An Analysis of Taste Variety within Households on Soft Drinks

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An analysis of Taste Variety within Households on Soft Drinks in France

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1 Introduction

Many studies of consumer choices allow to model the brand discrete choice. These models are largely used since Guadani and Little (1983) and Train (1986). The first set of papers allowing to extend discrete choice models are the discrete-continous models developed by Hanemann (1984) and, Dubin and McFadden (1984) and used later in marketing by Krishnamurthi and Raj (1988), Chiang (1991), Chintagunta (1993) and Dillon and Gupta (1996). These papers deal not only with brand choice behavior but with quantity choice for this brand chosen. However, panelists are often shoppers making decisions for the entire household. There may be different tastes within a household, which implies buying different products. For instance, children and parents may have very different tastes within a category for flavors, styles and colors or men and women for diet products. The variety of products bought during the shopping trip may also correspond to the shopping planed for different consumption occasions. Indeed the household may seek for variety from one consumption occasion to another one.

A recent marketing literature deals with the multiple discrete choice models. Dubé (2004, 2005) and Hendel (1999) estimate a structural model that allows households to purchase a bundle of products and suppose the shopping purchase occasions correspond to several future consumption occasions. During each consumption occasion, they assume a standard discrete choice model where only one product is consumed. Therefore, due to varying tastes across individual consumption occasions, a household consumes a variety of goods at the current purchase occasion. They take into account this taste variation assuming a normal distribution in the specification of the model. The number of consumption occasions is assumed to follow a poisson distribution. Kim, Allenby and Rossi (2002) consider a Kuhn Tucker approach to model the multiple discreteness of demand of goods. They propose a translated additive utility structure which allows to obtain corner and interior solutions of the maximization utility problem. This approach is a Dubé/Hendel alternative approach but has the advantage to allow different satiation parameters or diminishing returns to differ across products. This model does not allow to take into account the weak complementarity assumption, that is the subutility of a good not purchased is different from zero. On the other hand, they use a normal distribution for the error terms and that does not allow to have a closed form expression for the probability. Their model is not very practicable. Bhat (2005b) and Bhat and Sen (2006) extend the paper of Kim *et al.* assuming a different assumption on the distribution of the error terms. An Independently and Identically Distributed (IID) Gumbel instead of IID Normal assumption of the error terms allows to have a simple closed form expression for the discrete-continuous probabilities. Bhat (2005a) extends the previous papers using a more easy-to-interpret and general utility form.

Another current literature of the multiple continuous/discrete choice models is on environmental economics (von Haefen and Phaneuf, 2005; von Haefen, 2003; Phaneuf *et al.*, 2000 Phaneuf and Herrigues, 2000; Herrigues *et al.*, 2004). They suppose a linear expenditure system form for the

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utility function contrary to previous papers which consider a constant elasticity or substitution (CES) form. The important problem of their model is that they assume a deterministic subutility for the benchmark product (the outside numeraire option) in order to simplify the expression of the probability. So their model depends on the benchmark product and this implies different expressions and values for the probability for the same consumption pattern according to the benchmark product chosen. Another problem about these models is that they employ a numerical gradient method to estimate the Jacobian whereas we find an analytical expression for it. Their method implies a less precise and slower computation of the Jacobian.

The objective of this paper is to adapt the previous work of Bhat to a household choice behavior of food consumption. We want first to guess the bias in the estimation of price elasticities by not taking account of multiple discrete-continuous choice of consumers. Then, we want to analyze in the Soft Drink market whether consumers seek variety. Moreover, we deals with omitted variable problem that occurs in this type of consumer choice models. Our paper suggests that not taking into account the quantity choice could highly underestimate price elasticities and could then bias competition policy analyses.

The paper is organized as follows. Section 2 describes the Soft Drink market and the French available data on this sector. Section 3 presents the multiple continuous/discrete choice model and section 4 discusses the results. Section 5 concludes.

2 The Soft Drink market and Data

In 2006, according to the National Association of Soft Drinks, turnover of this industry reaches more than 2 billion euros, that is 1.5% of the total turnover of the food industry. This sector is dynamic since its production rises each year (for instance, +4% between 2005 and 2006). Refreshing drinks mainly include colas, fruit drinks, ice tea, fruit juices and nectars. In France, the total consumption of soft drinks reaches in average 60 liters per year and per individual. This consumption is comparatively weak with respect to the mean European consumption of soft drinks by 94 liters and the mean US consumption by 160 liters.

We use data from a consumer panel data collected by Kantar. We have a French representative survey of 9,472 households over the year 2005. This survey provides information on purchases of all food products (quantity, price, date, store, characteristics of goods) and on characteristics of households (number of children, number of persons, weight, height, age and sex of each member of the household...). From the panel data, we select the 13 main national brands of the soft drink industry and an 'aggregate' private label. These 14 products are differentiated according to the three main characteristics of products in this market: diet, pure juice and carbonated drink. We then analyze the consumer choice behavior through 35 differentiated products. We split the year 2005 into 13 periods of four weeks.

Our sample contains 167,111 observations over the 13 periods. Households buy 2.19 different products by period in average. This figure can vary from 1 to 14 and almost 60% of households buy more than one product in a period. This motivates that modeling only a unique consumer choice by period does not allow to account for the true consumption behavior. Table 4 shows that prices are very heterogeneous according to the product and can vary from 0.31€/liter to 2.29€/liter as well as the quantity choice. Indeed, the mean quantity vary across products (from 0.68 to 3.12 liters) and standard deviations are relatively large meaning that the quantity choice for a given product is also very heterogeneous. Average price for diet products is lower than for regular ones, and still products are in average more expensive than sparkling ones. Pure juice products, both regular and still, are more expensive than soft drinks like colas or tonics. Furthermore, diet products are bought in larger quantities than regular ones, sparkling products are also bought in larger quantities than still ones, and pure juice products are bought in fewer quantities than other ones.

3 The model

We suppose that households are faced to J products during T time periods. We add a $(J+1)$ product: the outside good that represents other brands in the sector considered purchased by households with very low market shares. We allow households to buy several products during the same period, that is households may select multiple products and multiple units of each contrary to traditional discrete choice models where a single alternative is only chosen among a set of available products. We then intend to model a multiple continuous-discrete choice behavior.

Let u_{jht} be the subutility of household h at time t to consume product j. We have chosen an additive utility structure because we suppose that products are not jointly consumed and then we suppose that the utility gained by the consumption of one product is not affected by the consumption of the others. Hence, the utility of household h at period t is:

$$U_{ht}(q_{ht}) = \sum_{j=1}^{J+1} u_{jht}(q_{jht}),$$

where q_{ht} is the vector of quantities bought for each product ($j = 1, 2, ..., J + 1$).

Each household maximizes its utility subject to the budget constraint $\sum_{j=1}^{J+1} p_{jt} q_{jht} \leqslant y_{ht}$, where p_{jt} is the price of product j at period t, q_{jht} is the quantity of product j bought by household h at time t, and y_{ht} is the expenditure of the group of products under study for household h at period t.[1]

To solve for optimal demand, we form the Lagrangian and apply the Kuhn-Tucker first order conditions. The Lagrangian function for this problem is given by:

$$\mathcal{L} = \sum_{j=1}^{J+1} u_{jht}(q_{jht}) - \lambda \left(\sum_{j=1}^{J+1} p_{jt} q_{jht} - y_{ht} \right),$$

where λ is the Lagrangian multiplier associated with the budget constraint.

The Kuhn-Tucker (KT) first order conditions are given by differentiating the Lagrangian:

$$u'_{jht}(q^*_{jht}) - \lambda p_{jt} \overset{q^*_{jht}}{\lhd} 0,$$

where q^*_{jht} is the optimal demand of household h for the product j at time t and $\overset{q^*_{jht}}{\lhd}$ is defined as:

$$\begin{aligned} \overset{q^*_{jht}}{\lhd} \text{ is } &= \text{ if } q^*_{jht} > 0, \text{ and} \\ \overset{q^*_{jht}}{\lhd} \text{ is } &\leqslant \text{ if } q^*_{jht} = 0. \end{aligned}$$

3.1 Random utility specification

As in Bhat (2005b), we specify a quasi-concave, increasing and continuously differentiable utility function with respect to the quantity bought $q_{ht} = (q_{1ht}, ..., q_{Jht}, q_{(J+1)ht})$ which belongs to the family of translated utility functions and we then assume the following form for the utility of household h at time t:

$$U_{ht}(q_{ht}) = \sum_{j=1}^{J+1} \frac{\gamma_j}{\alpha} \Psi(x_{jt}, \varepsilon_{jht}) \left\{ \left(\frac{q_{jht}}{\gamma_j} + 1 \right)^{\alpha} - 1 \right\},$$

where $\Psi(x_{jt}, \varepsilon_{jht})$ is the baseline utility for product j which captures the quality of product j through the characteristics x_{jt} of product j at time t and the idiosyncratic unobserved characteristics ε_{jht} of product j for household h at time t. We then suppose a random utility specification for the baseline utility Ψ. Besides, γ_j and α are parameters associated to product j to be estimated. Moreover, we suppose that the outside good $(J + 1)$ is an aggregate outside option which represents all other sugar beverages. We normalize its subutility to zero and then assume that $\Psi(x_{(J+1)t}, \varepsilon_{(J+1)ht}) = e^{\varepsilon_{(J+1)ht}}$.

[1]We do not allow for variation in expenditures allocated to soft drink purchases. Hence, we assume that households choose soft drink products given a fixed budget per period. The household can only switch his consumption from a bundle of products to another one.

The parameter γ_j enables corner solutions for indifference curves[2] and governs the level of satiation of product j, i.e. the level of consumption for product j from which a consumer has had enough[3] and the parameter α is the global satiation parameter, which allows to decrease the marginal utility when the consumption increases (Bhat, 2005a). This specification supposes the assumption of weak complementarity, i.e. if household h does not consume product j at time t, the corresponding subutility will be zero: $u_{jht} = 0$. Then the household does not receive any utility from this product at this period.

If we suppose the consumer chooses only one unit of a single alternative, $j = 1, ..., J+1$, i.e. $q_{jht} = 1$ and $\forall j' \neq j, q_{j'ht} = 0$, this specification is simply the expression of the multinomial logit model: $U_{jht} = \frac{\gamma_j}{\alpha}\Psi(x_{jt}, \varepsilon_{jht})\left\{\left(\frac{1}{\gamma_j}+1\right)^{\alpha} - 1\right\} \approx \Psi(x_{jt}, \varepsilon_{jht})$ when $\alpha \to 1$. Going back to the general case, note that $\alpha \to 1$ and high values of $\Psi(x_{jt}, \varepsilon_{jht})$ for product j only imply that we expect purchases of large quantities of this product only. On the other hand, small values of α imply multiple products purchased if the $\Psi(x_{jt}, \varepsilon_{jht})$'s are not too different from one j to another.

This function is valid if $\Psi(x_{jt}, \varepsilon_{jht}) > 0$, $\gamma_j > 0$ and $0 < \alpha < 1$[4]. To impose the three conditions, we suppose that:

(i) $\Psi(x_{jt}, \varepsilon_{jht}) = e^{\beta' x_{jt} + \varepsilon_{jht}}$, where β is a vector of parameters to be estimated. The exponential form guarantees the positivity of the baseline utility.

(ii) $\gamma_j = e^{\mu_j}$, which ensures $\gamma_j > 0$, and the μ_j's are estimated.

(iii) $\alpha = \frac{1}{1+e^{\delta}}$ and we estimate δ to obtain $\alpha \in (0, 1)$.

Note also that α and γ_j are the same for all households. This assumption is quite restrictive. This model could be extended to allow α and/or γ_j to depend on observed and/or unobserved characteristics.

3.2 Optimal demand

According to the previous specification of the utility function, the Lagrangian can be written as:

$$\mathcal{L} = \sum_{j=1}^{J+1} \frac{\gamma_j}{\alpha}\Psi(x_{jt}, \varepsilon_{jht})\left\{\left(\frac{q_{jht}}{\gamma_j}+1\right)^{\alpha} - 1\right\} - \lambda\left(\sum_{j=1}^{J+1} p_{jt}q_{jht} - y_{ht}\right)$$

and the KT first order conditions (for $j = 1, \ldots, (J+1)$) become:

$$\Psi(x_{jt}, \varepsilon_{jht})\left(\frac{q^*_{jht}}{\gamma_j}+1\right)^{\alpha-1} - \lambda p_{jt} \overset{q^*_{jht}}{\lhd} 0.$$

Besides, the optimal demand q^*_{jht} satisfies the budget constraint. As we assumed $y_{ht} > 0$, at least one of the $J+1$ alternatives was bought. Let j^0_{ht} be such an alternative ($q^*_{j^0_{ht}ht} > 0$). Then, the previous equations (given for $j = 1, \ldots, (J+1)$) lead to:

$$\lambda = \frac{\Psi(x_{j^0_{ht}t}, \varepsilon_{j^0_{ht}ht})\left(\frac{q^*_{j^0_{ht}ht}}{\gamma_{j^0_{ht}}}+1\right)^{\alpha-1}}{p_{j^0_{ht}t}}.$$

The previous equation enables to concentrate only on the J ($\forall j \neq j^0_{ht}$) remaining KT first order conditions and taking logarithms and replacing the perceived quality of the product considered by

[2]If γ_j is 0, the indifference curves are tangent to the axes, then there will be no corner solutions.

[3]We suppose that the level of satiation of product J+1 is equal to 1 in order to identify the other J+1 coefficients: γ_j for $j = 1, ..., J$ and α.

[4]$\alpha > 0$ comes from the division by α in the utility function, because we model a positive utility of consumption. $\alpha < 1$ because physiologically households should reach satiety after some quantities consumed: the marginal utility of consuming a larger quantity is positive, but decreasing in the quantity consumed.

its expression ($\Psi(x_{jt}, \varepsilon_{jht}) = e^{\beta' x_{jt} + \varepsilon_{jht}}$), we obtain the following simplified expression, $\forall j = 1, \ldots, (J+1)$ and $j \neq j^0_{ht}$:

$$V_{jht} + \varepsilon_{jht} \overset{q^*_{jht}}{\lhd} V_{j^0_{ht}ht} + \varepsilon_{j^0_{ht}ht},$$

where

$$V_{jht} = \beta' x_{jt} + (\alpha - 1) \ln \left(\frac{q^*_{jht}}{\gamma_j} + 1 \right) - \ln p_{jt}.$$

As $q^*_{j^0_{ht}ht}$ is determined by using the budget constraint ($y_{ht} = \sum_{j=1}^{J+1} p_{jt} q^*_{jht}$), the optimal quantity for alternative j^0_{ht} depends on the vector of optimal quantities of the other alternatives. Therefore the above KT conditions can be rewritten using:

$$V_{j^0_{ht}ht} = \beta' x_{j^0_{ht}t} + (\alpha - 1) \ln \left(\frac{y_{ht} - \sum_{j \neq j^0_{ht}} p_{jt} q^*_{jht}}{\gamma_{j^0_{ht}} p_{j^0_{ht}t}} + 1 \right) - \ln p_{j^0_{ht}t}.$$

Let $\mathcal{J}_{ht} = \left\{ j = 1, \ldots, (J+1) \mid q^*_{jht} > 0 \right\}$ be the set of alternatives which were bought by household h at time t, and $K_{ht} = |\mathcal{J}_{ht}|$ the number of alternatives which were bought by household h at time t. As we consider only cases where at least one alternative was bought ($K_{ht} \geqslant 1$), $\exists j^0_{ht} \in \mathcal{J}_{ht}$. Then, as previous equations were given for any j^0_{ht} and are symmetric in all other $j \neq j^0_{ht}$, we can, without loss of generality, reorder the alternatives so that $\widehat{j^0_{ht}} = 1$ and $\widehat{\mathcal{J}_{ht}} = \{1, \ldots, K_{ht}\}$, where $\widehat{\cdot}$ denotes the reordering operator.

Let $f(\varepsilon_{1ht}, \ldots, \varepsilon_{(J+1)ht})$ be the joint probability density function of ε_{jht} ($j = 1, \ldots, (J+1)$). The probability that household h purchases the first K_{ht} of the $(J+1)$ alternatives at time t is given by:

$$\Pr(\widehat{q^*_{1ht}}, \ldots, \widehat{q^*_{K_{ht}ht}}, \widehat{0}, \ldots, \widehat{0}) = \int_{\varepsilon_{1ht}=-\infty}^{+\infty} \cdots \int_{\varepsilon_{(J+1)ht}=-\infty}^{+\infty} f(\varepsilon_{1ht}, \ldots, \varepsilon_{(J+1)ht}) d\varepsilon_{1ht} \ldots d\varepsilon_{(J+1)ht}.$$

According to the KT conditions, $\forall j \in \widehat{\mathcal{J}_{ht}}$, $\varepsilon_{jht} = V_{1ht} + \varepsilon_{1ht} - V_{jht}$, leading to the following expression for the previous probability:

$$\begin{aligned} &\Pr(\widehat{q^*_{1ht}}, \ldots, \widehat{q^*_{K_{ht}ht}}, \widehat{0}, \ldots, \widehat{0}) = |Jac_{ht}| \times \\ &\int_{\varepsilon_{(K_{ht}+1)ht}=-\infty}^{V_{1ht}+\varepsilon_{1ht}-V_{(K_{ht}+1)ht}} \cdots \int_{\varepsilon_{(J+1)ht}=-\infty}^{V_{1ht}+\varepsilon_{1ht}-V_{(J+1)ht}} \int_{\varepsilon_{1ht}=-\infty}^{+\infty} f(\varepsilon_{1ht}, V_{1ht} - V_{2ht} + \varepsilon_{1ht}, \ldots, V_{1ht} - V_{K_{ht}ht} + \varepsilon_{1ht}, \varepsilon_{(K_{ht}+1)ht}, \ldots, \varepsilon_{(J+1)ht}) \\ &\qquad d\varepsilon_{(K_{ht}+1)ht} \ldots d\varepsilon_{(J+1)ht} d\varepsilon_{1ht}, \end{aligned}$$

where Jac_{ht} is the $(K_{ht} - 1) \times (K_{ht} - 1)$ Jacobian matrix which has for element (j, k):

$$Jac_{htjk} = \frac{\partial \left[V_{1ht} - V_{(j+1)ht} + \varepsilon_{1ht} \right]}{\partial q^*_{(k+1)ht}} = \frac{\partial \left[V_{1ht} - V_{(j+1)ht} \right]}{\partial q^*_{(k+1)ht}}.$$

Then, assuming that $\forall j \in [1, \ldots, (J+1)]$ the ε_{jht}'s are independently distributed across alternatives and have a centered (location parameter 0) Gumbell (also named type I extreme value) distribution of scale parameter σ and independent of the vector of variables x, price p and quantities q, the probability that household h purchases the first K_{ht} of the $(J+1)$ alternatives at time

t takes this final expression:

$$\Pr(\widehat{q^*_{1ht}}, \ldots, \widehat{q^*_{K_{ht}ht}}, \widehat{0}, \ldots, \widehat{0})$$

$$= \frac{(K_{ht}-1)!}{\sigma^{K_{ht}-1}} \left(\prod_{j \in \mathcal{J}_{ht}} \frac{(1-\alpha)}{q^*_{jht}+\gamma_j} \right) \left(\sum_{j \in \mathcal{J}_{ht}} \frac{q^*_{jht}+\gamma_j}{(1-\alpha)} \cdot \frac{p_{jt}}{p_{j^0_{ht}t}} \right) \frac{\prod_{j \in \mathcal{J}_{ht}} e^{\frac{V_{jht}}{\sigma}}}{\left(\sum_{j=1}^{J+1} e^{\frac{V_{jht}}{\sigma}} \right)^{K_{ht}}}.$$

The expression of the probability depends on all product prices and especially on product j^0_{ht} price. However, this price is constant in each individual likelihood function and then the estimation of parameters does not depend on this price, only the individual probability value will change[5]. The scale parameter σ should be positive because a price increase for product $j \in \widehat{\mathcal{J}_{ht}}$ should lead to a lower probability that consumer h purchases the $\widehat{\text{first}}$ K_{ht} of the $(J+1)$ alternatives at period t. Indeed, the probability is an increasing function of $\frac{\widehat{V_{jht}}}{\sigma} = \frac{\beta}{\sigma}' \widehat{x_{jt}} - \frac{1}{\sigma} \ln \widehat{p_{jt}} + \frac{(\alpha-1)}{\sigma} \ln \left(\frac{\widehat{q^*_{jht}}}{\widehat{\gamma_j}} + 1 \right)$. This parameter becomes identifiable as the inverse of the estimated price parameter and could depend on household characteristics.

It has to be noted that we obtain a closed form expression from this probability which can be simplified to the standard multinomial logit model when $K_{ht} = 1$ (i.e. only one good is chosen: j^0_{ht}) and $\sigma = 1$ (using the standard Gumbell distribution): $P_{j^0_{ht}ht} = \frac{e^{V_{j^0_{ht}ht}}}{\sum_{j=1}^{J+1} e^{V_{jht}}}$, $\forall j^0_{ht} \in [1, \ldots, (J+1)]$.

3.3 Omitted variable problem

The previous expression of household h purchases probability is deduced from the assumption that x, p and q are independent of the error disturbances ε_{jht}. The individual error term could be split up in two components: $\varepsilon_{jht} = \xi_{jt} + e_{jht}$ where ξ_{jt} is product-specific characteristics varying in time and observed by both consumers and producers, but not included in the estimated specification and e_{jht} is a consumer specific idiosyncratic taste varying across products and time. Some omitted product characteristics included in ξ_{jt} could be correlated with prices. For instance, we don't know the amount of advertising that firms invest each month for their brand. This is then included in the error term because advertising could be a determining factor in the choice process of households. As advertising is a non negligible part of the cost of soft drinks, it is obviously correlated with prices. Another example could be promotions that households face during trips and this omitted variable has an impact on the choice of the alternative. To solve the endogeneity problem of prices, we use a control function approach as in Petrin and Train (2010). We then regress prices on instrumental variables, that is input prices, as well as product and time fixed effects:

$$p_{jt} = W_t \gamma + \delta_j + \theta_t + \eta_{jt}$$

The estimated error term $\widehat{\eta}_{jt}$of the first stage includes some omitted variables as advertising variations, promotions. Introducing this term in the indirect utility V_{jht} allows to capture unobserved characteristics. We then write:

$$V_{jht} = \beta' x_{jt} + (\alpha - 1) \ln \left(\frac{q^*_{jht}}{\gamma_j} + 1 \right) - \ln p_{jt} + \lambda \widehat{\eta}_{jt},$$

where λ is the estimated parameter associated with the estimated error term of the first stage. The new error term $\xi_{jt} + e_{jht} - \lambda \widehat{\eta}_{jt}$ is now not correlated with prices.

[5]The choice of the 'first' good consumed impacts on the purchase probability of consumers. This could be problematic if our results depended on probabilities estimated. However, not only parameter estimates do not change whatever the choice of the first good but our elasticity results also do not depend on it. Indeed, we see in section 4.2 that elasticities depend only on demand parameters (through the maximization of the utility to recover quantities) and not on the probability estimates.

4 Results

We now describe estimation results of the multiple discrete-continuous choice model with and without taking into account the endogeneity problem. We also show price elasticities and compare them with a standard discrete choice model.

4.1 Estimation results

Table 1 and Appendix Table 5 present demand results when endogeneity problem is taken into account or not. We see that λ is positive and significant, meaning that the unobserved part explaining prices is positively correlated with prices. Moreover, the estimates of the other variables affecting utility are robust to instrumentation except for the taste of pure juice which becomes positive under the control function approach whereas it was negative. As expected, consumer price sensitivity is larger. Indeed, the price sensitivity of consumers is measured by $\frac{1}{\sigma}$, which gives 0.90 in the uncorrected model and 1.06 in the control function approach. Tastes for the diet characteristic and sparkling beverages are negative in average.

Parameter α, which represents the satiation parameter, is 0.17, meaning that consumers do not value so much an additional unit of beverage of the same product and prefer to get a unit of another product (if consumers approximatively value and saturate for both products in the same way). Indeed, an additional unit of the same product increases less the utility of consumers than a unit of another product.

Parameters γ_j vary between 0.691 and 4.897. Then, the threshold from which the consumer does not value so much an additional unit of product j is heterogeneous across products. It is interesting to see whether some product characteristics could explain this heterogeneity. As we can see in Table 2, only dummies for brand 2 and 11 are significantly positive. Indeed, diet, sparkling and pure juice characteristics as well as other brand dummies do not play any role in the value on the product satiety threshold. Consumers then significantly like more brands 2 and 11 since the threshold at which an additional unit is less valued is higher for those two brands than for the other ones.

	Mean (Std 10^{-3})		Mean (Std 10^{-3})		Mean (Std 10^{-3})
α	0.167 (0.309)	γ_1	2.142 (1.250)	γ_{20}	1.861 (0.943)
σ	0.942 0.345)	γ_2	3.356 (1.968)	γ_{21}	1.050 (1.563)
β_{Diet}	-1.988 (0.656)	γ_3	2.437 (0.439)	γ_{22}	0.979 (0.903)
$\beta_{Sparkling}$	-1.790 (0.499)	γ_4	3.629 (1.044)	γ_{23}	4.897 (2.166)
$\beta_{purejuice}$	0.007 (0.161)	γ_5	1.615 (0.554)	γ_{24}	1.704 (0.869)
Brand1	-1.345 (0.588)	γ_6	1.452 (1.113)	γ_{25}	1.325 (1.743)
Brand2	1.251 (0.334)	γ_7	1.745 (0.617)	γ_{26}	1.388 (0.740)
Brand3	-2.278 (0.888)	γ_8	1.693 (0.912)	γ_{27}	0.691 (1.071)
Brand4	-0.454 (0.397)	γ_9	1.573 (0.502)	γ_{28}	1.846 (0.271)
Brand5	-0.249 (0.341)	γ_{10}	1.496 (0.783)	γ_{29}	1.737 (0.296)
Brand6	-2.530 (0.923)	γ_{11}	1.975 (0.683)	γ_{30}	1.249 (1.059)
Brand7	-1.039 (0.580)	γ_{12}	1.464 (1.699)	γ_{31}	0.838 (1.329)
Brand8	-2.156 (0.867)	γ_{13}	1.409 (0.563)	γ_{32}	1.863 (0.378)
Brand9	-2.861 (1.194)	γ_{14}	1.160 (0.990)	γ_{33}	0.728 (1.735)
Brand10	-3.626 (1.306)	γ_{15}	1.778 (0.665)	γ_{34}	1.947 (0.647)
Brand11	-1.701 (0.807)	γ_{16}	2.013 (0.850)	λ	0.870 (0.668)
Brand12	-3.033 (1.186)	γ_{17}	0.867 (1.753)		
Brand13	-2.512 (1.188)	γ_{18}	1.311 (1.198)		
Brand14	-0.608 (0.138)	γ_{19}	1.729 (0.875)		
Log likelihood			-651,068		

Table 1: Demand results with endogeneity.

γ_j	Mean (Std)	Mean (Std)	Mean (Std)
Diet	-0.17 (0.31)		-0.09 (0.32)
Sparkling	0.39 (0.31)		0.12 (0.64)
Pure Juice	0.22 (0.28)		0.29 (0.43)
Brand1		1.29 (0.63)	1.34 (0.77)
Brand2		1.52 (0.63)	1.63 (0.77)
Brand3		0.07 (0.63)	0.26 (0.75)
Brand4		0.26 (0.63)	0.31 (0.77)
Brand5		0.07 (0.63)	0.15 (0.77)
Brand6		0.26 (0.63)	0.44 (0.75)
Brand7		-0.17 (0.63)	-0.11 (0.77)
Brand8		0.09 (0.54)	0.16 (0.64)
Brand9		0.06 (0.63)	0.05 (0.74)
Brand10		-0.00 (0.63)	-0.01 (0.74)
Brand11		1.47 (0.63)	1.47 (0.74)
Brand12		0.05 (0.63)	0.24 (0.75)
Brand13		-0.41 (0.63)	-0.23 (0.75)
Constant	1.60 (0.24)	1.45 (0.29)	1.32 (0.50)
R^2	0.06	0.26	0.46

Table 2: Regressions of satiation parameters on 3 sets of product characteristics.

	MLM		MDCCM	
	Model 1	Model 2	Model 3	Model 4
Brand1	-0.89 (0.00)	-1.09 (0.00)	-1.57 (0.19)	-1.85 (0.45)
Brand2	-0.89 (0.00)	-1.02 (0.06)	-1.59 (0.05)	-1.83 (0.06)
Brand3	-0.90 (0.00)	-1.09 (0.01)	-1.55 (0.22)	-1.80 (0.33)
Brand4	-0.90 (0.00)	-1.09 (0.01)	-1.53 (0.13)	-1.78 (0.23)
Brand5	-0.90 (0.00)	-1.09 (0.01)	-1.57 (0.10)	-1.84 (0.31)
Brand6	-0.90 (0.00)	-1.09 (0.00)	-1.53 (0.18)	-1.72 (0.23)
Brand7	-0.90 (0.00)	-1.09 (0.00)	-1.51 (0.16)	-1.82 (0.58)
Brand8	-0.91 (0.00)	-1.09 (0.00)	-1.55 (0.15)	-1.83 (0.22)
Brand9	-0.91 (0.00)	-1.10 (0.00)	-1.56 (0.11)	-1.82 (0.21)
Brand10	-0.90 (0.00)	-1.10 (0.00)	-1.49 (0.11)	-1.67 (0.16)
Brand11	-0.91 (0.00)	-1.08 (0.00)	-1.69 (0.12)	-1.93 (0.15)
Brand12	-0.90 (0.00)	-1.10 (0.00)	-1.51 (0.21)	-1.91 (0.74)
Brand13	-0.91 (0.00)	-1.10 (0.00)	-1.68 (0.81)	-2.14 (0.81)
Brand14	-0.88 (0.01)	-1.04 (0.00)	-1.49 (0.09)	-1.72 (0.15)
Endogeneity	No	Yes	No	Yes

Table 3: Own Price elasticities in multinomial logit models (MLM) and multiple discrete-continuous choice models (MDCCM).

4.2 Price elasticities

The objective of this paper is to compare consumer substitution patterns between the multiple discrete-continuous choice model presented above and the standard logit model representing discrete choices of households.

The quantities consumed by the household h at time t is based on the following problem:

$$\underset{q_{ht}}{Max} U_{ht}(q_{ht}) = \sum_{j=1}^{J+1} \frac{\gamma_j}{\alpha} \Psi(x_{jt}, \varepsilon_{jht}) \left\{ \left(\frac{q_{jht}}{\gamma_j} + 1 \right)^{\alpha} - 1 \right\}$$

subject to $y_{ht} = \sum_{j=1}^{J+1} p_{jt} q_{jht}$ and $\forall j = 1, ..., J+1, q_{jht} \geqslant 0$.

We use an optimization routine to solve this problem. Once we have estimated optimal quantities, we recover price elasticities of the aggregate demand estimated by evaluating a centered numerical derivative of quantities estimated. The elasticities reported in Table 3 are mean across periods. Model 1 and model 2 are standard multinomial logit models (MLM), the last one corrects the omitted variable problem. Estimation results of both models are presented in Appendix. Model 3 and model 4 are multiple discrete-continuous choice models (MDCCM) without and with solving the endogeneity problem respectively. We see that omitting the multiple discrete-continuous choice would lead to underestimate own price elasticities when we compare model 1 to model 3, and model 2 to model 4. Indeed, own price elasticities of model 4 are roughly twice larger than the ones of model 2. We also show that not taking into account omitted variable problem would also lead to underestimate price elasticities. Our model allows to introduce some heterogeneity in consumer substitution patterns across products without introducing some household heterogeneity. We see that own price elasticities can vary across brands and standard deviations in brackets show some heterogeneity within the brand, that is across products which are brands with different characteristics as diet, sparkling and pure juice characteristics.

5 Conclusion

This paper allows to compare consumer substitution patterns between a multiple discrete-continuous choice model and a multinomial logit demand model, which is a particular case of the first one. We model multiple brand and quantity choices of households in each purchase occasion. We then allow for taste variety within the household that is different tastes in a household composed of several persons. Our results suggest that consumers seek variety. Indeed, they prefer to buy several products rather than a large quantity of a single product. We find that consumers have a more elastic behavior allowing for a multiple discrete-continuous choice model since own price elasticities are larger. This result has important implications when analyzing competition policies between products and consumer welfare effects of regulations, price policies...

This work is currently being extended by introducing some household heterogeneity in the multiple discrete-continuous choice model to guess whether household characteristics impact on the brand choice and the quantity choice behaviors.

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7 Appendix

7.1 Descriptive Statistics

Products	Brand	Pur Juice	Diet	Carbonated	Price (std)	Quantity (std)
OG		yes/no	yes/no	yes/no	1.05 (0.05)	6.01 (8.04)
1	1			yes	0.75 (0.07)	5.47 (6.20)
2	1		yes	yes	0.74 (0.01)	7.16 (7.91)
3	2			yes	0.98 (0.01)	5.88 (6.22)
4	2		yes	yes	0.99 (0.01)	5.78 (6.65)
5	3				1.14 (0.02)	3.36 (3.02)
6	3		yes		1.11 (0.02)	3.09 (2.72)
7	4			yes	1.09 (0.02)	3.69 (3.31)
8	4		yes	yes	1.00 (0.02)	3.61 (2.96)
9	5			yes	1.14 (0.01)	3.05 (2.53)
10	5		yes	yes	1.03 (0.02)	3.02 (2.54)
11	6				1.00 (0.05)	4.11 (3.67)
12	6		yes		0.77 (0.01)	2.72 (1.39)
13	7			yes	1.02 (0.05)	3.28 (2.81)
14	7		yes	yes	0.87 (0.03)	2.61 (2.11)
15	8				1.26 (0.01)	3.16 (2.54)
16	8	yes			1.76 (0.01)	2.94 (2.59)
17	8		yes		1.79 (0.02)	1.72 (1.24)
18	9				1.80 (0.04)	2.33 (2.04)
19	9	yes			1.82 (0.02)	2.65 (2.29)
20	10				1.01 (0.05)	3.69 (3.45)
21	10	yes			1.26 (0.11)	2.59 (2.20)
22	11				1.80 (0.05)	1.95 (1.61)
23	11	yes			2.29 (0.02)	3.31 (2.76)
24	12				1.18 (0.01)	3.13 (2.41)
25	12		yes		1.10 (0.09)	2.56 (1.88)
26	13				1.99 (0.02)	2.52 (2.32)
27	13		yes		2.06 (0.02)	1.45 (0.92)
28	PL				0.80 (0.01)	4.79 (5.11)
29	PL	yes			1.17 (0.01)	3.50 (3.37)
30	PL		yes		0.55 (0.03)	3.09 (2.30)
31	PL	yes	yes		0.93 (0.07)	2.12 (2.15)
32	PL			yes	0.46 (0.01)	5.11 (5.60)
33	PL	yes		yes	0.91 (0.10)	5.49 (6.81)
34	PL		yes	yes	0.31 (0.00)	4.68 (5.62)

Table 4: Descriptive Statistics on Prices (€/liter) and Quantities (liters per household, year 2005).

7.2 Demand results

	Mean (Std 10^{-3})		Mean (Std 10^{-3})		Mean (Std 10^{-3})
α	0.017 (0.293)	γ_1	2.141 (1.250)	γ_{20}	1.858 (0.941)
σ	1.112 (0.330)	γ_2	3.350 (1.964)	γ_{21}	1.047 (1.557)
β_{Diet}	-2.309 (0.161)	γ_3	2.442 (0.439)	γ_{22}	0.979 (0.903)
$\beta_{Sparkling}$	-2.033 (0.482)	γ_4	3.620 (1.041)	γ_{23}	4.901 (2.168)
$\beta_{purejuice}$	-0.064 (0.631)	γ_5	1.614 (0.553)	γ_{24}	1.704 (0.869)
Brand1	-1.605 (0.580)	γ_6	1.457 (1.117)	γ_{25}	1.317 (1.730)
Brand2	1.411 (0.332)	γ_7	1.744 (0.617)	γ_{26}	1.388 (0.740)
Brand3	-2.700 (0.855)	γ_8	1.693 (0.912)	γ_{27}	0.869 (1.080)
Brand4	-0.620 (0.399)	γ_9	1.572 (0.502)	γ_{28}	1.840 (0.271)
Brand5	-0.386 (0.347)	γ_{10}	1.498 (0.784)	γ_{29}	1.736 (0.295)
Brand6	-2.972 (0.889)	γ_{11}	1.974 (0.683)	γ_{30}	1.245 (1.056)
Brand7	-1.295 (0.575)	γ_{12}	1.483 (1.722)	γ_{31}	0.839 (1.331)
Brand8	-2.571 (0.834)	γ_{13}	1.407 (0.562)	γ_{32}	1.865 (0.378)
Brand9	-3.435 (1.152)	γ_{14}	1.154 (0.985)	γ_{33}	0.665 (1.567)
Brand10	-4.251 (1.258)	γ_{15}	1.778 (0.665)	γ_{34}	1.950 (0.648)
Brand11	-2.087 (0.776)	γ_{16}	2.019 (0.853)		
Brand12	-3.598 (1.144)	γ_{17}	0.850 (1.73)		
Brand13	-3.077 (1.147)	γ_{18}	1.311 (1.198)		
Brand14	-0.658 (0.143)	γ_{19}	1.730 (0.876)		
Log Likelihood			-651,140		

Table 5: Demand results without endogeneity.

	Without endogeneity	With Endogeneity
	Mean (Std 10^{-3})	Mean (Std 10^{-3})
σ	1.077 (0.482)	0.902 (0.290)
β_{Diet}	-2.087 (0.848)	-1.781 (0.52)
$\beta_{Sparkling}$	-1.831 (0.625)	-1.607 (0.380)
$\beta_{purejuice}$	0.028 (0.182)	0.088 (0.119)
Brand1	-1.340 (0.713)	-1.106 (0.455)
Brand2	1.429 (0.474)	1.258 (0.297)
Brand3	-2.269 (1.083)	-1.890 (0.659)
Brand4	-0.395 (0.458)	-0.251 (0.300)
Brand5	-0.117 (0.383)	-0.061 (0.259)
Brand6	-2.542 (1.131)	-2.146 (0.692)
Brand7	-1.048 (0.710)	-0.811 (0.450)
Brand8	-2.154 (1.063)	-1.779 (0.644)
Brand9	-2.969 (1.507)	-2.439 (0.915)
Brand10	-3.772 (1.659)	-3.182 (1.007)
Brand11	-1.661 (0.969)	-1.320 (0.588)
Brand12	-3.120 (1.489)	-2.593 (0.906)
Brand13	-2.597 (1.491)	-2.067 (0.905)
Brand14	-0.514 (0.133)	-0.483 (0.094)
λ		0.008 (0.006)
Log likelihood	-464,064	-463,986

Table 6: Estimation results of the standard discrete choice model.