Market Lett (2006) 17:255–268
DOI 10.1007/s11002-006-7943-8

The no-choice option and dual response choice designs

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Abstract Choice set designs that include a constant or no-choice option have increased efficiency, better mimic consumer choices, and allow one to model changes in market size. However, when the no-choice option is selected no information is obtained on the relative attractiveness of the available alternatives. One potential solution to this problem is to use a dual response format in which respondents first choose among a set of available alternatives in a forced-choice task and then choose among the available alternatives and a no-choice option.

This paper uses a simulation to demonstrate and confirm the possible gains in efficiency of dual response over traditional choice-based conjoint tasks when there are different proportions choosing the no-choice option. Next, two choice-based conjoint analysis studies find little systematic violation of IIA with the addition/deletion of a no-choice option. Further analysis supports the hypothesis that selection of the no-choice option is more closely related to choice set attractiveness than to decision

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difficulty. Finally, validation evidence is presented. Our findings show that researchers can employ the dual response approach, taking advantages of the increased power of estimation, without concern for systematically biasing the resulting parameter estimates. Hence, we argue this is a valuable approach when there is the possibility of a large number of no-choices and preference heterogeneity.

Keywords Choice-based conjoint analysis · No-choice option · Choice models · Logit models

It has long been advanced that one should include a constant or no-choice option in choice-based conjoint designs. This alternative can be an option, such as "keep on shopping" that is the same for all respondents or it can be an option like "stay with my current product," which would vary across respondents, but is constant within respondent. For ease of exposition, we will refer to this option as the "no-choice option." Inclusion of the no-choice option increases design efficiency (Anderson and Wiley, 1992), better mimics the choice process in many situations (Louviere and Woodworth, 1983) directly measuring demand for specific tested products in the context of the entire market, and allows one to model market growth as more attractive alternatives are introduced.

Adding the no-choice option potentially raises several concerns. With the addition of a no-choice option, no information is obtained on the relative attractiveness of the available alternatives in a given choice set when the no-choice option is chosen. This means that the parameters associated with the available alternatives are estimated from fewer observations as the number of "no-choices" increases. Additionally, if the selection of the no-choice option is concentrated in certain choice sets the experiment could lose critical power, not only due to the lack of data, but also by degrading the properties of the information matrix, which could lead to the creation of bias.

These problems can occur when even a few attribute levels are unattractive to a subset of the population. These respondents would be most likely to select the no-choice option when these levels were present—thereby selectively withholding information that could contribute to parameter estimation. If one is monitoring markets over time, it may be desirable to include some people who are not currently planning to buy, but are waiting for prices to drop, performance to improve, or new features to appear. Knowing why some people are not currently in the market may be as valuable as knowing the preferences of those currently in the market.

One potential solution to this "no-choice" power and bias problem is to use a dual response format in which respondents are first asked to choose between the set of available alternatives in a forced-choice (i.e., without a no-choice option) task and then are asked to choose between the available alternatives and a no-choice option in a second task (i.e., a free-choice task).

Notwithstanding these advantages, there is a question whether this new task creates bias relative to the traditional free-choice task. Traditional and dual response task coefficient estimates would agree if the addition or deletion of the no-choice option did not violate IIA. That is, if (1) creating a forced-choice from the traditional free-choice task by deleting the no-choice option did not impact the relative probability of choosing any of the available alternatives and (2) the addition of the no-choice option in the

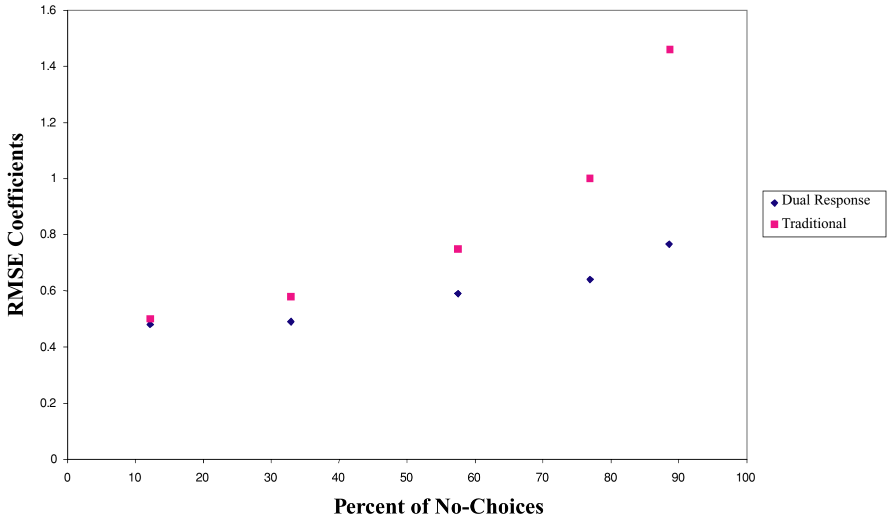

Fig. 1 RMSE between true and estimated coefficients

second stage of the dual response task drew proportionally (to probability of choice) from each of the available alternatives, the parameters associated with the available alternatives would be the same for the two tasks[1]—even if the level of no-choices differed between the two tasks. However, there is some evidence that the addition or deletion of a no-choice option systematically violates IIA in some choice situations (Dhar and Simonson, 2003).

This paper addresses these issues through simulation and empirical experiments. As background, the paper presents a simulation that compares the efficiency of dual response and traditional choice-based conjoint tasks at different levels of no-choice responses and reviews the relevant research to date. Next, it presents two experiments that examine violations of IIA and differences in parameter estimates and then compare the resulting choice validations.

Background

Simulation. Several simulations were run to examine the effect of the dual response format on individual-level hierarchical Bayes parameter estimates (Uldry et al., 2002). The following simulation summarized in Fig. 1 is representative. It assumes that 100 respondents choose the alternative with the highest utility. It varied the percent of no-choice responses and the response format (dual response or traditional single stage free-choice). The dependent variable was the root mean squared error (RMSE) of the individual coefficients.

[1] It may be possible (but less likely) for offsetting violations of IIA across these two tasks to create equivalent parameter estimates for the available alternatives.

Figure 1 shows that considerable gains in efficiency are possible with the dual response methodology as the percent of no-choices increases, with a decrease in RMSE of as much as 50%. The gains in any particular study will be a function of several factors including the mechanism leading to no-choice decisions, the distribution of no-choices across the sample, preference heterogeneity, and sample size.

Violations of IIA. Dhar and Simonson (2003) ran a series of experiments in which a choice was made among two or three alternatives described in terms of two attributes. The addition or deletion of a no-choice option violated IIA in most of their experiments. In particular, compromise alternatives (whose status as a conflict resolution mechanism is transparent) were more vulnerable to the no-choice option, which is also a conflict resolution mechanism, than other alternatives. Dominating alternatives tended to lose relatively less with the addition of a no-choice option. Additionally, people were more likely to choose the no-choice option in a two stage, forced-choice followed by free-choice task than in a single stage free-choice task. Finally, the no-choice option in the second free-choice task drew disproportionately from compromise alternatives. These findings suggest that while efficiency gains, as demonstrated by the simulation described in this paper, may be attractive, they may be offset by concerns related to potential violations of IIA.

Selection of the no-choice option. Dhar and Simonson's (2003) finding that the no-choice option drew disproportionately from compromise alternatives is consistent with other behavioral research that finds the selection of the no-choice option is correlated with decision difficulty (e.g., Tversky and Shaffir, 1992; Dhar, 1993). An alternative hypothesis, consistent with random utility maximization is that the no-choice option is more likely to be chosen when utility of the no-choice option exceeds that of any of the available alternatives. Huber and Pinnell (1994) used weights from a ratings-based conjoint task to calculate the sums and standard deviations of the utilities of the available alternatives in a series of free choices. They related these measures (among others) to the percent choosing the no-choice option and found support for both the choice set attractiveness and decision difficulty hypotheses.

Implications. Extending the results of Dhar and Simonson (2003) to choice-based conjoint analysis, one would expect differences in the relative choice proportions of the available alternatives between forced- and free-choice tasks. Additionally, if choice-based conjoint were used to model situations where deferring a purchase is a viable alternative, then deletion of a no-choice option might systematically bias the parameter estimates associated with the available alternatives.

The following experiments examine the impact of a no-choice option on the relative choice proportions of and parameter estimates associated with the available alternatives. Additionally, they examine the impact of making the no-choice option part of an initial free-choice task versus part of a free-choice task that follows a forced-choice task involving the available alternatives.

Study one

A two-by-two between subjects experiment was conducted in which 180 subjects evaluated MP3 players described in terms of nine attributes: brand name; size; presence or absence of an FM radio, voice recorder, and rechargeable battery; amount of memory; memory device; battery life; price; and lines of display. Brand name was effects-coded with two brand specific constants (BSCs), all two-level variables were effects-coded, and memory and price were mean centered. The no-choice option was coded with a zero/one alternative specific constant (Haaijer et al., 2001). Approximately half of the respondents participated in a traditional free-choice experiment in which they made a choice among one of three MP3 players and a no-choice option in each of fourteen choice sets, twelve for calibration and two for validation. The other half participated in a dual response choice experiment in which a forced choice among the first twelve sets of three MP3 players followed by a second choice including a no-choice option. They saw the same two free-choice validation sets as the first group. Additionally, approximately half of the subjects saw sets of more attractive MP3 players (i.e., more memory, longer battery life, and lower price) and the other half saw sets of less attractive players, from the same design, in order to assess the impact of overall attractiveness on the number of times the no-choice option was selected across all choice sets.

Free versus forced-choice. Dhar and Simonson (2003) found that the inclusion of a no-choice option drew disproportionately from some of the available alternatives. First, similar to Dhar and Simonson (2003), we compare the choice proportions of the available alternatives in a forced- (i.e., first stage of dual response task) versus a free-choice situation (traditional choice task). Second, we compare aggregate-level choice model parameter estimates from the same two tasks.[2]

A comparison of the relative choice proportions did not reveal a systematic change in relative preference for the three available alternatives when the no-choice option was added. Of the people choosing one of the three available alternatives, there was a significant difference ($p = .05$) between the forced and free-choice proportions in three of thirty-six comparisons (i.e., three available alternatives in each of twelve choice sets) involving the less attractive alternatives and in four of thirty-six comparisons involving the more attractive alternatives. There were no cases where the same difference was significant in both sets.

Table 1A shows the parameters and value of the log-likelihood function for the model estimated on the forced-choice, free-choice, and a model where the parameters were constrained to be the same up to a rescaling. Not counting the no-choice ASC, ten parameters are estimated in each of the first two unconstrained models. The constrained model has a total of nine fewer parameters (only one set of these ten parameters, but an additional scaling constant is estimated).

Using the Swait-Louviere (1993) test on the data from the respondents who saw the less attractive alternatives, the hypothesis of equal coefficients, up to a rescaling, cannot be rejected, as $\chi^2(9) = 11.4$. The rescaling coefficient of 1.62 means that the free-choice data have a lower portion of unexplained variance; however, there is no significant difference in the coefficients after rescaling. The data involving the more attractive alternatives also indicate no significant difference as $\chi^2(9) = 12$. Here, the rescaling constant is not significantly different from 1.0 and one cannot reject the hypothesis of coefficient equality.

Allowing a free-choice after a forced-choice. Dhar and Simonson (2003) found that if a forced-choice task is followed by a free-choice task, some alternatives tended to lose proportionally more than others. We examine this issue by comparing the choice

[2] We are ultimately interested in individual-level parameter estimates, these comparisons, like those of Dhar and Simonson (2003) are at the aggregate-level to examine systematic differences.

Table 1.A Comparison of logit models estimated on forced- and free-choices

	Less attractive alternatives			More attractive alternatives		
	Forced-choice	Free-choice	Constrained estimates	Forced-choice	Free-choice	Constrained estimates
Compaq	−0.170	0.158	0.016	0.031	0.252	0.174
Rio	0.084	−0.100	0.000	−0.257	−0.473	−0.313
No-choice	0.000	−0.315	−0.193		−0.879	−0.877
Memory	0.492	0.541	0.387	0.547	0.295	0.424
Form size	0.093	0.247	0.128	0.207	0.403	0.293
Rechargeable battery	0.347	0.644	0.377	0.453	0.553	0.489
FM	0.244	0.239	0.176	0.248	0.318	0.279
LCD screen size	0.208	0.302	0.193	0.225	0.175	0.198
Battery life	0.137	0.192	0.129	0.142	0.062	0.100
Price	−0.469	−0.864	−0.510	−0.797	−0.810	−0.789
Memory type	0.036	−0.043	−0.004	0.098	−0.035	0.035
Scaling constant			1.624			1.010
Loglikelihood	−459.2	−555.2	−1020.1	−444.3	−578.6	−1028.9
Sum		−1014.4			−1022.9	
Twice the difference			11.4			12

proportions of three available alternatives in the twelve choice tasks from the first and second stages of the dual response task.[3]

There was only one significant difference in the thirty-six comparisons involving the less attractive alternatives. In the data set based on the more attractive alternatives, there were five significant differences. These differences occurred in only three choice sets as one brand gained a significant amount and another lost a significant amount in two of the three. In nine (ten) of the twelve choice sets, the most popular available alternative gained share when a no-choice option was added with the less (more) attractive alternatives, but the increase was significant in only one (two) case(s).

Single stage vs dual response. Dhar and Simonson (2003) compared the choice proportions between a single step free-choice task and a two step forced-choice followed by a free-choice task. They found (1) that the percent of no-choices was significantly higher in the second task and (2) some alternatives lost proportionately more than others. Again, we first compare the difference in the choice proportions of each of the available alternatives in the single stage free-choice and dual response tasks, and then compare the parameters estimated from the two tasks.

There were four (one) significant differences in the thirty-six choice proportions among the less (more) attractive alternatives. In ten (eight) of twelve choice sets, the most preferred alternative gained relative share from the single-stage to the dual response format with the less (more) attractive alternatives, but it was significant in only two (one) cases. Again, this suggests no systematic differences between the single stage and dual response formats.

[3] No tests of coefficient equality are conducted on the choice models from the first stage and the second stage of the dual response model separately because all of the choices among the available alternatives are the same in the two stages.

Table 1.B Comparison of logit models estimated on single stage and dual response

	Less attractive alternatives			More attractive alternatives		
	Dual response	Single stage Free-choice	Constrained estimates	Dual response	Single stage Free-choice	Constrained estimates
Compaq	−0.108	0.158	0.026	0.121	0.252	0.172
Rio	0.098	−0.100	−0.004	−0.185	−0.473	−0.304
No-choice	1.608	−0.315	1.610	1.315	−0.879	1.308
Second no-choice			−0.212			−0.868
Memory	0.492	0.541	0.402	0.540	0.295	0.424
Form size	0.103	0.247	0.134	0.215	0.403	0.289
Rechargeable battery	0.354	0.644	0.392	0.442	0.553	0.482
FM	0.268	0.239	0.197	0.269	0.318	0.284
LCD screen size	0.209	0.302	0.201	0.224	0.175	0.195
Battery life	0.142	0.192	0.135	0.120	0.062	0.094
Price	−0.494	−0.864	−0.533	−0.797	−0.810	−0.784
Memory type	0.027	−0.043	−0.008	0.073	−0.035	0.028
Scaling constant			1.530			1.020
Loglikelihood	−802.7	−555.2	−1363	−825.6	−578.6	−1409.9
Sum		−1357.9			−1404.2	
Twice the difference			10.2			11.4

Table 1B gives the parameters and the value of the log-likelihood function for the models estimated on the single stage free-choice data (traditional logit framework), the dual response data, and the model where the BSC and attribute parameters were constrained to be the same up to a rescaling. The ASCs for the no-choice option are allowed to differ in the constrained model as a higher proportion of people chose the no-choice option in the dual response format. The hypothesis of equal coefficients up to a rescaling cannot be rejected. With the less attractive alternatives, $\chi^2(9) = 10.2$, which is not significantly different from zero. The rescaling coefficient of 1.53 is significantly different from one. Similarly, there is no significant difference in the coefficients, other than the no-choice ASC, with the more attractive alternatives as $\chi^2(10) = 11.4$. The rescaling coefficient was not significantly different from 1.0.

Proportion of time the no-choice alternative is chosen. With the less attractive alternatives, the proportion of no-choices increases from 13.9% in the single stage model to 57.7% in the dual response model. With more attractive alternatives, the corresponding percents are 9.2% and 46.6%. As expected, the proportion of no-choices is greater with the less attractive alternatives.

Next, we examined the relationship between the decision to forego choice and the attractiveness of the available alternatives and the difficulty of the decision. Utilities for the three available alternatives were estimated with the pooled logit coefficients between the first stage of the dual response task and the single stage task. The attractiveness of alternatives hypothesis suggests that the maximum utility of the three available alternatives is negatively related to the proportion of no-choices. The decision difficulty hypothesis suggests that the variance of the utilities of the available alternatives is negatively related to the proportion of no-choices.

Table 2.A Regressions relating the proportion of no-choices to choice set characteristics

	Less attractive alternatives		More attractive alternatives	
	Dual response	Single stage	Dual response	Single stage
Intercept	0.842[a]	0.308[a]	0.627[a]	0.191[b]
Maximum utility	−0.147[c]	−0.098[c]	−0.063[d]	−0.042
Variance in utilities	0.046	0.038	0.009	0.008
R^2	0.77	0.66	0.71	0.45

Table 2.B Regressions relating number of no-choice selections to number of attribute levels that are rejected

	Relabeled		Relabeled and swapped	
	Dual response	Traditional	Dual response	Traditional
Intercept	0.89[a]	0.38	2.04[a]	0.80[c]
Number of rejected levels		1.62[a]		1.67[a]
Increase in rejected levels between DR1 and DR2	2.48[a]		1.64[a]	
R^2	0.54	0.55	0.64	0.58

[a] – significantly different from zero $p = .001$
[b] – significantly different from zero $p = .01$
[c] – significantly different from zero $p = .05$
[d] – significantly different from zero $p = .10$

With the less attractive alternatives, Table 2A shows a significant negative relationship ($p = .05$) between maximum utility and proportion of no-choices in both the single stage and dual response regressions. The relationship between utility variance and no-choice was insignificant and positive in both regressions. With the more attractive alternatives, the relationship between maximum utility and number of no-choices was negative, but significant only in the dual response regression and the relationship between the variance in the utilities of the alternatives and proportion of no-choices was not significant.

Study two

The second study is similar to the first and will be reported in less detail. A total of 392 subjects evaluated laptop computers described in terms of three levels of six attributes: brand, microprocessor, size, pointing device, memory, and price. A two-by-two between subjects design was used. Approximately half the subjects received a traditional free-choice design and the other half received a dual response choice task. In both cases, 18 choice sets were created from a cyclical design and were modified in one of two ways to create different choice sets. All respondents received the same 8 validation choice sets that contained four available alternatives and a no-choice option. Attributes were effects-coded. The no-choice option was coded with a zero/one ASC.

In the second manipulation, approximately half the subjects received questionnaires in which relabeling, where a level of an attribute is relabeled for all choice sets, was

Table 3.A Comparison of logit models estimated on forced- and free-choices

	Relabeled design			Relabeled and swapped design		
	Free-choice	Forced-choice	Constrained estimates	Free-choice	Forced-choice	Constrained estimates
Dell	0.146	0.153	0.148	0.097	0.136	0.105
Toshiba	−0.001	−0.016	−0.009	0.091	0.086	0.077
Pentium	0.242	0.237	0.238	0.286	0.132	0.185
AMD	−0.015	−0.112	−0.071	−0.098	−0.06	−0.071
12 in/4 lbs	−0.068	0.018	−0.017	−0.013	−0.011	−0.01
14 in/6 lbs	0.074	0.044	0.054	0.012	0.009	0.009
TchPd	0.355	0.33	0.341	0.42	0.336	0.334
Eraser head	−0.184	−0.232	−0.212	−0.206	−0.167	−0.163
768 MB	0.41	0.397	0.402	0.365	0.386	0.333
512 MB	0.135	0.160	0.148	0.142	0.089	0.103
$999	0.275	0.337	0.310	0.355	0.252	0.268
$1199	0.089	0.106	0.097	0.133	0.083	0.095
Intercept	−0.248		−0.247	−0.457		−0.369
Scaling constant			1			1.25
Loglikelihood	−2313.03	−1913.03	−4233.06	−2087.26	−1729.5	−3822.8
Sum		−4226.06			−3816.76	
Twice the difference			14			12.08

used to improve utility balance (Huber and Zwerina, 1996). The other half received a utility balanced design that was created through both relabeling and swapping, where swapping involves switching two levels of an attribute among alternatives only within a single choice set (Sándor and Wedel, 2001).

Free versus forced-choice. Consistent with the first study, a comparison of the relative choice proportions did not reveal any evidence of a systematic change in relative preference for the three available alternatives when the no-choice option was added. Of the people choosing one of the three available alternatives, there was a significant difference ($p = .05$) between the forced and free-choice proportions in two of fifty-four (i.e., three available alternatives in each of eighteen choice sets) comparisons in both the relabeled data and the relabeled swapped data.

Table 3A gives the parameters and value of the log-likelihood function for the models estimated on the forced-choice, free-choice, and the model where the parameters were constrained to be the same up to a rescaling. Not counting the no-choice ASC, twelve parameters are estimated in each of the first two unconstrained models. The hypothesis of equal coefficients up to a rescaling cannot be rejected for either the relabeled or relabeled and swapped models, as $\chi^2(11) = 14.0$ and 12.08 espectively, neither of which is significantly different from zero.

Allowing a free-choice after a forced-choice. Second, we compare the choice proportions of the available alternatives using the data from the first and second stages of the dual response task. There were no significant differences in any of the fifty-four comparisons in either the relabeled or relabeled and swapped condition. In contrast to the MP3 players, there was no tendency for the most popular alternative to gain share when the no-choice option was added.

Table 3.B Comparison of logit models estimated on single stage and dual response

	Relabeled design			Relabeled and swapped design		
	Single stage Free-choice	Dual response	Constrained estimates	Single stage Free-choice	Dual response	Constrained estimates
Dell	0.146	0.151	0.147	0.097	0.14	0.107
Toshiba	−0.001	−0.018	−0.011	0.091	0.089	0.08
Pentium	0.242	0.234	0.236	0.286	0.133	0.185
AMD	−0.015	−0.109	−0.07	−0.098	−0.06	−0.071
12 in/4 lbs	−0.068	0.022	−0.013	−0.013	−0.011	−0.009
14 in/6 lbs	0.074	0.042	0.053	0.012	0.01	0.01
Touch pad	0.355	0.333	0.34	0.42	0.336	0.335
Eraser head	−0.184	−0.236	−0.213	−0.206	−0.165	−0.162
768 MB	0.41	0.397	0.4	0.365	0.386	0.335
512 MB	0.135	0.155	0.146	0.142	0.095	0.106
$999	0.275	0.335	0.305	0.355	0.254	0.27
$1199	0.089	0.104	0.098	0.133	0.083	0.096
Intercept		−0.119	−0.122		−1.173	−1.178
2nd Intercept	−0.248		−0.247	−0.457		−0.367
Scaling constant			1			1.25
Loglikelihood	−2313.03	−2880.7	−5200.8	−2087.26	−2228.5	−4321.9
Sum		−5193.73			−4315.76	
Twice the difference			14.14			12.28

Single stage vs dual response. When we compare the difference in the choice proportions of each of the available alternatives in the single stage free-choice and dual response tasks there were two significant differences among fifty-four comparisons in both the relabeled and relabeled and swapped conditions. The relative share of the most preferred alternative never increased significantly from the single-stage to the dual response task.

Table 3B gives the parameters and value of the log-likelihood function for the models estimated on the single stage free-choice data (traditional logit framework), the dual response data, and, and the model where the BSC and attribute parameters were constrained to be the same up to a rescaling. The ASCs for the no-choice option are allowed to differ in the constrained model. The hypothesis of equal coefficients up to a rescaling cannot be rejected for either the relabeled or the relabeled and swapped data sets as $\chi^2(11) = 14.1$ and 12.3, respectively.

Proportion of time the no-choice alternative is chosen. In the relabeled and swapped task the proportion of no-choices increases from 19.6% in the single stage model to 21.6% in the dual response model. In the relabeled task the proportion of no-choices drops from 15.0% in the single stage model to 8.4% with the dual response model.

In contrast to the MP3 players, regressing the proportion of no-choices in each set on maximum utility and the variance of the utilities did not result in any significant effects. However, Table 2B shows the results of an individual-level analysis in which the number of times each person selected the no-choice option is regressed on the

Table 4 Validation results

	Hit rates		MAD for choice shares	
	With no-choices	Without no-choices	With no-choices	Without no-choices
More attractive alternatives				
Traditional	0.47	0.58	0.124	0.129
DR	0.57	0.66	0.107	0.115
Less attractive alternatives				
Traditional	0.73	0.82	0.032	0.026
DR	0.43	0.68	0.126	0.036
Relabeled only				
Traditional	0.65	0.69	0.036	0.032
DR	0.62	0.65	0.039	0.033
Relabeled and swapped				
Traditional	0.63	0.65	0.038	0.036
DR	0.60	0.62	0.027	0.023

number of attribute levels s/he rejected.[4] All the R^2s are at least .54 and the number of rejected levels is highly significant. In the regressions involving the dual response tasks, the independent variable is the increase in the number of rejected levels between the first and second stages. After making a forced choice, the decision to select the no-choice option was related to rejecting one or more levels in the previously chosen alternative. Similarly, in the traditional tasks, the number of no-choices is highly related to the number of rejected levels. This suggests that no-choice responses are related to unattractive alternatives, not hard decisions.

Choice validations

Individual-level parameters were estimated from the calibration data using hierarchical Bayesian methods for a traditional choice model and a dual response model. The validation data consisted of two free choices among three available MP3 players and a no-choice option and of eight free choices among four available laptops and a no-choice option. Individual choices were forecast based on a max utility model and choice shares were based on an average of the individual choice probabilities. Because of differences in the number of times the no-choice option was selected in the dual response and traditional tasks, we performed validations both over all holdout choices and just over those choices in which one of the available alternatives was chosen to create a more level playing field.

The first two lines of Table 4 show the validation results for the more attractive MP3 players. Considering all choices, the dual response methodology had a hit rate of .57, compared to .47 for the traditional method. A similar difference is seen in the hit rates among only the available alternatives. Additionally, the dual response model

[4] One cannot distinguish between just never choosing an attribute level and its complete rejection, i.e., between a very low utility for a level and a rejection, but we will use the word rejection for ease of exposition.

has a lower mean absolute deviation, MAD, than the traditional model. With the less attractive alternatives, the dual response hit rate validations, .43, are much worse than the traditional model, .73. The low dual response hit rate is due primarily to the difference in predicted and actual no-choice proportions (.55 versus .30). When the validations are restricted to the available alternatives, the dual responsehit rate climbs to .68. This same general pattern is seen among the choice share MADs. There are no significant differences in the laptop data between the dual response methodology and the traditional method. In the level-playing field comparisons, the dual response model has hit rates of over .60 out of five choices (including the no-choice option) and over .66 out of four choices. Additionally, one should notice that there is much greater variation in the MP3 validations (across models, groups, and validation measures) than in the laptop data. We will comment on this in the summary.

Summary

In contrast to Dhar and Simonson (2003), we do not find systematic violations of IIA caused by the addition and deletion of the no-choice option. There were significant differences in about 8% of the MP3 player comparisons and 3% of the laptop comparisons, at a 5% significance level, and no systematic patterns. Equality of coefficients up to rescaling was never rejected in eight tests, indicating no systematic bias in the dual response parameter estimates. It is hypothesized that the difference between these results and those of Dhar and Simonson (2003) occurred because these products were described in terms of more than two attributes. When products are described in terms of a larger number of attributes there are usually no clear compromise alternatives, which are affected disproportionately when a no-choice option is added or deleted from the choice set.

Second, we examined the factors that might lead someone to choose the no-choice option. With the MP3 players, selection of the no-choice option was much more highly related to the attractiveness of the available alternatives than to decision difficulty. In the laptop data, there was no significant relationship among these aggregate level variables; however, an individual-level analysis indicated that no-choice decision was related to the presence of certain attribute levels, i.e., an elimination decision that varied by individual, but appears to be based on alternative attractiveness.

The dual response choice validations were high, but approximately equal to those of the traditional method, i.e., there was no significant difference in laptop validations and the dual response method validated significantly better (worse) with the more (less) attractive MP3 players. We attributed the greater variability in the MP3 validations to noise in the data. This could be due to smaller group sample sizes (45 versus 97 per group), a smaller number of validation choice sets (2 versus 8), or a more complex choice task (10 versus 6 attributes), but believe that it is probably due to a relative lack of familiarity to MP3 players and their associated attributes at the time of data collection (2002).

The inability of the dual response models to achieve significantly higher validations in this study is due partly to task similarity between the traditional free-choice calibration task and the free-choice validation task. Additionally, the percent of no-choice responses in the traditional task was at a level where our simulation (see Fig. 1) found little difference between traditional and dual response models. With a larger number of no-choice responses in the traditional task the efficiencies should increase. Finally, when a respondent selects the no-choice option frequently, that person's coefficients associated with the available alternatives are more heavily influenced by the average weights. With preference homogeneity less will be gained from the dual response method. There was some evidence in the laptop data that those people who selected the no-choice option in three or more choice sets had better validations with the dual response methodology.

This study was not able to examine which of these methods would offer better market place validations. It is likely that many of the respondents who always chose one of the available alternatives in these studies have not actually purchased a laptop or MP3 player in the year following the survey. In their consulting practice, the authors affiliated with The Modellers, have found that they must always adjust the percent of no purchases upwards from what is predicted by a choice study to more accurately portray marketplace data. The higher rate of no-choices like that for the dual response MP3 player data requires a much smaller (if any) adjustment than those of the traditional method.

We believe that the dual response methodology has great promise in situations when the no-choice option is likely to be chosen more than a small proportion of the time. One important application is monitoring markets that new people enter as products improve or prices go down. For many durable goods, the appropriate constant alternative may be staying with current product, which may also produce a larger number of no-choice selections and would be a good application for the dual response methodology. Finally, if the questionnaire is accompanied by a message stating that its purpose is to study people's preferences in order to design better products, respondents may be reluctant to choose the no-choice option too often if they felt they would not be providing useful information. The dual response format may offer a better estimate of the number times the no-choice option would be selected in the market place. Markets with greater preference heterogeneity are also good candidates for dual response studies. Finally, if the selection of the no-choice option is highly skewed (with many of the no-choices coming from a fraction of the respondents), this approach offers the possibility of improving the understanding of these people, even if the percent of no-choice selections in the population is relatively low.

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