Working Paper Series

Individual Level or Segmentation Based Market Simulation?

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Working Paper No. 41
June 1999

Working Paper Series

June 1999

SFB
'Adaptive Information Systems and Modelling in Economics and Management Science'

Vienna University of Economics
and Business Administration
Augasse 2–6, 1090 Wien, Austria

in cooperation with
University of Vienna
Vienna University of Technology

http://www.wu-wien.ac.at/am

This piece of research was supported by the Austrian Science Foundation (FWF) under grant SFB#010 ('Adaptive Information Systems and Modelling in Economics and Management Science').

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Abstract

In many studies, choice based conjoint analysis is used to build a market simulator to develop marketing strategies; i.e., shares-of-preference are taken as market share forecasts. However, conjoint data are collected in interview situations, which may differ considerably from real shopping behavior. In this paper, we test the internal and external validity of four commercial choice based conjoint pricing studies including a total of 43 brands. We use conjoint and sales data to assess the relative performance of two modern approaches to estimate conjoint parameters: the segmentation based Latent Class model and the individual level Hierarchical Bayes approach. Our paper confirms previous results of the internal superiority of the Hierarchical Bayes approach. The main result of our investigation is that internal validity does not predict external validity and that Latent Class shows the same real world performance as Hierarchical Bayes. Both models show an average error of 4.2% in market share level prediction and a correlation of 69% between conjoint forecasts and real market shares.

Keywords: Market Simulation, Choice Based Conjoint Analysis, Hierarchical Bayes, Latent Class, External Validity

1 INTRODUCTION

Conjoint analysis is one of the most important tools to support product development, pricing and positioning decisions in marketing practice (cf. Wittink, Vriens and Burhenne, 1994; Wittink and Cattin, 1989). Researchers have developed different types of conjoint analysis (rating, ranking, choice based) as well as different techniques to estimate parameters of conjoint models. As compared to ranking or rating based conjoint approaches, choice based (Louviere and Woodsworth 1983) conjoint analysis (CBC) seems more realistic in imitating real shopping behavior. In CBC respondents have to choose one among several alternative products. This is, of course, a less difficult task for respondents and more like real shopping than rating or ranking alternatives. In many studies, the CBC model is used to build a market simulator to develop marketing strategies; i.e., shares-of-preference are taken as market share forecasts. However, CBC data are collected in interview situations, which may differ considerably from real shopping behavior. In a typical interview, respondents (i) are observed by an interviewer, (ii) simulate several purchases within a few minutes, (iii) are shown hypothetical assortments, and (iv) do not have any monetary consequences. Thus, estimates of CBC part-worths are *not* based on real purchase acts, but on simulated choices. Consequently, marketing actions that are based on such models may not lead to the same effects as in interviews. Furthermore, CBC-models are static whereas market shares may change over time. Dynamic effects and other impacts which are not captured within a CBC study, such as increasing brand awareness, changes in the level of distribution (cf. Golanty 1995), life cycle effects, promotional activity, seasonal impacts, new market entrants, etc., may decrease the real world (external) validity of CBC models.

The current marketing literature on choice modeling shows a strong focus on developing new CBC estimation methodologies on one hand (see, e.g., Johnson 1997, Hagerty 1985, DeSarbo, Ramaswamy and Cohen 1995, Lenk, DeSarbo, Green, and Young 1996, Arora, Allenby, and Ginter 1998, Pinnell 1994/1995) and studies that test the internal validation (hold-out samples, Monte Carlo) of different approaches on the other hand (cf. Green, Krieger and Agrawal 1993, Vriens, Wedel and Wilms 1996, Garratt, Renken and Sigler 1998). However, due to the fact that up to date, there are almost no studies available that test the external validity of these new methodologies, we still do not know how good simulated purchases reflect real behavior. Neither performance on hold-out samples (see, e.g. Garratt, Lenken, Sigler 1998) of the interview data, nor Monte Carlo Analysis with artificial data (see, e.g., Vriens, Wedel and Wilms 1996) can help to answer this question. An empirical analysis of situations where both, interview and real shopping data are available, seems to be the only way to investigate the usefulness of CBC interview data for decision making. We only found two contributions that tested conjoint validity in terms of real sales data: The first paper which does not focus on external validation itself, is by Urban et al. (1997) who compare sales forecasts of a new camera with actual sales. A second contribution in this context is by Orme and Heft (1999) who investigate the external validation of three product categories. Developing market simulators based on aggregate logit, Latent Class and ICE (Individual Choice Estimation) models, they found that Latent Class and ICE predicted actual sales better than aggregate logit.

Although, there is a vanishing number of contributions that test the external validity of choice data in such a manner, there is a prominent group of researchers (Carson et al. 1994; Neslin et al. 1994; Winer et al. 1994; DeSarbo, Ramaswamy and Cohen 1995; Orme and Heft 1999) who have indicated the need for additional research concerning external validity of conjoint analysis. The key issue of our paper is the external validation of two CBC estimation methodologies, Latent Class and Hierarchical Bayes. Our empirical analysis is based on 43 different brands of four products. Our study is different from Orme and Heft (1999) in two major aspects. First, we use real (national) aggregate data and not only the shops in which the interviews where made. While shop validation is interesting when a study is made for a single outlet, aggregate validation is more interesting for producing firms, product developers or retail chains. Second, Orme and Heft discarded 45 transitional weeks wherein prices had recently changed. As we are not interested in showing high correlation with part of the real data but in testing the external validity, we make no scanning data selection.

The rest of the paper unfolds as follows: starting with the discussion of two alternative ways to estimate the model parameters (section 2), we proceed with the formulation of our hypotheses and measures (section 3). The description of our data (section 4) and results (section 5) is followed by an assessment of our outcomes.

2 MODELS

Researchers have proposed several techniques for CBC-parameter estimation. In this paper, we restrict ourselves to two of the more advanced methodologies, Latent Class (DeSarbo, Ramaswamy and Cohen 1995, Huber 1998) and Hierarchical Bayes (Lenk, DeSarbo, Green, and Young 1996, Allenby, Arora, Ginter 1995, Allenby and Ginter 1995). Both methodologies have not been externally validated on real shopping data. They have been validated, however, in terms of holdout performance and with artificial data. Huber (1998), who compares Hierarchical Bayes (HB) with Latent Class (LC) and Extended Latent Class (ICE) finds that HB does best in terms of finding the correct parameters; accuracy of predicting holdout choices was found to be similar for HB and ICE and slightly lower for LC models. Garratt, Renken and Sigler (1998) find that HB models are roughly four times as accurate in hit rate than logit.

Latent Class

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

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

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

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 and a validation set (2 choice sets per respondent). The model with highest out-of-sample hit rate is chosen for external validation.

Hierarchical Bayes

In contrast to the latent class model, individual-level estimates are obtained by a Hierarchical Bayes model. Lenk, DeSarbo, Green, and Young (1996) showed analytically and empirically that Hierarchical Bayes models do not require individual-level design matrices to be of full rank. This leads to the possibility of using fewer profiles per subject. Allenby and Lenk (1994 and 1995) applied Hierarchical Bayes models to brand choice. The individual (h) choice probabilities take the standard logit form:

$$P_h(j \in C_n) = \frac{exp\,(\beta_b(j,h) + p(j)\beta_p(h))}{\sum_{i \in C_n} exp\,(\beta_b(i,h) + p(i)\beta_p(h))} \qquad (2)$$

Heterogeneity across respondents is introduced by a multivariate normal distribution for the parameters (Arora, Allenby, and Ginter 1998) $\beta_{\mathbf{h}} = (\beta_b(.,h), \beta_p(.,h))$:

$$\beta_{\mathbf{h}} \sim \text{Normal}(\bar{\beta}_{\mathbf{h}}, D) \qquad (3)$$

Using the Metropolis-Hastings algorithm the parameters are drawn from the posterior distribution:

$$f(\beta_{\mathbf{h}}|\bar{\beta}_{\mathbf{h}}, D) \propto \exp[-\frac{1}{2}(\beta_{\mathbf{h}} - \bar{\beta}_{\mathbf{h}})' D^{-1} (\beta_{\mathbf{h}} - \bar{\beta}_{\mathbf{h}})]\Pi_n Pr_{hn} \qquad (4)$$

In our study 1000 draws of the parameters separated by 10 iterations were taken after a thermalisation of 10000 iterations.

3 MEASURES AND HYPOTHESES

From the choice data, we build probabilistic choice simulators of the BTL-type and determine the shares-of-preference 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. In order to test and compare the validity of choice-based conjoint approaches, we define two internal and two external criteria:

1. internal: hr, the out-of-sample hit rate, an often used internal validation measure. This measure is also interesting for the purpose of comparability with other studies.
2. internal: $\epsilon_{MS,P}$, the price elasticity of market shares. Price elasticity is a key figure to compare HB and LC solutions.
3. external: r^2_{ext}, the squared correlation between CBC-forecasts (Shares-of-Preference) and real scanning market shares (MS) when scanning prices are applied to the conjoint models. With pricing as the main purpose of these studies, only brand

and price utilities were estimated. Consequently, r^2_{ext} measures the quality of the price effects estimated from conjoint data. This is of capital interest because price elasticity directly influences optimal pricing decisions.

4. external: δ_{MS}, the absolute deviation between average market shares and CBC Shares-of-Preference. δ_{MS} measures the goodness of the level estimates (brand utilities). As several decisions in marketing and production planning depend on the forecasted market shares, this measure is especially interesting for new products.

In accordance with the mentioned literature, we expect higher internal validity of Hierarchical Bayes than Latent Class models. Here, internal validity is measured in terms of out-of-sample hit rates, hr. Hence, we predict that:

> H_1: HB estimation results in a higher out-of-sample hit rate than LC estimation.

An interesting aspect of our analysis is the question whether internal validity measures are a good indicator for the external validity of CBC models. If the correlation between internal and external validity measures is significantly different from zero, we can say that internal validity indicates higher external validity. Accordingly, we hypothesize:

> H_2: Significant positive correlation between internal and external validation and that HB shows higher external validity than the LC approach.

Our scanner data base includes information about two (dynamic) effects, which are not considered within the CBC study, promotional activity (features and handbills) and the degree of distribution. Our intention is to investigate whether the strength (measured in terms of squared correlation between weekly scanning market shares and weekly distribution/promotions) of these effects influences the external validity. We hypothesize:

> H_3: Brands with weak promotion/distribution impacts have a higher external validity.

4 DATA

In our analysis, we consider the following four product categories: mineral water (Cat1), shampoo (Cat2), shower gel (Cat3) and beer (Cat4). The conjoint-data analyzed here, were collected for four commercial pricing studies conducted between 1997 and 1999. The studies differed in the number of (a) respondents (128/220/224/510), (b) choice sets per person (14/20/20/30) and (c) concepts per choice set (6/6/5/6). For each category, a randomized choice experiment that included scanned images of the products was programmed into Ci3, the Sawtooth Software questionnaire program.

All questionnaires included brand and price attributes only. For Cat1, which included 2 packages sizes (1 liter, 1.5 liter), we used a metric price variable for each package size, without any further consideration of price-brand interactions. The questionnaire for the shampoo data (Cat2), included brand specific price ranges which were determined from the real world price ranges. Therefore, we modeled price-brand interactions for Cat2. Shower gel (Cat3) is a category with many different package sizes. We used one metric price variable for each package size. In the beer study (Cat4), three different price ranges were built in the questionnaire and each brand was assigned to one of three metric price variables. For categories 1, 3 and 4, we have also tested models with price-brand interactions. However, these models lead to similar results in terms of hit rate, so that we restrict the presentation of our results to the models without interactions for these three categories.

The scanning data for these product groups with a total of 43 brands were provided by AC Nielsen. The data consist of weekly sales, prices, feature/display and degree of distribution. Table 1 shows the number of periods, brands and time of the last observation for each product category.

Further details, concerning individual brands' market shares, and whether a brand is new or established on the market are given in Table 3. The majority of the brands is already established on the market and only 5 brands are introduced during the observed periods.

Table 1: Data set description

	Cat1 mineral water	Cat2 shampoo	Cat3 shower gel	Cat4 beer
SCANNING: nr. of weeks	95	108	104	108
SCANNING: nr. of brands	11	13	10	9
SCANNING: year/week of last obs.	97/43	98/19	98/23	99/7
CBC: nr. of respondents	128	220	224	510
CBC: choice sets per person	14	30	20	20
CBC: concepts per choice set	6	6	5	6
CBC: year/week of last interview	97/25	98/22	98/50	99/12

5 CBC-Validation Results

Internal validity

Our empirical results of the internal performance of the HB and LC estimation procedure is in line with the mentioned literature. Hierarchical Bayes estimation results in an out-of-sample hit rate of 67.14% whereas Latent Class[1] ends up with 44.02% only. This difference is significant (two-tailed t=5.634, 42 df) at the 1% level. Therefore, based on our empirical results, hypothesis H_1 is confirmed. This advantage in hit rate is due to simple shrinkage to individual level sample means (cf. Garratt, Renken and Sigler 1998).

External validity of the price utilities

Figure 1 plots r^2_{ext} of HB versus those of LC. To our astonishment, HB and LC show the same real world performance in terms of the fist external validity measure, r^2_{ext}. The t-statistic (t=-0.851, 42 df) shows that LC and HB do not have significantly different means[2].

This was not what we have expected from the internal validation of the CBC models. There, the holdout sample hit rate of HB is significantly higher than the LC hit rate for all product groups. This result is reflected in the insignificant ($\alpha = 0.05$) correlation between the internal measure (hit rate) and the external measures (r^2_{ext}, δ_{MS}). Consequently, H_2 is not supported empirically. For a more detailed analysis, we also calculated price elasticity for a 1% decrease in price from regular price (see Tables 2, 3). However, we did not find a significant difference in the mean of HB and LC price elasticity (two-tailed t=0.439, 42 df). The price elasticity of the HB and LC model are highly significant correlated ($r = 0.90$). This explains the similar real world performance of both CBC models.

External validity of the brand utilities

Figure 2 plots the market share level errors of HB versus those of LC. The difference

[1] For categories Cat1, Cat2, and Cat3, the highest hit rate was found for 3 classes. For Cat4, 2 latent classes where optimal in terms of hr.

[2] They have a highly significant correlation of r=0.82.

Table 2: CBC-Validation Results

measures (43 brands)	LC	HB
internal: hit rate (out-of-sample)	44.02%	67.14%
external: $r^2(MS : SoP)$	48.59%	47.09%
external: δ_{MS}	4.22%	4.26%
price elasticitys (-1%)	-1.11	-1.09

between average shares-of-preference and real average market shares, δ_{MS}, is 4.22% for the LC-model and 4.26% for the HB models. The t-statistic (t=0.144, 42 df) shows that the two models do not have significantly different market share level forecasts. We find a similar high correlation (r=0.91) between the HB and LC level errors as for r^2_{ext}.

Impact of dynamic external effects

The average strength of the impact on market shares is $r^2 = 0.20$ for the degree of distribution and $r^2 = 0.34$ for promotional activity, respectively. Especially new brands tend to show a high correlation with the degree of distribution. Although several brands' market shares are highly correlated with distribution[3]/promotional activities[4], we found that the strength of the external effects has no significant effect on the external validity (r^2_{ext}). Consequently, hypothesis H_3, does not find empirical support either.

6 DISCUSSION

First, we tested the *internal validity* of four commercial CBC pricing studies including a total of 43 brands. We have used Latent Class and Hierarchical Bayes estimation techniques and found that Hierarchical Bayes (hr=67.1%) clearly outperforms Latent Class (hr=44.0%) in terms of out-of-sample hit rate. Based on previous studies, this was what we have hypothesized. Second, we have tested the *external validity* by means of additional real world shopping data and found that - externally - Hierarchical Bayes is not superior to Latent Class: Both methods lead to an average market share bias of 4.2%. Furthermore, shares-of-preference forecasts of both approaches showed a similar high correlation (r=69%) with real market shares. Our results indicate that internal validity measures such as the out-of-sample hit rate do not appropriately forecast external validity. Consequently, the necessity for new measures that predict external validity rather than internal validity, remains an open research issue. Third, we have tested whether the strength of external effects (degree of distribution, promotional activities) decreases external validity. Our results showed that the degree of distribution shows a strong correlation for new brands but not for established brands. However, averaged over all brands, neither the degree of distribution nor promotional activities significantly decreased external validity.

Major advantages of disaggregate analyses such as HB arise when consumers are directly targeted. Individual level models tell us *who* prefers which brands or packages and gives additional supportive (attitudinal) information. Aggregate or segmentation based analyses which give up these advantages of individual analyses, are, however less (computing) time consuming than random coefficient models. Our analysis indicates that the two methods investigated here, LC and HB, are not different in terms of real world performance. Thus, if market simulations are developed from choice based conjoint models, we recommend to use Hierarchical Bayes when individuals are directly targeted and Latent Class otherwise.

[3]For promotional activities, this may be due to the fact that price promotions are typically accompanied by features or displays.

[4]Usually, the degree of distribution and market share level increase in the first periods resulting in a high correlation. In contrast to new brands, established brands show quite stable degrees of distribution.

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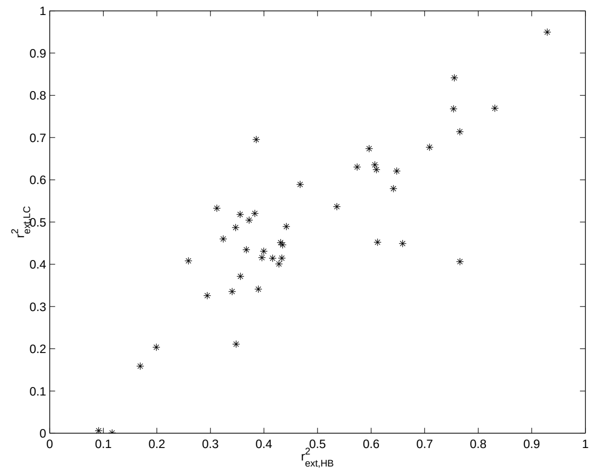

Figure 1: External validity of HB versus LC: squared correlation of Shares-of-Preference with real world shopping data (r^2_{ext})

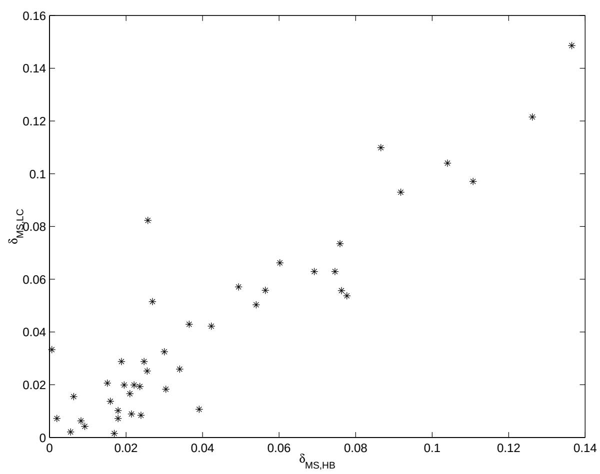

Figure 2: External validity of HB versus LC: market share bias (δ_{MS})

Acknowledgement

The authors wish to thank Martin Kaufmann from ACNielsen for his data support, Neeraj Arora, Greg Allenby, and James Ginter for sending us the source code of their Hierarchical Bayes routines. We would also like to express our gratitude to Leonhard Kehl who supported us with many useful information concerning the product groups considered in this paper. Furthermore, we would like to thank participants of the Marketing Science 1998 conference at INSEAD and the Sawtooth Software Conference in San Diego, 1999. Richard Johnson and Bryan Orme gave us some useful hints on previous versions of this manuscript. Markus Feurstein was supported by Austrian Science Foundation (FWF) under grant SFB #010.

Table 3: CBC-Validation Results

Category.	brand	new	MS [%]	r^2_{ext} [%] HB	r^2_{ext} [%] LC	δ_{MS} [%] HB	δ_{MS} [%] LC	hr [%] HB	hr [%] LC	ϵ_P HB	ϵ_P LC
1	1	n	19.8	75.5	84.1	7.6	5.6	71.4	60.7	-2.34	-1.64
1	2	y	3.7	9.1	0.6	2.6	2.5	71.4	47.6	-2.36	-2.20
1	3	n	26.0	83.1	76.9	2.7	5.2	83.3	86.1	-1.68	-1.30
1	4	y	2.5	43.5	44.6	0.5	0.2	84.2	63.2	-1.90	-2.10
1	5	n	16.2	70.9	67.7	6.0	6.6	70.0	40.0	-1.82	-1.99
1	6	y	0.5	32.4	46.0	2.0	2.0	53.8	46.2	-1.99	-2.07
1	7	n	13.8	75.4	76.8	1.8	1.0	72.7	54.5	-2.31	-1.79
1	8	n	1.7	92.9	95.0	4.9	5.7	55.6	33.3	-2.70	-1.81
1	9	n	2.4	39.6	41.6	1.9	2.9	66.7	44.4	-3.05	-2.27
1	10	n	6.8	11.7	0.1	3.9	1.1	50.0	33.3	-1.43	-1.52
1	11	n	6.6	46.8	58.9	2.4	1.9	50.0	37.5	-2.26	-1.79
2	1	n	6.8	64.8	62.1	2.6	8.2	76.2	23.8	-0.80	-0.52
2	2	n	32.6	61.2	45.2	13.7	14.9	66.7	19.4	-0.40	-0.26
2	3	n	5.1	38.6	69.5	1.5	2.1	16.7	2.4	-0.40	-0.73
2	4	y	3.7	39.0	34.1	3.0	1.8	73.1	10.5	-0.60	-0.70
2	5	n	2.1	35.6	51.8	7.5	6.3	72.0	10.1	-0.55	-0.60
2	6	n	1.4	37.2	50.4	0.2	0.7	80.0	0.0	-0.71	-0.82
2	7	n	4.4	42.8	40.1	2.5	2.9	62.5	3.2	-0.95	-1.28
2	8	n	6.7	76.6	40.6	2.1	1.7	50.0	7.3	-0.16	-0.03
2	9	n	6.6	43.1	45.1	0.1	3.3	68.8	6.5	-0.64	-0.43
2	10	n	13.3	36.7	43.4	3.4	2.6	77.3	8.9	-0.83	-0.58
2	11	y	5.8	65.9	44.9	1.7	0.1	66.7	6.0	-0.43	-0.38
2	12	n	6.7	64.2	57.9	2.1	0.9	87.5	6.5	-0.50	-0.54
2	13	n	5.0	34.8	21.1	1.8	0.7	58.8	6.9	-0.21	-0.15
3	1	n	7.3	41.6	41.4	10.4	10.4	91.7	100.0	-1.03	-1.27
3	2	n	4.9	44.2	48.9	3.6	4.3	33.3	77.8	-1.86	-2.60
3	3	n	0.7	61.0	62.4	3.0	3.2	0.0	0.0	-0.79	-1.38
3	4	n	21.4	60.7	63.5	9.2	9.3	62.5	56.3	-0.81	-0.81
3	5	n	12.2	76.6	71.4	2.4	0.8	55.6	44.4	-1.34	-1.35
3	6	n	21.0	29.4	32.6	12.6	12.1	50.0	83.3	-0.53	-0.59
3	7	n	9.6	40.0	43.1	4.2	4.2	75.0	87.5	-0.26	-0.34
3	8	n	9.0	59.6	67.4	0.6	1.6	42.9	0.0	-0.38	-0.75
3	9	n	9.6	43.3	41.5	11.1	9.7	90.0	50.0	-0.53	-0.69
3	10	n	4.3	34.1	33.5	0.9	0.4	46.2	61.5	-0.72	-0.95
4	1	n	20.4	53.6	53.6	5.6	5.6	75.4	61.5	-0.48	-0.89
4	2	n	10.8	35.6	37.2	1.6	1.4	78.7	63.9	-0.87	-0.84
4	3	n	15.2	38.3	52.0	2.2	2.0	83.3	77.8	-0.60	-0.64
4	4	n	6.5	34.7	48.7	8.7	11.0	91.8	93.2	-0.18	-0.55
4	5	n	17.5	25.9	40.8	7.6	7.4	68.1	42.6	-0.80	-1.10
4	6	n	2.1	16.9	15.9	0.8	0.6	54.5	0.0	-2.42	-2.35
4	7	n	9.7	57.4	63.0	6.9	6.3	53.3	0.0	-0.92	-1.36
4	8	n	5.1	31.2	53.3	5.4	5.0	75.0	40.4	-1.05	-1.14
4	9	n	12.3	19.9	20.4	7.8	5.4	81.1	94.4	-0.11	-0.66