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# MODELLING DRIVERS OF CONSUMER LIKING HANDLING CONSUMER AND PRODUCT EFFECTS

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**Abstract:** *The aim of the present paper is to approach the analysis of the relationship between overall liking and specific likings for eleven types of white corn tortilla chips. The main objective is to estimate a model for predicting the overall liking that also considers the heterogeneity in consumer liking. A further objective is to evaluate the adequacy of a single model for the different products. The first objective is achieved by using quantile regression, providing an estimate of the dependency relationship between overall and specific likings with respect to predefined quantiles, each corresponding to a specific segment of consumers. The second objective is achieved by using a specific strategy aimed at finding specific models for each product or group of similar products. The results show that the overall liking mostly depends on one specific liking, and its impact varies significantly for different segments of consumers. Furthermore, three different models are identified for three groups of products that differ in the same most important driver of the global model.*

**Keywords:** *drivers of liking, individual differences, product effect, quantile regression.*

## 1. INTRODUCTION AND MOTIVATION

The identification of drivers of consumer liking is one of the main goals and most important challenges in sensory and consumer studies (Moskovitz, 2001). The drivers of consumer liking comprise both the sensory intensity attributes of the products (intrinsic attributes) and the physical–chemical attributes (extrinsic attributes).

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Preference mapping and conjoint analysis are the most widely used methodologies in consumer and marketing research to investigate consumer liking and its relationships with intrinsic and extrinsic attributes. Preference mapping analyses the relationships between the ratings given by consumers on a set of products and the sensory attributes of the same set of products measured by a panel of expert judges (Carroll, 1972; McEwan, 1996; Næs et al., 2010). The two datasets, namely the matrix *products by sensory* descriptors and matrix *products by consumers*, are correlated by multivariate regression analysis to measure which sensory characteristics define the most appreciated products. In contrast, conjoint analysis (Green and Rao, 1971; Gustafsson et al., 2007) is the most used method when the liking drivers are categorical variables measuring extrinsic product characteristics. Here, the objective of the analysis is to measure the relative importance of the individual attributes, besides providing information on the liking for individual levels of the same attributes.

Although both extrinsic and intrinsic attributes are potential drivers of consumer liking, it is not always obvious that they are relevant to consumers. An alternative approach is to ask consumers to evaluate other aspects of the liking, as well as the overall liking (Bi and Chung, 2011; Olsen et al., 2012). Such aspects are sometimes referred to as specific likings or modalities. They allow us to outline optimal combinations of drivers that optimise the consumer liking. The analysis of the relationships between overall and specific likings cannot be pursued using preference mapping or conjoint analysis in the traditional way. Although some advanced analytical strategies have been proposed (Menichelli et al., 2013), the most commonly used techniques for analysing this type of data are simpler, and they implicitly assume that the data come from a homogeneous population. Under such an assumption, a single model relating overall and specific likings would be sufficient to represent all the observations. However, consumer heterogeneity is one of the most fundamental concepts in marketing strategies; thus, an aggregate analysis would not be advisable, since it may inappropriately aggregate members from heterogeneous subpopulations, thereby producing inconsistent parameter estimates. In other words, aggregate analysis aimed to obtain a synthesis valid for the entire population would engender unique coefficients that may not reflect any of the segments. Therefore, a segmentation strategy would be more appropriate, wherein the consumers are divided into groups to obtain models specific for each group. The two most common approaches are *a prior* and *a posteriori* classification. The former identifies segments based on consumer characteristics, mostly sociodemographic variables. The latter identifies segments exclusively on the basis of consumer liking. It is worth noting that *a priori segmentation* does not guarantee optimal segmentation for the model of interest. Indeed, the segments, although simple to obtain and understand, may not engender different models; that is, they may not behave differently in terms of the investigated variables.

The present work exploits quantile regression (QR) as a new *a posteriori* segmentation approach in the analysis of consumer liking. The great benefit of QR is the opportunity to estimate the whole distribution of the conditional quantiles of the response variable (Koenker and Basset, 1978). In QR, the estimate of a single value (conditional mean) is replaced by estimates of several values (conditional quantiles), through which the influence of the explanatory variables on the entire distribution of the dependent variable can be investigated. Recently, QR has been used in consumer studies for estimating the conditional quantiles of liking as functions of the consumer characteristics (Davino et al., 2015). Here, we propose to exploit QR to analyse the relationships between specific and overall liking from a twofold point of view. QR is used to evaluate the effect of specific likings on the different overall liking degrees. A single model, which we define as the *global model*, is used to measure the impact of specific likings on the overall liking, with three different conditional quantiles associated with different liking degrees. The term *global* emphasises how the model is estimated on all observations, that is considering all the consumers' ratings for all the products. The use of three different conditional quantiles permits us to consider individual differences in consumer liking. Specifically, the quantile of order 0.25 is used for low liking, the quantile of order 0.50 for median liking, and the quantile of order 0.75 for high liking. Furthermore, the QR-based strategy proposed by Davino and Vistocco (2018) to handle heterogeneity is adapted here for exploring how the dependence structure between the overall and specific likings varies according to the different products or groups of similar products. The analysis strategy consists of three main steps. The first objective is to identify the best model for each product or group of products, based on the quantile that best represents them. Subsequently, a different model is estimated for each group of products identified in the previous step (a group can also consist of a single product). Finally, the various estimated models, named *local models*, are compared to evaluate whether there are significant differences both for the whole model and the individual coefficients of the model. The proposed approach is illustrated through a case study on real data.

The rest of the paper is organised as follows. The data are described in Section 2, along with some evidence emerging from a preliminary analysis. The results are reported in Section 3, with the basic notation and methodology briefly introduced in Subsection 3.1, and the QR approach described in Subsections 3.2 (global model) and 3.3 (local models). Finally, some concluding remarks and directions for future avenues of research follow in Section 4.

## 2. TORTILLA CHIPS DATA: DESCRIPTION AND MAIN EVIDENCE

The proposed approach is implemented on data from 11 commercial toasted white corn tortilla chips products. We selected this well-known dataset for comparison purposes, since it was used in Meullenet et al. (2003, 2002) with the preference mapping approach and a proportional hazard model. The products were evaluated for appearance (`Appearance`), flavour (`Flavour`), texture (`Texture`) and overall impression (`Overall liking`) by a group of 73 consumers. Specifically, each consumer was asked to evaluate the appearance, flavour, texture, and overall impression of each sample on a 9–point hedonic scale, with 9 signifying 'like extremely' and 1 'dislike extremely'. The data was arranged in four matrices 73×11 (the 73 consumers expressed judgments on 11 products) for each of the four different aspects of liking. Table 1 summarizes some product information: a) the product label; b) the name of the producer; c) the shape of the products (round, strip and triangle); d) the salt and fat content (as a percentage of daily intake). For a more detailed description of the sensorial experiment, the interested reader is referred to Meullenet et al. (2002).

**Tab. 1: Product identifier, producer, shape and salt/fat content of the commercial toasted white corn tortilla chips**

| Product ID | Producer | Shape | Salt content (%) | Fat content (%) |
|---|---|---|---|---|
| BYW | Fleming Companies, Inc. | Triangle | 4 | 12 |
| GMG | Green Mountain Gringo | Strip | 5 | 13 |
| GUY | Guy's Snack Foods | Round | 3 | 9 |
| MED | Medallion Food Corporation | Triangle | 2 | 11 |
| MIS | Mission Food Corporation | Strip | 4 | 10 |
| MIT | Mission Food Corporation | Triangle | 4 | 10 |
| OAK | Oak Creek Farms | Round | 2 | 11 |
| SAN | Frito-Lay | Triangle | 5 | 8 |
| TOB | Frito-Lay | Round | 5 | 12 |
| TOM | Tom's Foods Inc. | Triangle | 5 | 10 |
| TOR | Frito-Lay | Triangle | 3 | 9 |

The distribution of overall liking is depicted in Figure 1. Specifically, it shows the overall liking for each product, from the product with the lowest median (bottom) to that with the highest median (top). The bottom panel shows the overall liking across products (labelled as *all* in the Figure). Each dot refers to a single liking; random jittering was used to reduce overlapping through the addition of a small amount of random variation to the location of each point (Wickham, 2016). The visual inspection of the conditional distributions reveals that the overall liking (bottom panel) and liking for the single products show a strong left skewness, with very high liking scores, even if the single products differ in location, scale and shape.

The conditional medians are depicted through triangles, with the two vertical segments showing the conditional first and third quartiles. Focussing on the median locations, it is possibile to detect three groups of products: TOB, with the highest liking equal to 8; TOR, TOM, SAN, MIT, MIS and BYW with a liking equal to 7; and the other products, with liking equal to 6. With respect to the third quartile, the products are instead divided into two groups: In the first group (TOB, TOR, TOM, SAN, MIT, MIS, BYW), 25% of the rating scores are higher than 8, while in the second group, this value is equal to 7. The first quartile is different, as its position would suggest four groups of products. The first group of products (GMG, GUY, MED and OAK) is the same as that suggested by the use of the medians, with approximately 25% of ratings scoring less than 4. Finally, TOB and SAN show the minimum interquartile ranges: the median and the third quartile coincide (equal to 8) in the case of TOB, while for SAN the median coincides with the first quartile (equal to 7).

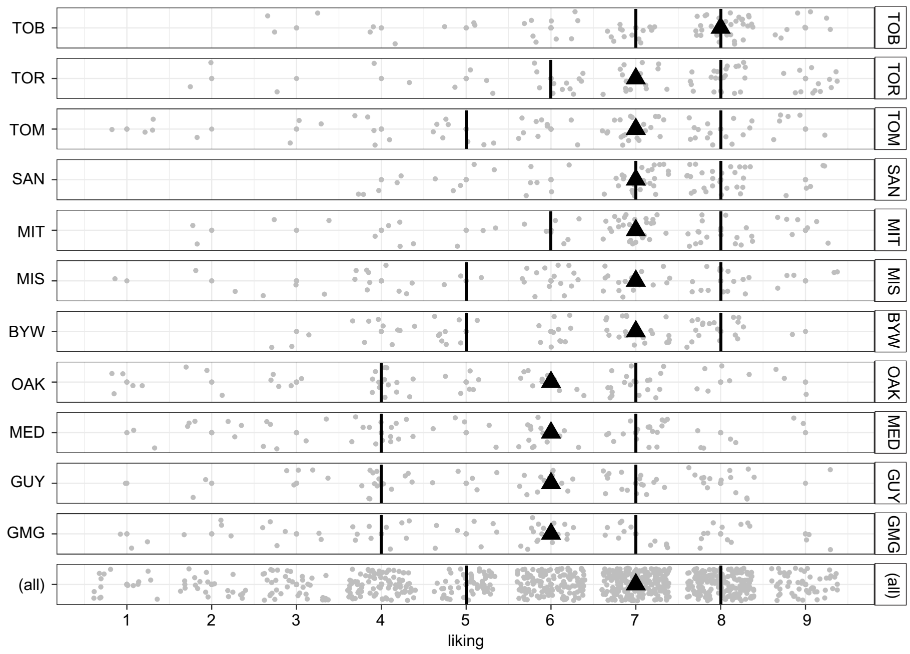


**Fig. 1: Liking distributions for the single products and accross products: dots refer to single likings with jittering used to avoid overlapping, triangles depict the conditional medians and the conditional first and third quartiles are shown using vertical segments.**

## 3. ANALYSING OVERALL LIKING AND SPECIFIC LIKING ATTRIBUTES

This paper proposes the use of QR to model the relationships between overall and specific likings, considering both heterogeneity in consumer liking and differences across products. The former is carried out by estimating a QR model on the whole dataset using different conditional quantiles for investigating the effects of the drivers on the whole conditional distribution of the overall liking. The latter exploits a strategy introduced in Davino and Vistocco (2018), which allows the products to be partitioned into groups and different models to be estimated for each of them. The main notation is briefly presented in the next subsection, along with the general idea of QR and the strategy used to partition the products and estimate the models for each detected group. Subsections 3.2 and 3.3 show the implemented strategy for tortilla chips data.

### 3.1. MAIN NOTATION AND REFERENCE METHODOLOGY

Let us consider data $(y_i, \mathbf{x}_i)$, $i = 1, \ldots, n$, for a response $y$ and a set of $p$ covariates $\mathbf{X}$. A typical regression model is formulated as:

$$y_i = \eta_i + \varepsilon_i, \tag{1}$$

where $\eta_i$ is a regression predictor formed in terms of the covariates $\mathbf{x}_i$. In this paper we restrict our consideration to the case of linear effects:

$$\eta = \beta_0 + \mathbf{x}_i^\top \beta. \tag{2}$$

The typical assumptions posed on errors (and hence response), $\varepsilon \sim \text{NID}(0, \sigma^2)$, do not consider the possibility that variance and higher order characteristics of the response may depend on covariates. Furthermore, in several applications, we could be interested in the whole conditional distribution of the response and modelling it at different locations. QR, as introduced in Koenker and Basset (1978), offers a possible approach for modelling the whole conditional distribution of $y$ without posing any parametric assumption for the error (and hence response) distribution. QR estimates separate models for different quantiles $\theta \in [0, 1]$:

$$\eta = \beta_0(\theta) + \mathbf{x}_i^\top \beta(\theta), \tag{3}$$

such that $P(\varepsilon_{i\theta} \leq 0) = \theta$. The separate models are interpretable in terms of regression models for the quantiles of the response. The conditional distribution of the response can be estimated using a dense set of conditional quantiles. Detailed discussion of QR is beyond the scope of this paper, but the interested reader is referred to Koenker (2005) and Davino et al. (2013).

In a nutshell, the most widespread algorithm (Koenker and D'Orey, 1987) for estimating the coefficients is a variant of the simplex algorithm proposed by Barrodale and Roberts (1973) for the least absolute problem. It exploits movement along the corner of the feasible region (exterior–point method). Interior–point methods move instead along the edges of the feasible region and are especially suitable to deal with large scale problems (Portnoy and Koenker, 1997). Several alternative QR estimators have been recently proposed. Among these, we point out the bayesian approach (Yu and Moyeed, 2001). It exploits the asymmetric Laplace distribution (Yu and Zhang, 2005) as likelihood function and it is valuable since it embeds QR in the likelihood framework. As regards inference, QR estimators are asymptotically normal distributed with different forms of the covariance matrix depending on the model assumptions (Koenker and Basset, 1978, 1982a,b). Resampling methods can represent a valid alternative to the asymptotic inference; they allow to estimate the standard errors of the parameters without requiring any assumption in relation to the error distribution (Gould, 1992). For a review on QR resampling methods, see Kocherginsky (2005).

If the data are row–partitioned according to a categorical variable (hereafter, a stratification variable), the classical QR model does not allow an evaluation of the difference in the dependence structure with respect to group membership. Two units sharing the same level of the stratification variable could indeed share a more similar dependence structure than two units belonging to different groups would. Davino and Vistocco (2018) introduced a strategy aiming to evaluate group effects through the assignment of a specific quantile to each group. The approach is structured in the three steps detailed below, where $m$ is used for denoting the number of groups (levels of the stratification variable) and $n_g$ the number of units in group $g$ ($g = 1,\ldots,m$). Moreover, hereafter, the intercept and slopes of the models are jointly stored in the $\beta$ vector, inserting a column vector of 1 in the $\mathbf{X}$ matrix.

1) **Identification of the best model for each group**

In the first step, a representative quantile is associated with each $g$ group by considering the stratification variable. For our study on the drivers of consumer liking, we use the product name as the stratification variable, that is, a categorical variable with 11 levels. Whereas such a variable is relevant for describing the data, the representative quantiles should be different; thus, it should also determine differences in the dependence structure among the groups. If, instead, the quantiles are similar, the group variable will not play a relevant role in describing the data. To compute the representative quantile of each group, we compute the rank percentiles of each statistical unit concerning the response variable, averaging them by groups. Specifically, the quantile representative of each group will be obtained as: $\theta_g^{best} = mean(rank\_perc(y_i))$ where *rank_perc* represents the location of scores in a distribution, $i = 1, \ldots, n_g$ and $g = 1, \ldots, m$. For a discussion on the use of the percentile ranks and the choice of the proper location index to summarise them, see Davino and Vistocco (2018).

2) **Estimation of the group dependence structure**

In the second step, QR is carried out on the whole sample using the representative quantiles, that is, the $m$ quantiles $\theta_g^{best}$ assigned to the $m$ groups in the previous step. Each of the $g$ estimated models provides a set of coefficients, one for each $j$–th regressor: $\hat{\beta}_j\left(\theta_g^{best}\right)$. Such coefficients can be arranged in a matrix $\hat{\mathbf{B}}\left(\theta^{best}\right)_{[p\times m]}$ ,which provides the effect of the $j$–th regressor in the $g$–th group. Each row of the estimated coefficient matrix holds the impact of the given regressor on the corresponding conditional quantile of the dependent variable; differences among the coefficients highlight differences in the group dependence structure. The coefficient matrix consists of $m$ column vectors, one for each considered conditional quantile, and hence for each group. The inspection of such a matrix allows the detection of the group dependence structure.

3) **Test of the differences among groups**

In the final step, the significance of the differences among the coefficients related to each group can be tested by exploiting the classical inferential tools available in the QR framework (Davino et al., 2013; Koenker, 2005). The group comparison can be carried out because the representative quantiles have been estimated for the whole sample, in contrast to an approach estimating separate models for each group. Koenker and Basset (1982a) proposed tests to evaluate the significance of the differences among the coefficients pertaining to different quantiles because, as the authors states, "Having estimated the parameters of several conditional quantile functions and noted discrepancies among the estimated slope parameters, the question naturally arises: Are these discrepancies 'significant'?". Two models estimated at two different quantiles can be compared using a joint tests on all slope parameters or separate tests on each of the slope parameter. The hypothesis of interest is that the slope coefficients of two models are identical and the test statistic is a variant of the Wald test described in Koenker and Basset (1982b). Let us consider the case of the comparison among the coefficients related to the $j$–th regressor and estimated at two different quantiles, $\theta_h^{best}$ and $\theta_k^{best}$: $H_0 : \beta_j(\theta_h^{best}) = \beta_j(\theta_k^{best})$. The test statistic will be:

$$T = \frac{\left[\hat{\beta}_j(\theta_h^{best}) - \hat{\beta}_j(\theta_k^{best})\right]^2}{var\left[\hat{\beta}_j(\theta_h^{best}) - \hat{\beta}_j(\theta_k^{best})\right]} \sim \chi^2_{1gdl} \tag{4}$$

Such a test statistic can be exploited both for pairwise comparison and a global test on all the slopes.

### 3.2. GLOBAL MODEL HANDLING CONSUMER EFFECT

The descriptive analysis of overall and liking drivers provided in Section 2 supports a more in–depth analysis. First, it is necessary to explore whether and how much specific liking attributes influence overall liking. This section describes the main results obtained from the estimation of a 'global model', namely a regression model considering the full panel of consumers and products. The analysis is carried out using both classical least squares (LS) and QR approaches. Table 2 reports the LS coefficients along with the QR coefficients for the three conditional quartiles (all coefficients are significant at $\alpha = 0.05$). The standard errors, used to evaluate the statistical significance of the coefficients, have been estimated using resampling methods (Parzen et al., 1994) as described in Section 3.1.

`Flavour` is the main driver of overall liking, followed by `Appearance` and `Texture`. The impact of `Flavour` decreases in the higher part of the distribution ($\theta \geq 0.50$); that is, the less satisfied consumers are more influenced by this attribute. `Appearance` slightly outperforms `Texture`, but only in the lowest quantile ($\theta = 0.25$). These results highlight suitable leverages for decision makers. To improve consumers' overall liking, it is advisable to act on `Flavour` and `Appearance`, as an improvement in these drivers has a higher effect on the left tail of the overall liking distribution.

**Tab. 2: LS (first column) and QR coefficients (from the second to the last column) for three distinct conditional quantiles. All coefficient are significant at $\alpha = 0.05$**

| | LS | $\beta(\theta = 0.25)$ | $\beta(\theta = 0.50)$ | $\beta(\theta = 0.75)$ |
|---|---|---|---|---|
| Intercept | 0.01 | -0.95 | 0.00 | 1.11 |
| Appearance | 0.21 | 0.21 | 0.17 | 0.16 |
| Flavour | 0.64 | 0.71 | 0.67 | 0.58 |
| Texture | 0.15 | 0.15 | 0.17 | 0.16 |

### 3.3. LOCAL MODELS HANDLING PRODUCT EFFECT

Once the effects of liking attributes on the overall liking have been investigated, the QR strategy outlined in Subsection 3.1 allows to further detail the study and detect product effects in the relationship among overall and liking drivers. First, the strategy proposed by Davino and Vistocco (2018) identifies the best model for each group, namely the conditional quantiles of the overall liking representative of each group. Such models are detected starting from the rank percentiles of each consumer in terms of the overall liking, represented in Figure 2. The representation exploits the same style used for Figure 1, but the dots refer to rank percentiles instead of single likings. Figure 2 suggests that a proper location index for each product can be the median, and it highlights that some products have similar distributions (highlighted by the same position of the median), as already outlined in Figure 1. The conditional quantiles determining the best models and corresponding products are as follows:

- $\theta = 0.33$ for the products MED, OAK, GMG and GUY;
- $\theta = 0.60$ for the products MIS, BYW TOM, MIT, SAN and TOR;
- $\theta = 0.91$ for the product TOB.

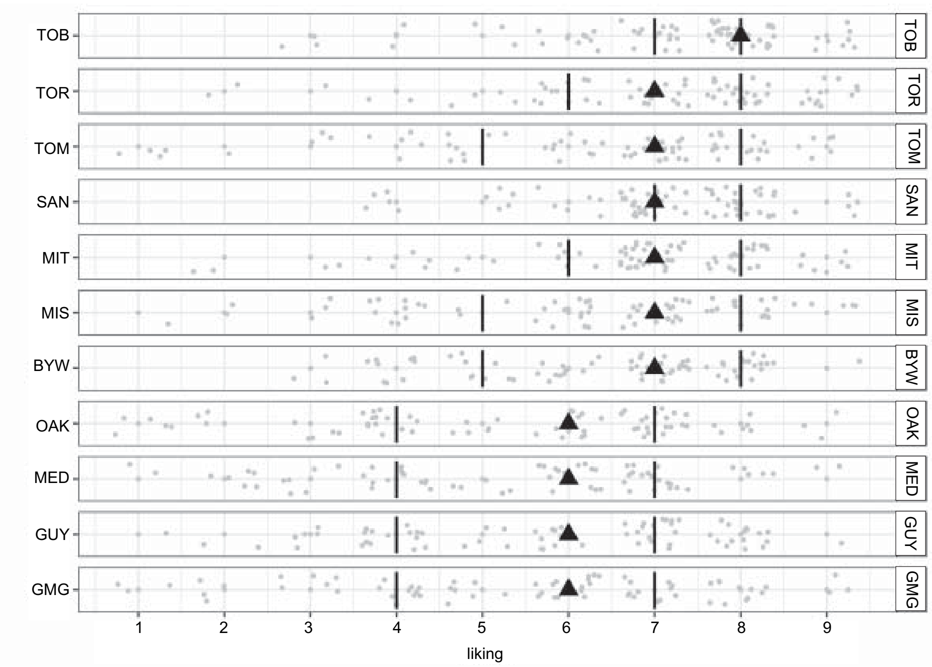


**Fig. 2: Rank percentiles of each product for the overall liking.**

In the second step, QR is carried out on the whole sample using the three identified quantiles. The results are shown in Table 3, and all the coefficients are significant at $\alpha = 0.05$. Some differences among the products emerge from the estimated coefficients. Since all of them are positive, they must be compared in terms of magnitude. `Flavour` has the highest impact on the overall liking for all three conditional models, but its effect is higher for the first two groups of products, which are best characterised by lower quantiles. `Appearance` has the second highest effect, which becomes higher for the TOB product.

In the final step, it is necessary to test the differences among the groups. Davino and Vistocco (2018) proposed exploiting the classical inferential tools available in the QR framework (Koenker and Basset, 1982a), for each regressor, to test whether the differences among the coefficients are significant. All the possible pairwise comparisons between the products must be considered. Pairwise comparisons should clearly be carried out if a joint test leads rejecting the null hypothesis of equal slopes associated with the different groups. The used statistical test is the variant of the Wald test introduced in Section 3.1, which can be used for both the tests, namely the joint test and pairwise comparisons. Table 4 shows the *p*–values derived from testing the differences on the whole model (first column) and each slope coefficient (second to last column). The results confirm the relevant role of `Flavour,` which is the unique driver playing a different role in the three groups and determines the results of the joint test independently.

**Tab. 3: LS (first column) and QR coefficients (from the second to the last column) for three distinct conditional quantiles. All coefficient are significant at $\alpha = 0.05$**

| | $\theta = 0.33$ (MED, OAK, GMG, GUY) | $\theta = 0.60$ (MIS, BYW TOM, MIT, SAN, TOR) | $\theta = 0.91$ (TOB) |
|---|---|---|---|
| Appearance | 0.16 | 0.16 | 0.19 |
| Flavour | 0.76 | 0.65 | 0.44 |
| Texture | 0.11 | 0.14 | 0.12 |

**Tab. 4: p–values derived from testing differences on each slope coefficient and on the whole model**

| | **Joint test** | **Appearance** | **Flavour** | **Texture** |
|---|---|---|---|---|
| I vs II | 0.000 | 0.964 | 0.000 | 0.398 |
| I vs III | 0.000 | 0.373 | 0.000 | 0.925 |
| II vs III | 0.000 | 0.263 | 0.000 | 0.821 |

Results can be further assessed by comparing the observed and estimated values of the response. Specifically, the added value of using a segmentation strategy through the three detected best models is evident if the best models for each group are compared with the wrong models. That is, if the best model for a given group is used to predict the response variable for the units belonging to another group, the results worsen to the extent that the groups differentiate with respect to the best quantiles. As an example, for the TOB product, Figure 3 shows the observed response variable (thick line) and estimated densities obtained using the best models associated with each group (different levels of grey).

The best model assigned to the TOB product (with $\theta^{best}$=0.91) provides the density closer to the observed distribution. On the contrary, if the TOB overall liking is estimated through the best model assigned to the second group ($\theta^{best}$=0.60) and even more the first group ($\theta^{best}$=0.33) , the observed and estimated densities move away.

## 4. CONCLUSION

In this paper, we presented a new approach for analysing the effects of drivers of liking on overall liking that exploited quantile regression. QR was used as an alternative to the classic LS to predict the overall liking, assessing the heterogeneity of consumers. In addition to the detection of the most important drivers, QR allowed us to evaluate the different effect of each driver concerning the diverse segments of consumers identified by different quantiles of overall liking. Furthermore, a strategy was proposed for dealing with the product effect. Such a strategy has highlighted the presence of three different models, which were significantly different when only one of the drivers was considered. The proposed procedure for treating the product effect can be also used to address in more depth the segmentation of consumers. As shown in the preliminary descriptive analysis, there was little consumer segmentation in the white corn tortilla chips: the vast majority of consumers expressed liking for a specific set of products. Given the small segmentation of consumers, it was decided to focus the analysis on the differences between the products. However, in many real cases, consumers show preferences for different products. In such situations, the proposed procedure can then be used to estimate models for different segments of consumers. This information, conveniently combined with additional consumer information like sociodemographic variables, would have significant managerial implications.

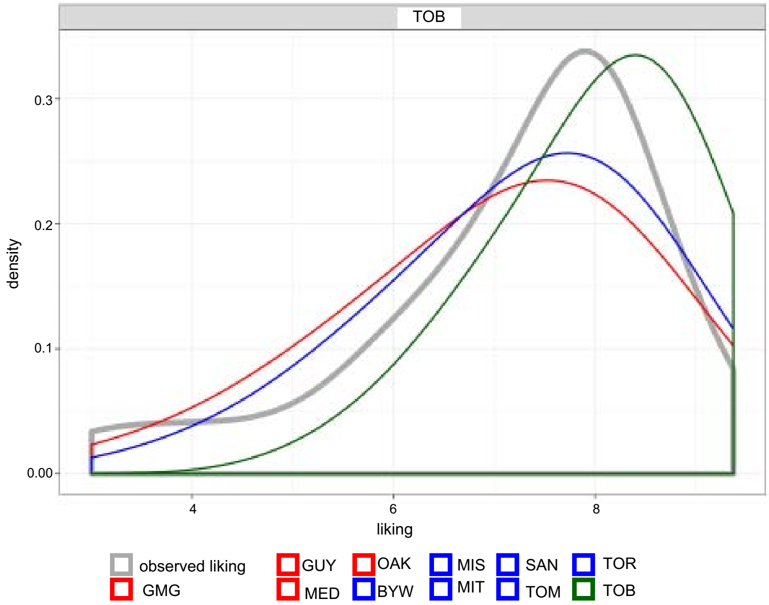


**Fig. 3: Comparisons among the models' predictions.**

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