Separating Negative and Positive Effects of Price with Choice-Based Conjoint Analyses

by Franziska Völckner and Henrik Sattler

Consumers use the price of a brand both as a signal for product quality and as a monetary constraint when choosing a brand. Consequently, price has two distinct roles whenever consumers evaluate a product, i.e., an informational (signal) role and an allocative (constraint) role. These two roles are conceptually distinct, yet measuring them becomes confounded due to the difficulties of empirically isolating their distinct effects. In practice, only the total effect of price is estimated, particularly by using conjoint analysis. The three main objectives of our research are: (1) to present a new methodology in a choice-based conjoint setting that is designed to isolate and estimate separate effects of price. A segment level analysis and an individual level analysis are conducted using latent class and hierarchical Bayes procedures to account for respondents’ heterogeneity; (2) to quantify the different effects of price by calculating price elasticities for each effect; and (3) to test the validity of the proposed methodology in an empirical setting within the scope of a large representative sample.

Keywords
Pricing, informational role of price, allocative role of price, choice-based conjoint analysis

1. Introduction

It is well known that price is a complex stimulus. At a minimum, price represents the amount of money that must be given up. However, many consumers perceive price more broadly than strictly as an outlay of economic resources. Numerous studies have provided evidence that many consumers use price as an indicator of product quality (e.g., Sattler/Rao 1997; Lichtenstein et al. 1993; Erickson/Ohansson 1985). Product quality in a broader sense comprises different dimensions, e.g., the quality of the physical product attributes, social desire of prominence and status (purchasing products with higher prices signals the achievement of a desired social rank to an audience of peers), or egocentric desires to give oneself a present. Thus, the perception of price as an indicator of quality is not a unidimensional one. Evidence suggests that the use of the price cue as a signal to indicate product quality varies across situations and products (e.g., Erdem 1998; Urbany et al. 1997). In addition, some consumers are simply more likely than others to use price as a general indicator of quality across situations and products (e.g., Lichtenstein et al. 1993).

These two distinct roles that price plays in consumers’ evaluation of alternative offerings in the marketplace can be labeled as the allocative (constraint) role of price and the informational (signal) role of price (Urbany et al. 1997, p. 45). The allocative effect is the consumer’s evaluation of the amount of money that must be sacrificed to satisfy consumption needs. In this respect, the price represents a financial burden, and higher prices therefore negatively affect purchase probabilities (negative role of price; Erickson/Ohansson 1985). Due to informational effects, some consumers may also perceive prices in a positive role, i.e., they assume a positive association between price and perceived quality (and vice versa) that result in positive price elasticity of demand. Consumers primarily tend to use price as a surrogate indicator
of product quality (possibly in conjunction with other extrinsic cues, e.g., brand or store name; Rao/Monroe 1989; Dodds/Monroe/Grewal 1991) if the quality evaluation is uncertain and the purchase consequently becomes risky (Urbeny et al. 1997). Scitovsky (1945) already acknowledged that price may serve as an indicator of product quality. Since then, more than 100 empirical studies have examined the relationship between price and perceived quality (e.g., Monroe/Dodds 1988; Dodds/Monroe/Grewal 1991; Brucks/Zeithaml/Naylor 2000).

Although these two roles of price are conceptually distinct, measuring them becomes confounded due to the difficulties of empirically isolating them. In practice, only the total effect of price is estimated, in particular by using conjoint analysis (Wittink/Vriens/Burhenne 1994; Balderjahn 1994; Hartmann/Sattler 2005). Gautschi/Rao (1990) have proposed a method for isolating the two different roles of price using rating-based and ranking-based conjoint analysis. Their method requires collecting data from two scenarios. One scenario is subject to a budget constraint and the other is not. Sattler/Rao (1997) empirically tested their method in a study.

The objective of this paper is to resume this line of research and present a new methodology for separating price effects using a choice-based conjoint (CBC) analysis approach. CBC has become the most frequently applied conjoint procedure for both scientific and commercial use (Hartmann/Sattler 2005). Choice-based conjoint analysis evidences important conceptual advantages and is perceived as having distinctly higher validity compared to ranking-based or rating-based conjoint analysis. CBC reveals preferences by examining discrete choice behavior. This method is perceived as representing the market process more realistically compared to rating or ranking based conjoint analysis (Louviere/Woodworth 1983). CBC is also less demanding for the respondent (DeSarbo/Ramaswamy/Cohen 1995; Louviere 1994). Finally, choice-based conjoint analysis lets us quantify the allocative and informational effects of price by calculating price elasticities for each effect. Models derived from choice data allow direct prediction of choice shares. Predicted shares subsequently permit comparison of price effects using elasticities that give an intuitive notion of the quantity of the effect. In the case of traditional conjoint analysis, it would be necessary to use simulators with questionable assumptions to transform ratings into choices (e.g., the first choice rule; Louviere/Woodworth 1983, p. 351; DeSarbo/Ramaswamy/Cohen 1995, p. 137). However, it has to be mentioned that from a statistical viewpoint choice tasks are not a very efficient way to learn about preferences. Choosing only one alternative from a set of products provides less data than constructing rank orders of alternatives. Moreover, CBC is only suitable for studies with relatively few product attributes. When faced with too much information respondents resort to simplification strategies to deal with the difficulty of the choice task (e.g., Sawtooth 1999).

The basic contributions of this paper are as follows: (1) we present a new methodology within a choice-based conjoint setting to isolate and estimate separate effects of price. A segment level analysis and an individual level analysis are conducted using a latent class approach and a hierarchical Bayes procedure to account for respondents’ heterogeneity. (2) We quantify the different effects of price (i.e., the total effect, the allocative role, and the informational role of price) by calculating price elasticities for each effect. (3) We test the validity of our proposed methodology within an empirical setting using a large representative sample.

The remaining portion of this paper is organized as follows: Section 2 describes the research design of our study. Section 3 presents the main results of our study. Section 4 summarizes our main findings.

2. Research Design

Our discussion thus far clearly indicates that price plays two distinct roles in consumers’ evaluation of a product, i.e., an informational role and an allocative role. The different views of price in the literature (e.g., Rosen 1974; Nagle 1984; Dodds/Monroe/Grewal 1991; Gijsbrechts 1993) and the general connotation of the two price effects suggest that the informational price effect is positive and that the allocative price effect is negative. The proposed methodology for separating and quantifying the two distinct roles of price requires collecting choice-based data from two different scenarios that are intended to measure only the specific roles of price.

- The 1st scenario provides a setting with budget constraint (full-price-to-pay). In the first scenario, respondents have to accomplish choice tasks under the assumption that the quoted price has to be paid (“Assume you have to pay the full price shown.”). This scenario is commonly used for conjoint measurement settings such as the choice-based conjoint. This scenario measures the total effect of price because the setting does not distinguish between the allocative and the informational role of price.

- The 2nd scenario provides a setting without budget constraint (gift). In the second scenario, the choice sets of the first scenario are presented to respondents again. Respondents are instructed under this scenario that a third party will pay the shown price thus supposedly eliminating the allocative effect of price (“Assume you don’t have to pay for the product. Your supermarket is celebrating its anniversary and is giving away the product for free.”). If the price still exhibits a role, then the role is assumed to constitute informational effects, i.e., the price is an indicator of quality.

In addition to the choice tasks we collected data to measure possible reasons for choosing a higher-priced product in the second scenario (gift scenario). Our findings indicate that respondents primarily chose a higher-priced product in the gift scenario because of the perception of a positive price-quality relationship (mean = 4.0 on a
seven-point Likert scale with 1 = absolutely disagree and 7 = absolutely agree) and the egocentric desire to make oneself a present (mean = 5.0 on a seven-point Likert scale with 1 = absolutely disagree and 7 = absolutely agree). Few respondents also decided in favor of a higher-priced product because of feelings of status and exclusivity that higher prices signal to other people about the purchaser (mean of 3.1 on a seven-point Likert scale with 1 = absolutely disagree and 7 = absolutely agree). Thus, price conveys information about product quality more broadly than strictly in terms of the quality of the physical product attributes.

As aforementioned, Sattler/Rao (1997) provide empirical evidence that – in principle – it is possible to separate the two distinct roles of price using the two scenarios within a rating-based and ranking-based conjoint-analysis setting. Against this background our paper is intended to test the reliability and validity (including face validity) of a choice-based conjoint methodology.

Utilities for the product attributes (including price) are estimated for each scenario based on the collected choice data. We estimated the utilities using two different approaches, i.e., a latent class approach and a hierarchical Bayes estimation. Both estimation methods account for respondents’ heterogeneity [1]. Latent class analysis for choice-based conjoint analysis is based on the assumption that the population of consumers belongs to a discrete number of homogenous subgroups that have identical preferences [2]. The latent class procedure, which is solely based on the choice behavior of the respondents, simultaneously tries to identify these latent segments, estimate the utility structure and calculate each respondent’s segment membership probability. Probability-based partitioning accommodates situations where consumers in a particular market segment display different preference patterns and allows them to be fractional members of multiple segments (Desarbo/Ramaswamy/Cohen 1995, p. 138). The latent class approach can often be used as a sufficiently accurate approximation, although the assumptions of a discrete number of segments and of individuals that are perfectly homogenous within these segments might be too restrictive for behavioral research contexts (Allenby/Arora/Ginter 1998, p. 384). If heterogeneity remains substantial within a segment, then it is better to infer individual estimates using a hierarchical Bayes approach [3]. The Bayesian approach solves the problem of scarcity of individual choice information by introducing additional information by way of the (prior) assumption that the part-worths of individuals are linked by a common multivariate normal distribution (Rossi/Allenby 1993; Arora/Huber 2001).

There is no conclusive evidence on whether a discrete number of classes (latent class approach) or a continuous distribution of consumer parameters (hierarchical Bayes procedure) are more appropriate for representing heterogeneity (Andrews/Ainslie/Currim 2002; Allenby/Arora/Ginter 1998; Wedel et al. 1999). Hence, selection of one of the two methods remains an empirical question (Wedel/Kamakura 2000). Comparing the latent class approach with the hierarchical Bayes procedure is a particularly interesting feature of this study. Our comparison provides empirical evidence on the method of estimation that performs better in terms of separating the allocative and informational role of price.

Estimated utilities are subsequently transformed into choice shares using the standard logit choice model (Louviere 1994; Arora/Huber 2001):

\[
s(i|\beta) = \frac{\exp(x_i\beta)}{\sum_{j=1}^{J} \exp(x_j\beta)},
\]

\[
s(i|j) = \text{probability of choosing } i \text{ from a choice set with } J \text{ alternatives},
\]

\[
x_i \text{ vector that describes the characteristics of alternative } i,
\]

\[
J \text{ set of alternatives in the choice set, } J = \{x_1, ..., x_i, ..., x_J\},
\]

\[
\beta \text{ parameter vector that reflects the preference structure of the segments (LC) or of an individual (HB)}.
\]

Each choice set \( J \) represents a realistic market setting that is identical in both scenarios (i.e., prices represent the relevant range of variation in the marketplace). By varying the prices for product profile \( i \) (e.g., brand \( i \)) within this market setting, we obtain ceteris paribus different choice shares for \( i \), which enable calculation of price elasticities. This procedure allows us to calculate elasticities for each scenario and each brand using:

\[
e_{\text{full-price-to-pay}} \text{ price elasticity for } i \text{ in the full-price-to-pay scenario, i.e., the total effect of price and price elasticity for } i \text{ in the gift scenario, i.e., the informational effect of price.}
\]

The total effect of price is therefore revealed by the estimate \( e_{\text{full-price-to-pay}} \), and the informational effect of price is reflected in the estimate \( e_{\text{gift}} \). The allocative effect of price can subsequently be computed as the difference \( e_{\text{full-price-to-pay}} - e_{\text{gift}} \). Gautchi/Rao (1990) and Sattler/Rao (1997) demonstrate that the allocative effect of price can be calculated as the difference between the total effect of price and the informational effect of price. Moreover, the results of the present study are plausible and thus support this assumption as well (see Section 3).

The proposed model for separating the informational and allocative effect of price was tested in an empirical setting with strawberry jam. Only information on the brands (two well-known brands and one new brand name) and price (€ 1.59, 1.99, and 2.39) were provided as cues for the product evaluation (€ = euro). For many fast moving consumer goods (FMCG) information other than brand and price are perceived to be only of secondary importance (e.g., Rao/Monroe 1989). Due to the low prices, we assumed that the respondents would not have any considerable cash benefit from the setting without payment (gift scenario; Sattler/Rao 1997). Information on package size and other characteristics (e.g., fruit content) were also provided but kept identical for each brand and in each scenario.
Choice sets were composed of three profiles, and each brand was presented once in each profile. Price levels were allowed to overlap within the choice task. A “none option” ("I would not buy any of these strawberry jams.") was available in addition to the three profiles (Louviere 1994). A total of 27 choice tasks were possible for each scenario. The 27 choice tasks represent all possible combinations of three brands and three price levels under the condition that price levels are allowed to overlap within one choice task. The tasks were assigned to nine different versions of questionnaires. The respondents were randomly allocated to one of the versions. Additional holdout choice sets were designed for the full-price-to-pay and the gift scenarios. Their settings were identical in every questionnaire version. The data from the holdout choice sets was not used for estimation, rather it was used to assess the ability of the estimates to predict the aggregate shares of holdout choices. Finally, one choice task for each of the full-price-to-pay and gift scenarios was repeated so that we could verify reliability (test-retest reliability; e.g., Ghiselli/Campbell/Zedeck 1981; Peter 1979). Table 1 summarizes the subsets of choice tasks.

Data was collected from a total of 355 respondents. It was drawn using a quota sampling procedure, with a representative structure for Germany in terms of the gender and age of consumers of frequently purchased consumer goods. We only selected subjects who responded favorably to each of several introductory filter questions. The filter questions were designed to confirm that respondents had some experience in buying strawberry jam and to ensure general interest in buying one of the brands presented. Every respondent had to answer 10 choice tasks which are displayed in Table 1.

### 3. Results

#### 3.1. Reliability

Choices that individuals make in real markets or in choice experiments often contain random components, caused, for example, by inattention. These kinds of choices are therefore not very reliable (Louviere 1994, p. 229; Huber 1997, p. 8). As mentioned above, one choice task was repeated for each of the full-price-to-pay and gift scenarios to verify reliability (test-retest reliability). Respondents who answered both reliability choice task pairs differently were excluded from further analysis to minimize bias by random choice behavior within parameter estimation. Thirty-four subjects (6.69 %) were excluded from the sample of 355 respondents. Exclusion improved average reliability to 87.2 % (first choice task pair) and 86.3 % (second choice task pair). This can be perceived as sufficiently good [4]. A total of 963 choices (3 choice tasks x 321 respondents) were subsequently available for estimating the full-price-to-pay scenario and another 963 choices were available for estimating the gift scenario.

Different estimation results were expected for the two scenarios because the scenarios induced many respondents to change their choice. For each respondent, we examined whether they chose a higher-priced product within the gift scenario (choice tasks 2, 4 and 6, see Table 1) compared to their choice within the full-price-to-pay scenario (choice tasks 1, 3, and 5). 54.83 % (choice task 1 vs. choice task 2), 47.35 % (choice task 3 vs. choice task 4), 48.29 % (choice task 5 vs. choice task 6) and 66.67 % (choice task 7 vs. choice task 8) of the respondents chose a higher-priced product when no price had to be paid.

#### 3.2. Hierarchical Bayes Estimation

We first analyzed at an individual level whether respondents behaved in line with the assumption of the dominating negative role of price under the full-price-to-pay scenario and the positive role of price under the gift scenario. The hierarchical Bayes estimation method proceeds in an iterative manner and recursively generates draws of model parameters (Arora/Huber 2001). Hence we had to ensure that the procedure was stationary prior to retrieving estimates from the hierarchical Bayes analysis. The time series plots of the Root-Likelihood values (geometric mean across all respondents’ likelihood values) showed that the process converged after a few thousand iterations (e.g., Sawtooth 2000). Nevertheless, a total of 25,000 preliminary iterations and another subsequent 10,000 iterations were used to generate parameter estimates, with every 10th iteration saved. Consequently, 1,000 utility draws were available for every subject. For the sake of analysis, each respondent’s utility could be represented by using this distribution of draws to account for the estimation variability (draw) or by the mean utility across these draws (mean; e.g., Huber/Train 2001). Table 2 summarizes the estimation results and provides information about the estimation variability.

<table>
<thead>
<tr>
<th>Subset</th>
<th>Purpose</th>
<th>Choice Task Numbers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation subset</td>
<td>Estimation of the total effect of price (full-price-to-pay)</td>
<td>#1, #3, and #5</td>
</tr>
<tr>
<td></td>
<td>Estimation of the informational effects of price (gift)</td>
<td>#2, #4, and #6</td>
</tr>
<tr>
<td>Prediction subset</td>
<td>Holdout choice set for assessment of predictive validity</td>
<td>#7 (full-price-to-pay) and #8 (gift)</td>
</tr>
<tr>
<td>Reliability subset</td>
<td>Choice sets for measuring the respondent’s reliability</td>
<td>#9 and #10 as repetition of the choice sets #1 and #2</td>
</tr>
</tbody>
</table>

Table 1: Choice task subsets
The box plots for the price level part-worths indicate that the price preference order changed from the preference of low prices under the full-price-to-pay scenario to the preference for high prices under the gift scenario. This trend was supported by significant negative correlations between the highest and lowest price levels between the scenarios (p < 0.01). Next, we examined on an individual level which respondents behaved according to the assumption of a dominating negative role of price under the full-price-to-pay scenario and a positive role of price under the gift scenario. Table 3 summarizes the respondents' price preference orders for the gift and the full-price-to-pay scenario [5].

The columns show a summary of individual price preference orders for the full-price-to-pay scenario. The table shows, for example, that 307 of the total of 321 respondents prefer lower prices in the full-price-to-pay scenario. The lines show the respondents' price preference orders for the gift scenario. For example, 259 respondents prefer higher prices in the gift scenario. Combining the findings of the two scenarios reveals that 254 respondents prefer lower prices in the full-price-to-pay scenario and higher prices in the gift scenario.

The results of the hierarchical Bayes procedure considerably support the proposition of a dominating allocative effect of price and a positive informational effect of price because 254 (79.13 %) respondents acted accordingly. Table 3 also illustrates that the behavior in the full-price-to-pay scenario is more homogenous (307 respondents, or 95.64 % of the sample, agreed that low prices were better than high prices) than in the gift scenario (259 respondents, or 80.69 %, believed high prices were better). The informational effect dominated the allocative effect only for three persons. This might be due to distinctive effects of prestige or narcissism. Thirteen people showed a negative price effect in the gift scenario, i.e., they chose low prices although they did not have to pay. This might be explained, for example, by a habitual tendency to choose low prices or a desire to demonstrate modesty to the interviewer (an assumed socially desired behavior).

Calculation of elasticities was embedded into a realistic market setting (i.e., prices corresponded approximately to the mean market prices), with brand A offered at \( c_1 = 1.59 \), brand B at \( c_2 = 1.99 \), and brand C at \( c_3 = 2.39 \). Table 4 shows the calculated elasticities for each scenario and each brand. The elasticities are based on the aggregated preference share across all respondents, which enables a more compact presentation of results.

Total price elasticity ranges between -1.60 and -4.23. The informational price elasticity is positive across the board and exhibits higher values for hypothetical brand B than for the well-established brands A and C. The latter instance is plausible because the respondents could not rely on the brand as an additional surrogate indicator of quality (Lich-
3.3. Latent Class Approach

The latent class model represents an alternative approach for incorporating consumer heterogeneity. The latent class model approximates a continuous distribution of heterogeneity by means of a discrete distribution. There has been some debate in the literature on whether a discrete number of classes (latent class model) or the continuous mixture approach is better. For example, Allenby/Arora/Ginter (1998) argue that continuous mixture distributions more appropriately model consumer heterogeneity because each consumer has a unique preference. However, research by Andrews/Ainslie/Currim (2002) implies that there is no conclusive evidence on which of the two approaches performs better. Hence, the question whether the distribution of heterogeneity is discrete (with a small number of mass points) or continuous should be answered from the data (Rossi/Allenby 1993, p. 172). In addition, Wedel/Kamakura (2000) argue that even though latent class models only approximate the true nature of heterogeneity, they are more consistent with how managers think about their markets and thus are more appealing from a managerial standpoint. Given these arguments, we conducted a latent class analysis in addition to the hierarchical Bayes estimation. Comparing the validity of the two approaches provides empirical evidence about the estimation method that performs better in separating the allocative and informational role of price.

A main-effects-only model with three latent classes emerged as the best solution for both the full-price-to-pay and the gift scenario (according to information criteria such as CAIC and measures of entropy based on membership probability). For the sake of comparing choice behavior across the two scenarios, we created discrete segments for each scenario by assigning the respondents to their most likely class by means of a posteriori membership probabilities [6]. We combined the three segments of the full-price-to-pay scenario with the three segments of the gift scenario by using a 3 × 3 cross table that resulted in 9 discrete groups. Table 5 shows this 3 × 3 cross table with group name, sample size n and joint frequency probability f.

We inspected the estimates of the main-effects-only model for each scenario for preliminary profiling of these segments. Four groups with very small sample size were merged to one group: The estimates revealed that Segment 3 in the full-price-to-pay scenario contained respondents that were most likely to choose the “none option”. The “none” choice was of no interest for a detailed analysis, and the 17 respondents were merged into one group again. The four subjects in cell Segment 2full-price × Segment 3gift were added because they showed inconsistent behavior. Subjects relied more on the brand attribute while favoring different brands under both scenarios. Group 6 (21 respondents or 6.5%), delineated by the dashed line, can therefore be seen as a residual group (e.g., Teichert 2000).

A within-segment analysis was conducted and price elasticities were calculated for each of the remaining six groups. Table 6 shows elasticities for the latent class analysis. Elasticities are not calculated if market shares were lower than 1%. This applies for brands B and C in latent class 5 (LC 5). The LC 5 segment is extremely dedicated to brand A. The notion of a dominating negative role of price in the full-price-to-pay scenario and a positive role of price in the gift scenario was generally reconfirmed. The total price elasticity is negative across the board and less than -1 in all but one case. Moreover, we only obtained positive values for informational price elasticity and only negative values for allocative price elasticity.

3.4. Validity of Allocative and Informational Price Effects

The validity of price effects was assessed by examining the ability of the latent class model and the hierarchical Bayes procedure to predict the aggregate choice shares of holdout tasks (Huber et al. 1993, p. 109). This study therefore presents the first empirical test of the validity of the informational (and allocative) price effect measured by means of choice-based conjoint analysis. Comparing the (predictive) validity of the latent class approach and the hierarchical Bayes procedure also enables us for the first time to empirically test which method performs better in measuring the informational (and allocative) effect of price.

<table>
<thead>
<tr>
<th>Elascity</th>
<th>Origin</th>
<th>Brand A</th>
<th>Brand B</th>
<th>Brand C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>(a) full-price-to-pay scenario</td>
<td>-1.60</td>
<td>-4.23</td>
<td>-3.65</td>
</tr>
<tr>
<td>Informational</td>
<td>(b) gift scenario</td>
<td>1.33</td>
<td>2.09</td>
<td>0.83</td>
</tr>
<tr>
<td>Allocative</td>
<td>(a) – (b)</td>
<td>-2.93</td>
<td>-6.33</td>
<td>-4.48</td>
</tr>
</tbody>
</table>

Table 4: Elasticities according to the hierarchical Bayes model

<table>
<thead>
<tr>
<th>Gift scenario</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Segment 1full-price</td>
<td>Group 1</td>
</tr>
<tr>
<td>Segment 2full-price</td>
<td>Group 2</td>
</tr>
<tr>
<td>Segment 3full-price</td>
<td>Group 3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>n = 45</td>
<td>n = 38</td>
<td>n = 157</td>
</tr>
<tr>
<td>f = 0.1402</td>
<td>f = 0.1184</td>
<td>f = 0.4891</td>
</tr>
</tbody>
</table>

| Segment 1gift | Group 1 |
| Segment 2gift | Group 2 |
| Segment 3gift | Group 3 |

<table>
<thead>
<tr>
<th>Group 4</th>
<th>Group 5</th>
<th>Group 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>n = 29</td>
<td>n = 31</td>
<td>n = 4</td>
</tr>
<tr>
<td>f = 0.0903</td>
<td>f = 0.0966</td>
<td>f = 0.0125</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Group 7</th>
<th>Group 8</th>
<th>Group 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>n = 6</td>
<td>n = 7</td>
<td>n = 6</td>
</tr>
<tr>
<td>f = 0.0125</td>
<td>f = 0.0218</td>
<td>f = 0.0187</td>
</tr>
</tbody>
</table>

| Total | 78 | 76 | 167 | 321 |

Table 5: Latent class 3 × 3 cross table

Das Erstellen und Weitergeben von Kopien dieses PDFs ist nicht zulässig.
To obtain share predictions, the part-worths for each method were transformed to choice shares for brand A at €1.59, brand B at €1.99, brand C at €2.39, and the “none option” using the logit transformation rule. The simulated shares were subsequently compared to the shares of the holdout choice. The difference between the predicted and the actual choices was assessed by each of three formulas of prediction accuracy, i.e., mean absolute error (MAE), root mean squared error (RMSE), and chi-square ($\chi^2$). The MAE formula treats all errors equally. The RMSE is more sensitive to prediction errors on large shares, and $\chi^2$ is more sensitive to prediction errors on small shares (Moore/Gray-Lee/Louviere 1998, p. 201 [7]).

In the case of the latent class analysis, the weighted sum of the segment shares was used to derive an aggregate share. The prediction error was therefore assessed at the aggregate level, and not at each segment level, to arrive at values that are comparable to the hierarchical Bayes estimation. We applied the first choice transformation rule given that individual level estimates were available for the hierarchical Bayes analysis. The rule assumes that each respondent will choose the profile that exhibits the highest utility, independent from the relative strength of preference within the choice set (Sawtooth 1999).

We separately present the assessment of the conformity of predicted shares with holdout shares for each holdout choice task (#7, full-price-to-pay scenario and #8, gift scenario) and for each estimation method (first column) in Table 7. As described in Section 2, 1,000 utility draws were available for every subject for the hierarchical Bayes estimation. Each respondent’s utility can therefore be represented using the distribution of draws (HB utility means in Table 7) or by using the mean utility across these draws (HB utility mean in Table 7; Huber/Train 2001) to assess the predictive validity of the estimation method.

Table 7 shows that the latent class model predicts very well and considerably better than the chance model. This is true for the gift scenario (i.e., the informational effect of price) and for the full-price-to-pay scenario. However,

### Table 7: Holdout prediction accuracy

<table>
<thead>
<tr>
<th>Estimation Method</th>
<th>Transformation</th>
<th>Holdout Choice Task #7</th>
<th>Holdout Choice Task #8</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MAE</td>
<td>RMSE</td>
<td>Chi-square</td>
</tr>
<tr>
<td>Chance*</td>
<td>0.97</td>
<td>5.63</td>
<td>126.68</td>
</tr>
<tr>
<td>Latent Class</td>
<td>0.13</td>
<td>0.87</td>
<td>5.94</td>
</tr>
<tr>
<td>HB utility means</td>
<td>Logit</td>
<td>0.27</td>
<td>1.63</td>
</tr>
<tr>
<td></td>
<td>First choice</td>
<td>0.34</td>
<td>2.06</td>
</tr>
<tr>
<td>HB utility draws</td>
<td>Logit</td>
<td>0.13</td>
<td>0.81</td>
</tr>
<tr>
<td></td>
<td>First choice</td>
<td>0.19</td>
<td>1.13</td>
</tr>
</tbody>
</table>

* The chance model predicted equal shares for each choice option, i.e., 25 %. Bold numbers: best model according to formula of prediction accuracy.
the hierarchical Bayes model, which captures heterogeneity at the individual level, outperforms the latent class model in all but one case. A continuous distribution of heterogeneity therefore seems to be more appropriate for measuring the informational (and allocative) effect of price— at least in this study.

The first choice transformation was additionally used for the hierarchical Bayes estimates to compute hit rates that verify whether the individual’s observed choice was equal to the predicted choice (Huber/Train 2001, p. 265; Huber et al. 1993, p. 109). The hit rates for the hierarchical Bayes model using utility means are 82.5 % (full price-to-pay scenario) and 86.6 % (gift scenario). Predictions are consequently wrong only for about 15 % of the respondents. This percentage rate can be perceived as a very good result in terms of the following hit benchmarks: 80 % for 2 alternatives and 9 attributes (Hartmann/Sattler 2004), 71 % for 4 alternatives and 5 attributes (Huber/Train 2001), and 66 % for 5 alternatives and 6 attributes (Johnson 1999).

4. Summary

This paper presents and empirically tests a choice-based conjoint methodology that is designed to separately estimate the allocative (constraint) and informational (signal) role of price. In practice, only the total effect of price is usually estimated in any brand choice or preference model. Our proposed methodology is able, by contrast, to separate negative and positive price effects. We are also able to quantify the allocative and informational role of price by calculating price elasticities. We estimate price effects using two different approaches, i.e., the hierarchical Bayes estimation and the latent-class approach. Both estimation methods account for heterogeneity among respondents. Our findings considerably support the assumption of a dominating allocative price effect and a substantial positive informational price effect. Our results are consistent with the hypothesis of total price elasticity less than -1, positive informational price elasticity and negative allocative price elasticity. The estimates revealed informational effects of price that represented approximately 15–30 % of the composite effect of price (informational plus allocative effect). The validity of price effects was assessed by examining the capability of the latent class approach and the hierarchical Bayes procedure to predict the aggregate choice shares of holdout tasks. Our study constitutes the first empirical test of the validity of the informational (and allocative) price effect as measured with choice-based conjoint analysis. We also discovered while comparing the (predictive) validity of the latent class approach with the hierarchical Bayes procedure that the latter performs better in measuring the informational (and allocative) effect of price.

Our study has important managerial implications. Our methodology enables marketers, in terms of market segmentation issues, to identify segments that differ in the magnitude of the allocative and informational effect of price. Identifying such segments forms the basis for targeted communication programs and pricing decisions that account for the divergent roles that price can play when consumers evaluate products. For example, marketers should not price their product “too low” in segments characterized by a substantial informational effect of price lest they run the risk of selling less at a lower price. A price decrease can make the product more affordable, yet on the other hand it might turn consumers away because they interpret the lower price as signalizing lower quality. Conversely, the effect on quality beliefs of a price increase within such segments (informational role of price) may offset the negative impact on the consumer’s wallet (allocative role of price).

Our study also reveals the necessity to determine the extent that positive and negative price effects are generally confounded in conjoint settings and in other preference models. Otherwise it remains unclear which role of price (informational or allocative) is contributing to the estimated price effect and any decision based on the estimated effect is potentially sub-optimal.

Notes

[1] An aggregate analysis is inappropriate because it does not consider that brand preference, price perception and price assessment are complex psychological factors that may be distributed quite heterogeneously across consumers. In terms of examining price effects, aggregation of individuals with heterogeneous preferences and experiences could provide misleading and biased results (e.g., Dickson/Sawyer 1990; DeSarbo et al. 1997).

[2] The latent class model is a subtype of finite mixture models in which all measured variables are discrete (Wedel/Kamakura 2000). DeSarbo/Ramaswamy/Cohen (1995) introduced applying the latent class approach to choice-based conjoint data. Their application is perceived as a generalization of Kamakura/Russell’s (1989) probabilistic segmentation approach that applied a latent class model to the multinominal logit estimation of scanner panel data (DeSarbo/Ramaswamy/Cohen 1995).


[4] Benchmark: 74 % correct replications for a choice set, with three alternatives that are defined by five attributes (Huber et al. 1993).

[5] Price preferences were examined using the main effects model.

[6] An alternative to this approach might be to use the a-posteriori membership probabilities themselves and calculate the corresponding elasticities as a weighted combination of each class elasticity. However, creating and inspecting discrete segments is more in line with manager opinion about consumer segments and thus more appealing from a managerial viewpoint.

[7] \[ MAE = \frac{\sum |N_i - \hat{N}_i|}{\sum N_i}, \quad RMSE = \sqrt{\frac{\sum (N_i - \hat{N}_i)^2}{\sum N_i}}, \quad \chi^2 = \frac{\sum (N_i - \hat{N}_i)^2}{\hat{N}_i}. \] (1)

In the equation \( N_i \) represents the number/proportion of respondents choosing brand \( i \) in the holdout choice task and \( \hat{N}_i \) represents the predicted number/proportion.
References


