# A Microeconometric Approach towards Strategic Product Positioning

## Application to a Product Launch in the Pharmaceuticals Market

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**Abstract.** In this paper we introduce an alternative approach towards predicting demand behavior prior to market entry. We argue that preference, choice and desired demand volume represent separate, albeit not independent components of customer behavior. To take this into account we propose a methodology that adopts elements from experimental choice, conjoint and panel data analysis as well as discrete/continuous models. The method is applied in a real-world case study, a pharmaceuticals market product launch, in which we demonstrate that focussing on choice or preference elicitation alone would imply a too narrow view of customer behaviour, and misleading marketing implications.

**Keywords:** Market entry, experimental choice, conjoint, discrete/continuous models, panel data analysis

**JEL Classification:** M21, C33,C34.

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## 1. Introduction

In order to forecast the potential success of product innovations prior to actually introducing the new concepts to the marketplace, firms face the problem of assessing the preference structures and demand behavior of their prospective customers. Historical demand data is generally not useful for this task since the established products do not necessarily possess the new attribute levels. To cope with this problem, two major research paths are pursued in the marketing literature and widely applied in practice: the conjoint measurement methodology and the experimental choice analysis.

In this paper we propose an alternative approach towards the quantification of demand behaviour prior to market entry. The method is designed to provide a single framework for analyzing consistently the main components of customer behavior: preferences, choice and demand volume. To achieve this objective, we formulate a model that adopts elements of conjoint measurement, experimental choice and panel data analysis as well as the discrete/continuous models.

The conjoint measurement methodology goes back to Luce and Tukey (1964) and comprises, according to the definition of Green and Srinivasan (1978), any decompositional method that estimates the structure of consumer preferences given overall evaluations of a set of alternatives that are pre-definied in terms of levels of different attributes (the so called factorial design).[1] Preference values for the attribute levels, referred to as part-worths, are estimated from these overall evaluations. The basic conjoint methodology has been extended in various directions: In order to cope with highly fractionated factorial designs, hybrid models have been proposed in which a respondent receives both a self-explicated evaluation task and a smaller set of full profiles for evaluation (see Green (1984) and Green and Krieger (1997) for overviews). Another conjoint research path develops procedures that collect only full-profile data, but introduces user-supplied parameter constraints. Examples are Allenby, Arora, and Ginter (1995), Srinivasan, Jain, and Malhotra (1983) and Lenk, DeSarbo, Green, and Young (1994). Another research development utilizes various means of data aggregation for market segmentation as in (Hagerty, 1985) and Green, Krieger, and Schaffer (1993).[2]

These conjoint procedures take judgements, i.e. intervally scaled measures of preferences or of the importance of attributes, as inputs. In contrast, Lou-

[1] Compositional methods involve asking respondents to assess the values for attribute levels and use these values to build up preferences for attribute bundles (full profiles). This method is also referred to as self-explicated preference data collection.

[2] Related cluster-based procedures have been proposed by Kamakura (1988), De Sarbo, Oliver, and Rangaswamy (1989), Wedel and Kistemaker (1989), Steenkamp and Wedel (1992) and Wedel and DeSarbo (1993). DeSarbo, Wedel, Vriens, and Ramaswamy's (1992) and Kamakura, Wedel, and Agrawal's (1994) methods produce a set of latent groups, with a single set of part-worths for each segment.

viere and Woodworth (1983) and Louviere (1988) have argued in favor of using choice-based rather than ratings-based data for the analysis of customer behaviour. Instead of making judgements on the likelihood of selecting an alternative, respondents should choose the best profile out of successive choice sets. Batsell and Louviere (1991) referred to this research approach as experimental choice analysis. Advocates of the experimental choice approach argue that the advantage over standard conjoint is that the respondent's task more directly represents real market behavior: Customers do not generally rate alternatives in terms of preferences. Instead, they simply choose.[3]

However, the experimental choice approach may be critizised on the grounds that in most market entry studies the pediction of the choice behaviour of potential customers is not sufficient. Instead, the primary interest of a firm is to estimate the expected demand volumes that can be generated by their product innovation. Discrete choice models that also account for volume decisions belong to the discrete/continuous (d/c) model family introduced by Dubin and McFadden (1984).[4] Yet, the d/c approach has not yet been combined with experimental designs and applied for market entry studies.

The methodology that we introduce in this paper adopts elements from all three research paths outlined above. The conjoint analysis contributes the factorial design of a full-profile study. In formulating the model we furthermore recognize that the setup for a full-profile conjoint study can be perceived as a panel like design, since we obtain repeated evaluations of the same respondent. This makes it possible to account for individual heterogeneity, and to employ the model for customer segmentation purposes. Furthermore, our approach adopts ideas of experimental choice analysis, since it involves modeling customer choice in an experimental design framework. Lastly, as in the d/c approach, choice and demand volume decisions are modeled as separate, but not independent components of customer behavior.

To illustrate the relevance of our approach, we apply the method to a real-world case study, a product launch of an innovative arthoris medicine in the pharmaceuticals market. Since physicians are responsible for selecting the appropriate pharmaceutical for their patients, it is their demand (i.e. prescription) behavior that mattered for the success of the product innovation. Immediately before our market entry study was conducted, a reform of the national health care system had severely sharpened the cost awareness of the physicians. This explains why our application reveals that preferences, choice, and demand vol-

[3]Data collection designs for experimental choice analysis have been proposed by Green and Krieger (1984), Steckel, DeSarbo, and Mahajan (1991), Anderson and Wiley (1992), Kuhfield, Tobias, and Garratt (1994) and Lazari and Anderson (1994). Econometric models applied for parameter estimation are of the discrete choice models of multinomial logit or probit type.

[4]Recent extensions of the basic model have been proposed by Hanemann (1994) and Bolduc and Sanga (1999).

ume can represent quite independent components of demand behavior. We find that physicians may find a drug profile with a combination of desirable attributes (e.g. reduced side effects, high efficacy) very attractive from the medical point of view, and implicitely assign a high preference value to these attribute levels. However, with respect to the prescription volume decision, i.e. the number of patients for which the drug is actually prescribed, the attribute "price" turns out to be the dominating factor. Furthermore, we find that choice and volume decision must not be confounded. A high quality/high price-product may achieve a significant choice probability, i.e will be prescribed by the vast majority of physicians. However, it may not be possible to establish it as a mass product that is prescribed for a large number of patients, thereby ensuring sustainable profit. We find that the importance ranking of attributes with respect to preference and choice is quite similar, but differs fundamentally with respect to demand volume. A methodology that focusses on preference elicitation and choice behavior alone would therefore imply misleading marketing strategies.

The remainder of the paper is organized as follows: In the next Section we will develop the methodology and outline the parameter estimation strategy. In section three we present the results of the empirical application. We conclude in Section four with a summary.

## 2. Methodology

### *2.1. Data Sampling*

The factorial design that provides the basis for the data collection is that of a traditional full-profile conjoint study. We identify $J$ attributes that sufficiently define the product, service or offering of interest. Attribute $j$ is defined on $M_j$ levels. An orthogonal main effects plan (see Plackett and Burman (1946)) is employed to generate a set of $K$ full profiles which are presented to a set of $N$ individuals for evaluation.[5] A respondent's first evaluation task is to decide whether a given attribute bundle meets the requirements for a product that the respondent would choose. Depending on the context of the study, the choice decision can refer to consumption, purchase or, as in our application, drug prescription. A respondent may choose an arbitrary set from the $K$ profiles presented. If a profile is chosen by the respondent, the second task is to provide information about the desired volume demand that is associated with the first step choice. The third evaluation task of the respondent is to provide preference ratings. In principle it is possible to obtain these ratings either for all or for the subset of accepted profiles only. In the sequel we assume that preference ratings are available on a 0-100 scale. This data collection procedure yields a sequence

[5] Using one of the alternative experimental designs mentioned in the previous section would also be possible.

of binary indicators, denoted by $d_{ik}$, which equal one if profile $k$ is chosen by consumer $i$ and zero otherwise; a sequence of desired demand volumes, $v_{ik}$, and a sequence of preference ratings, $u_{ik}$. The binary choice indicator $d_{ik}$ and the two censored variables $v_{ik}$ and $u_{ik}$ represent the observable dependent variables of the model.

### *2.2. Model*

When working with qualitative and limited dependent variables one assumes the existence of latent variables that are related to the observable values via a threshold model. We have to account for three of those indicators: The latent index $d^*_{ik}$ measures the unobservable propensity of respondent $i$ to choose profile $k$. $v^*_{ik}$ may be perceived as the latent volume demand propensity and $u^*_{ik}$ as respondent $i's$ latent preference propensity. A threshold model combines latent and limited dependent model variables:

$$d_{ik} = \begin{cases} 1 & \text{if} \quad d^*_{ik} > 0 \\ 0 & \text{if} \quad d^*_{ik} \leq 0 \end{cases} \tag{1}$$

$$v_{ik} = \begin{cases} v^*_{ik} & \text{if} \quad d^*_{ik} > 0 \\ 0 & \text{if} \quad d^*_{ik} \leq 0 \end{cases} \tag{2}$$

If preference ratings are available for selected profiles only, then we have

$$u_{ik} = \begin{cases} u^*_{ik} & \text{if} \quad d^*_{ik} > 0 \\ 0 & \text{if} \quad d^*_{ik} \leq 0 \end{cases} \tag{3}$$

otherwise $u_{ik}$ simply equals $u^*_{ik}$. Following Amemiya's (1984) classification, the equation array (1)-(3) represents the censoring scheme of an extended type two tobit model with an additional censored dependent variable and two superscripts (instead of one) that identify respondents and profiles.[6] The data collection using a full profile design can be perceived as panel study in that we obtain repeated profile evaluations from the same respondent. This allows us to account for individual unobservable heterogeneity by adopting a random effects specification. This implies that the model can be employed for customer segmentation purposes.

The latent variables are assumed to be dependent on the weights of the attribute levels present in the profile, a random variable that measures perception errors, and an unobservable heterogeneity component that influences the

[6]Note that $v^*_{ik} = 0$ in (2) and $u^*_{ik} = 0$ in (3) merely signify the event $d^*_{ik} \leq 0$ (c.f. Amemiya (1985)p. 385). Bivariate models with related censoring schemes were proposed by Cragg (1971), Deaton and Irish (1984), Blundell and Meghir (1987), Jones (1989) and Zabel (1993).

respondent's evaluation of each profile in the same way:

$$d_{ik}^{*} = \alpha_0^d + \sum_{j=1}^{J} \sum_{m=1}^{M_{j-1}} \alpha_{jm}^d x_{jmk} + \varepsilon_{ik}^d + \delta_i^d \quad (4)$$

$$v_{ik}^{*} = \alpha_0^v + \sum_{j=1}^{J} \sum_{m=1}^{M_{j-1}} \alpha_{jm}^v x_{jmk} + \varepsilon_{ik}^v + \delta_i^v \quad (5)$$

$$u_{ik}^{*} = \alpha_0^u + \sum_{j=1}^{J} \sum_{m=1}^{M_{j-1}} \alpha_{jm}^u x_{jmk} + \varepsilon_{ik}^u + \delta_i^u \quad (6)$$

$x_{jmk}$ denotes a binary indicator which equals one if attribute level $m$ of attribute $j$ is present in profile $k$, and zero otherwise. $\alpha_{jm}^d$, $\alpha_{jm}^v$ and $\alpha_{jm}^u$ denote the weight-coefficient associated with level $m$ of attribute $j$. The superscripts indicate that these coefficients are allowed to differ across equations. Identification is ensured by restricting that one weight coefficient of each attribute to be equal to zero. $\varepsilon_{ik}^u$, $\varepsilon_{ik}^d$ and $\varepsilon_{ik}^v$ denote errors in perception and $\delta_i^d$, $\delta_i^v$ and $\delta_i^u$ represent the heterogeneity components. In order to circumvent the incidental parameter problem a random-effects approach is chosen. We consider the following one-factor specification:

$$\delta_i^d = \gamma_0 \delta_i \quad (7)$$

$$\delta_i^v = \gamma_1 \delta_i \quad (8)$$

$$\delta_i^u = \gamma_2 \delta_i \quad (9)$$

The shift parameters $\gamma_0$, $\gamma_1$, $\gamma_2$ determine the strength and direction of the heterogeneity component $\delta_i$ in the three model equations.

### *2.3. Estimation*

We propose to use the maximum likelihood method for parameter estimation. The likelihood function is constructed from the following assumptions. First, we assume that the perception errors are independent across individuals and profiles, but that there exists an unrestricted covariance matrix of perception errors with respect to the evaluation of a full profile $k$:

$$\varepsilon_{ik} = (\varepsilon_{ik}^d, \varepsilon_{ik}^v, \varepsilon_{ik}^u)' \sim \text{i.i.d. } N(0, \Sigma) \quad (10)$$

where

$$\Sigma = \begin{bmatrix} 1 & . & . \\ \sigma_{d,v} & \sigma_v^2 & . \\ \sigma_{d,u} & \sigma_{v,u} & \sigma_u^2 \end{bmatrix}.$$

The variance of $\varepsilon_{ik}^d$ is restricted to one in order to ensure identification. Furthermore, we assume zero covariance between perception errors and attribute

levels:

$$\mathrm{E}(\varepsilon_{ik}x_{jmk})=0 \tag{11}$$

The random effects are assumed to be independent and normally distributed, as well as uncorrelated with attribute levels:

$$\delta_i \sim \text{i.i.d. } \mathrm{N}(0,1) \tag{12}$$

$$\mathrm{E}(\delta_i x_{jmk})=0 \tag{13}$$

Furthermore, errors in perception and individual effects are assumed to be uncorrelated:

$$\mathrm{E}(\varepsilon_{ik}\delta_i)=0 \tag{14}$$

This implies that, conditional on the individual effect, the likelihood of the event that respondent $i$ does not choose profile $k$

$$\begin{aligned} l_{ik}^0 &= P(d_{ik}=0 \mid x_{jmk}, \delta_i) \\ &= P(\varepsilon_{ik}^d \leq -\tau_{ik}^d) \\ &= 1-\Phi(\tau_{ik}^d) \end{aligned} \tag{15}$$

where

$$\tau_{ik}^d = \alpha_0^d + \sum_{j=1}^{J}\sum_{m=1}^{M_{j-1}} \alpha_{jm}^d x_{jmk} + \gamma_0\delta_i.$$

$\Phi(\cdot)$ denotes the cumulative density function of the standard normal distribution. (15) assumes that the respondent's preference ratings available for all profiles. When preference ratings are available for all profiles we have

$$l_{ik}^0 = \int_{-\infty}^{-\tau_{ik}^d} \phi_{bv}\left(\varepsilon_{ik}^d, u_{ik}-\tau_{ik}^u, \Sigma\right) d\varepsilon_{ik}^d \tag{16}$$

where

$$\tau_{ik}^u = \alpha_0^u + \sum_{j=1}^{J}\sum_{m=1}^{M_{j-1}} \alpha_{jm}^u x_{jmk} + \gamma_2\delta_i.$$

and

$$\Sigma_{d,u} = \begin{pmatrix} 1 & \sigma_{d,u} \\ \sigma_{d,u} & \sigma_d^2 \end{pmatrix}$$

$\phi_{bv}$ denotes the probability density function of the bivariate normal distribution.

The likelihood associated with the event that profile $k$ is chosen by respondent $i$ with desired volume demand $v_{ik}$ and preference ranking $u_{ik}$ is, conditional on the individual effect,

$$l_{ik}^+ = \int_{\tau_{ik}^d}^{\infty} \phi_{tv}\left(\varepsilon_{ik}^d, v_{ik}-\tau_{ik}^v, u_{ik}-\tau_{ik}^u, \Sigma\right) d\varepsilon_{ik}^d \tag{17}$$

where

$$\tau_{ik}^{v} = \alpha_0^v + \sum_{j=1}^{J} \sum_{m=1}^{M_{j-1}} \alpha_{jm}^v x_{jmk} + \gamma_1 \delta_i$$

where $\phi_{tv}$ denotes the probability density function of the trivariate normal distribution. Conditional on the individual effect, the sequence of respondent $i's$ evaluations of the $K$ profiles (accepted and non- accepted) is independent. The likelihood for the sequence is

$$l_i = \prod_{k=1}^{K} l_{ik}^{0^{(1-d_{ik})}} l_{ik}^{+^{d^{ik}}} \tag{18}$$

where $l_{ik}^0$ is either (15) or (16). Integrating out the individual-specific effect yields the marginal log likelihood function

$$\ln \mathcal{L} = \sum_{i=1}^{N} \ln \int_{-\infty}^{+\infty} l_i \cdot \phi\left(\delta_i\right) d\delta_i \tag{19}$$

Maximization of the (19) with respect to the part-worths, the shift parameters in (7)-(9) and the variances and covariances in (10) yields ML estimates for the parameters of interest. Some useful modifications for a facilitated computation of the log likelihood function (19) are presented in the appendix.

### *2.4. Using the model in applied marketing research*

To employ the model in applied research it is straightforward to transfer ideas from traditional conjoint analysis: The relative importance of attribute $j$ with respect to the latent variable choice propensity can be computed by the standard formula known from full-profile conjoint analysis

$$r_j^d = \frac{\left|\widehat{\alpha}_j^d\right| + \left|\breve{\alpha}_j^d\right|}{\sum_{j=1}^{J}\left|\widehat{\alpha}_j^d\right| + \sum_{j=1}^{J}\left|\breve{\alpha}_j^d\right|} \tag{20}$$

where $\widehat{\alpha}_j^d$, $\breve{\alpha}_j^d$ is the numerically largest (smallest) estimated part-worth of attribute $j$. The computation of relative importance indicators with respect to $v_{ik}^*$ and $u_{ik}^*$, is analogous. The choice probability, $P\left(d_{ik}=1\right)$, and expected volume demand, $E\left(v_{ik}\right)$, of a profile $k$, marginal on the individual-specific effect, is given by

$$P(d_{ik=1}) = \int_{-\infty}^{+\infty} \Phi\left(\tau_{ik}^d\right) \cdot \phi(\delta_i) d\delta_i \tag{21}$$

and

$$E(v_{ik}) = \int_{-\infty}^{+\infty} E\left(v_{ik} \mid d_{ik}^* > 0\right) \cdot \Phi\left(\tau_{ik}^d\right) \cdot \phi(\delta_i) d\delta_i. \tag{22}$$

A potentially different ranking of the importance of attributes with respect to choice, volume demand and preference ranking, and the sensitivity of a profile's choice probability(21) and its expected demand volume (22) toward changes in attribute levels convey information for product positioning and pricing strategies. Furthermore, the significance of the estimated $\gamma$-coefficients can be used to test the homogeneity of the sample on which the estimation is based. One should not be able to reject the null-hypothesis that all $\gamma-$ coefficients are equal to zero for a homogeneous customer segment.

The following specification test is constructed to test whether the choice and volume demand are indeed separate elements of demand behavior or whether a single latent variable is sufficient to explain the choice and volume demand decision. Consider the following censoring scheme as an alternative to the threshold model in (1)-(3):

$$v_{ik} = \begin{cases} v_{ik}^* & \text{if} \quad v_{ik}^* > 0 \\ 0 & \text{if} \quad v_{ik}^* \leq 0 \end{cases} \tag{23}$$

$$u_{ik} = \begin{cases} u_{ik}^* & \text{if} \quad v_{ik}^* > 0 \\ 0 & \text{if} \quad v_{ik}^* \leq 0 \end{cases} \tag{24}$$

In this model, a single latent variable, $v_{ik}^*$, determines the qualitative choice and the volume demand decision. This threshold model represents, according to Amemiya's (1984) classification, a type one tobit model with an additional censored dependent variable. The trivariate model reduces to this augmented tobit type 1 when imposing the restriction that $\alpha_{jm}^d = \alpha_{jm}^v \cdot \sigma_v^{-1}$, $\alpha_0^d = \alpha_0^v \cdot \sigma_v^{-1}$and $\rho_{d,v} = \frac{\sigma_{dv}}{\sigma_v}$, $\gamma_0 = \gamma_1 \cdot \sigma_v^{-1}$. Hence, a likelihood ratio statistic can be used to test these restrictions. If the LR test rejects the tobit specification then this is an indication that the choice and volume decision should be modeled as separate components of customer behavior.

## 3. Illustrative Industry Case Study

### *3.1. Institutional background and data*

For an illustrative application of the model introduced in the previous section, we use data from a market entry study that was carried out for Heumann Pharma, a leading European pharmaceuticals producer. In order to understand why this industry case study is a tailor-made application for the model introduced in the previous section, we have to provide some information about the background of the market situation at the time when the product launch was planned.

Heumann Pharma intended to introduce a product innovation in a national arthrosis prescriptions drug market at a time when the German pharmaceuti-

cal industry had to cope with a fundamental reform of the public health care system. The major implication of the reform was a tremendous increase in the cost awareness of the physicians which resulted from the introduction of rigid prescriptions budgets: Should a physician overdraw the prescription budget for a certain class of medicine (arthrosis drugs being one class), she would be liable to recourse to the health insurance scheme. Despite these implicit budget restrictions, the price of arthrosis drugs already established in the market varied significantly. Generica, i.e low priced drugs exploiting expired patents on substances, competed against highly priced brand products. The major side effect to consumers of traditional arthrosis drugs is exposure to the risk of stomach damage. Distinguishing it from existing products, Heumann's innovation provided stomach protection by containing a special protective substance. Previously, a physician had to ensure stomach protection by prescribing an additional drug. This, however, could induce additional side effects.

The key question for Heumann's market entry strategy was, whether the physicians would acknowledge the additional benefit of the product innovation, and whether it was possible to establish the new drug in the higher priced marked segment. Focus groups, in-depth physician interviews, and internal corporate expertise provided the sources to develop the set of relevant attributes and their levels. Table 1 contains an abbreviated version of the final design. For reasons of confidentiality all of the medical and pharmaceutical details that were contained in the original questionnaire are suppressed and the real prices disguised.

Insert table 1 about here

The four price levels represent the market entry prices for the new drug that were discussed by Heumann's project team. Price level A corresponds to that of a typical generica drug. Price level D is close to the prices of the most expensive drugs in the arthrosis market. Price level B is in the upper 30% quantile, and price level C in the upper 10% quantile of arthrosis drug prices. The market leader's product with proven efficacy and known and accepted side effects was chosen as a standard of comparison for the attributes "efficacy" and "side effects"."Stellapharma", "Lunapharma" and "Generica" are aliases for well known pharmaceutical producers.

From the possible 144 product profiles, an orthogonal array of 20 profiles (four more than the required minimum) was generated using a orthogonal main effects plan (Plackett and Burman (1946)). A random sample of 124 physicians had to decide for each profile whether it would be prescribed at all, and if so, for what percentage of the physician's total number of arthrosis patients. The respondents were also asked to provide a preference rating within the range of zero to 100% equivalence estimate to an ideal product for the selected profiles.

42.2% of the profiles that were presented to the physicians were accepted and given nonzero desired prescription volumes and preference ratings. For the accepted profiles, the average preference rating was 36.3 (standard deviation: 21.7). The average volume demand, expressed in the share of all arthrosis patients was 41% (standard deviation: 38%). The Pearson correlation coefficient between nonzero demand volumes and preference ratings was 0.62.

### *3.2. Estimation Results and Model Simulations*

Table 2 contains the maximum likelihood estimates of the model proposed in section two.

Insert table 2 about here

The signs and sizes of the estimated $\alpha$-coefficients are plausible from the medical and economical point of view. The shift parameters $\gamma_0$, $\gamma_1$ and $\gamma_2$ are all significantly different from zero. This indicates that individual heterogeneity plays an important role. The contribution of the random effect to the variance of the composite residuals $\varepsilon_{ik}^d + \gamma_0\delta_i$, $\varepsilon_{ik}^v + \gamma_1\delta_i$, $\varepsilon_{ik}^u + \gamma_2\delta_i$ differs significantly. Computing the ratio of random effect variance over total residual variance, we obtain $\frac{\gamma_0^2}{1+\gamma_0^2} = 0.323$, $\frac{\gamma_1^2}{\sigma_v^2+\gamma_1^2} = 0.172$, $\frac{\gamma_2^2}{\sigma_u^2+\gamma_2^2} = 0.369$. This implies that the sample is more homogeneous with respect to volume demand propensity. Part of the heterogeneity is due to the fact that the sample consists of two types of physicians, internists and general practitioners. In order to provide a customer segmentation, separate models for the two groups were also estimated. The significance of individual-specific effects was greatly reduced within each group.[7]

Insert figure 1 about here

Figure 1 shows that the ranking of the relative importance of the attributes is clearly different with respect to volume demand propensity on the one hand and preference and choice propensity on the other. With respect to preference propensity, the attributes stomach protection and price are the most important, followed by side effects and efficacy. The attribute manufacturer seems to be irrelevant. With respect to choice propensity, the relative importance ranking is quite comparable. The close relation between choice and preference is also revealed by the high correlation of the perception errors. The importance ranking with respect to volume demand propensity, however, is quite different. The attribute price dominates. The relative importance of the attributes stomach protection, side effects and efficacy is greatly reduced. Computing the specification test outlined in the previous section yields the LR statistic $\chi^2\,(12) = 460.9$

[7] Results based on the segmented samples are available upon request.

(p-value $< 0.00001$). Hence, the homogeneity of the choice and volume decision is clearly rejected. This indicates that volume and choice decision should indeed be modeled as separate components of customer behavior.

The impact of the $\alpha$-weights on choice probability and expected volume demand is nonlinear The marginal effect of changing the price level from A to B on choice probability and expected volume demand is not the same for all profiles. To give a relevant example, we use the formulae in (21) and (22), vary the price level, and compute estimates of expected volume demand and choice probabilities for two drug profiles. Profile I combines the attribute levels stomach protection provided, efficacy as reference product, side effects more than reference product and producing firm Stellapharma. This is an attribute-bundle that corresponds closely to Heumanns's real product. Profile II possesses identical attribute levels, with the exception of a reduced efficacy. The impact of price changes is reported in table 3. Changing the price level from A to B causes a change in choice probability for profile I (profile II) of -21% (-20%). The decrease in expected volume demand caused by changing the price from level A to level B is -50% (profile I) and -31% (profile II). Though the prescription probability for profile I does not drop below 30%, the expected volume demand at price level D is very low.

Insert table 3 about here

These results indicated the following conclusions for Heumann's marketing strategy. Establishing the product innovation as a veritable mass product would have only been possible at the price of a generica drug. At the top price level D, however, any significant volume demand seemed out of the question. Price level B (moderately expensive), however, would ensure a high prescription probability and a sustainable volume demand. The results for profile II reported in table 3 indicated that communicating its proven efficacy was essential for the market success of Heumann's product innovation. [8]

To conclude, focussing on preference elicitation and choice would clearly have not been sufficient in the context of this case study. It was certainly important for Heumann Pharma to know that physicians would acknowledge the benefit of the new attribute level stomach protection. Physicians are quite willing to prescribe a new high quality arthrosis drug that provides stomach protection despite a high price level. However, when it comes to the prescription volume decision, the cost component clearly dominates the physicians' demand behavior. Hence, introducing the pharmaceutical at a top level price, as might have been concluded from a preference or choice focussed analysis, was definetely not recommended.

[8] Actually, price level B was chosen as the market entry price and it remained unchanged afterwards. The product innovation became both a financial success and a well established arthrosis drug.

## 4. Summary and conclusion

We have proposed an alternative approach towards the quantification of demand behaviour prior to market entry. The method is designed to provide a single framework for analyzing consistently the main components of customer behavior: preferences, choice and demand volume. To achieve this objective, we have formulated a microeconometric model that adopts elements of conjoint, experimental choice and panel data analysis as well as the discrete/continuous models. The conjoint methodology contributes the factorial design of a full-profile analysis. Furthermore, we have argued that a full-profile conjoint study can be perceived as a panel like design, since repeated evaluations of the same respondent are obtained. We showed that by taking this into account the model can also be employed for customer segmentation purposes. Furthermore, we showed that our approach adopts ideas of experimental choice analysis, since it involves modeling customer choice in an experimental design framework. As in the discrete/continuous methodology, choice and demand volume decisions are modeled as separate, but not independent components of customer behavior.

We have applied the methodology to a product launch of an innovative arthoris medicine in the pharmaceuticals market. We find that physicians may find a drug profile with a combination of desirable attributes very attractive from the medical point of view, and implicitely assign a high preference value to these attribute levels. However, with respect to the prescription volume decision, the attribute "price" turns out to be the dominating factor. We also found that choice and volume decision must not be confounded. A high quality/high price-product could achieve a significant choice probability, i.e would be prescribed by the vast majority of physicians. However, it may have not been possible to establish the pharmaceutical as a mass product that would have been prescribed for a large number of patients. The importance ranking of attributes with respect to preference and choice was quite similar, but differed fundamentally with respect to demand volume. We showed that a methodology that would have focussed on preference elicitation and choice behavior would have implied misleading marketing strategies.

## A APPENDIX

For a facilitated evaluation of the log likelihood function in (19) we can utilize some properties of the multivariate normal distribution. We make use that

$$\tilde{\varepsilon}_{ik} = \left(\varepsilon^d_{ik} \mid \varepsilon^v_{ik}, \varepsilon^u_{ik}\right) \tag{A.1}$$

is distributed normal,

$$\tilde{\varepsilon}_{ik} \sim N\left(E\left(\tilde{\varepsilon}^d_{ik}\right), var\left(\tilde{\varepsilon}_{ik}\right)\right) \tag{A.2}$$

where

$$\begin{aligned} E\left(\tilde{\varepsilon}_{ik}\right) \quad = \quad & \frac{1}{\sigma_v^2 \cdot \sigma_u^2 - \sigma_{v,u}} \left[\left(v_{ik} - \tau^v_{ik}\right)\left(\sigma_u^2 \sigma_{d,v} - \sigma_{d,u}\sigma_{d,v}\right) + \right. \\ & \left. \left(u_{ik} - \tau^u_{ik}\right)\left(\sigma_v^2 \sigma_{d,u} - \sigma_{v,u}\sigma_{d,u}\right)\right] \end{aligned}$$

and

$$Var\left(\tilde{\varepsilon}_{ik}\right) = \frac{1}{\sigma_v^2 \cdot \sigma_u^2 - \sigma_{v,u}} \left(\sigma_u^2 \sigma_{d,v} - \sigma_{d,u}\sigma_{d,v}\right)\sigma_{d,v} + \left(\sigma_v^2 \sigma_{d,u} - \sigma_{v,u}\sigma_{d,v}\right)\sigma_{d,u}$$

Hence, we can write equation (17):

$$l^+_{ik} = \Phi\left(\frac{\tau^d_{ik} - E\left(\tilde{\varepsilon}_{ik}\right)}{\sqrt{Var\left(\tilde{\varepsilon}_{ik}\right)}}\right) \cdot \left(\sigma_v \sigma_u\right)^{-1} \cdot \phi_{bv}\left(v_{ik} - \tau^v_{ik}, u_{ik} - \tau^u_{ik}; \Sigma_{v,u}\right) \tag{A.3}$$

where $\phi_{bv}\left(\cdot\right)$denotes the p.d.f. of bivariate normal distribution and

$$\Sigma_{v,u} = \begin{pmatrix} \sigma_v^2 & \sigma_{v,u} \\ \sigma_{v,u} & \sigma_u^2 \end{pmatrix}$$

(A.3) facilitates the computation of the log likelihood (19). Butler and Moffitt's (1982) procedure can be used to evaluate the improper integral in (19). GAUSS programs for ML estimation of the trivariate model are available from the corresponding author upon request.

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TABLE 1
ATTRIBUTES AND ATTRIBUTE LEVELS
(ABBREVIATED VERSION)

| Attribute | Attribute Level |
|---|---|
| price (daily therapy cost)[a] | price level A |
| | price level B |
| | price level C |
| | price level D |
| stomach protection | provided [b] |
| | not provided |
| other side effects | as much as reference product [c] |
| | less side than reference product [d] |
| | more than reference product [e] |
| efficacy | as reference product [f] |
| | significantly less than as reference product [g] |
| producing firm [h] | Lunapharma |
| | Stellapharma |
| | Generica |

Notes:

[a] True prices are disguised. Price level A is that of a typical generica product (no name drug). Price level D is the price of the most expensive drug in the arthrosis market. Price level B is in the upper 30% quantile of prices and price level C in the upper 10% quantile of arthrosis drug prices.

[b] Medical details are suppressed. The questionnaire explained the protection mechanism in detail

[c] Side effects of the reference product (known to the respondents) were listed in the questionnaire.

[d] Which side effect are reduced was explained in detail in the questionnaire.

[e] Additional side effects were desribed in detail in the questionnaire.

[f] The reference product name is disguised.

[g] Medical details are suppressed.

[h] True names are diguised

TABLE 2
ESTIMATION RESULTS

| | $d^*$ | $v^*$ | $u^*$ |
|---|---|---|---|
| $\alpha$-weights | | | |
| **Constant** | -1.6618 | -0.2092 | -0.4037 |
| | (0.1566) | (0.0543) | (0.0515) |
| **Price** | | | |
| level A | 1.0159 | 0.7360 | 0.2871 |
| | (0.0950) | (0.0205) | (0.0266) |
| level B | 0.3661 | 0.0579 | 0.1046 |
| | (0.0676) | (0.0136) | (0.0201) |
| level D | -0.2747 | -0.1888 | -0.0672 |
| | (0.0822) | (0.0191) | (0.0222) |
| **Stomach protection** | | | |
| provided | 1.2557 | 0.2048 | 0.3616 |
| | (0.0992) | (0.0258) | (0.0301) |
| **Other side effects** | | | |
| more than reference product | -0.6918 | -0.0850 | -0.2029 |
| | (0.1204) | (0.0269) | (0.0316) |
| less than reference product | 0.3885 | 0.0676 | 0.1093 |
| | (0.0588) | (0.0137) | (0.0156) |
| **Efficacy** | | | |
| as reference product | 0.8229 | 0.1378 | 0.2266 |
| | (0.0840) | (0.0190) | (0.0265) |
| **Producer** | | | |
| Stellapharma | -0.0392 | 0.0168 | -0.0012 |
| | (0.0524) | (0.0134) | (0.0134) |
| Lunapharma | -0.1462 | -0.0113 | -0.0440 |
| | (0.0673) | (0.0162) | (0.0174) |
| $\gamma_0$ | 0.6069 | | |
| | (0.0706) | | |
| $\gamma_1$ | | 0.0918 | |
| | | (0.1846) | |
| $\gamma_2$ | | | 0.1628 |
| | | | (0.1803) |
| $\sigma_v$ | | 0.2012 | |
| | | (0.1177) | |
| $\sigma_u$ | | | 0.2712 |
| | | | (0.1527) |
| $\rho_{d,v} = \frac{\sigma_{d,v}}{\sigma_v}$ | | 0.5366 | |
| | | (0.0735) | |
| $\rho_{d,u} = \frac{\sigma_{d,u}}{\sigma_u}$ | | 0.9978 | |
| | | (0.0010) | |
| $\rho_{v,u} = \frac{\sigma_{v,u}}{\sigma_u \sigma_v}$ | | 0.5282 | |
| | | (0.0550) | |
| log $\mathcal{L}$ | | -3358.31 | |
| Type one tobit test | | $\chi^2(12) = 460.9$ , p-value $< 0.00001$ | |

Note:

ML estimation performed using the GAUSS programs written by the authors on a RS-6000 UNIX workstation. Robust standard errors in parenthesis.

TABLE 3
ESTIMATES OF EXPECTED VOLUME DEMAND AND CHOICE PROBABILITIES

| | Profile I [a] | | Profile II [b] | |
|---|---|---|---|---|
| | choice prob. | expected vol.[c] | choice prob. | expected vol.[c] |
| | $P(D_I = 1)$ | $E(V_I)$ | $P(D_{II})$ | $E(V_{II})$ |
| price level A | 0.726 | 0.628 | 0.4586 | 0.360 |
| price level B | 0.518 | 0.125 | 0.2547 | 0.046 |
| price level C | 0.394 | 0.085 | 0.1654 | 0.027 |
| price level D | 0.307 | 0.029 | 0.1136 | 0.007 |

Notes:

[a] Profile I attribute levels: stomach protection provided; efficacy as reference product; producer: Stellapharma; other side effects: more than reference product.

[b] Profile II attribute levels: stomach protection provided; efficacy less than reference product; producer: Stellapharma; other side effects: more than reference product.

[c] Share of arthrosis patients.

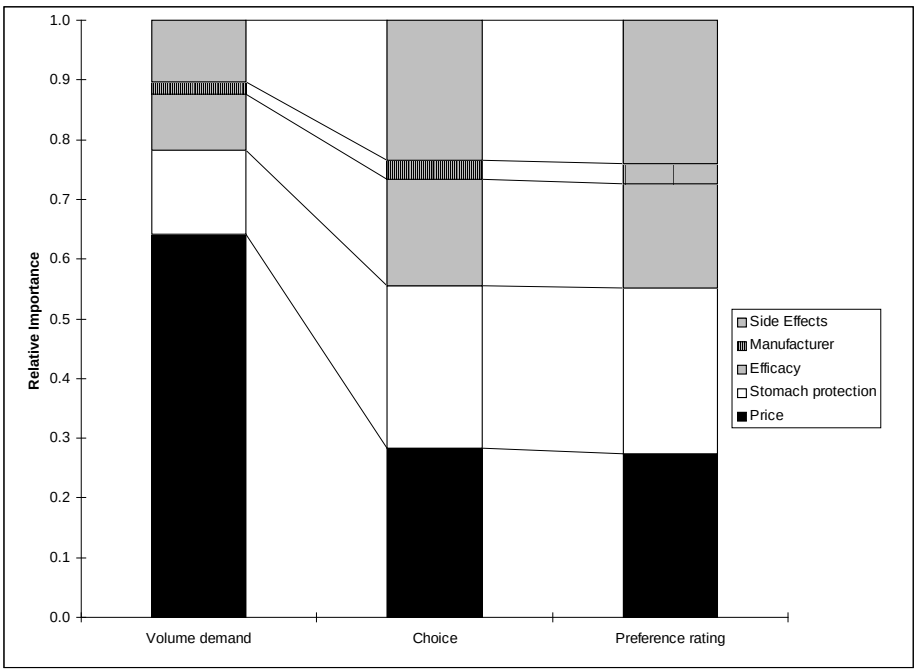


FIGURE 1.– Relative Importance of Attributes