticities for August 2017.

Table 23: RCL: Own and cross price elasticities (3)

Code	IMW	ISB	ISD	KUN	MIL	MLL	NEG	NOR	NOP	PAL
AMS	0.3709	0.0006	0.0929	0.0247	0.0169	0.0036	0.0026	0.5805	0.5154	0.0378
ANB	0.2226	0.0002	0.1141	0.0098	0.0067	0.0001	0.0008	4.1980	0.0841	0.1648
ANP	0.1630	0.0006	0.0439	0.0257	0.0180	0.0321	0.0028	0.2496	2.2123	0.0192
ANR	0.3053	0.0006	0.0738	0.0229	0.0160	0.0115	0.0030	0.4565	1.0557	0.0310
BAL	0.3734	0.0006	0.0931	0.0241	0.0165	0.0041	0.0026	0.5755	0.5560	0.0379
BIE	0.3713	0.0006	0.0918	0.0231	0.0159	0.0050	0.0027	0.5623	0.6300	0.0374
BRA	0.1814	0.0006	0.0431	0.0111	0.0076	0.0261	0.0029	0.2422	1.2073	0.0165
BUD	0.4167	0.0006	0.1129	0.0325	0.0226	0.0042	0.0026	0.8343	0.6943	0.0632
CDB	0.4365	0.0005	0.1153	0.0273	0.0188	0.0012	0.0024	0.9741	0.3311	0.0584
COR	0.1705	0.0001	0.1921	0.0034	0.0024	0.0001	0.0003	3.9968	0.0541	0.3037
DIO	0.2078	0.0005	0.0512	0.0155	0.0106	0.0106	0.0026	0.2895	0.7697	0.0196
GRO	0.1920	0.0006	0.0491	0.0255	0.0179	0.0262	0.0029	0.2933	1.9002	0.0215
GUI	0.1993	0.0005	0.0494	0.0173	0.0118	0.0072	0.0024	0.2900	0.6044	0.0189
HEI	0.1339	0.0000	0.0970	0.0024	0.0016	0.0000	0.0002	5.5041	0.0214	0.1803
IGU	0.2029	0.0006	0.0493	0.0132	0.0091	0.0165	0.0028	0.2749	0.9782	0.0188
IGS	0.1908	0.0004	0.0430	2.8524	1.9873	0.0007	0.0019	0.3324	0.2867	0.0163
IMC	0.3324	0.0005	0.0843	0.0275	0.0187	0.0020	0.0024	0.5829	0.3716	0.0347
IML	0.0018	0.0000	0.0023	0.0000	0.0000	2.3916	0.0001	0.0007	5.3770	0.0005
IMR	0.1168	0.0000	0.1586	0.0006	0.0004	0.0000	0.0001	3.7465	0.0200	0.2670
IMS	0.4440	0.0005	0.1170	0.0273	0.0188	0.0015	0.0024	0.9436	0.3616	0.0594
IMW	-13.8188	0.0004	0.1262	0.0221	0.0152	0.0004	0.0018	1.9841	0.2171	0.1059
ISB	0.1727	-6.6859	0.0424	0.0190	0.0129	0.0040	0.0023	0.2802	0.4047	0.0164
ISD	0.2692	0.0002	-17.3627	0.0122	0.0084	0.0004	0.0010	3.1163	0.1483	0.2336
KUN	0.2001	0.0004	0.0515	-10.5843	2.0126	0.0008	0.0017	0.3206	0.4128	0.0188
MIL	0.2006	0.0004	0.0521	2.9359	-11.6285	0.0009	0.0017	0.3191	0.4233	0.0189
MLL	0.0168	0.0003	0.0074	0.0035	0.0025	-25.3350	0.0019	0.0115	3.1917	0.0020
NEG	0.1832	0.0005	0.0453	0.0186	0.0126	0.0049	-7.4118	0.2842	0.4680	0.0174
NOR	0.1362	0.0000	0.1003	0.0024	0.0017	0.0000	0.0002	-6.5463	0.0224	0.1846
NOP	0.1175	0.0005	0.0376	0.0247	0.0174	0.0456	0.0025	0.1769	-21.5972	0.0159
PAL	0.1674	0.0001	0.1730	0.0033	0.0023	0.0001	0.0003	4.2502	0.0464	-16.3364
PAT	0.3206	0.0005	0.0862	0.0289	0.0196	0.0004	0.0021	1.2096	0.2103	0.0483
PAK	0.1667	0.0006	0.0391	0.0102	0.0071	0.0326	0.0030	0.2214	1.3195	0.0149
Q90	0.0151	0.0003	0.0075	0.0030	0.0021	0.5241	0.0017	0.0092	3.3372	0.0020
QBC	0.3488	0.0005	0.0882	0.0267	0.0182	0.0024	0.0024	0.5844	0.4134	0.0362
QBO	0.2049	0.0005	0.0507	0.0165	0.0112	0.0087	0.0025	0.2909	0.6845	0.0194
QCR	0.0645	0.0006	0.0143	0.0072	0.0051	0.1312	0.0029	0.0786	2.0924	0.0053
QLI	0.3733	0.0006	0.0927	0.0236	0.0162	0.0045	0.0027	0.5701	0.5897	0.0378
QNI	0.3069	0.0004	0.1002	0.0212	0.0144	0.0002	0.0015	2.5623	0.1610	0.0924
QST	0.3685	0.0006	0.0909	0.0229	0.0158	0.0055	0.0027	0.5555	0.6616	0.0371
SAN	0.2037	0.0005	0.0505	0.0167	0.0114	0.0083	0.0025	0.2909	0.6639	0.0193
SAR	0.3076	0.0005	0.0780	0.0281	0.0191	0.0016	0.0023	0.5801	0.3221	0.0325
SFF	0.2043	0.0006	0.0497	0.0135	0.0092	0.0157	0.0027	0.2776	0.9527	0.0190
SFL	0.3880	0.0005	0.1036	0.0285	0.0195	0.0007	0.0022	1.0805	0.2655	0.0542
SFS	0.2046	0.0005	0.0507	0.0166	0.0113	0.0086	0.0025	0.2909	0.6793	0.0194
SCH	0.3854	0.0005	0.1030	0.0286	0.0195	0.0007	0.0022	1.0853	0.2632	0.0540
SCN	0.2081	0.0006	0.0512	0.0152	0.0103	0.0114	0.0026	0.2882	0.8038	0.0195
SOL	0.1992	0.0002	0.0994	0.0091	0.0062	0.0001	0.0007	4.5596	0.0704	0.1508
STE	0.0378	0.0000	0.0377	0.0000	0.0000	0.0000	0.0000	2.0878	0.0023	0.0809
STN	0.3925	0.0005	0.1048	0.0284	0.0194	0.0007	0.0022	1.0718	0.2698	0.0546
WAR	0.0976	0.0000	0.0844	0.0005	0.0003	0.0000	0.0000	4.7964	0.0071	0.1654

Elasticities for August 2017.

Table 24: RCL: Own and cross price elasticities (4)

Code	PAT	PAK	Q90	QBC	QBO	QCR	QLI	QNI	QST	SAN
AMS	0.3430	0.1411	0.0017	0.1633	0.0003	0.0809	0.3440	0.3957	0.3502	0.0000
ANB	0.1686	0.0263	0.0000	0.0592	0.0001	0.0068	0.1167	0.3036	0.1157	0.0000
ANP	0.1664	0.2906	0.0181	0.1131	0.0003	0.2930	0.2823	0.1776	0.3100	0.0000
ANR	0.2938	0.2291	0.0060	0.1583	0.0003	0.1755	0.3518	0.3334	0.3667	0.0000
BAL	0.3435	0.1502	0.0020	0.1658	0.0003	0.0889	0.3515	0.3978	0.3583	0.0000
BIE	0.3414	0.1657	0.0025	0.1683	0.0003	0.1034	0.3597	0.3961	0.3677	0.0000
BRA	0.1749	0.2911	0.0143	0.1188	0.0003	0.2766	0.2964	0.1907	0.3227	0.0000
BUD	0.3905	0.1254	0.0022	0.1803	0.0003	0.0663	0.3626	0.4583	0.3617	0.0000
CDB	0.3939	0.0993	0.0006	0.1772	0.0002	0.0373	0.3593	0.4701	0.3586	0.0000
COR	0.0753	0.0096	0.0001	0.0234	0.0000	0.0025	0.0458	0.1919	0.0453	0.0000
DIO	0.2048	0.1942	0.0056	0.1146	0.0003	0.1554	0.2624	0.2224	0.2782	0.0000
GRO	0.1951	0.2838	0.0145	0.1244	0.0003	0.2689	0.3010	0.2114	0.3261	0.0000
GUI	0.2102	0.1552	0.0037	0.1074	0.0002	0.1166	0.2341	0.2211	0.2454	0.0000
HEI	0.0861	0.0059	0.0000	0.0159	0.0000	0.0015	0.0287	0.2472	0.0281	0.0000
IGU	0.1940	0.2417	0.0088	0.1193	0.0003	0.2091	0.2855	0.2135	0.3065	0.0000
IGS	0.2953	0.0357	0.0003	0.1046	0.0001	0.0159	0.1576	0.2832	0.1477	0.0000
IMC	0.3320	0.1047	0.0010	0.1458	0.0002	0.0532	0.2947	0.3676	0.2979	0.0000
IML	0.0002	0.0948	1.8420	0.0007	0.0000	1.2730	0.0052	0.0004	0.0085	0.0000
IMR	0.0354	0.0019	0.0000	0.0060	0.0000	0.0006	0.0115	0.1389	0.0115	0.0000
IMS	0.4009	0.1046	0.0007	0.1817	0.0002	0.0411	0.3683	0.4783	0.3673	0.0000
IMW	0.3305	0.0676	0.0002	0.1427	0.0002	0.0189	0.2856	0.4275	0.2834	0.0000
ISB	0.2168	0.1068	0.0020	0.0952	0.0002	0.0735	0.1876	0.2115	0.1926	0.0000
ISD	0.1896	0.0339	0.0002	0.0770	0.0001	0.0089	0.1514	0.2979	0.1491	0.0000
KUN	0.2690	0.0376	0.0004	0.0989	0.0001	0.0192	0.1632	0.2671	0.1590	0.0000
MIL	0.2667	0.0379	0.0004	0.0983	0.0001	0.0196	0.1636	0.2655	0.1598	0.0000
MLL	0.0175	0.5008	0.2914	0.0379	0.0003	1.4577	0.1306	0.0113	0.1596	0.0000
NEG	0.2143	0.1223	0.0025	0.0994	0.0002	0.0867	0.2038	0.2153	0.2110	0.0000
NOR	0.0856	0.0062	0.0000	0.0164	0.0000	0.0016	0.0299	0.2450	0.0293	0.0000
NOP	0.1173	0.2898	0.0265	0.0915	0.0003	0.3320	0.2442	0.1214	0.2754	0.0000
PAL	0.0786	0.0096	0.0000	0.0234	0.0000	0.0024	0.0457	0.2035	0.0451	0.0000
PAT	-8.3308	0.0641	0.0002	0.1335	0.0002	0.0210	0.2546	0.3820	0.2532	0.0000
PAK	0.1629	-14.5271	0.0181	0.1167	0.0004	0.3140	0.2970	0.1756	0.3257	0.0000
Q90	0.0142	0.4998	-25.9165	0.0327	0.0003	1.5431	0.1154	0.0090	0.1426	0.0000
QBC	0.3364	0.1158	0.0012	-10.2833	0.0002	0.0610	0.3129	0.3791	0.3171	0.0000
QBO	0.2078	0.1742	0.0045	0.1112	-9.5155	0.1350	0.2490	0.2226	0.2625	0.0000
QCR	0.0738	0.4347	0.0772	0.0851	0.0004	-20.1060	0.2494	0.0671	0.2873	0.0000
QLI	0.3430	0.1575	0.0022	0.1673	0.0003	0.0956	-13.1762	0.3978	0.3634	0.0000
QNI	0.2827	0.0512	0.0001	0.1113	0.0001	0.0141	0.2185	-10.2498	0.2173	0.0000
QST	0.3395	0.1719	0.0027	0.1687	0.0003	0.1095	0.3615	0.3937	-14.2395	0.0000
SAN	0.2084	0.1694	0.0043	0.1103	0.0003	0.1302	0.2454	0.2224	0.2583	-9.3316
SAR	0.3263	0.0913	0.0008	0.1371	0.0002	0.0444	0.2693	0.3512	0.2711	0.0000
SFF	0.1956	0.2360	0.0084	0.1190	0.0003	0.2022	0.2834	0.2152	0.3038	0.0000
SFL	0.3654	0.0820	0.0003	0.1567	0.0002	0.0281	0.3134	0.4291	0.3131	0.0000
SFS	0.2079	0.1730	0.0045	0.1110	0.0003	0.1338	0.2481	0.2226	0.2615	0.0000
SCH	0.3642	0.0812	0.0003	0.1558	0.0002	0.0278	0.3111	0.4271	0.3108	0.0000
SCN	0.2034	0.2021	0.0060	0.1157	0.0003	0.1638	0.2671	0.2218	0.2838	0.0000
SOL	0.1586	0.0220	0.0000	0.0506	0.0001	0.0057	0.0978	0.3000	0.0970	0.0000
STE	0.0172	0.0002	0.0000	0.0013	0.0000	0.0000	0.0018	0.0681	0.0016	0.0000
STN	0.3676	0.0833	0.0003	0.1584	0.0002	0.0287	0.3175	0.4326	0.3172	0.0000
WAR	0.0528	0.0012	0.0000	0.0052	0.0000	0.0003	0.0081	0.1886	0.0077	0.0000

Elasticities for August 2017.

Table 25: RCL: Own and cross price elasticities (5)

Code	SAR	SFF	SFL	SFS	SCH	SCN	SOL	STE	STN	WAR
AMS	0.2246	0.0445	0.1091	0.1445	0.0175	0.0119	0.2767	0.0387	0.0712	0.0167
ANB	0.0851	0.0105	0.0486	0.0389	0.0078	0.0030	0.5834	1.4395	0.0315	0.3576
ANP	0.1433	0.0707	0.0539	0.1890	0.0086	0.0170	0.1207	0.0207	0.0352	0.0072
ANR	0.2101	0.0630	0.0947	0.1845	0.0152	0.0159	0.2286	0.0252	0.0618	0.0115
BAL	0.2264	0.0468	0.1100	0.1499	0.0176	0.0124	0.2773	0.0364	0.0718	0.0160
BIE	0.2277	0.0504	0.1101	0.1583	0.0176	0.0132	0.2749	0.0330	0.0719	0.0150
BRA	0.1497	0.0720	0.0581	0.1946	0.0093	0.0174	0.1279	0.0066	0.0380	0.0050
BUD	0.2494	0.0428	0.1240	0.1451	0.0199	0.0117	0.3347	0.1297	0.0808	0.0351
CDB	0.2455	0.0366	0.1257	0.1287	0.0201	0.0102	0.3570	0.1564	0.0820	0.0460
COR	0.0330	0.0039	0.0227	0.0146	0.0036	0.0011	0.4806	1.8837	0.0147	0.3628
DIO	0.1547	0.0522	0.0642	0.1535	0.0103	0.0132	0.1506	0.0095	0.0419	0.0063
GRO	0.1598	0.0708	0.0629	0.1926	0.0101	0.0172	0.1439	0.0216	0.0410	0.0081
GUI	0.1524	0.0435	0.0624	0.1347	0.0100	0.0112	0.1498	0.0107	0.0406	0.0067
HEI	0.0252	0.0024	0.0197	0.0091	0.0032	0.0007	0.6863	2.1803	0.0126	0.4890
IGU	0.1547	0.0623	0.0631	0.1750	0.0101	0.0153	0.1441	0.0080	0.0413	0.0058
IGS	0.1803	0.0165	0.0727	0.0772	0.0118	0.0053	0.1870	0.0055	0.0465	0.0062
IMC	0.2120	0.0351	0.0993	0.1217	0.0159	0.0096	0.2610	0.0505	0.0646	0.0198
IML	0.0005	0.0077	0.0002	0.0099	0.0000	0.0012	0.0003	0.0000	0.0001	0.0000
IMR	0.0089	0.0008	0.0098	0.0030	0.0016	0.0002	0.4243	3.4432	0.0063	0.3836
IMS	0.2509	0.0382	0.1284	0.1335	0.0206	0.0106	0.3582	0.1451	0.0838	0.0425
IMW	0.1987	0.0267	0.1045	0.0972	0.0167	0.0076	0.4310	0.5728	0.0681	0.1434
ISB	0.1494	0.0323	0.0575	0.1106	0.0093	0.0087	0.1430	0.0127	0.0371	0.0071
ISD	0.1075	0.0139	0.0595	0.0513	0.0095	0.0040	0.4588	1.2179	0.0388	0.2646
KUN	0.1643	0.0160	0.0694	0.0710	0.0112	0.0050	0.1777	0.0060	0.0446	0.0061
MIL	0.1629	0.0160	0.0691	0.0706	0.0112	0.0050	0.1767	0.0060	0.0444	0.0060
MLL	0.0398	0.0777	0.0072	0.1551	0.0011	0.0159	0.0060	0.0007	0.0048	0.0003
NEG	0.1502	0.0359	0.0593	0.1183	0.0095	0.0095	0.1457	0.0119	0.0384	0.0069
NOR	0.0257	0.0025	0.0200	0.0095	0.0032	0.0007	0.6771	2.1694	0.0128	0.4836
NOP	0.1126	0.0675	0.0387	0.1746	0.0062	0.0159	0.0824	0.0186	0.0253	0.0056
PAL	0.0332	0.0039	0.0231	0.0145	0.0037	0.0011	0.5155	1.9346	0.0150	0.3840
PAT	0.2044	0.0248	0.0955	0.0958	0.0153	0.0072	0.3330	0.2528	0.0619	0.0753
PAK	0.1453	0.0761	0.0544	0.2024	0.0087	0.0182	0.1173	0.0059	0.0356	0.0045
Q90	0.0339	0.0746	0.0060	0.1445	0.0010	0.0150	0.0048	0.0006	0.0040	0.0002
QBC	0.2164	0.0381	0.1032	0.1288	0.0165	0.0104	0.2677	0.0465	0.0672	0.0187
QBO	0.1537	0.0478	0.0636	0.1440	0.0102	0.0122	0.1509	0.0101	0.0414	0.0065
QCR	0.0978	0.0903	0.0259	0.2167	0.0041	0.0204	0.0423	0.0023	0.0170	0.0016
QLI	0.2273	0.0485	0.1103	0.1540	0.0177	0.0128	0.2767	0.0347	0.0720	0.0155
QNI	0.1628	0.0202	0.0829	0.0759	0.0133	0.0058	0.4660	0.7404	0.0539	0.1989
QST	0.2276	0.0517	0.1096	0.1614	0.0176	0.0135	0.2728	0.0319	0.0716	0.0146
SAN	0.1534	0.0467	0.0633	0.1416	0.0102	0.0119	0.1507	0.0102	0.0413	0.0065
SAR	-8.4269	0.0314	0.0937	0.1129	0.0151	0.0088	0.2514	0.0560	0.0608	0.0212
SFF	0.1549	-11.7287	0.0635	0.1725	0.0102	0.0151	0.1454	0.0082	0.0415	0.0059
SFL	0.2246	0.0308	-10.7924	0.1120	0.0179	0.0087	0.3454	0.2014	0.0729	0.0593
SFS	0.1536	0.0475	0.0635	-9.3262	0.0102	0.0121	0.1508	0.0101	0.0414	0.0065
SCH	0.2237	0.0306	0.1112	0.1113	-10.7859	0.0087	0.3448	0.2035	0.0724	0.0599
SCN	0.1549	0.0540	0.0643	0.1572	0.0103	-10.5335	0.1501	0.0092	0.0420	0.0063
SOL	0.0750	0.0088	0.0430	0.0331	0.0069	0.0025	-10.6785	1.5147	0.0278	0.3890
STE	0.0024	0.0001	0.0036	0.0003	0.0006	0.0000	0.2165	-4.5370	0.0023	0.3906
STN	0.2262	0.0313	0.1131	0.1133	0.0181	0.0089	0.3464	0.1978	-11.0148	0.0582
WAR	0.0093	0.0005	0.0109	0.0021	0.0018	0.0002	0.5730	4.0249	0.0069	-11.7960

Elasticities for August 2017.

Table 26: Merger simulation results: Scenario (a). Logit per brand.

Firm	M. costs	Shares		% Shares	Prices		% prices
		Pre-	Post-		Pre-	Post-	
Andes Blanca	4.81	1.59	1.64	3.2%	8.14	8.28	1.7%
Andes Porter	5.43	0.16	0.16	3.2%	8.76	8.90	1.6%
Andes Red Lager	4.36	0.00	0.00	3.2%	7.69	7.83	1.8%
Báltica	1.55	0.03	0.03	3.2%	4.88	5.02	2.8%
Brahma Chopp	4.08	27.00	27.88	3.2%	7.41	7.55	1.8%
Corona	17.23	1.23	1.27	3.2%	20.56	20.70	0.7%
Iguana	2.20	2.56	2.64	3.2%	5.53	5.67	2.5%
Iguana Summer	8.04	0.49	0.51	3.2%	11.37	11.50	1.2%
Negra Modelo	22.01	0.01	0.01	3.2%	25.33	25.47	0.5%
Norte	3.73	0.80	0.82	3.2%	7.06	7.20	1.9%
Norte Porter	3.25	0.00	0.00	3.2%	6.58	6.72	2.1%
Patagonia	15.42	0.66	0.68	3.2%	18.75	18.89	0.7%
Patagonia Küné	14.02	0.23	0.24	3.2%	17.35	17.48	0.8%
Quilmes 1890	6.26	1.10	1.13	3.2%	9.59	9.72	1.4%
Quilmes Bajo Cero	3.49	2.81	2.90	3.2%	6.82	6.96	2.0%
Quilmes Bock	7.14	1.01	1.04	3.2%	10.47	10.61	1.3%
Quilmes Cristal	5.08	24.72	25.52	3.2%	8.41	8.55	1.6%
Quilmes Lieber	4.08	0.32	0.33	3.2%	7.41	7.54	1.8%
Quilmes Night	5.25	0.01	0.01	3.2%	8.57	8.71	1.6%
Quilmes Stout	6.77	2.64	2.72	3.2%	10.10	10.23	1.4%
Stella Artois	10.96	7.07	7.29	3.2%	14.29	14.42	1.0%
Stella Artois Noire	10.57	0.72	0.75	3.2%	13.90	14.04	1.0%
Amstel	7.24	0.23	0.26	13.8%	9.47	9.42	-0.6%
Bieckert	3.74	0.04	0.04	13.8%	5.97	5.92	-1.0%
Budweiser	4.96	5.65	3.35	-40.6%	7.19	8.43	17.2%
Córdoba	4.18	0.47	0.53	13.8%	6.41	6.35	-0.9%
Guinness	39.85	0.00	0.00	13.8%	42.08	42.02	-0.1%
Heineken	9.80	3.82	4.35	13.8%	12.03	11.97	-0.5%
Imperial Cream Stout	8.10	0.39	0.44	13.8%	10.33	10.27	-0.6%
Imperial Lager	7.44	1.42	1.62	13.8%	9.67	9.62	-0.6%
Imperial Red Lager	6.94	0.17	0.19	13.8%	9.17	9.11	-0.6%
Imperial Scotch Ale	7.05	0.11	0.13	13.8%	9.28	9.22	-0.6%
Imperial Weissbier	6.91	0.08	0.09	13.8%	9.14	9.08	-0.6%
Kunstmann	22.19	0.01	0.02	13.8%	24.42	24.37	-0.2%
Palermo	3.40	1.58	1.79	13.8%	5.63	5.57	-1.0%
Salta Negra	6.34	0.21	0.24	13.8%	8.57	8.52	-0.7%
Salta Rubia	5.03	0.51	0.58	13.8%	7.26	7.20	-0.8%
Santa Fe Frost	4.31	1.00	1.13	13.8%	6.54	6.49	-0.9%
Santa Fe Lager	4.95	0.08	0.09	13.8%	7.18	7.13	-0.8%
Santa Fe Stout	5.24	0.07	0.08	13.8%	7.47	7.41	-0.8%
Schneider	4.82	4.22	4.80	13.8%	7.05	6.99	-0.8%
Schneider Negra	4.99	0.01	0.01	13.8%	7.22	7.16	-0.8%
Sol	15.52	0.14	0.16	13.8%	17.75	17.69	-0.3%
Diosa	2.29	0.01	0.00	-46.0%	4.33	5.75	33.0%
Grolsch	10.36	0.52	0.28	-46.0%	12.40	13.83	11.5%
Isenbeck Blanca	5.53	2.67	1.44	-46.0%	7.57	9.00	18.8%
Isenbeck Dark	8.46	0.03	0.02	-46.0%	10.50	11.92	13.6%
Miller	9.45	0.76	0.41	-46.0%	11.49	12.92	12.4%
Miller Lite	4.39	0.00	0.00	-46.0%	6.43	7.85	22.2%
Warsteiner	10.40	0.68	0.37	-46.0%	12.44	13.87	11.5%

Table 27: Merger simulation results: Scenario (b). Logit per brand.

Firm	M. costs	Shares		% Shares	Prices		% prices
		Pre-	Post-		Pre-	Post-	
Andes Blanca	4.81	1.59	1.60	0.8%	8.14	8.13	-0.1%
Andes Porter	5.43	0.16	0.16	0.8%	8.76	8.76	-0.1%
Andes Red Lager	4.36	0.00	0.00	0.8%	7.69	7.69	-0.1%
Báltica	1.55	0.03	0.05	69.3%	4.88	3.84	-21.2%
Brahma Chopp	4.08	27.00	27.23	0.8%	7.41	7.41	-0.1%
Corona	17.23	1.23	1.24	0.8%	20.56	20.55	-0.0%
Iguana	2.20	2.56	4.33	69.3%	5.53	4.49	-18.7%
Iguana Summer	8.04	0.49	0.83	69.3%	11.37	10.33	-9.1%
Negra Modelo	22.01	0.01	0.01	0.8%	25.33	25.33	-0.0%
Norte	3.73	0.80	1.35	69.3%	7.06	6.02	-14.7%
Norte Porter	3.25	0.00	0.00	69.3%	6.58	5.55	-15.7%
Patagonia	15.42	0.66	0.66	0.8%	18.75	18.74	-0.0%
Patagonia Küné	14.02	0.23	0.23	0.8%	17.35	17.34	-0.0%
Quilmes 1890	6.26	1.10	1.11	0.8%	9.59	9.58	-0.1%
Quilmes Bajo Cero	3.49	2.81	2.83	0.8%	6.82	6.81	-0.1%
Quilmes Bock	7.14	1.01	1.02	0.8%	10.47	10.47	-0.1%
Quilmes Cristal	5.08	24.72	24.93	0.8%	8.41	8.41	-0.1%
Quilmes Lieber	4.08	0.32	0.32	0.8%	7.41	7.40	-0.1%
Quilmes Night	5.25	0.01	0.01	0.8%	8.57	8.57	-0.1%
Quilmes Stout	6.77	2.64	2.66	0.8%	10.10	10.09	-0.1%
Stella Artois	10.96	7.07	7.13	0.8%	14.29	14.28	-0.0%
Stella Artois Noire	10.57	0.72	0.73	0.8%	13.90	13.89	-0.0%
Amstel	7.24	0.23	0.22	-2.6%	9.47	9.54	0.7%
Bieckert	3.74	0.04	0.04	-2.6%	5.97	6.04	1.1%
Budweiser	4.96	5.65	3.28	-42.0%	7.19	8.28	15.2%
Córdoba	4.18	0.47	0.46	-2.6%	6.41	6.48	1.0%
Guinness	39.85	0.00	0.00	-2.6%	42.08	42.14	0.2%
Heineken	9.80	3.82	3.72	-2.6%	12.03	12.09	0.5%
Imperial Cream Stout	8.10	0.39	0.38	-2.6%	10.33	10.39	0.6%
Imperial Lager	7.44	1.42	1.38	-2.6%	9.67	9.74	0.7%
Imperial Red Lager	6.94	0.17	0.16	-2.6%	9.17	9.24	0.7%
Imperial Scotch Ale	7.05	0.11	0.11	-2.6%	9.28	9.34	0.7%
Imperial Weissbier	6.91	0.08	0.08	-2.6%	9.14	9.20	0.7%
Kunstmann	22.19	0.01	0.01	-2.6%	24.42	24.49	0.3%
Palermo	3.40	1.58	1.53	-2.6%	5.63	5.69	1.1%
Salta Negra	6.34	0.21	0.20	-2.6%	8.57	8.64	0.7%
Salta Rubia	5.03	0.51	0.50	-2.6%	7.26	7.33	0.9%
Santa Fe Frost	4.31	1.00	0.97	-2.6%	6.54	6.61	1.0%
Santa Fe Lager	4.95	0.08	0.08	-2.6%	7.18	7.25	0.9%
Santa Fe Stout	5.24	0.07	0.07	-2.6%	7.47	7.54	0.8%
Schneider	4.82	4.22	4.11	-2.6%	7.05	7.11	0.9%
Schneider Negra	4.99	0.01	0.01	-2.6%	7.22	7.28	0.9%
Sol	15.52	0.14	0.14	-2.6%	17.75	17.82	0.4%
Diosa	2.29	0.01	0.01	-11.5%	4.33	4.58	5.9%
Grolsch	10.36	0.52	0.46	-11.5%	12.40	12.66	2.0%
Isenbeck Blanca	5.53	2.67	2.36	-11.5%	7.57	7.83	3.3%
Isenbeck Dark	8.46	0.03	0.03	-11.5%	10.50	10.75	2.4%
Miller	9.45	0.76	0.67	-11.5%	11.49	11.74	2.2%
Miller Lite	4.39	0.00	0.00	-11.5%	6.43	6.68	3.9%
Warsteiner	10.40	0.68	0.60	-11.5%	12.44	12.70	2.0%

Table 28: Merger simulation results: Scenario (a). Nested Logit per brand.

Firm	M. costs	Shares		% Shares	Prices		% prices
		Pre-	Post-		Pre-	Post-	
Andes Blanca	1.54	1.59	1.63	2.7%	8.14	8.97	10.2%
Andes Porter	2.16	0.16	0.16	2.7%	8.76	9.59	9.5%
Andes Red Lager	1.09	0.00	0.00	2.7%	7.69	8.52	10.8%
Báltica	0.30	0.03	0.03	5.5%	4.88	4.95	1.4%
Brahma Chopp	0.81	27.00	27.73	2.7%	7.41	8.24	11.2%
Corona	15.97	1.23	1.29	4.8%	20.56	21.14	2.8%
Iguana	0.95	2.56	2.70	5.5%	5.53	5.60	1.2%
Iguana Summer	4.77	0.49	0.50	2.7%	11.37	12.19	7.3%
Negra Modelo	20.74	0.01	0.01	4.8%	25.33	25.91	2.3%
Norte	0.46	0.80	0.82	2.7%	7.06	7.89	11.7%
Norte Porter	-0.02	0.00	0.00	2.7%	6.58	7.41	12.6%
Patagonia	14.16	0.66	0.69	4.8%	18.75	19.33	3.1%
Patagonia Küné	12.76	0.23	0.24	4.8%	17.35	17.93	3.3%
Quilmes 1890	2.99	1.10	1.13	2.7%	9.59	10.42	8.6%
Quilmes Bajo Cero	0.22	2.81	2.88	2.7%	6.82	7.65	12.1%
Quilmes Bock	3.87	1.01	1.04	2.7%	10.47	11.30	7.9%
Quilmes Cristal	1.81	24.72	25.39	2.7%	8.41	9.24	9.8%
Quilmes Lieber	0.81	0.32	0.33	2.7%	7.41	8.24	11.2%
Quilmes Night	1.98	0.01	0.01	2.7%	8.57	9.40	9.7%
Quilmes Stout	3.50	2.64	2.71	2.7%	10.10	10.92	8.2%
Stella Artois	9.69	7.07	7.40	4.8%	14.29	14.86	4.0%
Stella Artois Noire	9.31	0.72	0.76	4.8%	13.90	14.48	4.2%
Amstel	7.10	0.23	0.29	29.0%	9.47	9.68	2.1%
Bieckert	3.24	0.04	0.04	8.1%	5.97	6.00	0.4%
Budweiser	5.02	5.65	0.50	-91.2%	7.19	12.44	73.0%
Córdoba	4.24	0.47	0.76	62.5%	6.41	6.41	-0.0%
Guinness	39.71	0.00	0.00	29.0%	42.08	42.28	0.5%
Heineken	9.66	3.82	4.93	29.0%	12.03	12.23	1.7%
Imperial Cream Stout	8.15	0.39	0.63	62.5%	10.33	10.33	-0.0%
Imperial Lager	7.50	1.42	2.31	62.5%	9.67	9.67	-0.0%
Imperial Red Lager	7.00	0.17	0.27	62.5%	9.17	9.17	-0.0%
Imperial Scotch Ale	7.10	0.11	0.18	62.5%	9.28	9.28	-0.0%
Imperial Weissbier	6.96	0.08	0.13	62.5%	9.14	9.14	-0.0%
Kunstmann	22.05	0.01	0.02	29.0%	24.42	24.63	0.8%
Palermo	2.90	1.58	1.70	8.1%	5.63	5.66	0.4%
Salta Negra	6.40	0.21	0.34	62.5%	8.57	8.57	-0.0%
Salta Rubia	5.09	0.51	0.83	62.5%	7.26	7.26	-0.0%
Santa Fe Frost	4.37	1.00	1.62	62.5%	6.54	6.54	-0.0%
Santa Fe Lager	5.01	0.08	0.14	62.5%	7.18	7.18	-0.0%
Santa Fe Stout	5.30	0.07	0.11	62.5%	7.47	7.47	-0.0%
Schneider	4.87	4.22	6.85	62.5%	7.05	7.05	-0.0%
Schneider Negra	5.04	0.01	0.01	62.5%	7.22	7.22	-0.0%
Sol	15.38	0.14	0.18	29.0%	17.75	17.95	1.1%
Diosa	2.51	0.01	0.00	-77.2%	4.33	7.16	65.4%
Grolsch	10.38	0.52	0.13	-74.8%	12.40	15.55	25.4%
Isenbeck Blanca	5.71	2.67	0.20	-92.5%	7.57	13.13	73.5%
Isenbeck Dark	8.63	0.03	0.00	-92.5%	10.50	16.06	53.0%
Miller	9.47	0.76	0.19	-74.8%	11.49	14.64	27.4%
Miller Lite	4.41	0.00	0.00	-74.8%	6.43	9.58	49.0%
Warsteiner	10.42	0.68	0.17	-74.8%	12.44	15.59	25.3%

Table 29: Merger simulation results: Scenario (b). Nested Logit per brand.

Firm	M. costs	Shares		% Shares	Prices		% prices
		Pre-	Post-		Pre-	Post-	
Andes Blanca	1.54	1.59	1.65	3.7%	8.14	8.68	6.6%
Andes Porter	2.16	0.16	0.16	3.7%	8.76	9.30	6.2%
Andes Red Lager	1.09	0.00	0.00	3.7%	7.69	8.23	7.0%
Báltica	0.30	0.03	0.02	-31.3%	4.88	12.98	166.1%
Brahma Chopp	0.81	27.00	28.00	3.7%	7.41	7.95	7.3%
Corona	15.97	1.23	1.30	5.4%	20.56	20.81	1.2%
Iguana	0.95	2.56	1.76	-31.3%	5.53	13.64	146.6%
Iguana Summer*	4.77	0.49	0.00	-100.0%	11.37	1281.22	11172.5%
Negra Modelo	20.74	0.01	0.01	5.4%	25.33	25.59	1.0%
Norte*	0.46	0.80	0.00	-100.0%	7.06	1278.72	18015.2%
Norte Porter*	-0.02	0.00	0.00	-100.0%	6.58	1267.39	19149.9%
Patagonia	14.16	0.66	0.69	5.4%	18.75	19.00	1.3%
Patagonia Küné	12.76	0.23	0.24	5.4%	17.35	17.60	1.5%
Quilmes 1890	2.99	1.10	1.14	3.7%	9.59	10.13	5.6%
Quilmes Bajo Cero	0.22	2.81	2.91	3.7%	6.82	7.36	7.9%
Quilmes Bock	3.87	1.01	1.05	3.7%	10.47	11.01	5.2%
Quilmes Cristal	1.81	24.72	28.00	13.3%	8.41	8.95	6.4%
Quilmes Lieber	0.81	0.32	0.33	3.7%	7.41	7.95	7.3%
Quilmes Night	1.98	0.01	0.01	3.7%	8.57	9.11	6.3%
Quilmes Stout	3.50	2.64	2.73	3.7%	10.10	10.64	5.3%
Stella Artois	9.69	7.07	7.45	5.4%	14.29	14.54	1.8%
Stella Artois Noire	9.31	0.72	0.76	5.4%	13.90	14.15	1.8%
Amstel	7.10	0.23	0.23	1.4%	9.47	9.80	3.4%
Bieckert	3.24	0.04	0.01	-75.3%	5.97	15.92	166.6%
Budweiser	5.02	5.65	0.50	-91.1%	7.19	12.16	69.0%
Córdoba	4.24	0.47	0.64	36.2%	6.41	6.46	0.8%
Guinness	39.71	0.00	0.00	1.4%	42.08	42.41	0.8%
Heineken	9.66	3.82	3.87	1.4%	12.03	12.35	2.7%
Imperial Cream Stout	8.15	0.39	0.53	36.2%	10.33	10.38	0.5%
Imperial Lager	7.50	1.42	1.93	36.2%	9.67	9.72	0.5%
Imperial Red Lager	7.00	0.17	0.23	36.2%	9.17	9.22	0.5%
Imperial Scotch Ale	7.10	0.11	0.15	36.2%	9.28	9.32	0.5%
Imperial Weissbier	6.96	0.08	0.11	36.2%	9.14	9.19	0.5%
Kunstmann	22.05	0.01	0.02	1.4%	24.42	24.75	1.3%
Palermo	2.90	1.58	0.39	-75.3%	5.63	15.58	176.7%
Salta Negra	6.40	0.21	0.29	36.2%	8.57	8.62	0.6%
Salta Rubia	5.09	0.51	0.69	36.2%	7.26	7.31	0.7%
Santa Fe Frost	4.37	1.00	1.36	36.2%	6.54	6.59	0.7%
Santa Fe Lager	5.01	0.08	0.11	36.2%	7.18	7.23	0.7%
Santa Fe Stout	5.30	0.07	0.09	36.2%	7.47	7.52	0.6%
Schneider	4.87	4.22	5.74	36.2%	7.05	7.10	0.7%
Schneider Negra	5.04	0.01	0.01	36.2%	7.22	7.27	0.7%
Sol	15.38	0.14	0.14	1.4%	17.75	18.08	1.8%
Diosa	2.51	0.01	0.00	-85.2%	4.33	15.20	251.2%
Grolsch	10.38	0.52	0.43	-16.4%	12.40	13.07	5.4%
Isenbeck Blanca	5.71	2.67	3.06	14.7%	7.57	7.93	4.7%
Isenbeck Dark	8.63	0.03	0.04	14.7%	10.50	10.85	3.4%
Miller	9.47	0.76	0.63	-16.4%	11.49	12.16	5.8%
Miller Lite	4.41	0.00	0.00	-16.4%	6.43	7.10	10.4%
Warsteiner	10.42	0.68	0.57	-16.4%	12.44	13.11	5.4%

* The large price increase means that these brands should be discontinued

Table 30: Merger simulation results: Scenario (a). Random Coefficients Logit per brand.

Firm	M. costs	Shares		% Shares	Prices		% prices
		Pre-	Post-		Pre-	Post-	
Andes Blanca	6.05	1.59	1.48	-7.1%	8.14	8.56	5.2%
Andes Porter	7.32	0.16	0.16	3.9%	8.76	8.80	0.4%
Andes Red Lager	6.53	0.00	0.00	17.6%	7.69	7.65	-0.5%
Báltica	3.77	0.03	0.03	1.5%	4.88	4.93	1.0%
Brahma Chopp	5.15	27.00	27.32	1.2%	7.41	7.85	5.9%
Corona	18.72	1.23	1.31	5.9%	20.56	20.58	0.1%
Iguana	4.12	2.56	2.23	-12.9%	5.53	5.77	4.3%
Iguana Summer	9.82	0.49	0.52	5.3%	11.37	11.39	0.2%
Negra Modelo	23.40	0.01	0.01	2.6%	25.33	25.34	0.0%
Norte	5.61	0.80	0.81	2.4%	7.06	7.14	1.2%
Norte Porter	5.32	0.00	0.00	2.1%	6.58	6.63	0.7%
Patagonia	16.99	0.66	0.71	7.3%	18.75	18.77	0.1%
Patagonia Küné	15.69	0.23	0.24	4.9%	17.35	17.35	0.0%
Quilmes 1890	7.97	1.10	1.17	7.1%	9.59	9.64	0.6%
Quilmes Bajo Cero	5.06	2.81	2.35	-16.4%	6.82	7.20	5.5%
Quilmes Bock	8.82	1.01	1.09	8.1%	10.47	10.52	0.5%
Quilmes Cristal	5.26	24.72	25.56	3.4%	8.41	8.84	5.1%
Quilmes Lieber	5.79	0.32	0.31	-3.9%	7.41	7.58	2.4%
Quilmes Night	7.01	0.01	0.01	5.5%	8.57	8.64	0.8%
Quilmes Stout	8.46	2.64	2.84	7.7%	10.10	10.15	0.5%
Stella Artois	12.53	7.07	7.79	10.2%	14.29	14.36	0.5%
Stella Artois Noire	12.22	0.72	0.79	9.5%	13.90	13.93	0.2%
Amstel	8.66	0.23	0.27	20.4%	9.47	9.49	0.2%
Bieckert	5.25	0.04	0.04	7.4%	5.97	5.99	0.2%
Budweiser	6.44	5.65	0.48	-91.5%	7.19	9.18	27.6%
Córdoba	5.67	0.47	0.53	12.6%	6.41	6.43	0.3%
Guinness	40.25	0.00	0.00	2.4%	42.08	42.08	0.0%
Heineken	11.17	3.82	6.97	82.4%	12.03	12.05	0.2%
Imperial Cream Stout	9.51	0.39	0.47	19.9%	10.33	10.35	0.2%
Imperial Lager	8.86	1.42	1.96	38.1%	9.67	9.69	0.2%
Imperial Red Lager	7.95	0.17	0.18	6.0%	9.17	9.20	0.3%
Imperial Scotch Ale	8.03	0.11	0.12	6.0%	9.28	9.31	0.3%
Imperial Weissbier	8.34	0.08	0.09	13.3%	9.14	9.16	0.2%
Kunstmann	23.41	0.01	0.02	3.7%	24.42	24.42	0.0%
Palermo	4.91	1.58	1.77	12.3%	5.63	5.65	0.3%
Salta Negra	7.78	0.21	0.23	7.9%	8.57	8.58	0.1%
Salta Rubia	6.49	0.51	0.62	21.7%	7.26	7.28	0.2%
Santa Fe Frost	5.80	1.00	1.07	7.6%	6.54	6.56	0.2%
Santa Fe Lager	6.42	0.08	0.10	21.8%	7.18	7.20	0.2%
Santa Fe Stout	6.71	0.07	0.07	7.8%	7.47	7.48	0.2%
Schneider	6.29	4.22	7.74	83.5%	7.05	7.06	0.2%
Schneider Negra	6.46	0.01	0.01	7.9%	7.22	7.23	0.2%
Sol	16.88	0.14	0.15	9.2%	17.75	17.76	0.0%
Diosa	3.71	0.01	0.00	-54.6%	4.33	4.90	13.2%
Grolsch	11.67	0.52	0.07	-85.8%	12.40	14.15	14.1%
Isenbeck Blanca	6.94	2.67	0.13	-95.0%	7.57	9.92	31.0%
Isenbeck Dark	9.76	0.03	0.01	-64.3%	10.50	11.34	8.1%
Miller	10.76	0.76	0.09	-88.7%	11.49	13.45	17.0%
Miller Lite	5.76	0.00	0.00	-62.0%	6.43	7.16	11.4%
Warsteiner	11.69	0.68	0.09	-87.4%	12.44	14.36	15.4%

Table 31: Merger simulation results: Scenario (b). Random Coefficients Logit per brand.

Firm	M. costs	Shares		% Shares	Prices		% prices
		Pre-	Post-		Pre-	Post-	
Andes Blanca	6.05	1.59	1.38	-13.0%	8.14	8.36	2.7%
Andes Porter	7.32	0.16	0.17	7.4%	8.76	8.61	-1.7%
Andes Red Lager	6.53	0.00	0.00	5.7%	7.69	7.60	-1.1%
Báltica	3.77	0.03	0.04	56.1%	4.88	4.53	-7.1%
Brahma Chopp	5.15	27.00	25.22	-6.6%	7.41	7.65	3.2%
Corona	18.72	1.23	1.25	1.0%	20.56	20.42	-0.7%
Iguana	4.12	2.56	6.66	159.9%	5.53	4.92	-11.1%
Iguana Summer	9.82	0.49	1.00	104.6%	11.37	10.72	-5.7%
Negra Modelo	23.40	0.01	0.01	-0.3%	25.33	25.20	-0.5%
Norte	5.61	0.80	1.80	125.9%	7.06	6.45	-8.7%
Norte Porter	5.32	0.00	0.00	78.8%	6.58	6.12	-7.1%
Patagonia	16.99	0.66	0.68	2.6%	18.75	18.60	-0.8%
Patagonia Küné	15.69	0.23	0.23	0.0%	17.35	17.22	-0.7%
Quilmes 1890	7.97	1.10	1.22	10.9%	9.59	9.41	-1.9%
Quilmes Bajo Cero	5.06	2.81	2.38	-15.3%	6.82	6.95	2.0%
Quilmes Bock	8.82	1.01	1.11	10.4%	10.47	10.29	-1.7%
Quilmes Cristal	5.26	24.72	25.35	2.5%	8.41	8.55	1.7%
Quilmes Lieber	5.79	0.32	0.33	2.7%	7.41	7.32	-1.2%
Quilmes Night	7.01	0.01	0.01	11.4%	8.57	8.40	-2.0%
Quilmes Stout	8.46	2.64	2.91	10.5%	10.10	9.92	-1.8%
Stella Artois	12.53	7.07	7.70	9.0%	14.29	14.13	-1.1%
Stella Artois Noire	12.22	0.72	0.78	7.4%	13.90	13.73	-1.2%
Amstel	8.66	0.23	0.17	-25.5%	9.47	9.58	1.1%
Bieckert	5.25	0.04	0.03	-20.9%	5.97	6.05	1.2%
Budweiser	6.44	5.65	0.43	-92.4%	7.19	8.93	24.2%
Córdoba	5.67	0.47	0.35	-25.3%	6.41	6.51	1.5%
Guinness	40.25	0.00	0.00	-8.8%	42.08	42.08	0.0%
Heineken	11.17	3.82	4.57	19.7%	12.03	12.09	0.5%
Imperial Cream Stout	9.51	0.39	0.29	-26.2%	10.33	10.44	1.1%
Imperial Lager	8.86	1.42	1.22	-14.3%	9.67	9.77	0.9%
Imperial Red Lager	7.95	0.17	0.14	-14.5%	9.17	9.22	0.5%
Imperial Scotch Ale	8.03	0.11	0.10	-14.9%	9.28	9.32	0.5%
Imperial Weissbier	8.34	0.08	0.06	-26.4%	9.14	9.24	1.1%
Kunstmann	23.41	0.01	0.01	-21.1%	24.42	24.51	0.3%
Palermo	4.91	1.58	1.18	-25.1%	5.63	5.73	1.7%
Salta Negra	7.78	0.21	0.16	-22.4%	8.57	8.65	0.9%
Salta Rubia	6.49	0.51	0.39	-23.3%	7.26	7.36	1.4%
Santa Fe Frost	5.80	1.00	0.79	-21.1%	6.54	6.62	1.1%
Santa Fe Lager	6.42	0.08	0.06	-23.2%	7.18	7.28	1.4%
Santa Fe Stout	6.71	0.07	0.05	-21.6%	7.47	7.55	1.0%
Schneider	6.29	4.22	4.98	18.2%	7.05	7.10	0.7%
Schneider Negra	6.46	0.01	0.01	-21.5%	7.22	7.29	1.0%
Sol	16.88	0.14	0.11	-24.6%	17.75	17.85	0.5%
Diosa	3.71	0.01	0.01	-28.4%	4.33	4.46	3.2%
Grolsch	11.67	0.52	0.42	-18.8%	12.40	12.64	1.9%
Isenbeck Blanca	6.94	2.67	2.88	8.1%	7.57	7.73	2.0%
Isenbeck Dark	9.76	0.03	0.02	-31.7%	10.50	10.67	1.6%
Miller	10.76	0.76	0.72	-4.8%	11.49	11.70	1.8%
Miller Lite	5.76	0.00	0.00	-30.0%	6.43	6.58	2.3%
Warsteiner	11.69	0.68	0.63	-7.1%	12.44	12.66	1.8%

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