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Improving Predictive Validity of Choice-Based Conjoint Models

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Improving Predictive Validity of Choice-Based Conjoint Models

Abstract

Up to date, it is unclear how Choice-Based Conjoint (CBC) models perform in terms of forecasting (external) real world aggregate shop data. In this contribution, we measure the performance of a Latent Class CBC model - not with an experimental holdout sample - but with aggregate real world scanning data. We find that the CBC model does not accurately predict real world market shares. In order to improve the forecasting performance, we propose a correction scheme based on external scanner data. Our analysis based on 8 brands shows that the use of the proposed correction vector improves the performance measure considerably.

Keywords: Choice Based Conjoint Analysis, External Validity, Latent Class Models

1 Introduction

Choice Based Conjoint (CBC) analysis (Louviere and Woodworth 1983) is one of the most frequently used methods for pricing decisions. The popularity of this methods as compared to ranking based conjoint analyses is due to several advantages (see, e.g., Pinnell 1995, or DeSarbo, Ramaswamy and Cohen 1995) of this methodology:

- data collection: simulated purchase decisions are more realistic than rankings or ratings
- the derived part-worth utilities reflect impact on product choice rather than a change in ratings or rankings
- product specific attributes or levels can easily be accommodated and brand specific utilities can be estimated
- CBC analysis allows for a none-choice or other option
- conjoint design: CBC is more flexible in designs than traditional conjoint analysis

Most studies (e.g., Green, Krieger and Agrawal 1993) on the validity and performance of conjoint approaches rely on internal validity measures. There, interview data are split into two parts, where the first is used for model estimation and the second (holdout sample) is used for model validation. Holdout samples are, however, only able to capture validity of preference or simulated choice, but not of actual behavior or real market shares. This is also the reason that one of the most useful concepts to validate and compare methodologies, i.e. Monte Carlo Analysis (see, e.g., Vriens, Wedel and Wilms 1996), does not provide final confidence into conjoint methodologies. Because of the fact that conjoint analysis is heavily used by managers[1] and investigated by researchers, external validity is of capital interest. Although predictive validity is of high practical relevance, even internal holdout judgements are examined in only 9% of the projects (Wittink, Vriens, Burhenne 1994). External validity studies, i.e., analyses that investigate the correspondence of interview based shares-of-preference with real market shares, are not available. There is, however, a prominent group of researchers (Carson et al. 1994; Neslin et al. 1994; Winer et al. 1994) who have indicated the need for additional research concerning external validity of conjoint analysis. DeSarbo, Ramaswamy and Cohen (1995) propose to perform a validation assessment of their approach. This is our primary objective.

In the following, we investigate the external validity of the Latent Class CBC model and derive a methodology for incorporating market dynamics to the conjoint model.

[1] Wittink and Cattin (1989) document 1062 commercial applications of conjoint analysis of 66 firms in the United States for the period 1981-1985. For Europe, Wittink, Vriens and Burhenne (1994) report 956 uses of conjoint analysis by 59 firms for the period 1986-1991.

2 Design of the Validation Study

In our study, the validity of the Latent Class CBC model is tested for 8 different brands of mineral water. With pricing of different packages as the main purpose of this conjoint study[2] - a CBC analysis was designed with brand names (A1-A8) and (b) prices (B1-B9) as attributes. The personal interviews with a total of 128 respondents were collected in the 25th week of 1997 at three different locations (shopping malls) using the Sawtooth interview software. Each respondent got shown 14 choice sets with five concepts per set plus a none-choice or other option. The respondents were asked to pick one of the concepts shown.

As an external validation of the Latent Class CBC model, we use real world scanning data, consisting of 95 weekly price and sales data (Jan. 1996 - Oct. 1997). To test our methodology of incorporating scanning information, we split the 95 weeks of scanner data to 7 quarters and use the last 6 quarters for validation only.

2.1 The Latent Class CBC Model

DeSarbo, Ramaswamy and Cohen (1995) propose to use a latent class version of CBC to overcome the limitations of aggregate analyses or a priori segmentations. The authors generalize the Kamakura, Russell (1989) scanner data response methodology to a latent class CBC model considering within subject replications over choice sets.

The respondent's (segment specific) choice probability for segment s, P_s, is given by

$$P_s(j \in C_n) = \frac{exp\,(\beta_b(j,s) + p(j)\beta_p(s))}{\sum_{i \in C_n} exp\,(\beta_b(i,s) + p(i)\beta_p(s))} \tag{1}$$

where $\beta_b(j, s)$ is the intrinsic utility of brand $j = 1, \ldots, J$ to segment $s = 1, \ldots, S$ and $\beta_p(s)$ the price utility for segment s. The "none-option or other brand" has a price utility of zero.

$n = 1, \ldots, N$ choice sets
C_n = specific brands in the nth choice set
$s = 1, \ldots, S$ market segments
$p(j)$ price of brand j in choice set C_n

The share of preference (SoP) can then be written as

$$SoP(j) = \sum_{s=1}^{S} \alpha_s P_s(j) \tag{2}$$

where α_s represents the relative segment size of s.

For estimation of the CBC segment specific parameters we use the proposed maximum likelihood procedure. For the determination of the number of segments, we split the data into an estimation (12 choice sets per respondent) and a validation set (2 choice sets per respondent). The model with highest out of sample hit rate is chosen for external validation. The hit rate is defined as the percentage of correctly predicted choices. For the data at hand the three segment solution[3] with segment sizes (α) of 0.38, 0.23 and 0.39, respectively, has the highest hit rate (47.6%). The parameter estimates of the 3 class solution are shown in Table 1.

[2]The survey study of conjoint analysis by Wittink, Vriens and Burhenne (1994) identifies pricing as the number one purpose of conjoint studies in Europe.

[3]Winer et al. (1994) find that latent class approaches seem to handle household heterogeneity fairly well with a small number of segments.

Table 1: Parameter estimates for the Latent Class CBC model

parameter	s1	s2	s3
$\beta_b(1)$	1.143	0.132	0.013
$\beta_b(2)$	1.901	0.019	0.087
$\beta_b(3)$	-1.564	-0.090	-0.380
$\beta_b(4)$	-1.212	-0.409	0.009
$\beta_b(5)$	0.352	-1.043	-0.853
$\beta_b(6)$	-0.042	-1.084	-0.477
$\beta_b(7)$	-4.313	0.243	-1.165
$\beta_b(8)$	-1.203	-0.564	-0.948
$\beta_b(\text{none})$	-1.354	-2.243	-5.000
β_p	-0.240	-0.105	-0.959

2.2 Validity Measures

From the choice data, we build probabilistic choice simulators of the BTL-type and determine the shares-of-preference (SoP) of all available products based on the real world prices of each period. The CBC estimates of the shares-of-preference based on market prices are then matched with the scanning data market shares (MS).

We measure the validity of the CBC model by means of squared correlation between SoP and MS, (r^2). High values of r^2 indicate good estimates of the price utility.

Our second measure is Variance Accounted For (VAF),

$$VAF = 1 - MSE(SoP, MS)/\sigma^2(MS), \tag{3}$$

where MSE(SoP,MS) denotes the mean squared error between CBC forecasts and the actual market shares of a brand over all periods, and $\sigma^2(MS)$, the variance of the market shares. Often management is not only interested in a high correlation between SoP and MS, but in good estimates of the real market shares. Therefore, we include the VAF measure and do not only focus on r^2, which is insensitive to different levels.

In order to measure the different levels of average market shares ($\bar{MS}$) and average shares-of-preferene ($S\bar{o}P$) we define the following measure:

$$\Delta_{MS} = abs(\bar{MS} - S\bar{o}P) \tag{4}$$

High values of Δ_{MS} indicate a large difference between the CBC model's forecasts and real market share levels; i.e., a low validity of the brand utilities.

2.3 Results

Table 2 shows the brand specific measures of the external validation. The columns, show the brand index, VAF, r^2, Δ_{MS}, and the average market share for each brand. The average, market share weighted correlation, r^2, between MS and SoP is 60.5% which indicates that price effects are nicely captured by the Latent Class CBC model. This is reflected by Figure 1, which displays the time series of the real MS (fat line) and the SoP (thin line). Although the SoP are highly correlated with MS, we can identify two major problems:

- Interview bias: the levels of SoP and MS differ considerably for most of the brands; i.e., the brand utilities are biased. This may have different reasons, such as availability (degree of distribution), representativeness of the respondents or other interview/design biases.
- Stationarity: market shares may show a drift (brand 2) or a shock (brand 7). This may be caused by (sudden) changes of the degree of distribution (brand 7) or other external effects.

The other two measures, VAF and Δ_{MS}, reflect these two problems: VAF is less than zero for all brands except brand 4. Market share weighted VAF is as low as -21.6. The difference between SoP and MS, Δ_{MS}, is 3.7% on (MS weighted) average. For brands 5 and 6 the difference is even higher than MS itself. As the optimal pricing strategy (the target of such a study) is not only dependent on the price effect but also on the market share level, the marketing consequences of these problems are drastic. Therefore, the use of CBC share-of-preference estimates should in general not be taken as forecasts of the market shares without adjustment of the external effects. An approach to cope with that problem is the calculation of a correction vector. In the following section, we demonstrate, how scanner data sources can be used to account for such external effects, without changing the price utilities of the CBC model.

Table 2: Standard model: Variance Accounted For (VAF) and r^2 for all brands, distance between average shares-of-preference and real market share levels and average market shares

brand	VAF	r^2	Δ_{MS}	$\bar{MS}$
1	-3.26	0.825	0.040	0.208
2	-0.79	0.349	0.033	0.275
3	-5.56	0.807	0.067	0.175
4	0.70	0.752	0.015	0.148
5	-928.62	0.282	0.059	0.016
6	-158.26	0.576	0.034	0.026
7	-0.09	0.254	0.018	0.079
8	-3.98	0.621	0.024	0.071

3 Improving Predictive Performance

Other effects than price, brand or package may lead to significant changes of market shares, too. Building up channels of distribution may cause shifts in market shares (Golanty 1995). Life-cycle theory suggests that products follow a certain pattern of ups-and-downs during their time on the market. However, static conjoint models do not account for such effects. Due to the cross-sectional time-series nature, POS scanner data are an interesting source to improve choice modeling (Winer et al. 1994). Due to the fact that marketing managers think in terms of segments and want to address the consumers in the segments based on additional socio-demographic information, interview data (where such additional data can be collected) are typically prefered to aggregate scanner data models. Otherwise, one could directly estimate market share models from scanner data.

If real market shares are known from the ACNielsen Retail Index (NRI), or other data sources, a correction vector can be calculated as the fraction between average market shares from the NRI and the shares-of-preference forecasted by the CBC model at average observed prices. Due to the potentially evolving nature of market shares, we propose to use an adaptive correction scheme, which calculates the correction factors based on last quarters average market shares. The advantage of this method is, that the use of a factor has no effect on the price elasticity and only corrects brand utility which we identified as the mayor source of error in our primary analyis. Because of the fact, that many companies receive quarterly reports about last quarters market shares, this is a very simple and practically feasable solution to the problem.

The correction procedure works as follows:

1. take average prices and market shares of the last quarter from NRI
2. compute the shares-of-preference as a function of the NRI prices
3. calculate the fraction of market shares and shares-of-preference

4. multiply this correction vector with the shares-of-preference of the forcasting period (weeks of the next quarter)
5. normalize the forecasts to one (market share condition)

Table 3: Correction factors for each brand and quarter Q_i

brand	Q1	Q2	Q3	Q4	Q5	Q6
1	1.43	1.31	1.25	1.21	1.24	1.26
2	1.17	1.16	1.17	1.17	1.18	1.13
3	1.72	1.65	1.76	1.58	1.60	1.55
4	0.86	0.89	0.90	1.00	0.90	0.92
5	0.26	0.24	0.24	0.21	0.21	0.21
6	0.41	0.44	0.44	0.40	0.41	0.44
7	0.60	0.61	0.64	0.84	0.87	0.97
8	0.80	0.78	0.75	0.70	0.71	0.76

The quarter specific correction factors are presented in Table 3. Factors larger (lower) than one increase (decrease) the shares-of-preference. A factor of one does not change brand utility. There seems to be a tendency of the CBC model to overestimate (underestimate) the market shares of smaller (larger) brands. The time dependence of the factors emphasizes the necessity for quarterly updates. The price utilities, which are not changed by this procedure seem to be valid for longer periods of time (see Figure 2) than the brand utilities. Consequently, it seems possible to use the model as a management tool over a longer time horizon when brand utilities are updated by the proposed methodology.

Table 4 shows that use of a correction vector significantly improves the results for all measures considered. Market share weighted r^2 increases from 60.5% to 67.3%. Market share weighted VAF reaches 59.7% and is positive for each individual brand. The correction vector corrects shares-of-preference to the correct market share level of the past quarter. Therefore, Δ_{MS} decreases to 1.1%.

Table 4: External effect model: Variance Accounted For (VAF) and r^2 for all brands, distance between average shares-of-preference and real market share levels and average market shares

brand	VAF	r^2	Δ_{MS}	$\bar{MS}$
1	0.737	0.821	0.008	0.208
2	0.366	0.489	0.016	0.275
3	0.743	0.743	0.010	0.175
4	0.696	0.730	0.014	0.148
5	0.410	0.486	0.001	0.016
6	0.461	0.490	0.001	0.026
7	0.604	0.806	0.009	0.079
8	0.590	0.620	0.005	0.071

4 Conclusion

In our study we examined the performance of an interview based Latent Class CBC model in terms of external aggregate POS scanning data. Our error measures indicate that the CBC model provides good estimates of the price utilities. However, the brand utilities show serious defects such that market share levels differ considerably from shares-of-preference. As the brand utility influences pricing decisions, such a model should not directly be used for pricing. We identified two mayor sources of this problem, namely the interview bias and market dynamics. Therefore, we proposed a correction vector scheme which dynamically updates the brand utilities. This correction scheme is based on the relation between last quarters' average share of preference and average market share. Thus it is simple, improves next quarters forecasts, makes it a valid base for pricing and due to the fact that most companies receive (at least) quarterly market share information, it is feasible from a practical point of view.

Of course, a single study is only a first step towards the external validation of CBC models and a lot more needs to be done. In future it would be interesting to see papers that investigate the impact of external effects on external validity for different products, numbers of respondents and attributes.

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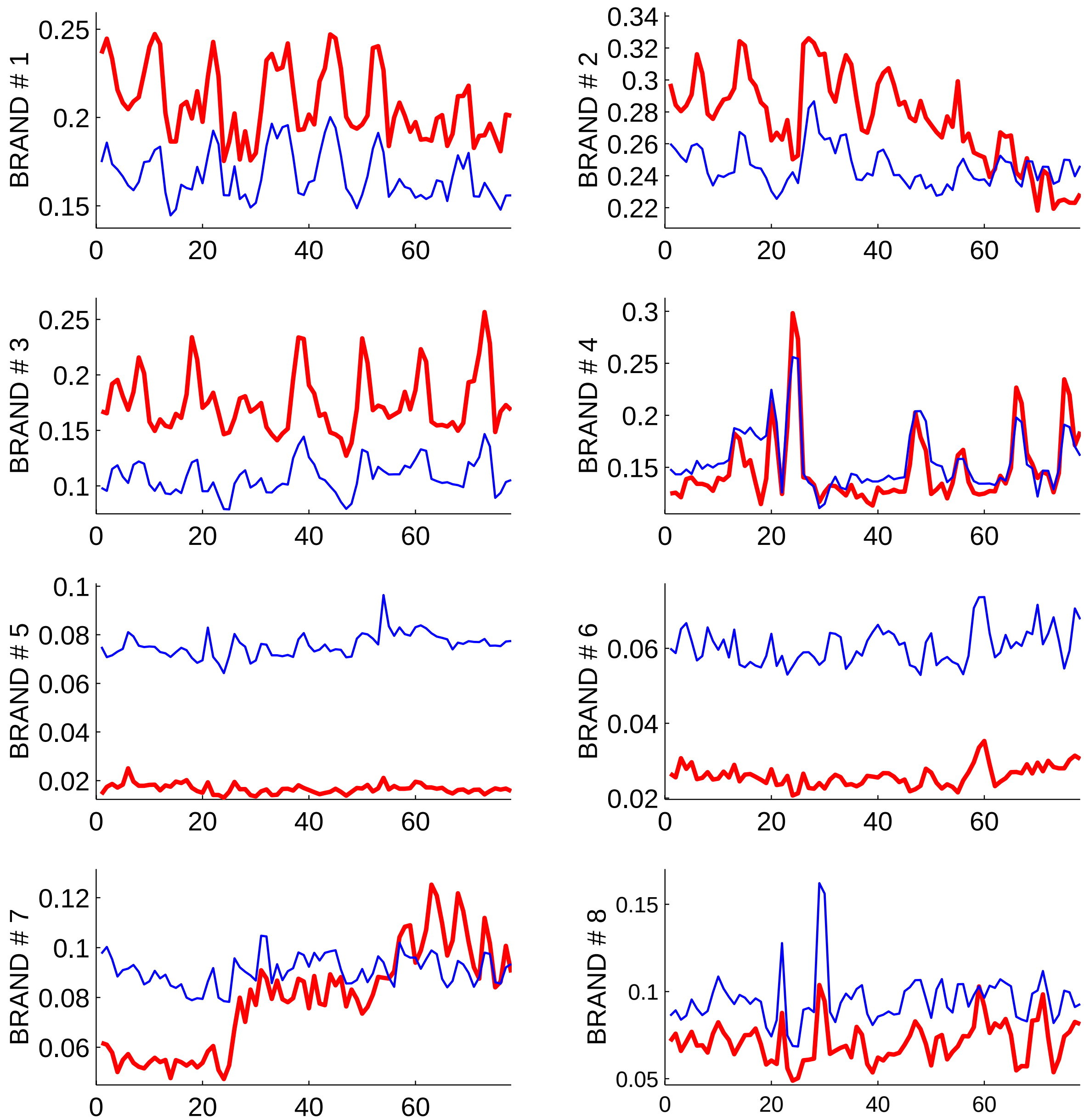

Figure 1: Real market shares (fat line), shares-of-preference (thin line) of the Latent Class CBC model

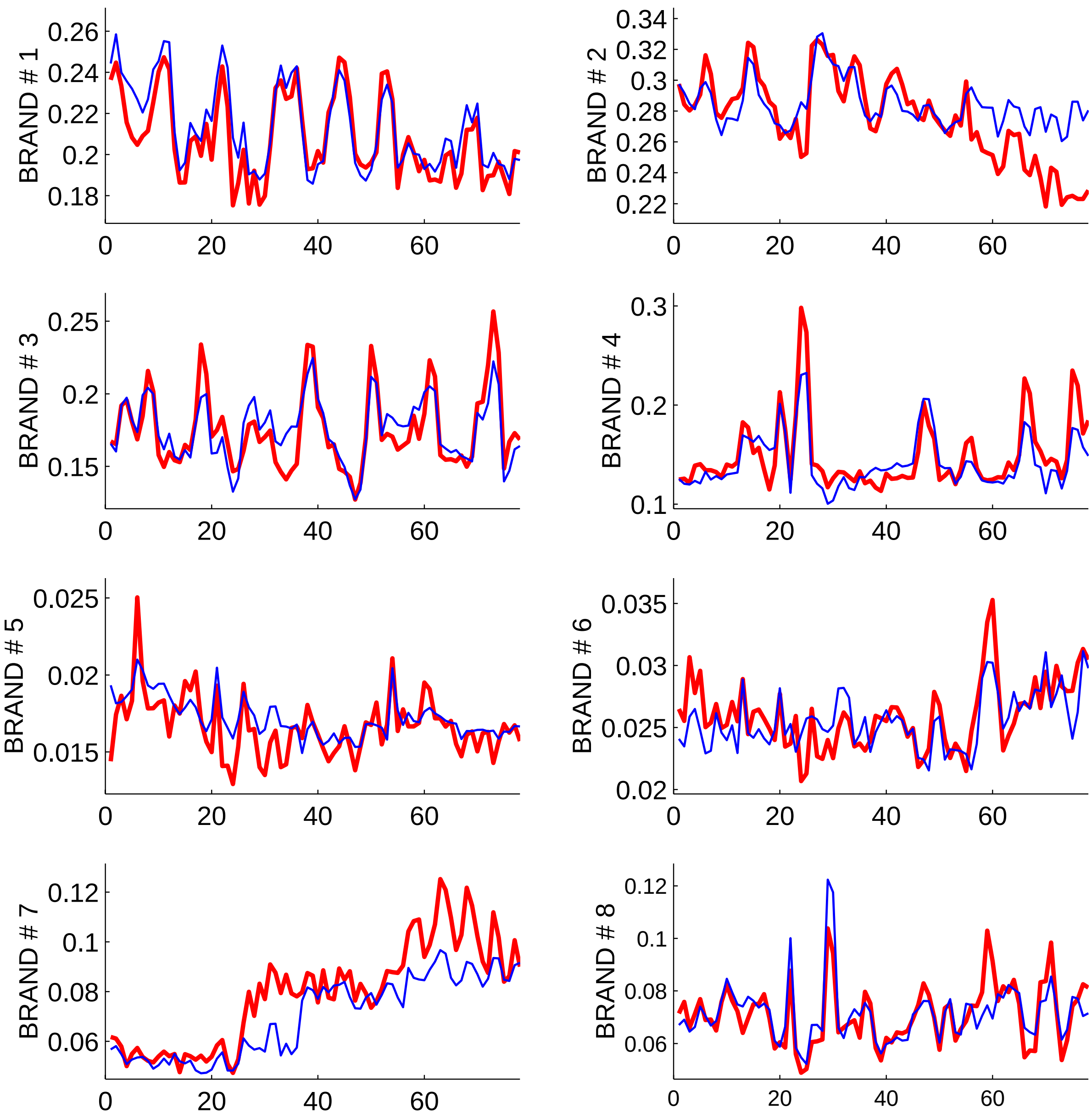

Figure 2: Real market shares (fat line), quarterly updated shares-of-preference (thin line) of the Latent Class CBC model