

Bayesian Beer Market Estimation

Simulating Nash Equilibrium Market Outcomes with
Bayesian Analysis of Choice-Based Conjoint Data

Term Paper

submitted to

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1 Introduction and a Primer on the Beer Market

Which beer would Thomas Bayes, the famous philosopher and statistician that first described Bayes' Theorem (Bayes 1763) prefer? Though a particular preference by Bayes for a certain product cannot be inferred and this question remains unanswered by the present study, modern Bayesian methods provide a sophisticated way to estimate today's customers' individual preferences based on their choices. This paper uses Bayesian methods applied on choice-based conjoint (CBC) data to simulate Nash equilibrium market outcomes in the beer market. The remainder is structured as follows: First, this section introduces the beer market and the assumptions necessary for further analysis. Then, section 2 motivates the analytical model, while chapter 3 introduces the data set and hypothesizes the expected relationships between the market simulation metrics. The paper then introduces the heterogeneous MNL model with BLP-type indirect utilities and presents its results (section 4), followed by a discussion of the resulting beer market simulation. The last section concludes by discussing managerial and research implications that can be derived from the present analysis.

The leading international breweries today face the challenges of decreasing beer consumption in Europe, new trends such as craft beer and increased regulatory pressure (JP Morgan 2018). The second largest brewery worldwide after Anheuser-Busch InBev is Heineken, owning more than 300 brands including well-known ones such as Amstel (Heineken 2019). To counter the threads by the aforementioned trends, Heineken can merge with other beer brands to incrementally increase their profits through leveraging higher price setting power due to market consolidation. Though Heineken already acquired Amstel in 1968 (Oliver & Colicchio 2011, p. 49), this paper looks at the merger from today's perspective. The goal of this research is to assess whether a merger of Heineken and Amstel, based on today's customer preferences and market conditions would still be considered beneficial. Towards this end, the present study subsequently derives the producer surplus of Heineken and Amstel before and after the merger and compares that to a potential merger of Heineken with another national brand, Estrella.

2 The Necessity of Enhancing the Standard MNL Model

Historically, marketing research has heavily relied on Conjoint Analysis as a tool to measure consumers' preferences by asking them to choose between different products that imply trade-offs (Green & Srinivasan 1990). This is a method to derive consumers' preferences in a more credible way than to ask them which brand or feature they prefer, since this often yields trivial results¹. Choice-based conjoint data enables researchers to calculate counterfactual scenarios, such as what happens to a company's market share if a competitor changes its price (Huber et al. 2001). To analyze choice-based conjoint data, market research has focused on the Multinomial Logit (MNL) Model. Unfortunately, the MNL model is based on two strong and unrealistic assumptions (Elrod et al. 1992). First, choices should be independent of irrelevant alternatives (IIA). This means that consumer's choices are not influenced by the presence or absence of another, supposedly irrelevant other choice option. However, numerous examples have been constructed to easily show that this assumption is often violated, most famously the blue and red bus example by McFadden (1973). Especially for substitute products, this assumption therefore does not hold. Modeling very similar choices with a traditional MNL model is hence not desirable. The second strong assumption that is required for MNL estimation is homogeneity in preferences across consumers. This implies that consumer's preferences—expressed by the beta coefficients—are identical for all consumers, which does not hold in reality. Literature has acknowledged those violations and proposed the heterogeneous MNL, a more flexible model that relaxes the IIA assumption and allows for differences in preferences by modeling individual MNL models for every single customer (Steckel & Vanhonacker 1988).

When taking the beta coefficients from this hierarchical MNL model to simulate individual choices as well as aggregate market outcomes and equilibrium prices, the standard approach was to assume that all prices in the choice set were within the consumer's unobserved budget. Pachali et al. (2017b) argue that this simplification can lead to a

¹i.e. preferring the cheap vs. the expensive good or valuing the better quality good more than the low quality product.

serious over-estimation of equilibrium prices. They claim that this is still the case if priors such as sign constraints are included and reasonably specified in the estimation as by Sonnier et al. (2007) and Allenby et al. (2014). Instead of manipulating the data a priori until derived estimates mirror the desired price ranges, this paper follows Pachali et al. (2017b) and applies a model specification which is capable of inferring previously unobserved budgets additionally to sign constraints for β_{price} . To that matter, the present study implements the indirect utility model by Berry et al. (1995). It is superior to the price screening model proposed by Gilbride & Allenby (2004), since it models a continuous choice probability dependent on price. Logit choice probabilities need to be continuous at every draw in order to derive a pure-strategy Nash equilibrium (Morrow & Skerlos 2011, Pachali et al. 2017b).

Concluding this section, the analytical model implemented in this study addresses three serious shortcomings of most common methods to conduct a market simulation and derive profit-maximizing prices. It relaxes the IIA assumption, allows for heterogeneous individual-level consumer preferences, and infers unobserved budgets. Those three model specifications are believed to yield more realistic and less biased estimates (Chandukala et al. 2008, Pachali et al. 2017b).

3 Exogenous Variables and Expected Relationships

While the previous section motivated the analytical model and presented model extensions to relax unrealistic assumptions, this part introduces the empirical application of those tools. This paper analyzes a choice-based conjoint data set for choices among different beer brands obtained by the market research institute Kantar TNS. The data set recorded preferences for canned beer presumably in the Spanish market. $N = 407$ respondents participated in the study and chose among $p = 10$ alternatives per choice task (nine beer brands and one outside option). Every participant performed $t = 15$ choice tasks. In total, 15 distinct beer brands and one outside alternative were included in the study, while the subjects were only presented with a subset of p alternatives, always including the outside alternative (i.e. no purchase). The data set consists multiple brands of the same brewery—four Amstel beers and two Estrella and Mahou beers

each. The remaining seven beer brands based on their brand names are assumed to belong to different companies. Additionally to the brand names, the price was displayed to the subjects, which ranged from 0.22 to 0.74 €.

Consistent with economic theory, there should be a negative relationship between price and demand. The less competition and hence more market power is present, the higher should be the prices, which should come with less demand for beer. Demand is measured in relative market share in this model, which means a decrease in the inside goods' shares should come with an increase in the outside option's share (i.e. more consumers drop out of the market and do not purchase any product). Besides price and market share, profit is the most important metric that is optimized by the individual players in the market. Though there is a clear intuition how prices and market shares develop dependent on the competitive scenario, no trivial statement can be made about profits. With higher prices comes usually a lower market share—thus we cannot tell a priori which effect should have a stronger impact on profits. To come up with an estimate for profits, this study assumes constant marginal costs of 0.192 € per 0.33 cl can across all producers. This estimation is based on Heineken's costs reported in the 2018 annual report (Heineken 2019). The author assumes the data set to be ten years old, hence the 2018 variable costs are discounted by the compounded average inflation rate of the last decade. Since standard beer consists of the same ingredients and the degree of economies of scale is assumed to not differ significantly between the considered subset of large breweries, Heineken's marginal costs are assumed to be a good approximation for all other brands' marginal costs.

Profit will then be used to calculate the producer surplus before and after the Heineken–Amstel merger. This metric enables an assessment whether there is any incremental profit to this transaction. Since the preferences for Heineken and Amstel are most similar² in the considered subset of the market, the expected incremental profit of a merger between Heineken and Amstel should be higher than the sum of individual profits of a merger between brands that have less correlated preferences, such as Heineken and Estrella. While the next section introduces the underlying analytical model and its

²see section 4 for the beta coefficients of the individual brands and their interpretation

result, detailed market simulation outcomes are discussed in section 5.

4 Model Description and Results

Based on the motivation for the analytical model described in section 2, this section first discusses the implemented model and then presents its results. This study uses a heterogeneous MNL model and utilizes Bayesian methods to generate the individual-level beta coefficients and the specification of the prior distribution. One of the assumptions of the standard MNL model is homogeneity in preferences across all consumers. To allow for different preferences, every consumer needs to be described by an individual MNL model. However, since every participant only recorded $t = 15$ choice tasks, there are not enough observations to reliably estimate such a model. That is why this study uses Bayesian estimation with the Markov Chain Monte Carlo (MCMC) routine to sample the individual-level betas and estimate the parameters for the prior distribution.

The resulting beta coefficients are a measure of customer preferences—a greater beta translates to a higher preference for a product, while a negative value implies dis-utility from that good for the consumer. The distribution of betas can then be used to compute market shares either based on posterior means, the posterior of the hierarchical prior, or the lower-level non-smooth model (Pachali et al. 2017*a*). This paper makes use of the latter, since the first two methods have serious shortcomings and the latter combines the advantages from both methods. Using the posterior means as an estimate for beta ignores posterior uncertainty and focuses too much on the middle of the market. Optimal products will therefore tend to concentrate around the mean preferences without much differentiation between brands because it underestimates the preference heterogeneity in the population. The second method—drawing from the hierarchical prior—relies too much on the assumptions about the distributional parameters. According to Pachali et al. (2017*a*), the lower-level non-smooth method generally outperforms the first two approaches and has more desirable characteristics.

While most market simulations do not account for consumer’s budget, this study uses a heterogeneous MNL model with BLP-type indirect utility (Berry et al. 1995), that

accounts for budgets inferred from choices and the minimum and maximum price chosen as proposed by Pachali et al. (2017b). Since the probability function from this model is differentiable, one can use the derivatives-based fixed point approach for a relatively quick estimation (Morrow & Skerlos 2011).

The implemented model constrains the beta coefficients for price and budget. Both are restricted to positive values only, which makes the model much more realistic. Usually one would assume the price coefficients to be negative only, however in the BLP-type specification there is a reward for not using up the entire budget. Hence, β_{price} must be positive (Pachali et al. 2017b). In some cases, it makes sense to additionally impose ordinal constraints on the betas among brands. This would be beneficial if there were a clear and strict preference for individual specifications of the products in question (i.e. a higher quality *ceteris paribus* is always more desirable). For this particular beer data set, this cannot reasonably be justified, since there is no objective order of beers.

This part described the implemented heterogeneous MNL model with BLP-type indirect utility. The remainder of this section focuses on the model results and specifically discusses the estimated distributions of the beta coefficients. To estimate the betas, the MCMC routine ran for 100,000 iterations, while keeping every 15th draw. This led to the loglikelihood values displayed in figure 1. After removing the first 3,100 values as burn-in, from a visual inspection one can assume that the algorithm converged—the time series appears to be stationary in figure 2.

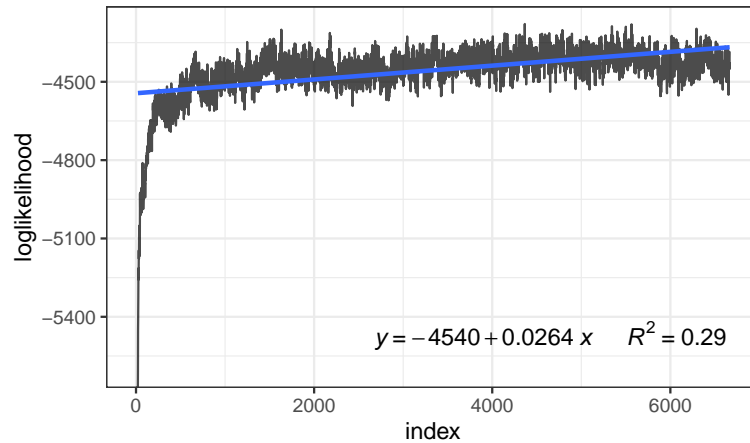


Figure 1: Loglikelihood values of the MCMC routine with 100,000 iterations, keeping every 15th draw

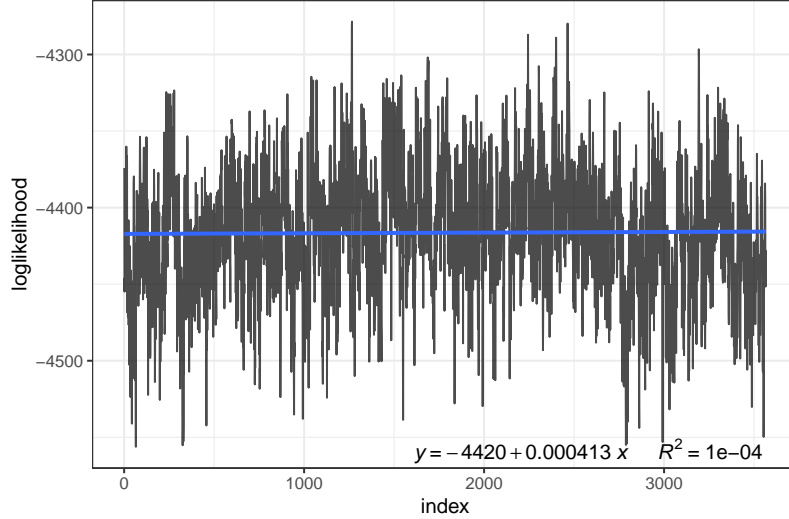


Figure 2: Loglikelihood values of the MCMC routine, after removing the first 3,100 observations

The model yields the distribution of betas for all 15 brands as well as for budget and price. Since the thorough analysis of 17 coefficients would be beyond the scope of this paper, only five presumably interesting brands³ were analyzed in detail. The results for the entire data set can be found in the appendix in figures 8 and 9. A beta distribution with more probability mass in the positive domain of the density plot relative to others indicates that this brand is more preferred by the average customer. Looking at the density plot for the beta coefficients of the five select beers (figure 3), there are some interesting differences in preferences: First, Heineken has the highest mean and its distribution is visibly shifted to the right, compared to the other brands. This indicates a higher preference for Heineken given identical prices for the average customer. Secondly, both Estrella brands have less variant beta distributions, which hints at a less heterogeneous consumer segment. On the other hand, both Amstel beers are characterized by high variance distributions with most probability mass in the negative domain, compared Estrella and Heineken. That means that Amstel is the least preferred beer for many consumers in this subset and even comes with dis-utility for those customers having $\beta_i < 0$.

The density plot reveals very similar preferences for both Amstel beers. It is therefore interesting to have a look at the bivariate density plot that displays their joint beta

³Amstel Clasica Lata, Amstel Extra Lata, Estrella Damm Lata, Estrella Galicia Lata and Heineken

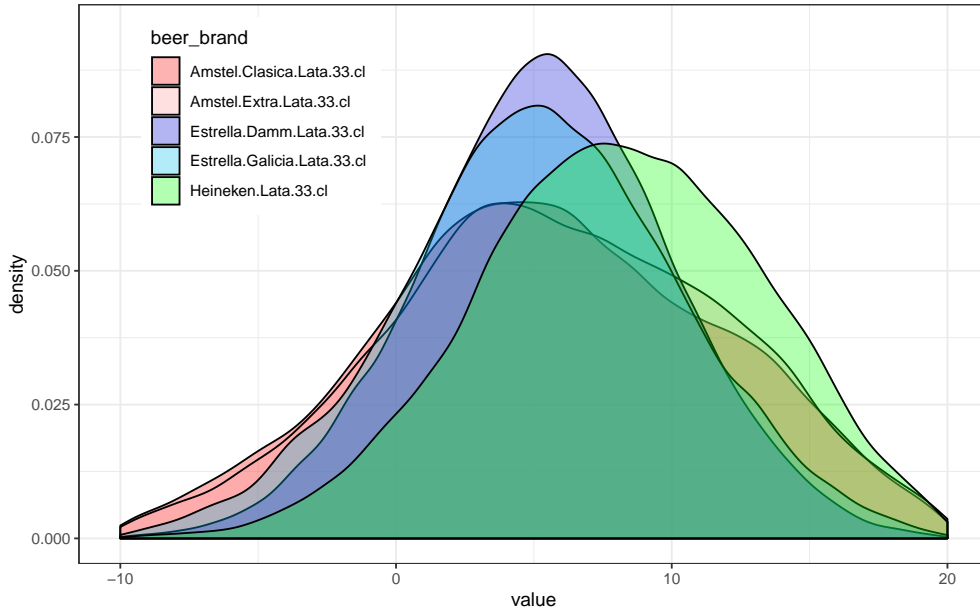


Figure 3: Density plot for betas of five distinct brands

distribution. Figure 4 reveals that there is a slightly higher preference in the sample for Amstel Extra Lata compared to Amstel Clasica Lata. This finding will subsequently explain large price discrepancies between those brands in a monopoly (see section 5).

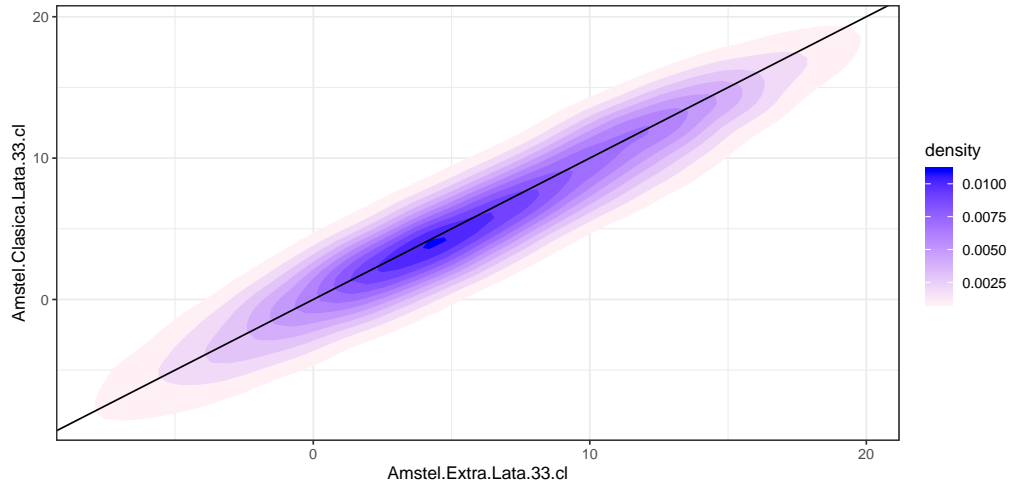


Figure 4: Bivariate density plot for two Amstel brands displaying slightly higher preferences for Amstel Extra Lata

Not only the density plots of beta distributions are of interest—their similarity in terms of correlation can quantify how similar preferences for individual brands are compared to another one. The higher the correlation between two brands, the more similar are customers' preferences for those two beers. Most importantly, this implicates that there

is a high price-competition between those brands. If there is a high correlation between preferences, customers regard two brands as good substitutes and therefore are mainly guided by the beer's price in their purchase decision. Turning to the subset of beers at hand, the two Amstel brands are almost perfectly correlated ($\rho = 0.95$), followed by a correlation coefficient of 0.72 and 0.75 for the Amstel brands with Heineken. This provides a first clue that Amstel and Heineken find themselves in a strong price competition, because they serve similar customers. Contrary to that, a low correlation between the two beta coefficients implies that those brands compete less price-wise, since they serve different segments of the market. Especially noteworthy is that Estrella has the least correlated beta distributions compared to all other brands, which indicates that they compete least for similar customers compared to Heineken and Amstel.

Lastly, the correlation matrix also displays the correlation of betas for beer brands with betas for price. This is an indicator how sensitive customers are to price changes. Interestingly, customers of Estrella Galicia Lata are found to be almost completely price insensitive ($\rho = 0.02$), while Heineken's customers are most influenced by price changes ($\rho = 0.52$). All else equal, a price increase by Heineken will cause a greater customer churn than the same price increase for Estrella, since the latter's customers are least price sensitive and might be influenced mainly in their purchasing decision by quality rather than price.

5 Simulating Nash Equilibria in Four Different Market Scenarios

However interesting the beta coefficients as measures of preferences might be, they do not serve as an intuitive metric and only provide a very abstract economic interpretation in terms of preferences. To enhance the usefulness of the hierarchical Bayesian MNL model, the resulting distributions of beta coefficients can be translated into Nash equilibrium prices, shares and profits. This section describes the beer market simulation and its results for the relevant subset of five brands in four different scenarios from full competition to monopoly. A focus will be set on the difference between the two scenarios in the middle: brand competition and merge competition, where the first

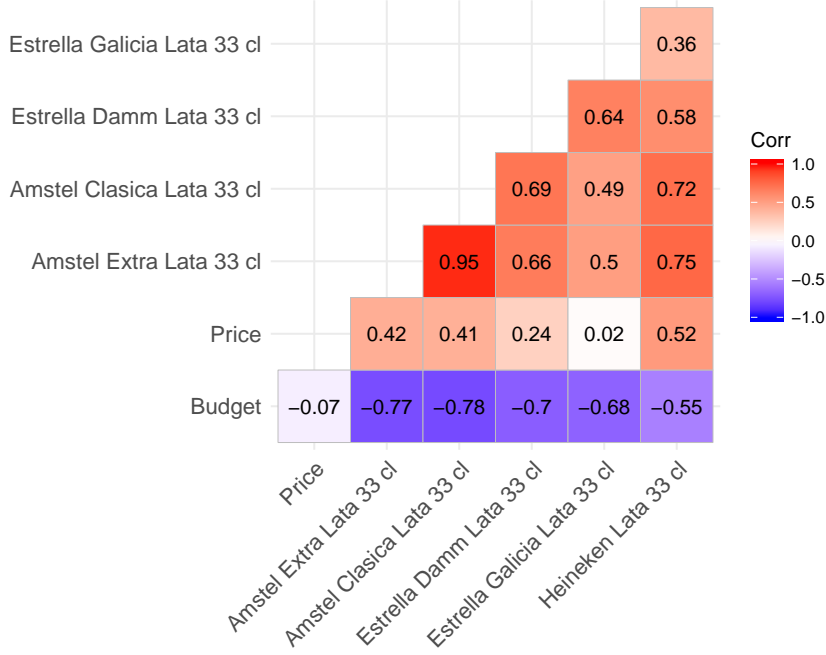


Figure 5: Correlation of betas for price, budget and five brands

refers to a market environment before the Heineken–Amstel merger and the latter to a duopoly in which Heineken–Amstel only competes against Estrella.

To compare the different scenarios, three metrics are calculated: First, dynamic Nash equilibrium prices p_i , which refer to the i^{th} beer’s profit-optimal price. Equilibrium price in this case means that a deviation for all players from its respective price would no longer result in a higher profit. Based on that, the market shares MS_i are computed for all brands as well as for the outside good (i.e. consumers choose to not purchase any beer). Combining price and market share with marginal costs⁴ enables the calculation of the product of contribution margin and market share, which is proportional to profits⁵:

$$Profit_i \propto (p_i - MC) * MS_i = CM_i * MS_i$$

Those three metrics provide a clear overview over market outcomes on individual brand level. However, it is also of high interest to quantify the aggregate market result, which

⁴as stated in section 3, this study assumes constant marginal costs of $MC = 0.192 \text{ €}$ across all products.

⁵no assumption about the market size is made. A simple multiplication of the market size with the formula above would yield profits.

can be achieved by computing the weighted average price in the market

$$\bar{p}_m = \sum_{i=1}^n p_i * MS_i,$$

where m describes the market situation and n refers to the number of players plus one outside good at $p_{outside} = 0$. By including the outside share at a price of 0, this metric quantifies a trade-off between the beers' prices and the outside share. Higher market power leads to two changes that adversely affect \bar{p} : First, individual prices increase leading to an increase in \bar{p} . Second, the outside share increases since some customers drop out of the market, which comes with lower inside shares and hence causes \bar{p} to decrease. If the weighted average price remained constant after a merger in the market, that means the increase in individual prices is compensated by the increase in the outside share. This enables a conclusion about which effect dominates in certain situations.

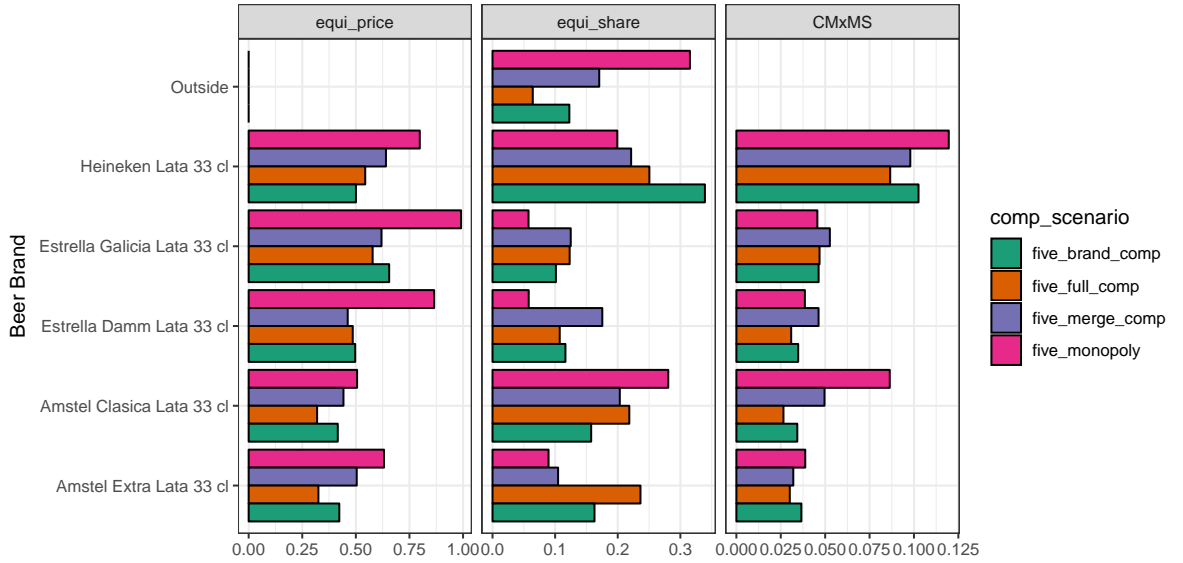


Figure 6: Prices and market shares in a profit-maximizing Nash equilibrium for five brands and outside option in a brand competition vs. merge setting

Figure 6 visualizes the market outcomes in terms of prices, market shares and profits for each of the four market scenarios. Overall, the results appear to be in line with economic theory. The remainder of this section discusses the individual market scenario outcomes and its implications. Assuming full competition (i.e. all brands compete against each other), prices for most individual brands as well as \bar{p} are lowest. As

expected, lowest prices come with the lowest outside share of 6.4%. It is interesting to note that Heineken's price is in between Amstel's (lower) and Estrella's prices (higher). Even though it is more than 20 cents pricier than Amstel's two beers, its market share at 25% is the highest among all beers. This result is in line with the distribution of the model's beta coefficients. The average consumer prefers Heineken over all other brands and Amstel is the least preferred brand. It is therefore not surprising that even though Heineken charges higher prices than Amstel, its market share is higher.

Now assume competition according to the beer brands, i.e. both Amstel beers, both Estrella beers, and Heineken each belong to a different owner (brand competition). In this market of three players, weighted average prices increase from 0.41 to 0.43 € despite a rise in the outside share by nearly six percentage points. A look at the individual prices suggests that thanks to its greater market power, Amstel increases their prices to nearly match Heineken's. Remember that the correlation between the betas of Heineken and Amstel is relatively high, which means they serve similar customer segments and hence price compete strongly. Still, Heineken's beta distribution is shifted to the right of Amstel's distributions⁶, which means that consumers on average prefer Heineken over Amstel. Since the prices of the three brands are now more similar than before, this translates to a drastic increase in Heineken's market share to more than one third of the entire market and a modest decrease in both Amstel's shares by around seven percentage points each.

The research question whether a merger between Heineken and Amstel would yield an incremental profit beyond the sum of the individual profits can now be answered by changing the ownership matrix so that those three beers belong to the same owner and thus not price compete anymore. This market is now a duopoly with two players (Heineken together with Amstel vs. Estrella) and referred to as the merge competition scenario. Table 1 displays the weighted average price and the producer surplus before and after the merger and quantifies the absolute and relative difference between those two scenarios. While \bar{p} increases by 3.3%, the producer surplus even increases by 3.5%. This represents the incremental profit due to higher market consolidation and

⁶see figure 4 for the beta distribution density plots of the five beers.

Table 1: Weighted average prices in the entire market and producer surplus for three merged brands before vs. after the merger

	\bar{p} (€)	PS_m (€)
Before merger	0.428	0.173
After merger	0.442	0.180
Δ	+0.014	+0.007
$\Delta\%$	+3.3%	+3.5%

less price competition with beer brands that targeted similar-preference customers. The sole competitor Estrella’s relative market power compared to the new Amstel–Heineken firm decreases. Nevertheless, thanks to the consolidation, its absolute market power appears to increase. Though their prices remain relatively constant, their profits increase due to a higher market share. This is counter-intuitive at first—but has a logical explanation. Looking at the distribution of beta coefficients in figure 3, it becomes clear that preferences are higher for Estrella than for Amstel, on average. As Amstel’s prices in this scenario approach Estrella’s, the latter becomes more attractive which leads to higher market shares and profits for both Estrella beers. In line with expectations, the outside share further increases to 17% in the duopoly.

Based on the highest correlation of Heineken’s with Amstel’s preference coefficients, the incremental profit of a potential Heineken–Amstel merger was expected to be higher than a merger between brands that serve less similar consumers according to their preferences. However, the market simulation does not support that claim. While Heineken together with Amstel generates an additional producer surplus of 3.5%, a merger of Heineken with the other competitor Estrella increases the sum of individual profits by 9.4%. The hypothesized influence of preference similarity on the incremental profits of a merger might be overruled by other market dynamics. One possible explanation might be related to the brands’ different customer segments. While Heineken’s and Estrella’s prices in the brand competition scenario are similar, a merger between them would result in significantly higher prices for Estrella’s brands. This could enable a stronger customer segmentation where Estrella better captures the potential of the high-value customers, while Heineken presents itself as the preferred alternative for

the medium-value customers. Judging from the market simulation, this segmentation might be a factor that leads to a higher incremental profit of a Heineken–Estrella merger compared to a Heineken–Amstel merger, even though the latter two brands previously find themselves in higher price competition.

While the first scenario represented one extreme market constellation—full competition—the last one scrutinizes the other extreme—a monopoly. As expected, all individual prices increase and are highest among all four scenarios. This translates in a weighted average price of 0.46 €, even though almost one third of the consumers drop out of the market. Interestingly, while all individual prices increase, the individual profits do not rise by the same magnitude due to a significant decrease in market share for most brands. Notably, the cheapest beer in this scenario is one exception to that. Amstel Clasica Lata at $p = 0.50$ € increases its profits by almost 75% compared to the duopoly, while Amstel Extra Lata’s profits only increase marginally. This could be explained by the slightly higher preference of the average consumer for Amstel’s Extra Lata beer over Clasica Lata visualized in the bivariate density plot of preferences for both brands in figure 4. Since there is no competition anymore, the firm uses this slight preference for Extra Lata and exploits the consumers’ higher willingness to pay for the more preferable beer, while the remaining Amstel Clasica Lata captures all consumers that would otherwise have dropped out of the market.

This section described the outcomes in particular market scenarios and compared them to each other. However, it is still lacking a general statement about the hypothesized relationship between price and market share (i.e. demand). Section 3 stated that according to standard economic theory, a higher price should be associated with lower demand. To check this hypothesis, figure 7 displays a price–market share scatterplot of all inside good market outcomes over the four market scenarios with five beer brands.

The negative beta coefficient ($\beta_1 = -0.22$) in a simple linear regression model described by $MS_i = \beta_0 + \beta_1 * price_i + \epsilon$ suggests that this expected relationship is also reflected in the simulated market outcomes. This is in line with the imposed constraints on the beta coefficients for price in the MNL model. Those were assumed to be strictly positive in order to model a reward for not using up the entire budget in the BLP-

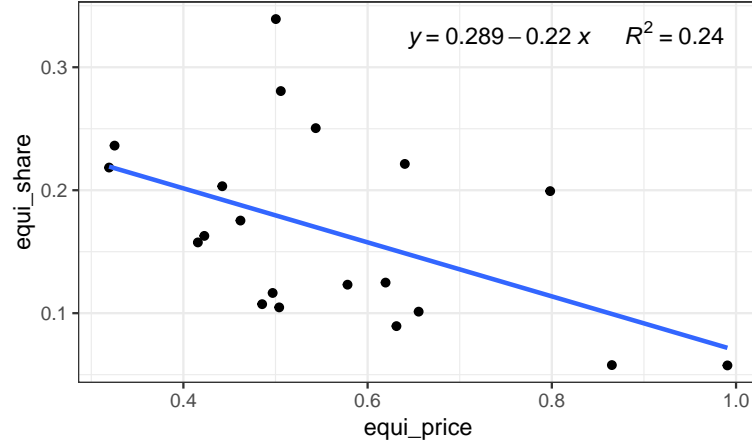


Figure 7: Price–market share scatter plot with linear regression model fit for all four competitive scenarios with five brands excluding the outside good.

type indirect utility model (Berry et al. 1995). On average, an increase in beer prices of $\Delta p_i = 0.10$ €, ceteris paribus is associated with a 2.2 percentage points decrease in market share. The results from this market simulation yield interesting findings for both practitioners and researchers. Those will be discussed in the following last section.

6 Concluding Thoughts on Managerial and Research Implications

The implications resulting from this market simulation can be divided into two parts: The first one discusses managerial ones, while the second part outlines suggestions for further research, especially in terms of model enhancement. Taking a look at the Heineken-Amstel merger from the producer’s side, it generated an incremental profit of 3.5%. This increase in profits is solely due to higher market power and the thereby increased ability to raise prices. Furthermore, a merger would potentially also reduce costs due to synergies, thus even increase the profits by a larger margin. It is important to note that both players in the market benefited from the consolidation. Even the outside party in this merger, Estrella, increased their profits compared to the scenario with three players in the market. This indicates that in this case, Estrella’s prices can be raised with less competition—even though Estrella’s market power decreased relatively compared to the new Heineken–Amstel company.

With the present model and derived prices as well as market shares, it is straightforward to compute the producer surplus as the sum of individual profits. Also, average prices considerably increase with a higher degree of market consolidation. Consumer surplus can therefore be assumed to decrease. Contrary to the producer surplus, the implemented methodology can however not quantify the consumer surplus for the market simulation. When deciding whether to approve a merger of two firms from the regulator's point-of-view, economic theory argues that the overall welfare should increase (Perry & Porter 1985). If the producers' gains in terms of surplus outweigh the losses in consumer surplus then, strictly from an economic standpoint, the merger increases welfare and should be approved. However, if consumers' losses were higher than producers' additional surplus, the merger would be welfare decreasing and should be prohibited. Unfortunately, this study cannot infer any statements about this since the consumer surplus cannot be calculated with the implemented methodology. So far, no study known to the author derives consumer welfare from a MNL model in combination with BLP-type indirect utilities. Future research should therefore combine BLP's approach to account for budgets in MNL models with the methodology to derive consumer surplus from those models as proposed by Train (2015). Weighing the losses and gains against each other would then enable well-informed decisions by regulatory authorities whether to accept or reject a merger based on welfare calculations.

A Appendix

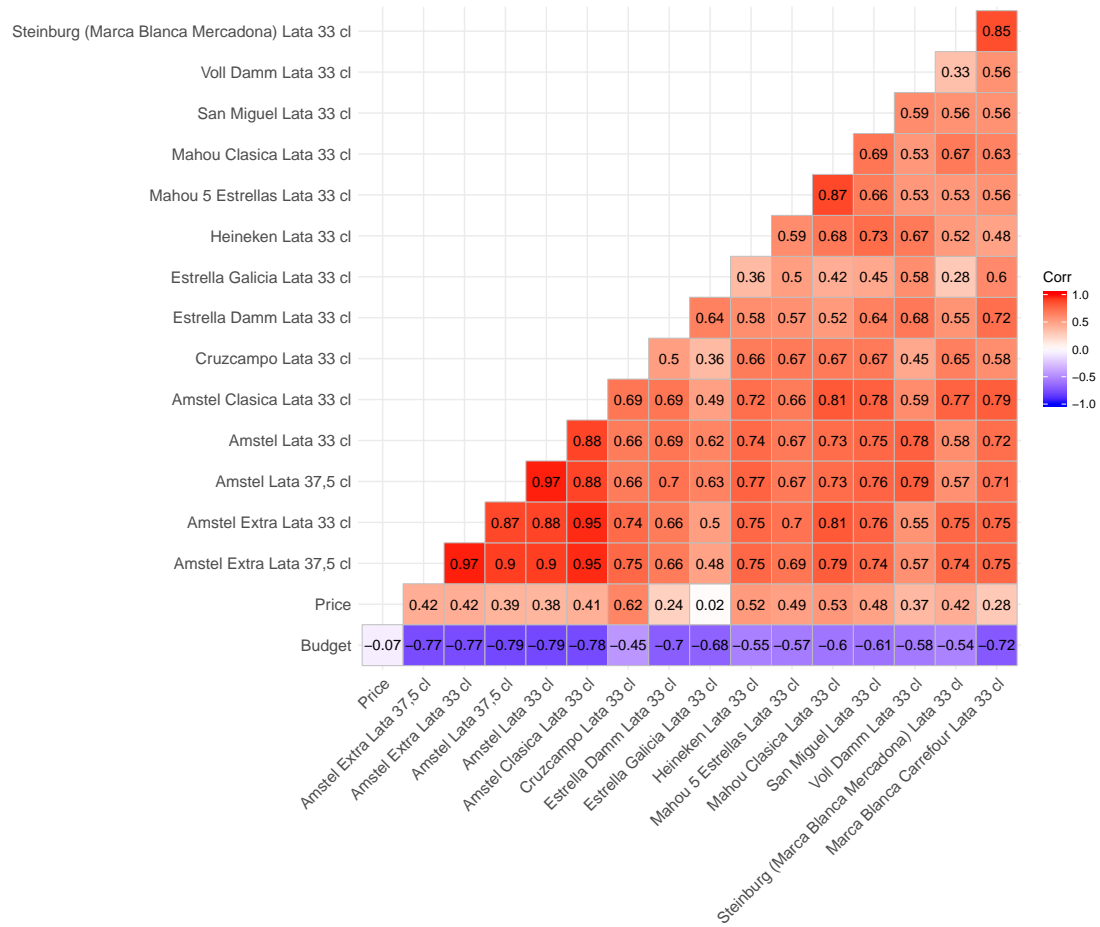


Figure 8: Correlation of betas for price, budget and all 15 brands

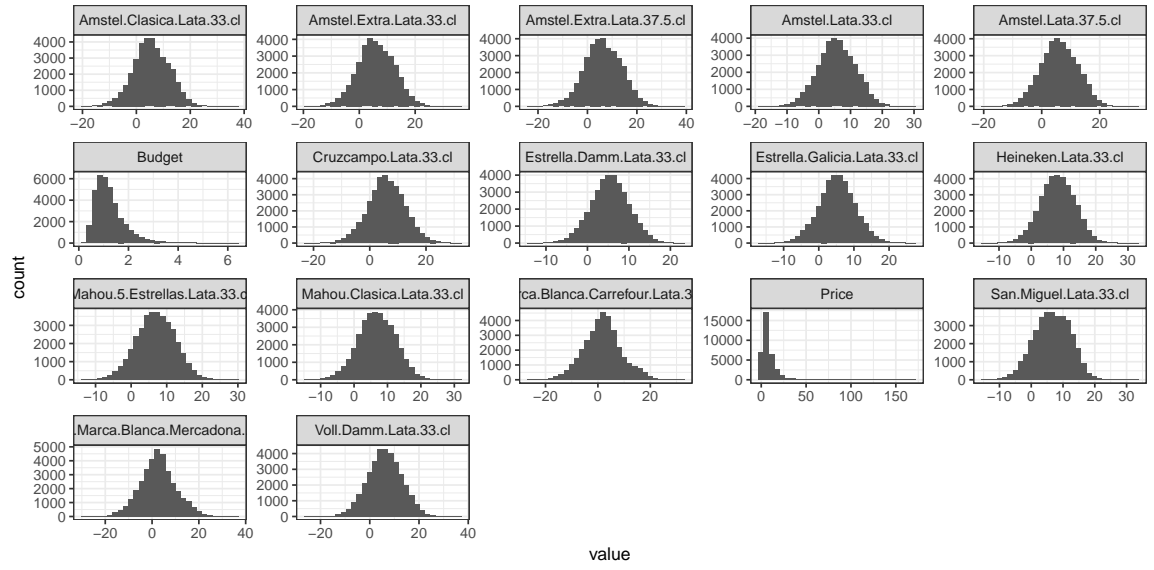


Figure 9: Histograms of betas for price, budget and all 15 brands

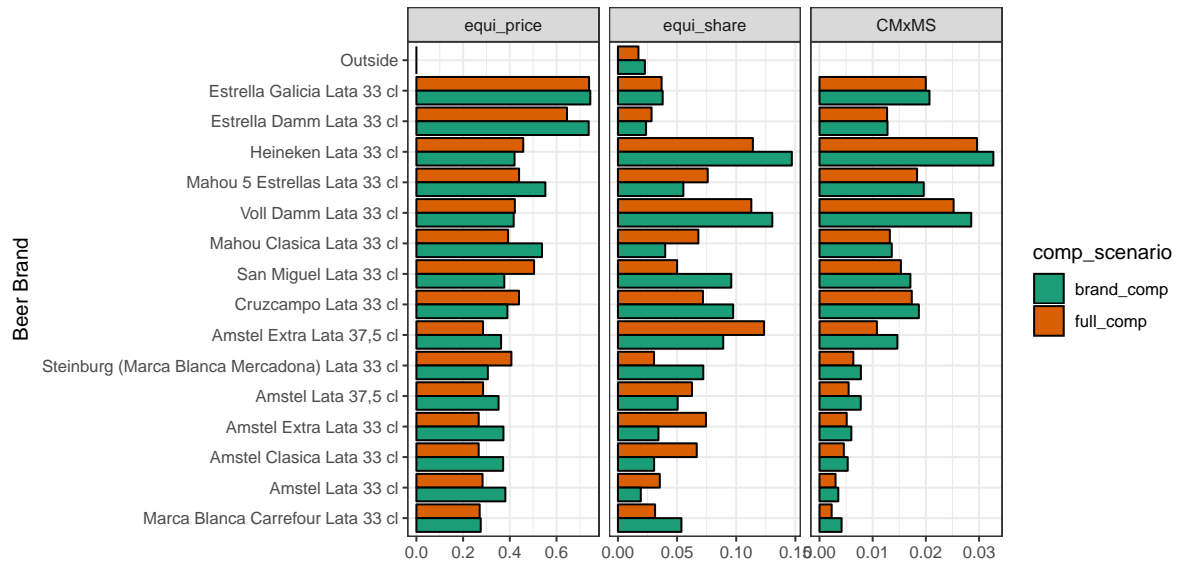


Figure 10: Prices and market shares in a profit-maximizing Nash equilibrium for all 15 brands and outside option in a full vs. brand competition setting

B R Code

Listing 1: Estimation of the hierarchical Bayesian MNL model and MCMC sampling routine

```
1 #####
2 ##### Simulation & Estimation - Nash with Budget
3 ##### BLP-type of indirect utility
4 #####
5
6 rm(list=ls())
7
8 # LOAD LIBRARIES
9 library(xtable)
10 library(devtools)
11 library(MASS)
12 library(Rcpp)
13 library(RcppArmadillo)
14 library(bayesm)
15 library(ggplot2)
16 library(ggpmisc)
17 library(tikzDevice)
18 library(plyr)
19 library(latex2exp)
20 library(FixedPoint)
21 library(dplyr)
22 library(reshape2)
23 library(tidyr)
24 library(ggcorrplot)
25
26 load("100k_MCMC_corrected.RData")
27
28 ###Increase memory capacities
29 memory.limit(size=100000000)
30
31 load("Estimation_Data_Beer_20170423.Rdata")
32 products = c("Amstel Extra Lata 37,5 cl","Amstel Extra Lata 33 cl","Amstel Lata 37,5
33             cl","Amstel Lata 33 cl","Amstel Clasica Lata 33 cl",
34             "Cruzcampo Lata 33 cl","Estrella Damm Lata 33 cl","Estrella Galicia Lata
35             33 cl","Heineken Lata 33 cl","Mahou 5 Estrellas Lata 33 cl",
36             "Mahou Clasica Lata 33 cl","San Miguel Lata 33 cl","Voll Damm Lata 33 cl"
37             ,"Steinburg (Marca Blanca Mercadona) Lata 33 cl",
38             "Marca Blanca Carrefour Lata 33 cl")
39
40 #reorder that price is first in the design matrix
41 for (i in 1:length(E_Data$lgtdata)){
42   E_Data$lgtdata[[i]]$X <- E_Data$lgtdata[[i]]$X[,c(16,1:15)]
43 }
44
45 #Number of players
46 nplayers = 15
47
48 #####
49 #####Run BLP Budget model#####
50 #####
51 ##Load complete sampler now...
52 Rcpp::sourceCpp("rhierMnlRwMixture_rcpp_loop_Illus_BLP_type.cpp",showOutput = FALSE)
53 source('rhierMnlRwMixture_main_untuned_BC.R')
54
55 #number of constrained coefficients (budget & price)
56 nvar_c = 2
57 #position of price coefficient in design matrix
58 pr=1
59
60 ###Prior setting
61 Amu = diag(1/10, nrow = nvar_c, ncol = nvar_c)
62 mustarbarc = matrix(rep(0, nvar_c), nrow = nvar_c)
```

```

63 Prior = list(ncomp=1, Amu = Amu, mustarbarc = mustarbarc, nu = nu, V = V)
64 Mcmc = list(R=30000, keep=3) #, s=1.6)
65 #,s=c(0.1,0.5,0.5,0.5)
66 out_BC = rhierMnlRwMixture_SR(Data=E_Data,Prior=Prior,Mcmc=Mcmc,nvar_c=nvar_c,pr=pr,
    starting_budget = log(0.74))
67
68 betastar_HB_BC = out_BC$betadraw
69 compdraw_HB = out_BC$nmix$compdraw
70 probdraw_HB = out_BC$nmix$probdraw
71 rejection = out_BC$rejection
72 loglike_BC = out_BC$loglike
73
74 ###Compute rejection rate of sampler
75 rej_rate_indi = apply(rejection,2,mean)
76 summary(rej_rate_indi)
77 rej_rate_agg = mean(rej_rate_indi)
78 rej_rate_agg
79
80
81 #####
82 ###Get rid of burnin###
83 #####
84
85 # check visually how much burn-in is required
86 plot(out_BC$loglike, type="l")
87
88 data.frame(loglikelihood = out_BC$loglike) %>%
89   mutate(index = row_number()) %>%
90   ggplot(aes(x = index, y = loglikelihood)) +
91     geom_line(alpha = 0.7) +
92     geom_smooth(method = "lm", se = FALSE) +
93     stat_poly_eq(formula = y ~ x, aes(label = paste(..eq.label.., ..rr.label.., sep
        = "~~~~~")),
94                 parse=TRUE,label.x.npc = "right", label.y.npc = 0.1,
95                 output.type = "expression") +
96   theme_bw()
97
98
99 burnin = 3100
100 R = dim(betastar_HB_BC)[3]
101
102 betastar_HB_BC = betastar_HB_BC[,,(burnin+1):R]
103 compdraw_HB = compdraw_HB[(burnin+1):R]
104 probdraw_HB = probdraw_HB[(burnin+1):R]
105 rejection = rejection[(burnin+1):R,]
106 loglike_BC = loglike_BC[(burnin+1):R]
107 plot(loglike_BC, type="l")
108
109 data.frame(loglikelihood = loglike_BC) %>%
110   mutate(index = row_number()) %>%
111   ggplot(aes(x = index, y = loglikelihood)) +
112     geom_line(alpha = 0.7) +
113     geom_smooth(method = "lm", se = FALSE) +
114     stat_poly_eq(formula = y ~ x, aes(label = paste(..eq.label.., ..rr.label.., sep = "~~~~~")),
115                 parse=TRUE,label.x.npc = "right", label.y.npc = 0.01,
116                 output.type = "expression") +
117   theme_bw()
118
119
120 lmdata <- data.frame(loglikelihood = loglike_BC) %>%
121   mutate(index = row_number())
122 lm(loglike_BC ~ index, data = lmdata) %>%
123   summary()
124
125 R = dim(betastar_HB_BC)[3]
126 N = dim(betastar_HB_BC)[1]
127
128 ###Heterogeneity distribution lower level model non-smoothed
129 l=10

```

```

130 betastar_BC_LLMns <- array(0,dim=c(R*1,dim(betastar_HB_BC)[2]))
131 index_r = rep(rank(runif(R)),1)
132 index_n = rep(rank(runif(N)),round((R*1)/N)+1)
133
134 #data generation
135 for(i in 1:(R*1)){
136   betastar_BC_LLMns[i,] = betastar_HB_BC[index_n[i],,index_r[i]]
137 }
138 #transform betastardraws to betadraws
139 beta_BC_LLMns = betastar_BC_LLMns
140 beta_BC_LLMns[,1] = exp(betastar_BC_LLMns[,1])
141 beta_BC_LLMns[,2] = exp(betastar_BC_LLMns[,2])
142
143 summary(beta_BC_LLMns)

```

Listing 2: Computing dynamic Nash equilibria in different competitive scenarios via the fixed point algorithm

```

1 #####
2 ###Nash optimization
3 #####
4
5 ### Load functions for Fixed-point approach
6 source('Morrow_Skerlos_Implementations_BC_BLP_MarkupEquations_Final_Efficient.R')
7 Rcpp::sourceCpp("Speed+_MS_BC_BLP_Efficient.cpp",showOutput = FALSE)
8
9 #####
10 # Nash Equilibrium Prices and Shares for all 15 brands
11 #####
12
13 # ingredients
14 nplayers = 15 + 1 ## 15 inside + outside
15 min_p = 0.22
16 prices_init = c(rep(min_p,nplayers - 1),0)
17 designBase = rbind(diag(nplayers-1),rep(0,nplayers-1))
18 Xdata = cbind(prices_init,designBase); colnames(Xdata)[1] = "PRICE"
19 Ownership = array(0,dim=c(nplayers,nplayers))
20 Ownership[1:(nplayers-1),1:(nplayers-1)] = diag((nplayers-1))
21
22 # define which brands compete on price, i.e. are owned by different companies
23 # without any specification, all brands compete (owned by different companies)
24 #Ownership[1,2] <- 1
25 #Ownership[2,1] <- 1
26
27 inside_row=which(rowSums(Ownership) != 0, arr.ind = TRUE)
28 p0=Xdata[inside_row,"PRICE"]
29 costBase = as.vector(prices_init*0.9)
30 MC = costBase[inside_row]
31
32 ### Run Fixed-Point algorithm with Xi-markup equation (reliable and fast: See Table 3
   in paper for comparison)
33 p_Markup_Xi_FixedPoint_BC_BLP = FixedPoint(Function = function(price_vec) FixedPoint_
   BLP_Xi(price_vec,MC=MC, ownership=Ownership,Xdata=Xdata,beta_draws=beta_BC_LLMns,
   pr=1), Inputs = p0, MaxIter = 10000, ConvergenceMetricThreshold = 1e-10, Method =
   "Anderson")
34
35 p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint
36
37 # Overview optimal prices & shares
38 Optimal_prices <- array(0,dim=c(nplayers,2))
39 rownames(Optimal_prices) = c(products[1:(nplayers-1)],"Outside")
40 colnames(Optimal_prices) = c("Equilibrium Price","Equilibrium Shares")
41 # Save equi-prices
42 Optimal_prices[, "Equilibrium Price"] <-c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint,0)
43 # Check for all of the 15 brands -> change one, keep all the others fixed
44 computeShares_BC_BLP <- function(prices, beta, design, pr = 1) {
45   fullDesign <- cbind(prices,design) ##put prices to the last position here
46   probabilities_BC_BLP_log_cpp(beta,fullDesign,pr)

```



```

47 }
48 Optimal_prices[, "Equilibrium Shares"] <- as.vector(computeShares_BC_BLP(Optimal_prices
49   [, "Equilibrium Price"], beta_BC_LLMns, designBase, pr=1))
50 round(Optimal_prices, 2)
51 # store results in data frame
52 res_matrix <- data.frame(
53   product = c(products[1:(nplayers-1)], "Outside"),
54   equi_price = as.numeric(c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint, 0)),
55   equi_share = as.vector(computeShares_BC_BLP(Optimal_prices[, "Equilibrium Price"],
56     beta_BC_LLMns, designBase, pr=1)))
57
58 # create list to store different competitive scenarios
59 scenarios <- list("full_comp" = res_matrix)
60
61 #####
62 # Ownership according to brand names (ie all Amstel go to the same company)
63 #####
64
65 # ingredients
66 nplayers = 15 + 1 ### 15 inside + outside
67 min_p = 0.22
68 prices_init = c(rep(min_p, nplayers - 1), 0)
69 designBase = rbind(diag(nplayers-1), rep(0, nplayers-1))
70 Xdata = cbind(prices_init, designBase); colnames(Xdata)[1] = "PRICE"
71 Ownership = array(0, dim=c(nplayers, nplayers))
72 Ownership[1:(nplayers-1), 1:(nplayers-1)] = diag((nplayers-1))
73
74 # define which brands compete on price, i.e. are owned by different companies
75 # Amstel (five brands)
76 for (i in 1:5){
77   for (k in 1:5){
78     Ownership[i,k] <- 1
79   }
80 }
81 # Estrella (two brands)
82 for (i in 7:8){
83   for (k in 7:8){
84     Ownership[i,k] <- 1
85   }
86 }
87 # Mahou (two brands)
88 for (i in 10:11){
89   for (k in 10:11){
90     Ownership[i,k] <- 1
91   }
92 }
93
94 inside_row=which(rowSums(Ownership) != 0, arr.ind = TRUE)
95 p0=Xdata[inside_row, "PRICE"]
96 costBase = as.vector(prices_init*0.9)
97 MC = costBase[inside_row]
98
99 ### Run Fixed-Point algorithm with Xi-markup equation (reliable and fast: See Table 3
100   in paper for comparison)
101 p_Markup_Xi_FixedPoint_BC_BLP = FixedPoint(Function = function(price_vec) FixedPoint_
102   BLP_Xi(price_vec, MC=MC, ownership=Ownership, Xdata=Xdata, beta_draws=beta_BC_LLMns,
103   pr=1), Inputs = p0, MaxIter = 10000, ConvergenceMetricThreshold = 1e-10, Method =
104   "Anderson")
105
106 p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint
107
108 Optimal_prices <- array(0, dim=c(nplayers, 2))
109 rownames(Optimal_prices) = c(products[1:(nplayers-1)], "Outside")
110 colnames(Optimal_prices) = c("Equilibrium Price", "Equilibrium Shares")
111 # Save equi-prices
112 Optimal_prices[, "Equilibrium Price"] <- c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint, 0)
113 computeShares_BC_BLP <- function(prices, beta, design, pr = 1) {
114   fullDesign <- cbind(prices, design) ###put prices to the last position here
115   probabilities_BC_BLP_log_cpp(beta, fullDesign, pr)

```

```

112 }
113 Optimal_prices[, "Equilibrium Shares"] <- as.vector(computeShares_BC_BLP(Optimal_prices
114   [, "Equilibrium Price"], beta_BC_LLMns, designBase, pr=1))
115 round(Optimal_prices, 2)
116
117 # store results in data frame
118 res_matrix <- data.frame(
119   product = c(products[1:(nplayers-1)], "Outside"),
120   equi_price = as.numeric(c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint, 0)),
121   equi_share = as.vector(computeShares_BC_BLP(Optimal_prices[, "Equilibrium Price"],
122     beta_BC_LLMns, designBase, pr=1)))
123
124
125 # add to results list
126 scenarios[["brand_comp"]] <- res_matrix
127
128
129 #####
130 # Only two Amstel, two Estrella and one Heineken (Ownership according to brands)
131 #####
132
133 # ingredients
134 nplayers = 5 + 1
135 min_p = 0.22
136 prices_init = c(rep(min_p, nplayers - 1), 0)
137 designBase = rbind(diag(nplayers-1), rep(0, nplayers-1))
138 Xdata = cbind(prices_init, designBase); colnames(Xdata)[1] = "PRICE"
139 Ownership = array(0, dim=c(nplayers, nplayers))
140 Ownership[1:(nplayers-1), 1:(nplayers-1)] = diag((nplayers-1))
141
142 # define which brands compete on price, i.e. are owned by different companies
143 # Amstel (two brands)
144 for (i in 1:2){
145   for (k in 1:2){
146     Ownership[i,k] <- 1
147   }
148 }
149 # Estrella (two brands)
150 for (i in 3:4){
151   for (k in 3:4){
152     Ownership[i,k] <- 1
153   }
154 }
155
156
157 inside_row=which(rowSums(Ownership) != 0, arr.ind = TRUE)
158 p0=Xdata[inside_row, "PRICE"]
159 costBase = as.vector(prices_init*0.9)
160 MC = costBase[inside_row]
161
162 ### Run Fixed-Point algorithm with Xi-markup equation (reliable and fast: See Table 3
163   in paper for comparison)
164 p_Markup_Xi_FixedPoint_BC_BLP = FixedPoint(Function = function(price_vec) FixedPoint_
165   BLP_Xi(price_vec, MC=MC, ownership=Ownership, Xdata=Xdata, beta_draws=beta_BC_LLMns
166   [, (c(1,2,4,7,9,10,11))], pr=1), Inputs = p0, MaxIter = 10000,
167   ConvergenceMetricThreshold = 1e-10, Method = "Anderson")
168
169 p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint
170
171 Optimal_prices <- array(0, dim=c(nplayers, 2))
172 rownames(Optimal_prices) = c(products[c(2,5,7,8,9)], "Outside")
173 colnames(Optimal_prices) = c("Equilibrium Price", "Equilibrium Shares")
174 # Save equi-prices
175 Optimal_prices[, "Equilibrium Price"] <- c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint, 0)
176 computeShares_BC_BLP <- function(prices, beta, design, pr = 1) {
177   fullDesign <- cbind(prices, design) ###put prices to the last position here
178   probabilities_BC_BLP_log_cpp(beta, fullDesign, pr)
179 }
180 Optimal_prices[, "Equilibrium Shares"] <- as.vector(computeShares_BC_BLP(Optimal_prices

```

```

177     [, "Equilibrium Price"], beta_BC_LLMns[, c(1,2,4,7,9,10,11)], designBase, pr=1))
178 round(Optimal_prices, 2)
179
180 # store results in data frame
181 res_matrix <- data.frame(
182   product = rownames(Optimal_prices),
183   equi_price = as.numeric(c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint, 0)),
184   equi_share = as.vector(computeShares_BC_BLP(Optimal_prices[, "Equilibrium Price"],
185                                             beta_BC_LLMns[, c(1,2,4,7,9,10,11)],
186                                             designBase, pr=1)))
187
188 # add to results list
189 scenarios[["five_full_comp"]] <- res_matrix
190
191 #####
192 # Only two Amstel, two Estrella and one Heineken (Merger Amstel and Heineken, bc
193   highly correlated betas)
194 #####
195 # ingredients
196 nplayers = 5 + 1
197 min_p = 0.22
198 prices_init = c(rep(min_p, nplayers - 1), 0)
199 designBase = rbind(diag(nplayers-1), rep(0, nplayers-1))
200 Xdata = cbind(prices_init, designBase); colnames(Xdata)[1] = "PRICE"
201 Ownership = array(0, dim=c(nplayers, nplayers))
202 Ownership[1:(nplayers-1), 1:(nplayers-1)] = diag((nplayers-1))
203
204 # define which brands compete on price, i.e. are owned by different companies
205 # Amstel (two brands)
206 for (i in c(1:2, 5)){
207   for (k in c(1:2, 5)){
208     Ownership[i, k] <- 1
209   }
210 }
211 # Estrella (two brands)
212 for (i in 3:4){
213   for (k in 3:4){
214     Ownership[i, k] <- 1
215   }
216 }
217
218 inside_row = which(rowSums(Ownership) != 0, arr.ind = TRUE)
219 p0 = Xdata[inside_row, "PRICE"]
220 costBase = as.vector(prices_init * 0.9)
221 MC = costBase[inside_row]
222
223 ### Run Fixed-Point algorithm with Xi-markup equation (reliable and fast: See Table 3
224   in paper for comparison)
225 p_Markup_Xi_FixedPoint_BC_BLP = FixedPoint(Function = function(price_vec) FixedPoint_
226   BLP_Xi(price_vec, MC=MC, ownership=Ownership, Xdata=Xdata, beta_draws=beta_BC_LLMns
227   [, c(1,2,4,7,9,10,11)], pr=1), Inputs = p0, MaxIter = 10000,
228   ConvergenceMetricThreshold = 1e-10, Method = "Anderson")
229
230 p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint
231
232 Optimal_prices <- array(0, dim=c(nplayers, 2))
233 rownames(Optimal_prices) = c(products[c(2,5,7,8,9)], "Outside")
234 colnames(Optimal_prices) = c("Equilibrium Price", "Equilibrium Shares")
235 # Save equi-prices
236 Optimal_prices[, "Equilibrium Price"] <- c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint, 0)
237 computeShares_BC_BLP <- function(prices, beta, design, pr = 1) {
238   fullDesign <- cbind(prices, design) ###put prices to the last position here
239   probabilities_BC_BLP_log_cpp(beta, fullDesign, pr)
240 }
241 Optimal_prices[, "Equilibrium Shares"] <- as.vector(computeShares_BC_BLP(Optimal_prices
242   [, "Equilibrium Price"], beta_BC_LLMns[, c(1,2,4,7,9,10,11)], designBase, pr=1))
243

```

```

239 round(Optimal_prices,2)
240
241 # store results in data frame
242 res_matrix <- data.frame(
243   product = rownames(Optimal_prices),
244   equi_price = as.numeric(c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint,0)),
245   equi_share = as.vector(computeShares_BC_BLP(Optimal_prices[, "Equilibrium Price"],
246                                             beta_BC_LLMns[,c(1,2,4,7,9,10,11)],
247                                             designBase,pr=1)))
248
249 # add to results list
250 scenarios[["five_merge_comp"]] <- res_matrix
251
252 #####
253 # Heineken and Estrella Merger
254 #####
255
256 # ingredients
257 nplayers = 5 + 1
258 min_p = 0.22
259 prices_init = c(rep(min_p,nplayers - 1),0)
260 designBase = rbind(diag(nplayers-1),rep(0,nplayers-1))
261 Xdata = cbind(prices_init,designBase); colnames(Xdata)[1] = "PRICE"
262 Ownership = array(0,dim=c(nplayers,nplayers))
263 Ownership[1:(nplayers-1),1:(nplayers-1)] = diag((nplayers-1))
264
265 # define which brands compete on price, i.e. are owned by different companies
266 # Amstel (two brands)
267 for (i in c(1:2)){
268   for (k in c(1:2)){
269     Ownership[i,k] <- 1
270   }
271 }
272 # Estrella (two brands)
273 for (i in c(3:4,5)){
274   for (k in c(3:4,5)){
275     Ownership[i,k] <- 1
276   }
277 }
278
279 inside_row=which(rowSums(Ownership) != 0, arr.ind = TRUE)
280 p0=Xdata[inside_row,"PRICE"]
281 costBase = as.vector(prices_init*0.9)
282 MC = costBase[inside_row]
283
284 ### Run Fixed-Point algorithm with Xi-markup equation (reliable and fast: See Table 3
285   in paper for comparison)
286 p_Markup_Xi_FixedPoint_BC_BLP = FixedPoint(Function = function(price_vec) FixedPoint_
287   BLP_Xi(price_vec,MC=MC, ownership=Ownership,Xdata=Xdata,beta_draws=beta_BC_LLMns
288   [,c(1,2,4,7,9,10,11)],pr=1), Inputs = p0, MaxIter = 10000,
289   ConvergenceMetricThreshold = 1e-10, Method = "Anderson")
290
291 p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint
292
293 Optimal_prices <- array(0,dim=c(nplayers,2))
294 rownames(Optimal_prices) = c(products[c(2,5,7,8,9)],"Outside")
295 colnames(Optimal_prices) = c("Equilibrium Price","Equilibrium Shares")
296 # Save equi-prices
297 Optimal_prices[, "Equilibrium Price"] <-c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint,0)
298 computeShares_BC_BLP <- function(prices, beta, design, pr = 1) {
299   fullDesign <- cbind(prices,design) ##put prices to the last position here
300   probabilities_BC_BLP_log_cpp(beta,fullDesign,pr)
301 }
302 Optimal_prices[, "Equilibrium Shares"] <- as.vector(computeShares_BC_BLP(Optimal_prices
303   [, "Equilibrium Price"], beta_BC_LLMns[,c(1,2,4,7,9,10,11)],designBase,pr=1))
304
305 round(Optimal_prices,2)
306
307 # store results in data frame

```

```

303 res_matrix <- data.frame(
304   product = rownames(Optimal_prices),
305   equi_price = as.numeric(c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint,0)),
306   equi_share = as.vector(computeShares_BC_BLP(Optimal_prices[, "Equilibrium Price"],
307                                           beta_BC_LLMns[,c(1,2,4,7,9,10,11)],
                                           designBase,pr=1)))
308
309
310 # add to results list
311 scenarios[["five_merge_comp_estr"]] <- res_matrix
312
313 #####
314 # Only two Amstel, two Estrella and one Heineken (Full Competition)
315 #####
316
317 # ingredients
318 nplayers = 5 + 1
319 min_p = 0.22
320 prices_init = c(rep(min_p,nplayers - 1),0)
321 designBase = rbind(diag(nplayers-1),rep(0,nplayers-1))
322 Xdata = cbind(prices_init,designBase); colnames(Xdata)[1] = "PRICE"
323 Ownership = array(0,dim=c(nplayers,nplayers))
324 Ownership[1:(nplayers-1),1:(nplayers-1)] = diag((nplayers-1))
325
326 inside_row=which(rowSums(Ownership) != 0, arr.ind = TRUE)
327 p0=Xdata[inside_row,"PRICE"]
328 costBase = as.vector(prices_init*0.9)
329 MC = costBase[inside_row]
330
331 ### Run Fixed-Point algorithm with Xi-markup equation (reliable and fast: See Table 3
332   in paper for comparison)
333 p_Markup_Xi_FixedPoint_BC_BLP = FixedPoint(Function = function(price_vec) FixedPoint_
334   BLP_Xi(price_vec,MC=MC, ownership=Ownership,Xdata=Xdata,beta_draws=beta_BC_LLMns
335   [,c(1,2,4,7,9,10,11)],pr=1), Inputs = p0, MaxIter = 10000,
336   ConvergenceMetricThreshold = 1e-10, Method = "Anderson")
337
338 p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint
339
340 Optimal_prices <- array(0,dim=c(nplayers,2))
341 rownames(Optimal_prices) = c(products[c(2,5,7,8,9)],"Outside")
342 colnames(Optimal_prices) = c("Equilibrium Price","Equilibrium Shares")
343 # Save equi-prices
344 Optimal_prices[, "Equilibrium Price"] <-c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint,0)
345 computeShares_BC_BLP <- function(prices, beta, design, pr = 1) {
346   fullDesign <- cbind(prices,design) ##put prices to the last position here
347   probabilities_BC_BLP_log_cpp(beta,fullDesign,pr)
348 }
349 Optimal_prices[, "Equilibrium Shares"] <- as.vector(computeShares_BC_BLP(Optimal_prices
350   [, "Equilibrium Price"], beta_BC_LLMns[,c(1,2,4,7,9,10,11)],designBase,pr=1))
351
352 round(Optimal_prices,2)
353
354 # store results in data frame
355 res_matrix <- data.frame(
356   product = rownames(Optimal_prices),
357   equi_price = as.numeric(c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint,0)),
358   equi_share = as.vector(computeShares_BC_BLP(Optimal_prices[, "Equilibrium Price"],
359                                           beta_BC_LLMns[,c(1,2,4,7,9,10,11)],
                                           designBase,pr=1)))
360
361 # add to results list
362 scenarios[["five_full_comp"]] <- res_matrix
363
364 #####
365 # Only two Amstel, two Estrella and one Heineken (Monopoly)
366 #####
367
368 # ingredients
369 nplayers = 5 + 1

```

```

366 min_p = 0.22
367 prices_init = c(rep(min_p, nplayers - 1), 0)
368 designBase = rbind(diag(nplayers-1), rep(0, nplayers-1))
369 Xdata = cbind(prices_init, designBase); colnames(Xdata)[1] = "PRICE"
370 Ownership = array(0, dim=c(nplayers, nplayers))
371 Ownership[1:(nplayers-1), 1:(nplayers-1)] = diag((nplayers-1))
372
373 # define which brands compete on price, i.e. are owned by different companies
374 # All five belong to the same owner
375 for (i in 1:5){
376   for (k in 1:5){
377     Ownership[i,k] <- 1
378   }
379 }
380
381 inside_row=which(rowSums(Ownership) != 0, arr.ind = TRUE)
382 p0=Xdata[inside_row,"PRICE"]
383 costBase = as.vector(prices_init*0.9)
384 MC = costBase[inside_row]
385
386 ### Run Fixed-Point algorithm with Xi-markup equation (reliable and fast: See Table 3
    in paper for comparison)
387 p_Markup_Xi_FixedPoint_BC_BLP = FixedPoint(Function = function(price_vec) FixedPoint_
    BLP_Xi(price_vec, MC=MC, ownership=Ownership, Xdata=Xdata, beta_draws=beta_BC_LLMns
    [, (c(1,2,4,7,9,10,11))], pr=1), Inputs = p0, MaxIter = 10000,
    ConvergenceMetricThreshold = 1e-10, Method = "Anderson")
388
389 p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint
390
391 Optimal_prices <- array(0, dim=c(nplayers, 2))
392 rownames(Optimal_prices) = c(products[c(2,5,7,8,9)], "Outside")
393 colnames(Optimal_prices) = c("Equilibrium Price", "Equilibrium Shares")
394 # Save equi-prices
395 Optimal_prices[, "Equilibrium Price"] <- c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint, 0)
396 computeShares_BC_BLP <- function(prices, beta, design, pr = 1) {
397   fullDesign <- cbind(prices, design) ###put prices to the last position here
398   probabilities_BC_BLP_log_cpp(beta, fullDesign, pr)
399 }
400 Optimal_prices[, "Equilibrium Shares"] <- as.vector(computeShares_BC_BLP(Optimal_prices
    [, "Equilibrium Price"], beta_BC_LLMns[, (c(1,2,4,7,9,10,11))], designBase, pr=1))
401
402 round(Optimal_prices, 2)
403
404 # store results in data frame
405 res_matrix <- data.frame(
406   product = rownames(Optimal_prices),
407   equi_price = as.numeric(c(p_Markup_Xi_FixedPoint_BC_BLP$FixedPoint, 0)),
408   equi_share = as.vector(computeShares_BC_BLP(Optimal_prices[, "Equilibrium Price"],
    beta_BC_LLMns[, (c(1,2,4,7,9,10,11))], designBase, pr=1)))
409
410
411
412 # add to results list
413 scenarios[["five_monopoly"]] <- res_matrix

```

Listing 3: Computation of weighed average prices and profits (i.e. *CMxMS*)

```

1 #####
2 # Compute Average Prices in the Market, Weighted by Market Share
3 #####
4
5 w_a_p_full_comp <- t(scenarios[["full_comp"]]$equi_price) %*% scenarios[["full_comp"]]
    $equi_share
6 w_a_p_brand_comp <- t(scenarios[["brand_comp"]]$equi_price) %*% scenarios[["brand_comp"]
    ]$equi_share
7
8 w_a_p_five_full_comp <- t(scenarios[["five_full_comp"]]$equi_price) %*% scenarios[["
    five_full_comp"]]$equi_share

```

```

9 w_a_p_five_brand_comp <- t(scenarios[["five_brand_comp"]][equi_price) %>% scenarios[["
  five_brand_comp"]][equi_share
10 w_a_p_five_monopoly <- t(scenarios[["five_monopoly"]][equi_price) %>% scenarios[["five
  _monopoly"]][equi_share
11 w_a_p_five_merge <- t(scenarios[["five_merge_comp"]][equi_price) %>% scenarios[["five_
  merge_comp"]][equi_share
12 w_a_p_five_merge_estr <- t(scenarios[["five_merge_comp_estr"]][equi_price) %>%
  scenarios[["five_merge_comp_estr"]][equi_share
13
14 w_a_p_brand_comp / w_a_p_full_comp
15 w_a_p_five_brand_comp / w_a_p_five_full_comp
16
17 # compute average annual welfare loss for typical German consumer with the merger
18 welf_loss_avg <- 102/(1/3)*(w_a_p_five_merge - w_a_p_five_brand_comp)
19 welf_loss_total <- welf_loss_avg * 82000000
20
21
22 #####
23 # Compute contribution margin * market share for all scenarios
24 #####
25 MC <- rep(0.198, 15)
26 for (i in 1:length(scenarios)) { #
27   # position of outside good
28   out_pos <- length(scenarios[[i]][equi_price)
29
30   # compute contribubtion margin times market share for every brand in every scenario
    in the list
31   scenarios[[i]]$CMxMS <- c((scenarios[[i]][-out_pos, "equi_price"] - MC[1:out_pos-1])
    * scenarios[[i]][-out_pos, "equi_share"], NA)
32
33 }
34
35 # compute CMxMS for both Amstel and Heineken before and after merger
36 CMxMS_full_comp <- sum(scenarios$five_full_comp[c(1,2,5), "CMxMS"])
37 CMxMS_before <- sum(scenarios$five_brand_comp[c(1,2,5), "CMxMS"])
38 CMxMS_after <- sum(scenarios$five_merge_comp[c(1,2,5), "CMxMS"])
39 CMxMS_monop <- sum(scenarios$five_monopoly[c(1,2,5), "CMxMS"])
40
41 CMxMS_before_estr <- sum(scenarios$five_brand_comp[c(3:5), "CMxMS"])
42 CMxMS_after_estr <- sum(scenarios$five_merge_comp_estr[c(3:5), "CMxMS"])
43
44
45 CMxMS_after / CMxMS_before
46 CMxMS_monop / CMxMS_full_comp
47 CMxMS_monop / CMxMS_after
48
49 CMxMS_after_estr / CMxMS_before_estr

```

Listing 4: Plotting correlations, beta densities, histograms, market outcomes, and a price-market share scatterplot

```

1 #####
2 # Plotting
3 #####
4
5 # corrrplot of betas for all 15 brands
6 colnames(beta_BC_LLMns) <- c("Budget", "Price", products)
7 windows()
8 cor(beta_BC_LLMns) %>%
9   ggcorrplot(type = "lower", lab = TRUE)
10
11 cor(beta_BC_LLMns[,c(1,2,4,7,9,10,11)]) %>%
12   ggcorrplot(type = "lower", lab = TRUE)
13
14
15 # histogram of all betas
16 beta_BC_LLMns %>%
17   data.frame() %>%

```

```

18     gather(key = "beer_brand") %>%
19     ggplot(aes(value)) +
20     geom_histogram() +
21     facet_wrap(~beer_brand, scales = "free") +
22     theme_bw()
23
24 # density plot of five brands (all in one)
25 beta_BC_LLMns[,c(4,7,9,10,11)] %>%
26   data.frame() %>%
27   gather(key = "beer_brand") %>%
28   ggplot(aes(value)) +
29   geom_density(aes(fill = beer_brand), position="identity", alpha = 0.3) +
30   xlim(c(-10, 20)) +
31   ylim(c(0, 0.095)) +
32   scale_fill_manual(values = c("#FD0505", "#FF9A9A", "#000CD3", "#00C1EA", "green")) +
33   theme_bw() +
34   theme(legend.position = c(0.2, 0.8),
35         legend.direction = "vertical")
36
37 # density plot of five brands (separate)
38 beta_BC_LLMns[,c(2,4,7,9,10,11)] %>%
39   data.frame() %>%
40   gather(key = "beer_brand") %>%
41   ggplot(aes(value)) +
42   geom_density(aes(fill = beer_brand), position="identity") +
43   xlim(c(-10, 25)) +
44   ylim(c(0, 0.13)) +
45   scale_fill_manual(values = c("#FD0505", "#FF9A9A", "#000CD3", "#00C1EA", "green", "
46     grey"), guide = FALSE) +
47   facet_wrap(~beer_brand) +
48   theme_bw()
49
50 # basic plot of one scenario
51 scenarios[["brand_comp"]] %>%
52   melt() %>%
53   ggplot(aes(x = reorder(product, value) , y = value)) +
54   geom_bar(stat = "identity", position = "dodge") +
55   coord_flip() +
56   theme(axis.text.x = element_text(angle = 90)) +
57   facet_wrap(~variable, scales = "free_x") +
58   theme_bw()
59
60 # uses all competitive situations in the scenarios list and plots them side by side
61 windows()
62 scenarios[c("brand_comp", "full_comp")] %>%
63   melt() %>%
64   rename(comp_scenario = L1) %>%
65   ggplot(aes(x = reorder(product, value) , y = value, fill = comp_scenario)) +
66   geom_bar(stat = "identity", colour="black", position = "dodge") +
67   coord_flip() +
68   labs(x = "Beer Brand",
69        y = NULL) +
70   facet_wrap(~variable, scales = "free_x") +
71   scale_fill_brewer(palette = "Dark2") +
72   theme_bw()
73
74 # only five brands #c("five_full_comp", "five_brand_comp", "five_monopoly", "five_
75   merge_comp")
76 scenarios[c("five_full_comp", "five_brand_comp", "five_merge_comp", "five_monopoly")]
77   %>%
78   melt() %>%
79   rename(comp_scenario = L1) %>%
80   ggplot(aes(x = reorder(product, value) , y = value, fill = comp_scenario)) +
81   geom_bar(stat = "identity", colour="black", position = "dodge") +
82   coord_flip() +
83   labs(x = "Beer Brand",
84        y = NULL) +
85   facet_wrap(~variable, scales = "free_x") +
86   scale_fill_brewer(palette = "Dark2") +
87   theme_bw()

```



```

85
86 # price-share scatterplot, w/o outside option (either for single scenario or all)
87 #scenarios[["brand_comp"]] %>%
88 scenarios[c("five_full_comp", "five_brand_comp", "five_merge_comp", "five_monopoly")]
89   %>%
90 bind_rows() %>%
91   filter(product != "Outside") %>%
92   ggplot(aes(x = equi_price, y = equi_share)) +
93   geom_point() +
94   geom_smooth(method = "lm", se = FALSE) +
95   stat_poly_eq(formula = y ~ x, aes(label = paste(..eq.label.., ..rr.label.., sep =
96     "~~~~~")),
97     parse=TRUE, label.x.npc = "right",
98     output.type = "expression") +
99   theme_bw()
100
101 cor(scenarios[["brand_comp"]]$equi_price, scenarios[["brand_comp"]]$equi_share)
102
103 # bivariate density plot
104 hist(beta_BC_LLMns[,c(4,7)])
105 beta_BC_LLMns[,c(4,7)] %>%
106 data.frame() %>%
107 gather(key = "beer_brand") %>%
108 ggplot(aes(value)) +
109 geom_density(aes(fill = beer_brand), position="identity")
110
111 data.frame(beta_BC_LLMns[,c(4,7)])%>%
112 ggplot(aes_string(x = "Amstel.Extra.Lata.33.cl", y = "Amstel.Clasica.Lata.33.cl")) +
113 stat_density_2d(aes(fill = ..level..), geom = "polygon")+
114 scale_fill_continuous(low="lavenderblush", high="blue")+
115 geom_abline(slope = 1) +
116 labs(fill = "density") +
117 #theme(legend.title = element_text("density")) +
118 theme_bw()

```

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Frankfurt am Main, July 21, 2019



Lukas Jürgensmeier