BEST-WORST SCALING

Theory, Methods and Applications

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(With Invited Chapters on Applications)

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Chapter 10

When the ayes don't have it: supplementing an accept/reject DCE with a Case 2 best-worst scaling task

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10.1 Introduction

Accept/reject and other questions with binary alternatives, such as favor/oppose and like/dislike, are common in the discrete choice experiment literature. They usually take the form of offering respondents a binary choice, in which the two alternatives are the current status quo and an alternative. There can be a single choice set or a sequence of choice sets. A recent example is the study by Day *et al.* (2012), who investigated whether consumers would pay an additional charge to have a public water supply that had fewer days with lower-quality taste/smell and color.

A common difficulty with such questions is that a sizable fraction of the population of interest may not shift from choosing one alternative to the other for any plausible difference in attribute values. For example, with a new product, there may be a limited number of people prepared to try it initially, although the larger potential fraction of the population who may buy the product in the longer run might have clear preferences over possible attribute levels that would influence a firm's design decisions. Another common example comes from politics. In places with a well-established two-political-party system, most voters are unlikely to switch their vote from their current party to the other party in the current election cycle. However, this does not mean that voters are indifferent to the candidates/positions of the opposing party. In environmental valuation studies, it is common to see a sizable fraction of the public opposed to an improvement in the status quo level of the environmental good being studied because they ideologically oppose additional government action. What is important to recognize is that, when a consumers are forced to pay for a good or experience a policy change, it cannot be inferred that they are indifferent to specific attribute levels even though they favor or oppose all the alternatives to the current status quo. Common to all these situations is an inability to extract as much information about preferences as researchers would like, because of constraints on either the range of plausible attribute levels or the rate of adoption/switching in the short run. In situations such as these, a Case 2 best-worst scaling task can be a valuable addition to a binary or multiple choice task.

Table 10.1 *Attributes and levels in the voting task*

Attribute	Level
Year in which the scheme begins	Start 2010 Start 2012
How the revenues raised are used	Redistribute to poor and seniors Reduce GST
Invest 20% of revenues in R&D	Do not invest in R&D Invest 20 in R&D
Exempt transport-related activities	Do not exempt transport Exempt transport
Exempt energy-intensive industries	Do not exempt energy Exempt energy

10.2 Australian climate policy alternatives

This chapter considers data from a survey involving 388 people randomly sampled from a weighted version of the Pureprofile online panel designed to be representative of voting-age Australians. It is useful to first look at the sequence of binary-choice voting questions, because our implementation of a Case 2 BWS task served as a natural prequel to this more familiar and commonly used voting task. In this case respondents were asked if they would vote for each of 16 emissions trading schemes paired against the status quo of no ETS. Each emissions trading plan was described by a combination of five attributes, each of which has the two possible levels shown in Table 10.1. Since each of the five attributes has two levels, there are 2^5 (32) possible ETSs. We divided the 32 possible schemes into two sets of 16, each of which had the statistical property that all main effects and two-way interactions for the five attributes can be estimated (under the assumption that all higher-order interactions equal zero).

Graphs of all the main effects and two-way interactions are shown in Figure 10.1.[1] It is important to note that the ranges on the Y-axis (aggregate sample choice proportions) differ slightly from graph to graph. Nonetheless, a common feature of all graphs is that the *range* of effects displayed on the Y-axis is relatively small. Mean choice proportions for each of the main effects are shown in Table 10.2 and are consistent with the graphs: they have a narrow range, with only "Start year" and "20% in R&D" displaying a difference in mean choice proportions. In turn, this result suggests the sample respondents were (1) largely indifferent to attributes when voting for schemes, (2) very heterogeneous in their responses to the attributes when voting for the schemes,[2] or (3) a combination of both.

[1] Carson, Louviere and Wei (2010) provide a discussion about why these attributes were central to the policy debate that took place in Australia and look at data from an earlier survey using these attributes to define a possible emissions trading scheme. Their results are similar to those reported here, suggesting temporal stability at the aggregate level over about a one-year time period.

[2] From a political science median voter perspective, it not surprising to see the public split into roughly equal proportions on these attributes, as they are the ones that the major parties decided to contest with respect to competing visions of the details of an emissions trading scheme. A Liberal Party leadership shift in 2009 resulted in the party being opposed to the implementation of any ETS.

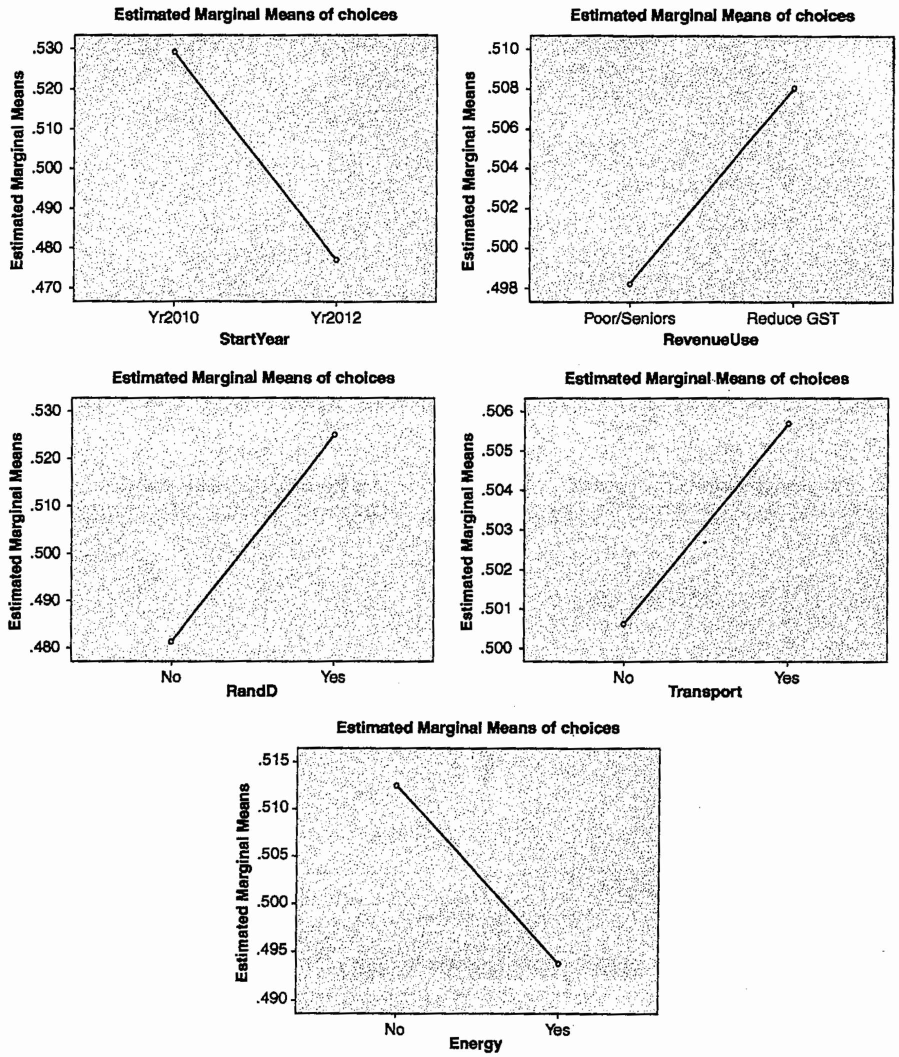

Figure 10.1a Attribute main effects: emissions trading schemes

One way to illustrate the narrow range of choice proportions (the percentage voting "Yes" for a particular ETS paired with the status quo) is to calculate the proportion voting "Yes" for each of the 32 possible ETS options in the survey. Table 10.3 sorts the 32 schemes from highest to lowest voting percentage, and shows that 13 of the possible schemes got majority support. We suggest some caution in interpreting these proportions, as 93 people voted "Yes" in every scenario (which makes sense if a respondent is concerned about climate change but does not care a lot about the details of the particular ETS to be implemented).

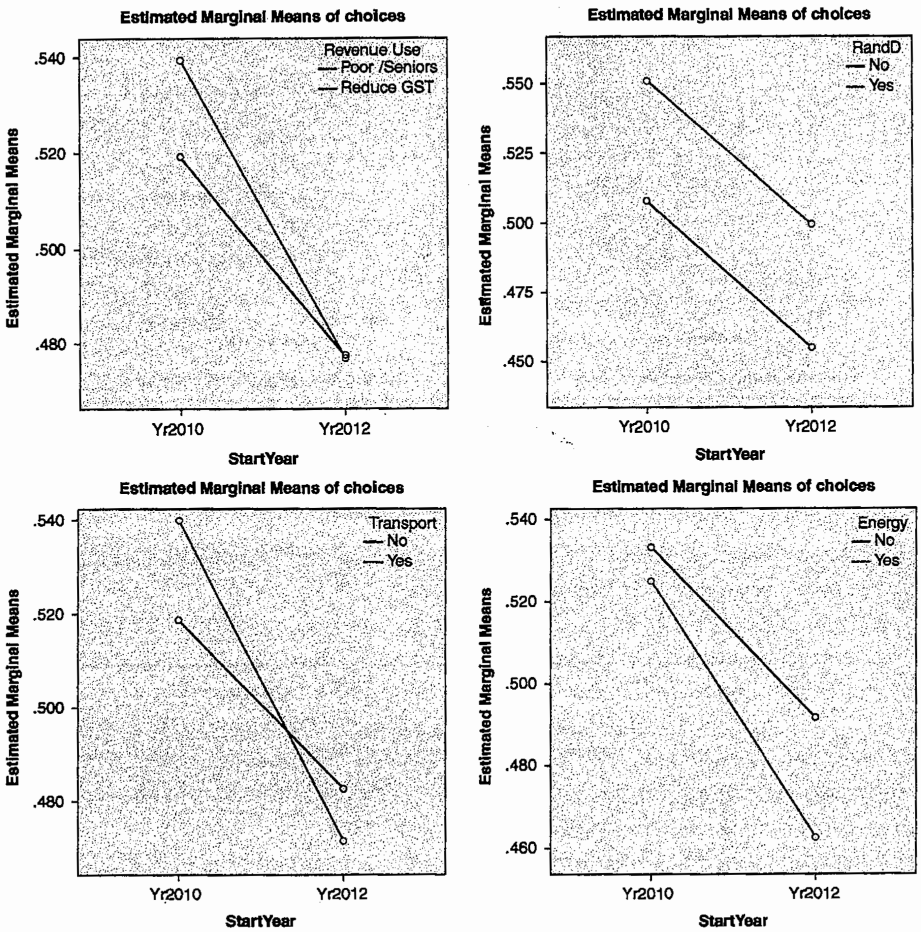

Figure 10.1b Attribute two-way interactions: emissions trading schemes

One can count the attribute levels for each of the majority-supported schemes to "suggest" what may underlie the choices. For example, all 13 majority schemes were to start in 2010. Six would reduce the Goods and Services Tax, while the rest (seven) would redistribute revenues to poor and senior citizens. Ten of the majority schemes invest 20 percent of revenues in R&D related to reducing carbon emissions. Seven schemes do not exempt transport-related activities or industries, and nine schemes do not exempt energy-intensive industries. This suggests that the sample was most homogeneous about the starting year (2010 versus 2012), and was fairly homogeneous towards investing 20 percent in R&D and not exempting energy-intensive industries. In turn, this suggests that other attributes matter very little and/or a large fraction of respondent are indifferent to differences in them.

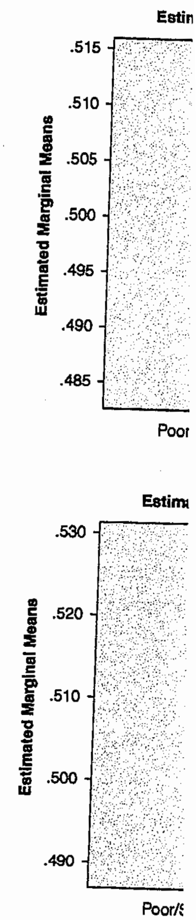

Figure 10.1b (cont

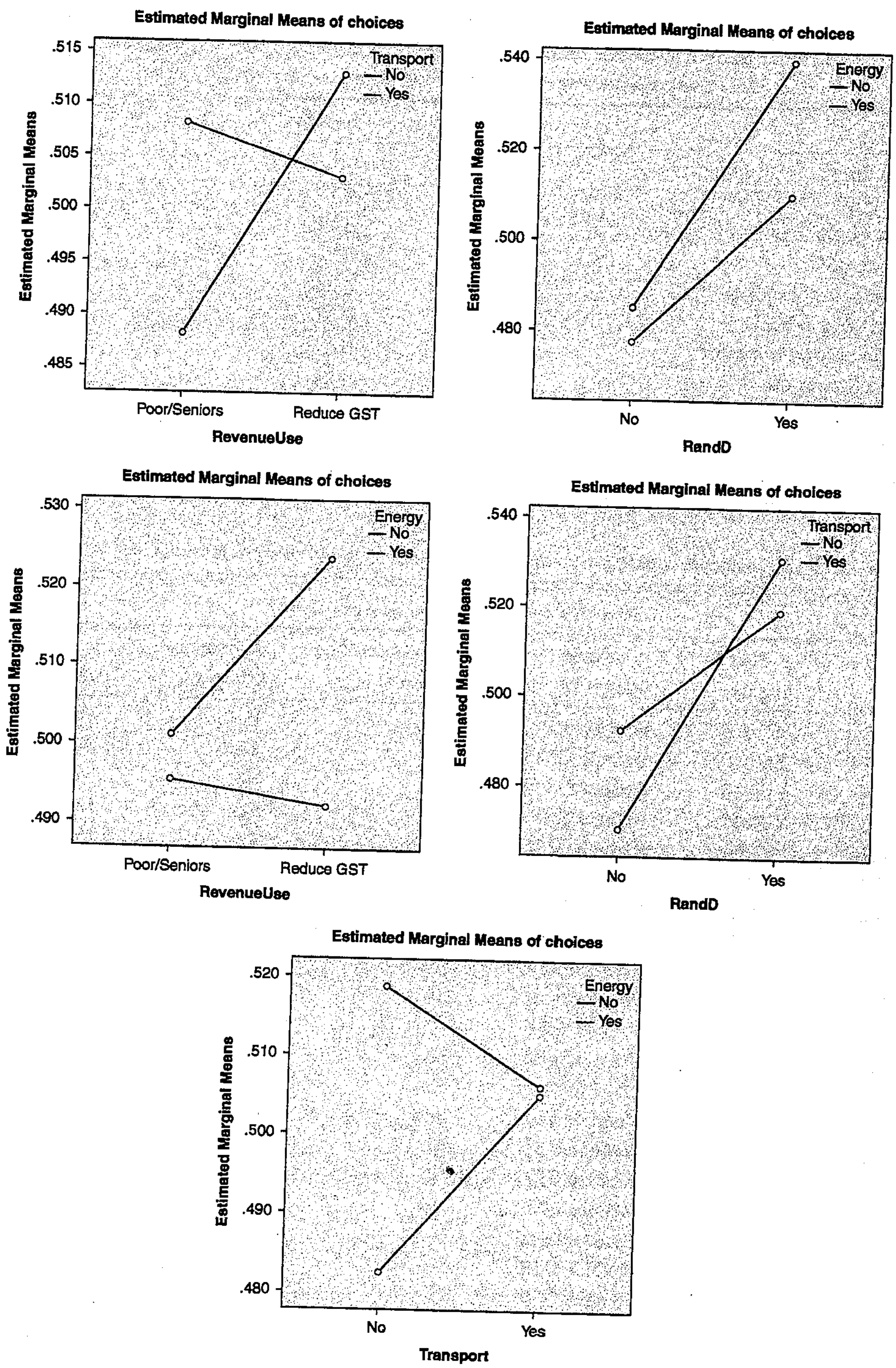

Figure 10.1b (cont.)

Table 10.2 *Attribute main effect means from the voting task*

Mean votes percentage by level	
Level	Vote %
Start 2010	0.53
Start 2012	0.48
Redistribute to poor and seniors	0.50
Reduce GST	0.51
Do not invest in R&D	0.48
Invest 20% in R&D	0.53
Do not exempt transport	0.50
Exempt transport	0.51
Do not exempt energy	0.51
Exempt energy	0.49
Total	0.50

Table 10.3 *All possible emissions trading schemes sorted by proportion voting "Yes"*

Sorted vote percentage by design matrix					
Vote	1. Plan begins	2. Income will go to	3. Invest 20% in R&D	4. Exempt transport	5. Exempt energy
0.660	Yr2010	Poor/seniors	No	Yes	Yes
0.613	Yr2010	Reduce GST	Yes	Yes	Yes
0.603	Yr2010	Reduce GST	Yes	No	No
0.588	Yr2012	Reduce GST	Yes	No	No
0.582	Yr2010	Reduce GST	No	Yes	No
0.572	Yr2010	Poor/seniors	Yes	Yes	No
0.562	Yr2010	Reduce GST	Yes	No	Yes
0.546	Yr2010	Poor/seniors	Yes	No	Yes
0.546	Yr2012	Poor/seniors	Yes	Yes	No
0.546	Yr2010	Poor/seniors	No	No	No
0.531	Yr2010	Reduce GST	Yes	Yes	No
0.510	Yr2010	Poor/seniors	Yes	No	No
0.505	Yr2012	Poor/seniors	Yes	No	Yes
0.490	Yr2012	Poor/seniors	Yes	No	No
0.485	Yr2010	Reduce GST	No	No	No
0.485	Yr2010	Reduce GST	No	No	Yes
0.479	Yr2012	Reduce GST	Yes	Yes	No
0.474	Yr2012	Poor/seniors	Yes	Yes	Yes
0.474	Yr2012	Reduce GST	No	No	Yes
0.469	Yr2012	Reduce GST	Yes	Yes	Yes
0.469	Yr2010	Poor/seniors	Yes	Yes	Yes
0.464	Yr2012	Reduce GST	No	No	No

Table 10.3 (con

Vote	1. Pl begi
0.464	Yr20
0.464	Yr20
0.459	Yr20
0.454	Yr20
0.443	Yr20
0.443	Yr20
0.438	Yr20
0.438	Yr20
0.433	Yr20
0.412	Yr20

Table 10.4 *Obs*

Total "Yes" votes
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Table 10.3 (*cont.*)

Sorted vote percentage by design matrix					
Vote	1. Plan begins	2. Income will go to	3. Invest 20% in R&D	4. Exempt transport	5. Exempt energy
0.464	Yr2012	Poor/seniors	No	No	No
0.464	Yr2012	Poor/seniors	No	Yes	Yes
0.459	Yr2012	Reduce GST	No	Yes	No
0.454	Yr2010	Reduce GST	No	Yes	Yes
0.443	Yr2012	Poor/seniors	No	Yes	No
0.443	Yr2012	Reduce GST	Yes	No	Yes
0.438	Yr2012	Reduce GST	No	Yes	Yes
0.438	Yr2010	Poor/seniors	No	Yes	No
0.433	Yr2012	Poor/seniors	No	No	Yes
0.412	Yr2010	Poor/seniors	No	No	Yes

Table 10.4 *Observed numbers of "Yes" votes in the sample*

Total "Yes" votes	Frequency	Percentage in sample
0	40	0.103
1	24	0.062
2	20	0.052
3	20	0.052
4	24	0.062
5	30	0.077
6	17	0.044
7	19	0.049
8	21	0.054
9	14	0.036
10	17	0.044
11	11	0.028
12	18	0.046
13	9	0.023
14	17	0.044
15	29	0.075
16	58	0.149

We next consider the total number of "Yes" votes for the sample displayed in Table 10.4, which shows that about 25 percent of the sample always voted "No" or always voted "Yes," providing no preference information for attributes/levels. A further 24 percent voted "No" or "Yes" almost every time, again giving little attribute/level preference information. Thus, almost 50 percent of the sample in the voting task responded extremely, providing little information about how the sample is likely to respond to changes in attribute levels; however, schemes that will attract majority support (a majority "Yes" vote) can clearly be identified. This suggests that some (perhaps many) of the 49 percent with extreme responses were using accept/reject rules that are not well approximated by additive indirect utility functions, and, indeed, some (perhaps many) may have behaved deterministically.

10.3 Case 2 best-worst scaling task

We combined the binary-choice voting task with a Case 2 best-worst scaling task, such that each of the 388 survey respondents reported the attribute levels that they thought were, respectively, the best and worst aspects of each scheme described. An example of this task is depicted in Figure 10.2, which shows that survey respondents were asked to tick one box for the best and a second box for the worst attribute level. Each respondent completed this task in conjunction with the accept/reject task – that is, we showed respondents one emissions trading scheme description at a time, and they were asked to choose the best and worst aspects of each scheme description and then tell us whether they would vote "Yes" or "No" for it. Thus, despite the fact that many respondents made extreme choices in the voting task, they each provided a complete set of Case 2 BWS choices. This allows us to analyze the choice data for the aggregate sample and each person.

We begin with the attribute level choices for the aggregate sample. Table 10.5 contains the mean best and worst choice sample proportions and their associated standard deviations. These results suggest that there may be more to the voting preferences than meets the eye. Specifically, we can immediately "see" large differences in best and worst choice proportions for levels of start year, redistribution of revenues and investing in R&D. By way of contrast, exemptions for transport and energy show much smaller differences.

Marley, Flynn and Louviere (2008) showed that the best and worst choices in Case 2 BWS tasks can be placed on a common scale (see Chapter 3). Thus, we can use the results in Table 10.5 to calculate additional sample measures, such as (1) best-minus-worst choice proportion differences, (2) the square root of best divided by worst choice proportions and (3) the natural logarithm of the square root of best divided by worst choice proportions. The first measure is a difference scale of the latent "bestness" of a level centered at zero. Ratios

The best aspect of this plan is (tick one box below):	Aspects of plan 1	The worst aspect of this plan is (tick one box below):
☐	Start plan in 2012	☐
☐	Use revenues to reduce GST	☐
☐	Do not invest 20% in R&D	☐
☐	Exempt transport	☐
☐	Exempt energy	☐

Figure 10.2 Example Case 2 BWS task for emissions trading scheme options

Table 10.5 *Agg*

Level
Start 2010
Start 2012
Redistribute to pc
Reduce GST
Do not invest in I
Invest 20% in R&
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Exempt energy

Table 10.6 *Calc*

Level
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Table 10.5 *Aggregate sample mean best-worst choices by attribute level*

Level	Best mean %	Worst mean %	Best SD	Worst SD
Start 2010	0.33	0.17	0.471	0.377
Start 2012	0.14	0.36	0.349	0.479
Redistribute to poor and seniors	0.38	0.17	0.486	0.376
Reduce GST	0.43	0.09	0.496	0.291
Do not invest in R&D	0.07	0.25	0.249	0.434
Invest 20% in R&D	0.23	0.10	0.421	0.305
Do not exempt transport	0.09	0.22	0.293	0.416
Exempt transport	0.12	0.23	0.321	0.423
Do not exempt energy	0.09	0.20	0.280	0.398
Exempt energy	0.12	0.20	0.323	0.401

Table 10.6 *Calculation of best and worst measures from Table 5 results*

Level	Best mean %	Worst mean %	B% – W%	SQRT (B% / W%)	Ln(SQRT (B% / W%))
Start 2010	0.330	0.170	0.160	1.393	0.332
Start 2012	0.140	0.360	–0.220	0.624	–0.472
Redistribute to poor and seniors	0.380	0.170	0.210	1.495	0.402
Reduce GST	0.430	0.090	0.340	2.186	0.782
Do not invest in R&D	0.070	0.250	–0.180	0.529	–0.636
Invest 20% in R&D	0.230	0.100	0.130	1.517	0.416
Do not exempt transport	0.090	0.220	–0.130	0.640	–0.447
Exempt transport	0.120	0.230	–0.110	0.722	–0.325
Do not exempt energy	0.090	0.200	–0.110	0.671	–0.399
Exempt energy	0.120	0.200	–0.080	0.775	–0.255

of differences are meaningful quantities on this scale, but differences between levels cannot be directly compared. The second measure is a ratio scale of "bestness" that should be proportional to the best choice proportions, which we test below. This scale allows one to compare differences between levels and make meaningful statements about ratios of measures (for example, this level is twice as "best" as that level). Measure three also is a difference scale centered around zero, and should be proportional to the best-minus-worst difference scores, which we also test below. Finally, the measures in Table 10.5 are choice proportions; as such, they are estimates of choice probabilities on an absolute scale ranging between zero and one, allowing one to make meaningful statements about ratios of choice proportions (for example, level A is half as likely to be chosen best as level B).

The calculations are given in Table 10.6, with relationships between the measures graphically displayed in Figures 10.3a, 10.3b and 10.3c. The figures indicate that the

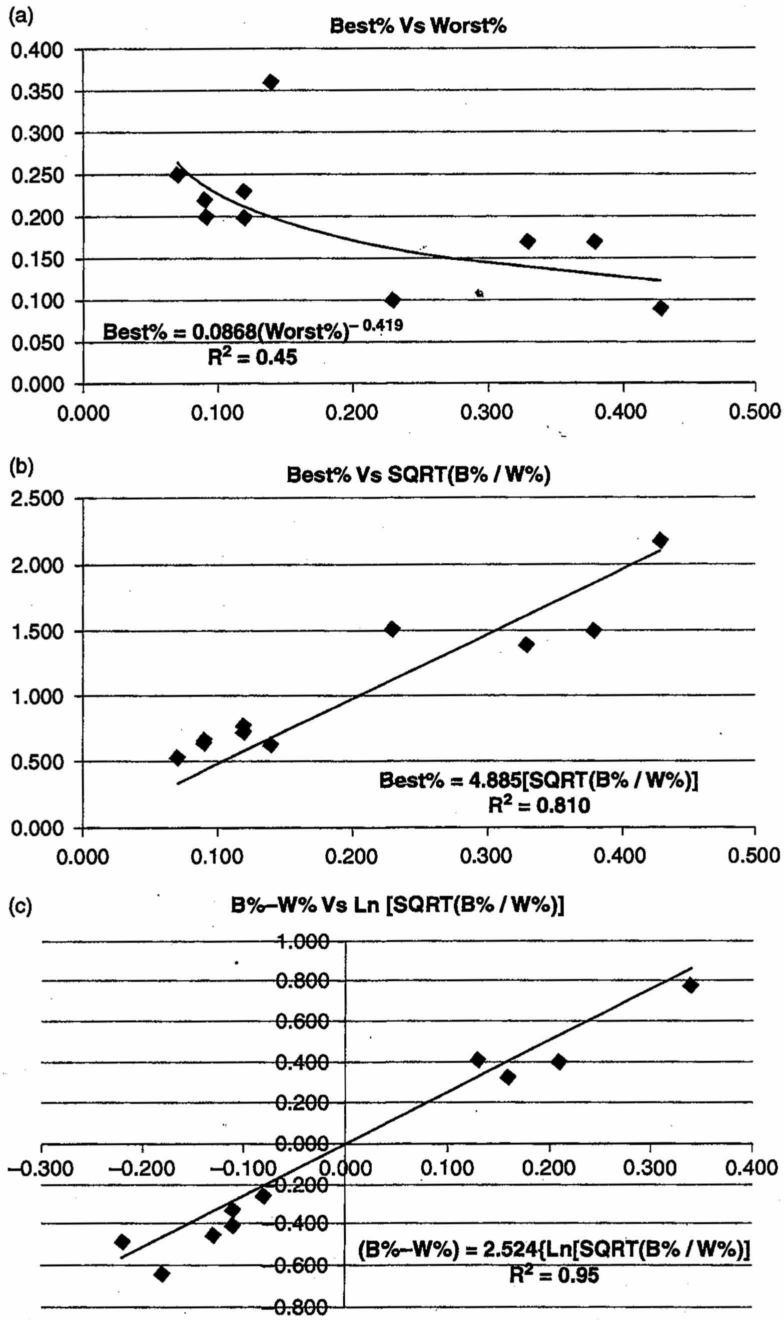

Figure 10.3 Relationships between calculated BWS measures for aggregate sample

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assumption that aggregate-sample best choice proportions are inversely related to their worst proportion counterparts is not well satisfied. However, the relationships between (a) best proportions minus worst proportions and the natural log of the square root of the ratio of best proportions to worst proportions and (b) best proportions and the square root of the ratio of best proportions divided by worst proportions better satisfy the assumption of proportionality of measures. Possible reasons for the unsatisfactory fit of the relationship between best and worst proportions are (1) preference heterogeneity (that is, the choices of attribute levels differ across respondents), (2) differences in choice consistency (error variability) in best and worst choices and/or (3) different rules (choice processes) for making best and worst choices.

We consider choice (preference) heterogeneity by calculating best and worst choice totals for each attribute level for each person and then cluster-analyzing them. This allows us to test differences in best and worst choices of attribute levels to determine if this is at least partially responsible for the poor fit of the assumed relationship between best and worst proportions. Additionally, the cluster analysis is interesting in its own right, as it can reveal potentially meaningful differences in respondents that can shed light on the voting choices. Work by Dimitriadou, Dolničar and Weingessel (2002) and Dolničar and Leisch (2010) suggests that, if there is structure underlying the data of interest (here, the individual best and worst choices), all cluster procedures will find it; however, they also showed that, if there is no structure underlying the data, many methods will give results suggesting that there is structure. We use Ward's hierarchical tree clustering approach, as this allows us to see where clusters form and how they agglomerate and separate (that is, if we go from three to four clusters, we know exactly where the people who become cluster four come from). Table 10.7 contains the aggregate summary results of a six-cluster solution for the 388 respondents in our sample; we stopped at six clusters because additional clusters had few respondents.

The columns in Tables 10.7a to 10.7c are labeled C1 to C6, representing the six clusters. Each of the three tables (a to c) has a different measure; for example, Table 10.7a displays best-minus-worst difference scores. We graphed (not shown here) clusters 1 to 6 against the sample averages, which strongly suggested that the cluster differences were not large (in other words, it is likely that there is no real multi-modal structure underlying the best-worst choices). Thus, the sample is very homogeneous but displays large variability in the choice consistency, or the sample differences can be represented by some type of probability distribution. We begin by testing cluster differences in a simple but compelling way with principal components analysis. The null hypothesis of interest is that only one component underlies each set of measures, and the collection of all 18 measures (3 BWS measures × 6 clusters).

The results of this analysis suggest that only one component underlies the data. Table 10.8a provides a singular value decomposition in terms of the three measures used with the first component in all cases explaining over 90 percent of the variance. Table 10.8b looks at the same type of analysis but now using all three measures in Table 10.8a together. It seems clear that there is no underlying structure beyond one component.

Table 10.7 *Calculations derived from the most and least Case 2 BWS choices*

a *Best-minus-worst difference scores*

Means	Best-minus-worst difference scores					
Alt	C1	C2	C3	C4	C5	C6
Start 2010	0.140	0.077	0.213	0.175	0.136	0.183
Start 2012	−0.123	−0.304	−0.163	−0.295	−0.216	−0.169
Poor and seniors	0.213	0.240	0.098	0.267	0.245	0.187
Reduce GST	0.360	0.369	0.321	0.295	0.436	0.277
Not invest R&D	−0.211	−0.115	−0.213	−0.183	−0.219	−0.144
Invest R&D	0.113	0.093	0.187	0.089	0.139	0.135
Not exempt transport	−0.076	−0.163	−0.175	−0.094	−0.102	−0.179
Exempt transport	−0.221	−0.064	−0.075	−0.099	−0.175	−0.063
Not exempt energy	−0.032	−0.125	−0.138	−0.065	−0.120	−0.194
Exempt energy	−0.164	−0.006	−0.054	−0.089	−0.125	−0.031

b *Square root of best choices (counts) divided by worst choices (counts)*

Means	SQRT(best/worst)					
Alt	C1	C2	C3	C4	C5	C6
Start 2010	1.316	1.165	1.688	1.414	1.358	1.396
Start 2012	0.777	0.529	0.661	0.545	0.593	0.724
Poor and seniors	1.607	1.572	1.189	1.792	1.550	1.400
Reduce GST	2.184	2.143	2.116	2.100	2.483	1.902
Not invest R&D	0.521	0.661	0.495	0.554	0.383	0.528
Invest R&D	1.367	1.300	1.693	1.323	1.647	1.672
Not exempt transport	0.776	0.540	0.553	0.750	0.699	0.544
Exempt transport	0.512	0.816	0.813	0.744	0.591	0.816
Not exempt energy	0.876	0.539	0.616	0.793	0.642	0.485
Exempt energy	0.514	0.979	0.843	0.744	0.688	0.910

c *Natural log of the square root quantities in Table 4b*

Means	Ln[SQRT(best/worst)]					
Alt	C1	C2	C3	C4	C5	C6
Start 2010	0.274	0.153	0.524	0.347	0.306	0.334
Start 2012	−0.253	−0.636	−0.414	−0.607	−0.522	−0.323
Poor and seniors	0.474	0.452	0.173	0.583	0.438	0.337
Reduce GST	0.781	0.762	0.750	0.742	0.910	0.643
Not invest R&D	−0.652	−0.413	−0.703	−0.591	−0.961	−0.639
Invest R&D	0.312	0.263	0.526	0.280	0.499	0.514
Not exempt transport	−0.253	−0.616	−0.593	−0.287	−0.359	−0.610
Exempt transport	−0.669	−0.203	−0.207	−0.295	−0.527	−0.203
Not exempt energy	−0.132	−0.617	−0.485	−0.232	−0.443	−0.724
Exempt energy	−0.666	−0.021	−0.170	−0.296	−0.374	−0.094

oices

:5	C6
0.136	0.183
0.216	−0.169
0.245	0.187
0.436	0.277
0.219	−0.144
0.139	0.135
0.102	−0.179
0.175	−0.063
0.120	−0.194
0.125	−0.031

C5	C6
1.358	1.396
0.593	0.724
1.550	1.400
2.483	1.902
0.383	0.528
1.647	1.672
0.699	0.544
0.591	0.816
0.642	0.485
0.688	0.910

5	C6
).306	0.334
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).438	0.337
).910	0.643
).961	−0.639
).499	0.514
).359	−0.610
.527	−0.203
.443	−0.724
.374	−0.094

Table 10.8a *Singular value decomposition results for measures (principal components analysis)*

	Best–worst differences		SQRT(best/worst)		Ln[SQRT(best/worst)]	
Component	Eigenvalue	% of variance	Eigenvalue	% of variance	Eigenvalue	% of variance
1	5.581	93.013	5.629	93.817	5.444	90.738
2	0.202	3.368	0.207	3.442	0.360	5.997
3	0.151	2.514	0.108	1.807	0.127	2.109
4	0.041	0.681	0.029	0.475	0.039	0.653
5	0.022	0.362	0.022	0.360	0.020	0.335
6	0.004	0.061	0.006	0.099	0.010	0.168

Table 10.8b *Principal components analysis results for all three measures*

	Analysis combining all three measures	
Component	Eigenvalue	% of variance
1	16.486	91.588
2	0.737	4.092
3	0.456	2.534
4	0.170	0.947
5	0.081	0.448
6	0.043	0.240
7	0.011	0.062
8	0.008	0.046
9	0.007	0.041
10 to 18 = 0		

We now produce histograms for the 10 attribute levels for the best-minus-worst difference scores; the PCA results indicate that results are the same for all measures, so we discuss only the BWS scores. Histograms are calculated for the entire data set, which is why there are so many observations (80 observations × 388 people), but the graph would be identical for one observation per person. In Figure 10.4, look at the first row of the figure that has the two start date attribute levels, 2010 and 2012. The average difference scores for 2012 are lower than those for 2010. The data also are multi-modal, with spikes at −1 and +1, but the mass of the distribution is concentrated near zero, suggesting that many people were indifferent about start year. In the case of how to use the revenues collected by the scheme, many people chose to give the revenues to the poor and seniors every time that choice was available (+1), although on average the mean for reducing the GST is higher. So, there seem to be many individual differences as well as a lot of indifference (mass again centered near zero). For investing in research and development, the sample clearly favors investing 20

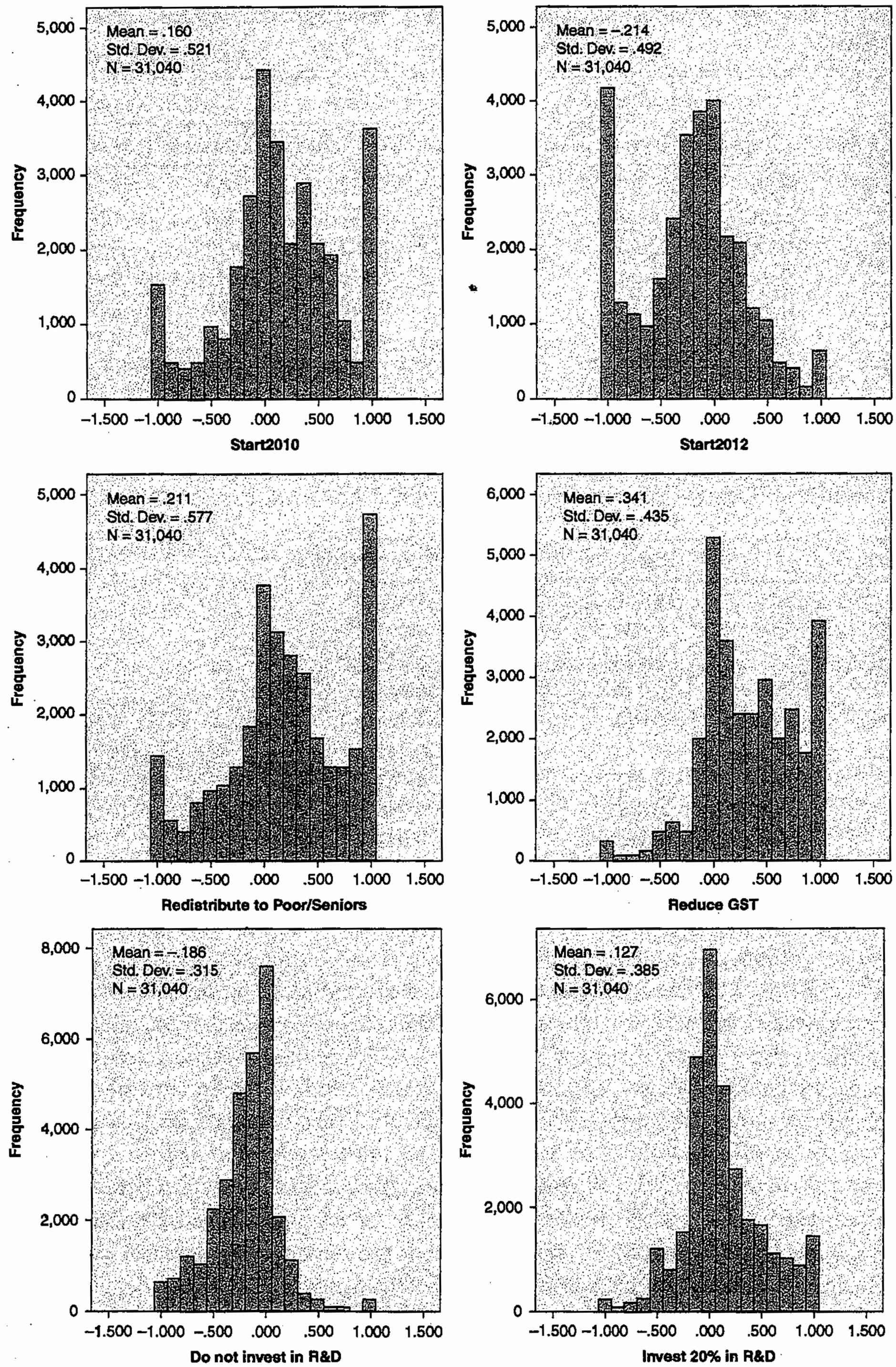


Figure 10.4 Histograms for BWS scores for each attribute level

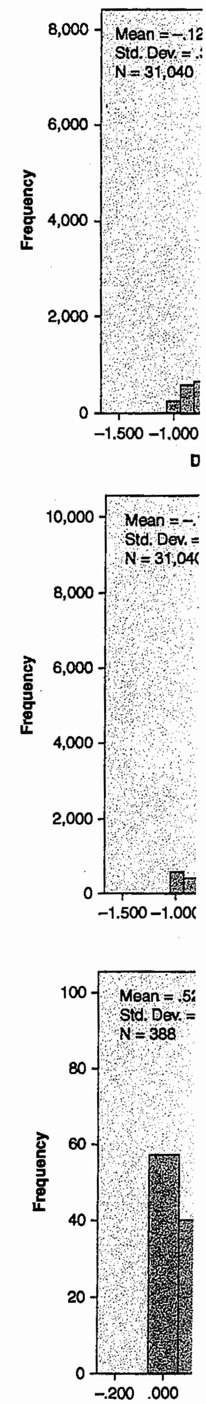
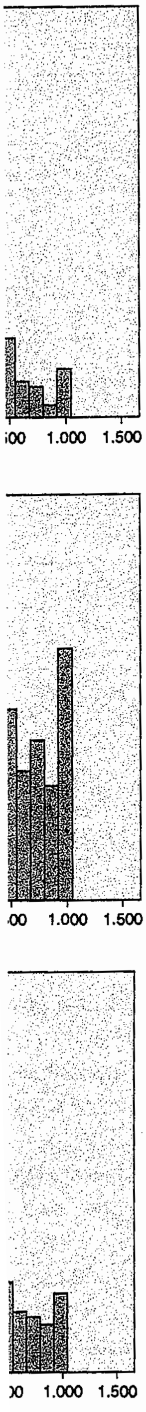
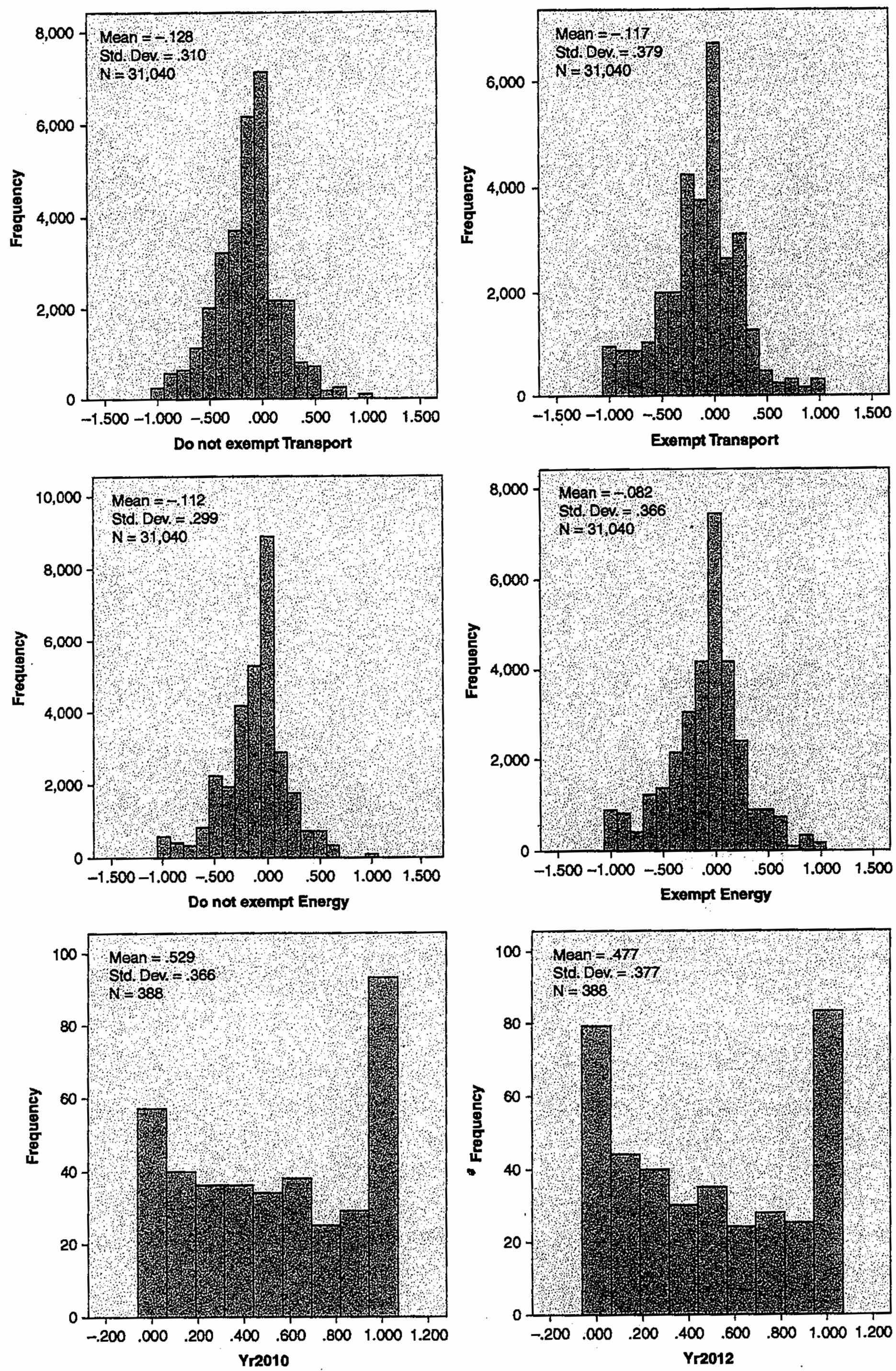


Figure 10.4 (cont.





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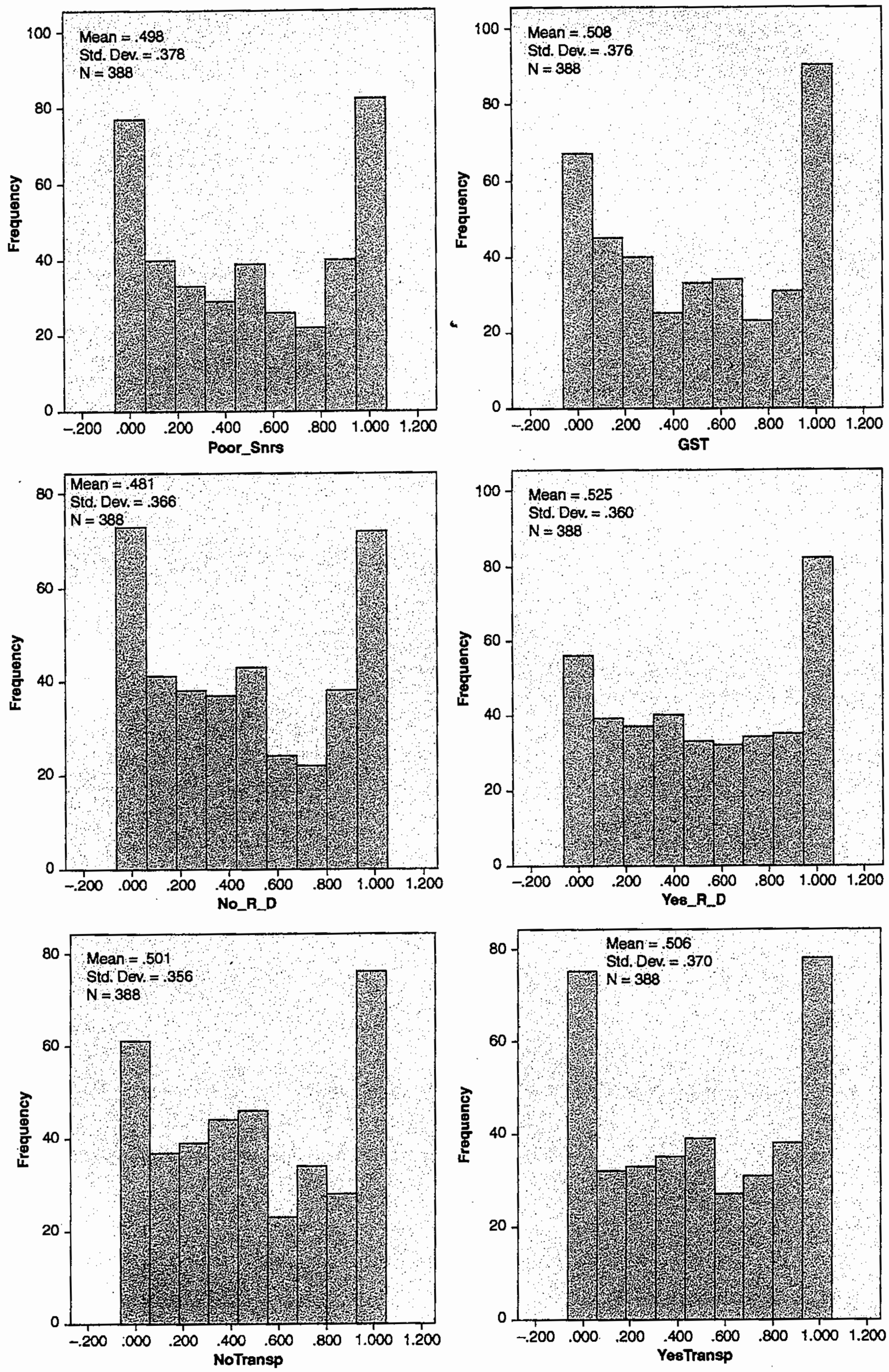

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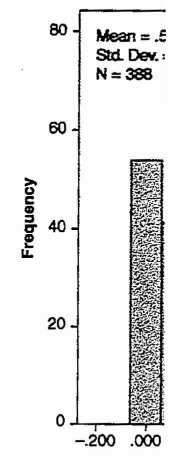

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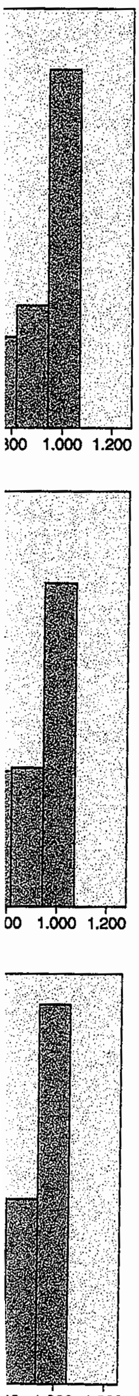

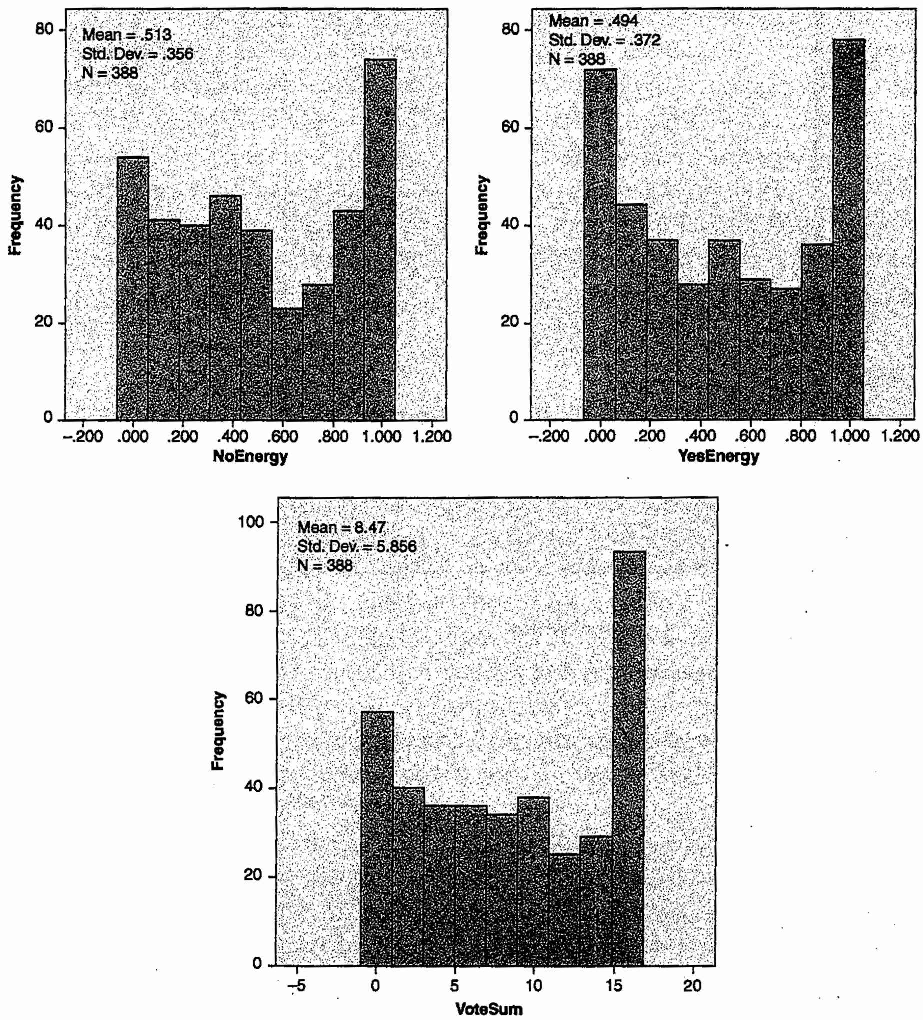

Figure 10.4 (cont.)

percent of the revenues raised in R&D, with a clear mode at +1 for the latter level, together with a large proportion of indifferent people. Both transport exemption levels were relatively unpopular (both have negative means), and only a few people chose either level consistently as best or worst, with many indifferent to both levels. Both energy attribute levels also have negative means, but a few people consistently chose them as the worst levels (−1), with many indifferent (near zero).

We also investigate the degree to which respondents were consistent in their choices by fitting linear probability models to each person's best and worst choices, and calculating the residuals from these regressions for each person. We then square the residuals and display their distribution in a histogram in Figures 10.5a and 10.5b, which are, respectively, the

(a)

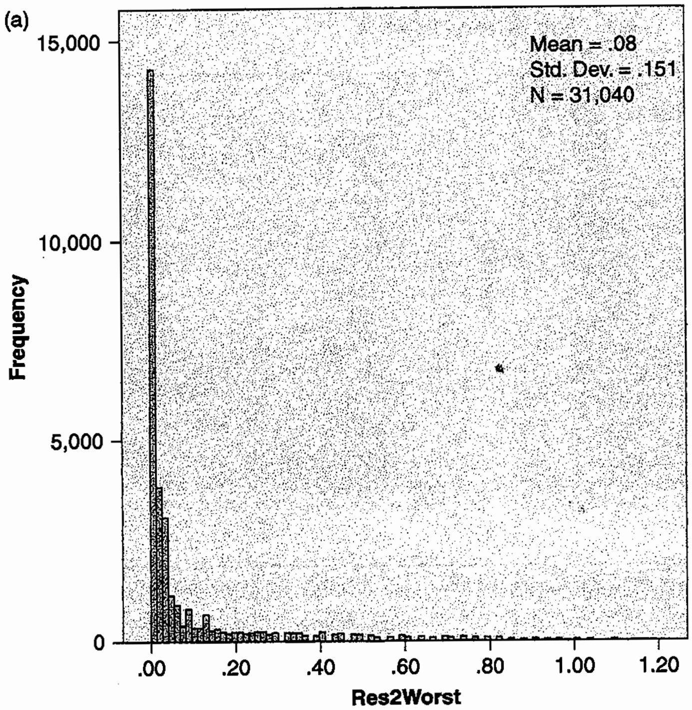

Figure 10.5(a) Residuals squared for worst

(b)

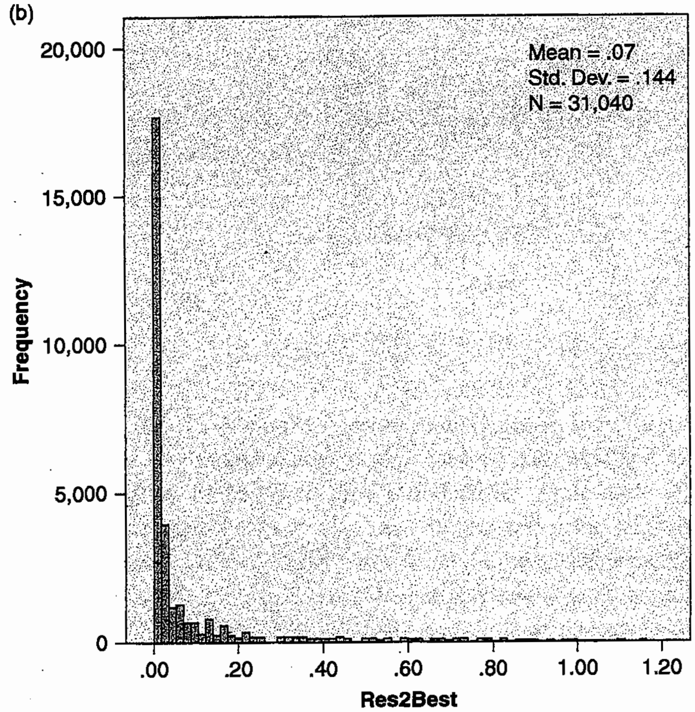

Figure 10.5(b) Residuals squared for best

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mean squared residuals for best and worst choices. These histograms suggest that the vast majority of people were very consistent in their choices, and that they were slightly more consistent in making best choices than worst choices. Taken together, the histograms suggest that many people were deterministic or nearly so in their best and worst choices of attribute levels. The histograms also indicate that it would be difficult to tell a well-behaved random coefficient story for this sample. In other words, although one can estimate statistical choice models from these data that allow for a distribution of utility estimates over the respondents, it is unclear (1) why one would want to do that in this case and (2) whether such a statistical representation would be stable over space and time in any meaningful way.

10.4 Relationship to covariates

Therefore, it is likely that a more insightful approach is to determine if one can capture "observable" (as opposed to "unobservable") preference heterogeneity in the sample by allowing choices of attribute levels for the two tasks to differ by particular covariate measures in the survey, as we now show.

We begin by calculating simple best-minus-worst difference scores. We use the 1, 0 choice indicator measures in the data to construct a new variable that takes on the values −1 (level chosen worst), 0 (level not chosen as either best or worst) and +1 (level chosen best). Ultimately, we wish to ask if we can predict these three outcomes statistically using available covariates as predictors. Two obvious statistical models that can be used for this purpose are (1) unconditional (polychotomous) multinomial logit regression and (2) ordinal regression. We do not illustrate using these statistical models to test for relationships with the covariates because the number of possible terms is too large.

In any case, before fitting models one should "look" at one's data, which we do by cross-tabbing the best-minus-worst difference scores with the covariates. We examine these results and the associated chi-square tests. There are many cross-tab tables for this data set, so, in the interests of space and because this is a case study chapter, we present only a few results (tables). Specifically, we cross-tab the BWS difference scores with available covariate measures, for each attribute level. We now discuss a few of the more interesting results.

We categorize the tables by the attribute level to which they pertain. For example, the first set of three tables relates to the attribute level "Starting the scheme in 2010." Table 10.9a indicates that respondents who agreed that global warming probably has been happening were much more likely to choose that level as most (+1), while those who disagreed were more likely to choose it as least (−1). Table 10.9b looks at political parties, and shows that Greens were more likely to choose 2010 as most (+1) and Liberals were most likely to choose it as least (−1).[3] So, more left-leaning voters favored starting in 2010, but more right-leaning voters favored starting in 2012.

[3] Labour is the major center-left party and, at the time of the survey, formed the government with the Greens, who have an environmentalist orientation. The Liberal Party is the mainstream center-right party, and is often in a coalition with the Nationals, who are strong in rural areas. The (Liberal) Democrats have a libertarian orientation.

Table 10.9 *Cross-tab plans that start in 2010*

a *Start in 2010*

		BWS			
		−1	0	+1	Total
Do you think global warming probably has been happening, or it probably hasn't been happening?	Has been	14.8%	49.5%	35.6%	100.0%
	Has not been	29.3%	51.0%	19.7%	100.0%
Total		17.1%	49.8%	33.1%	100.0%

Notes: Pearson chi-square = 82.142; df = 2; Sig < 0.000.

b *Start in 2010*

		BWS			
		−1	0	+1	Total
Which political party do you identify the most with:	Labour	16.6%	47.1%	36.3%	100.0%
	Liberals	23.1%	52.6%	24.4%	100.0%
	Greens	6.3%	52.4%	41.3%	100.0%
	Nationals	15.0%	55.0%	30.0%	100.0%
	Democrats	14.6%	45.8%	39.6%	100.0%
	None	17.4%	50.9%	31.7%	100.0%
Total		17.1%	49.8%	33.1%	100.0%

Notes: Pearson chi-square = 62.439; df = 10; Sig < 0.000.

The next tables relate to giving part of the revenues raised to help the poor and senior citizens. Table 10.10a tabulates BWS scores with age, which indicates that the older the respondent, the more likely he/she was to choose this level as most, while at the same time being less likely to choose it as least. Table 10.10b tabulates household income with the BWS scores, suggesting that the higher the household income, the less likely a respondent was to choose this level as most (+1), and instead he/she is more likely to choose it as least (−1). Conversely, poorer respondents were more likely to choose it as most (+1).

The next results refer to using the revenues to reduce the GST. Table 10.11a tabulates those agreeing with implementing a scheme that reduces more emissions even if it costs more. Respondents who disagreed were much more likely to choose this level as most (+1). Table 10.11b tabulates political affiliation with the level, showing that those most likely to choose reducing GST (+1) had no political affiliation, those least likely to choose reducing GST as most were the Greens, while the Nationals were least likely to choose reducing GST as least (−1).

The next set of tables give results for investing 20 percent of the revenues in research and development related to reducing emissions and sustainable technologies. Table 10.12a looks at how serious respondents think global warming will be for Australia's future

Table 10.10 *Cr*

a *Giving reven*

Which age group

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b *Giving reven*

Household incom

Total

Notes: Pearson ch

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Table 10.12b lo
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Table 10.10 *Cross-tab giving the revenues to the poor and senior citizens*

a *Giving revenues to poor and seniors*

		BWS			
		−1	0	+1	Total
Which age group are you in?	18–19	20.1%	50.7%	29.2%	100.0%
	20–24	26.6%	41.0%	32.4%	100.0%
	25–29	23.5%	42.6%	33.8%	100.0%
	30–34	22.1%	46.3%	31.6%	100.0%
	35–39	11.0%	45.3%	43.8%	100.0%
	40–44	16.1%	51.4%	32.5%	100.0%
	45–49	12.5%	43.6%	43.9%	100.0%
	50–54	11.0%	51.9%	37.1%	100.0%
	55–59	18.5%	38.6%	42.9%	100.0%
	60–64	9.5%	47.0%	43.5%	100.0%
	65–69	0.0%	14.6%	85.4%	100.0%
	70+	0.0%	31.3%	68.8%	100.0%
Total		17.0%	44.9%	38.1%	100.0%

Notes: Pearson chi-square = 169.371; df = 22; Sig < 0.000.

b *Giving revenues to poor and seniors*

		BWS			
		−1	0	+1	Total
Household income	Below $25,000	5.7%	29.8%	64.6%	100.0%
	$25,000 to $50,000	9.1%	47.2%	43.7%	100.0%
	$50,000 to $75,000	13.3%	41.2%	45.5%	100.0%
	$75,000 to $100,000	23.4%	46.6%	30.0%	100.0%
	$100,000 to $125,000	24.6%	45.3%	30.1%	100.0%
	$125,000 to $150,000	20.1%	56.4%	23.5%	100.0%
	$150,000 to $200,000	26.6%	54.9%	18.5%	100.0%
	Above $200,000	20.3%	47.7%	32.0%	100.0%
Total		17.0%	44.9%	38.1%	100.0%

Notes: Pearson chi-square = 252.268; df = 14; Sig < 0.000.

crossed with investing in R&D. It indicates that the more serious respondents think the problem will be, the more they are likely to choose this level as most (1), whereas the less serious respondents thought it was, the more likely the level chosen was least (−1). Table 10.12b looks at attitudes towards technological breakthroughs fixing global warming with choice of the level as most or least, and shows that the more faith is expressed in technological advances solving the problems, the more likely investing in R&D is chosen as

Table 10.11 *Cross-tab using the revenues to reduce the GST*

a *Using revenues to reduce the GST*

		BWS			
		−1	0	+1	Total
Should Australia adopt a plan that requires an 80% reduction in greenhouse gases by 2050 instead of a 60% reduction even if the plan will have substantially higher costs?	Yes	10.2%	51.8%	38.0%	100.0%
	No	8.1%	41.0%	51.0%	100.0%
Total		9.3%	47.2%	43.5%	100.0%

Notes: Pearson chi-square = 51.984; df = 2; Sig < 0.000.

b *Using revenues to reduce the GST*

		BWS			
		−1	0	1	Total
Which political party do you identify the most with:	Labour	9.6%	49.7%	40.7%	100.0%
	Liberal	9.6%	45.5%	44.9%	100.0%
	Green	12.8%	64.2%	22.9%	100.0%
	National	2.5%	52.5%	45.0%	100.0%
	Democrats	10.4%	62.5%	27.1%	100.0%
	None	7.6%	37.5%	54.9%	100.0%
Total		9.3%	47.2%	43.5%	100.0%

Notes: Pearson chi-square = 105.436; df = 10; Sig < 0.000.

most (+1). Conversely, the less faith is expressed, the more likely it is chosen as least (−1). Table 10.12c shows that professionals were most likely to choose the level as most (1), while production and transport workers were least likely to choose it as most (1). Laborers and related workers were most likely to choose the level as least (−1). Finally, Table 12d shows that Greens were most likely to choose this level as most (+1), whereas Nationals were more likely to choose it as least (−1).

The final set of tables pertains to exempting energy-intensive industries. Table 10.13a tabulates where respondents live in connection with this question. Respondents in Brisbane and Perth were most likely to choose this level as most (+1), while respondents in the Australian Capital Territory (ACT) and Tasmania were least likely to choose it as most (+1). Conversely, respondents in South Australia other than in Adelaide and respondents in the Northern Territory were most likely to choose the −1 level, while Brisbane respondents were least likely to choose the −1 level. Table 10.13b shows that respondents affiliated with Greens and Democrats were least likely to choose this level as most (1). Nationals were

Table 10.12 Cr

a Investing 20 p

If nothing is done
the future, how
think it will be

Total

Notes: Pearson ch

b Investing 20 p

How much faith c
breakthroughs
problems in the

Total

Notes: Pearson ch

c Investing 20 p

Which of the follo
describes your
occupation?

Total

Table 10.12 *Cross-tab investing 20 percent of the revenues in R&D*

a *Investing 20 percent of revenues in R&D*

		BWS			
		−1	0	+1	Total
If nothing is done to reduce global warming in the future, how serious a problem do you think it will be for Australia?	Extremely serious	7.5%	64.2%	28.3%	100.0%
	Very serious	10.4%	64.8%	24.8%	100.0%
	Somewhat serious	11.6%	73.1%	15.2%	100.0%
	Slightly serious	14.7%	66.5%	18.8%	100.0%
	Not serious at all	18.1%	69.0%	13.0%	100.0%
Total		10.4%	66.6%	23.1%	100.0%

Notes: Pearson chi-square = 74.010; df = 8; Sig < 0.000.

b *Investing 20 percent of revenues in R&D*

		BWS			
		−1	0	+1	Total
How much faith do you have that technological breakthroughs will solve major environmental problems in the future?	A lot	9.7%	55.2%	35.0%	100.0%
	Some	9.8%	69.2%	21.0%	100.0%
	Little	11.7%	69.5%	18.8%	100.0%
	None	14.6%	74.3%	11.1%	100.0%
Total		10.4%	66.6%	23.1%	100.0%

Notes: Pearson chi-square = 77.503; df = 6; Sig < 0.000.

c *Investing 20 percent of revenues in R&D*

		BWS			
		−1	0	+1	Total
Which of the following best describes your current occupation?	Manager or administrator	11.2%	55.4%	33.5%	100.0%
	Small business owner/partner	10.4%	62.1%	27.5%	100.0%
	Professional (e.g. doctor, architect, solicitor, etc.)	7.7%	55.3%	37.0%	100.0%
	Associate professional (e.g. police, nurse, technician)	10.7%	73.2%	16.1%	100.0%
	Tradesperson or related worker	11.0%	71.3%	17.6%	100.0%
	Clerical, sales and service worker	12.3%	66.7%	21.1%	100.0%
	Production and transport worker	6.3%	85.4%	8.3%	100.0%
	Laborer or related worker	15.6%	69.5%	14.8%	100.0%
	Other	9.8%	73.7%	16.5%	100.0%
Total		10.4%	66.6%	23.1%	100.0%

d *Investing 20 percent of revenues in R&D*

		BWS			
		−1	0	1	Total
Which political party do you identify the most with?	Labor	11.3%	67.2%	21.4%	100.0%
	Liberals	8.3%	67.9%	23.7%	100.0%
	Greens	7.3%	49.3%	43.4%	100.0%
	Nationals	32.5%	50.0%	17.5%	100.0%
	Democrats	4.2%	56.3%	39.6%	100.0%
	None	10.8%	71.9%	17.3%	100.0%
Total		10.4%	66.6%	23.1%	100.0%

Notes: Pearson chi-square = 117.501; df = 10; Sig < 0.000.

most likely to choose it as most (1). Democrats and Greens were most likely to choose this level as least (−1), and Nationals were least likely to choose it as least (−1).

One might well ask why one rarely sees tests of unobservable heterogeneity that extend beyond a few covariates. The answer is that (1) there is little to no theory to guide hypothesis testing and model selection, and (2) there typically are many possible effects that could be estimated. For example, if you consider only the tables above, there are several binary attitudinal measures (two categories), political party (six), age (nine), location (13), occupation (nine), two questions about how much faith one has in technological solutions to climate change (four) and how serious global warming might be (five), and household income (eight), to name only the ones illustrated. There are 10 attribute levels that could be chosen as most or least or not chosen as either (three). Thus, if we want to test the covariates mentioned against whether or not each attribute level is chosen as most or least, there are three response outcomes $(-1, 0, +1) \times 10$ attribute levels × (several 2s), $\times 6 \times 9 \times 13 \times 9 \times 4 \times 5 \times 8$, or 242,611,200 possible cells that could be observed if we fully cross all the measures. Typically, one considers only the main effects; hence, there are (two non-referenced outcome categories × 10 levels) $\times (3 + 5 + 8 + 12 + 8 + 3 + 4 + 7) = 20 \times 50 = 1{,}000$. Each covariate main effect has degrees of freedom equal to the number of categories minus one, so the total covariate's main effects are the additive component of the expression. They are estimated for each attribute level and two of the response outcome categories. We, in fact, estimated an unconditional (polychotomous) multinomial logit model for each level. Appendix 10.A contains statistical estimation results for giving the revenues to the poor and senior citizens and using the revenues to reduce the GST. The size and complexity of these tables should make it obvious why we do not report results for the other eight levels or attempt to interpret the results here but, instead, leave it to those who may be interested to peruse.

Table 10.13 C

a *Exempting e*

In which locatio

Total

Notes: Pearson c

b *Exempting e*

Which political p

Total

Notes: Pearson c

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Table 10.13 *Crosstab exempting energy-intensive industries*

a *Exempting energy-intensive industries*

		BWS			
		−1	0	+1	Total
In which location do you live?	Sydney	19.6%	68.1%	12.3%	100.0%
	Other NSW	15.8%	70.7%	13.5%	100.0%
	Melbourne	24.2%	64.6%	11.2%	100.0%
	Other Victoria	16.9%	70.0%	13.1%	100.0%
	Brisbane	8.6%	71.9%	19.5%	100.0%
	Other Queensland	19.3%	72.4%	8.3%	100.0%
	Adelaide	21.6%	68.5%	9.9%	100.0%
	Other South Australia	33.0%	59.1%	8.0%	100.0%
	Perth	15.8%	68.2%	16.1%	100.0%
	Other WA	25.0%	67.9%	7.1%	100.0%
	ACT	30.1%	67.0%	2.8%	100.0%
	Tasmania	22.1%	70.2%	7.7%	100.0%
	Northern Territory	41.7%	41.7%	16.7%	100.0%
Total		20.1%	68.1%	11.8%	100.0%

Notes: Pearson chi-square = 96.795; df = 24; Sig < 0.000.

b *Exempting energy-intensive industries*

		BWS			
		−1	0	+1	Total
Which political party do you identify the most with?	Labor	19.0%	70.3%	10.7%	100.0%
	Liberals	15.7%	68.3%	16.0%	100.0%
	Greens	38.9%	53.5%	7.6%	100.0%
	Nationals	20.0%	55.0%	25.0%	100.0%
	Democrats	45.8%	52.1%	2.1%	100.0%
	None	16.9%	71.3%	11.8%	100.0%
Total		20.1%	68.1%	11.8%	100.0%

Notes: Pearson chi-square = 116.025; df = 10; Sig < 0.000.

10.5 Discussion and concluding remarks

The purpose of this chapter was to provide a case study comparison of Case 2 and Case 3 best-worst tasks. We focused on a comparison of emissions trading schemes in Australia based on a study of a random sample of voting-age Australians in 2009. We compared a more traditional DCE (Case 3) format whereby survey respondents decided whether or not to vote for a particular ETS described by five 2-level attributes with a Case 2 task in which they chose, respectively, the best and worst attribute levels in each ETS profile (description, treatment combination). We noted that Cases 2 and 3 are complementary in so far as they provide different measures and insights into the values of attribute levels. For example, Case 2 places each of the 10 attribute levels on a common scale, whereas Case 3 measures each attribute level on separate scales for each attribute. In fact, the latter property of Case 3 measures is a key reason that economists developed Hicksian welfare measures such as willingness to pay; it puts these quantities on a common scale (such as dollars), allowing attribute-level comparisons with a common numeraire.

We showed that the Case 3 aggregate sample results actually had large underlying differences in respondents on some attributes/levels, such as start year and distribution of revenues. There also were many people who always voted "No" or "Yes" – a common result in binary discrete choice DCE tasks. We also showed that there were common attribute levels associated with the sample of emissions trading schemes that received more than 50 percent "Yes" votes, such that all had a starting year of 2010, a majority had an investment of 20 percent of revenues raised in R&D activities and a majority did not exempt energy-intensive industries. We compared these results to the Case 2 BWS results, which showed non-continuous, multi-modal distributions of choices on most attributes. We also showed that we could identify statistical differences in the choices made in the Case 2 task that were related to individual covariate differences such as age, gender and income. Thus, the Case 2 results provided more nuanced, complementary insights into the distribution of choices and their relationship with observable individual differences measured by the covariates.

Appendix 10.A MNL estimation of least and most choice for two attribute levels

Table 10.A1 *Listing and description of covariates used in analyses*

Covariates and associated levels used in the MNL estimation		N
	−1	527
BWS	0	1395
	1	1182
Q1. Which of the three ways is the one that you most prefer the government to use to reduce greenhouse gas emissions?	Taxes	760
	Permits	744
	Technical standards	1600
Q10. From what source do you get most of your information about global warming?	Internet	896
	Magazines	112
	Meetings	80
	Newspapers	520
	Radio	80
	Television	1008
	Other	408

Table 10.A1 (co

Covariates and ass

Q11. Which one o
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carbon dioxide

DX3. In which loc

DX5. What is you

DX7. Which of th
home ownershi

DX8. Which of th
household?

Table 10.A1 (*cont.*)

Covariates and associated levels used in the MNL estimation		N
Q11. Which one of these options do you think that the government should most concentrate on to reduce carbon dioxide emissions?	Getting people to conserve more energy at home	680
	Getting people to take public transport rather than drive	464
	Installing more wind and solar power	1648
	Building nuclear power plants	312
DX3. In which location do you live?	Sydney	552
	Other NSW	304
	Melbourne	520
	Other Victoria	160
	Brisbane	256
	Other Queensland	192
	Adelaide	232
	Other South Australia	88
	Perth	336
	Other WA	56
	ACT	176
	Tasmania	208
	Northern Territory	24
DX5. What is your marital status?	Single	880
	Married/couple	1840
	Separated/divorced/widowed	384
DX7. Which of the following best describes your current home ownership status?	Own home with mortgage	1264
	Own home without mortgage	592
	Rent	960
	Other	288
DX8. Which of the following best describes your household?	Single person	632
	Single adult with children at home	176
	Peer group flatting together	224
	Young couple – no children	384
	Young family – mainly pre-school children	440
	Middle family – mainly school-aged children	368
	Mature family – mainly teenage children or older	488
	Middle aged couple –no children/ no children at home	224
	Older couple –no children/no children at home	168

Table 10.A1 (*cont.*)

Covariates and associated levels used in the MNL estimation		N
DX9. Which of the following best describes your work status?	Full-time work – self-employed	312
	Full-time work – employee	1304
	Part-time work (less than 35 hours a week)	584
	Unemployed – looking for work	144
	Unemployed – not looking for work	48
	Full-time student	144
	Retired	200
	Household duties	368
DX10. Which of the following best describes your current occupation?	Manager or administrator	448
	Small business owner/partner	280
	Professional (e.g. doctor, architect, solicitor, etc.)	416
	Associate professional (e.g. police, nurse, technician)	224
	Tradesperson or related worker (e.g. plumber, carpenter, etc.)	136
	Clerical, sales or service worker	456
	Production or transport worker	96
	Laborer or related worker	128
	Other	920
DX11. Which of the following statements best describes you?	English is my main language	2936
	English is not my main language	168
DX12. Are you the main income earner in your household?	Yes	1384
	No	1040
	Joint/equal	680
DX19. Which political party do you identify the most with?	Labor	1288
	Liberal	624
	Green	288
	National	40
	Democrats	48
	None	816

Table 10.A2 S
(*poor and senic*

Effect	−2
Intercept	304
Q3_1	304
Q3_2	304
Q3_3	304
Q3_4	304
Q3_5	304
Q4	305
Q5	307
Q6	305
Q7	305
Q8	305
Q9	304
Q12	304
Q13	304
Q14	305
Q15	307
DX1	305
DX2	305
DX6	304
DX14	310
DX15	305
DX16	305
DX17	304
DX18	304
Q1	307
Q10	306
Q11	306
DX3	317
DX5	304
DX7	308
DX8	311
DX9	316
DX10	322
DX11	304
DX12	305
DX19	309

Table 10.A2 *Summary MNL model estimation results for levels 3 and 4 (poor and seniors + GST)*

	Give revenues to poor and seniors				Use revenues to reduce the GST			
Effect	−2 LL	Chi-sq.	df	Sig	−2 LL	Chi-sq.	df	Sig
Intercept	3041.305	0.000	0	–	2686.809	0.000	0	–
Q3_1	3041.786	0.481	2	0.786	2693.743	6.934	2	0.031
Q3_2	3042.740	1.434	2	0.488	2690.885	4.076	2	0.130
Q3_3	3046.034	4.728	2	0.094	2688.554	1.745	2	0.418
Q3_4	3043.866	2.560	2	0.278	2687.126	0.317	2	0.853
Q3_5	3047.914	6.609	2	0.037	2704.385	17.576	2	0.000
Q4	3050.231	8.926	2	0.012	2696.575	9.766	2	0.008
Q5	3070.832	29.527	2	0.000	2699.773	12.964	2	0.002
Q6	3055.514	14.208	2	0.001	2703.989	17.180	2	0.000
Q7	3050.475	9.170	2	0.010	2713.450	26.641	2	0.000
Q8	3054.643	13.338	2	0.001	2688.617	1.808	2	0.405
Q9	3042.226	0.921	2	0.631	2697.987	11.178	2	0.004
Q12	3041.374	0.069	2	0.966	2697.156	10.347	2	0.006
Q13	3046.818	5.512	2	0.064	2693.651	6.842	2	0.033
Q14	3053.514	12.209	2	0.002	2699.642	12.833	2	0.002
Q15	3075.189	33.883	2	0.000	2697.384	10.575	2	0.005
DX1	3053.640	12.334	2	0.002	2687.049	0.240	2	0.887
DX2	3057.049	15.744	2	0.000	2707.686	20.877	2	0.000
DX6	3048.702	7.397	2	0.025	2689.338	2.529	2	0.282
DX14	3107.223	65.917	2	0.000	2695.395	8.586	2	0.014
DX15	3055.979	14.673	2	0.001	2694.105	7.296	2	0.026
DX16	3058.219	16.913	2	0.000	2687.931	1.122	2	0.571
DX17	3044.340	3.035	2	0.219	2697.667	10.858	2	0.004
DX18	3044.391	3.086	2	0.214	2690.823	4.014	2	0.134
Q1	3074.336	33.030	4	0.000	2697.039	10.230	4	0.037
Q10	3069.640	28.335	12	0.005	2720.417	33.608	12	0.001
Q11	3066.051	24.745	6	0.000	2700.644	13.835	6	0.032
DX3	3179.257	137.951	24	0.000	2755.015	68.206	24	0.000
DX5	3048.528	7.222	4	0.125	2696.316	9.507	4	0.050
DX7	3080.969	39.664	6	0.000	2710.881	24.072	6	0.001
DX8	3117.930	76.625	16	0.000	2756.130	69.321	16	0.000
DX9	3163.770	122.464	14	0.000	2716.691	29.882	14	0.008
DX10	3221.552	180.246	16	0.000	2749.562	62.753	16	0.000
DX11	3042.038	0.732	2	0.693	2697.571	10.762	2	0.005
DX12	3056.647	15.341	4	0.004	2689.497	2.688	4	0.611
DX19	3097.129	55.824	10	0.000	2734.930	48.121	10	0.000

Table 10.A3 *MNL model parameter estimation results for two levels (poor and seniors + GST)*

BWS outcome		BWS outcome = least (−1)				BWS outcome = most (+1)			
		Est.	S.E.	Wald	Sig	Est.	S.E.	Wald	Sig
−1	Intercept	−0.974	1.414	0.475	0.491	−0.237	1.874	0.016	0.899
	Q3_1	0.159	0.236	0.454	0.500	0.553	0.290	3.625	0.057
	Q3_2	−0.240	0.240	0.996	0.318	−0.370	0.291	1.613	0.204
	Q3_3	0.190	0.145	1.711	0.191	0.212	0.175	1.455	0.228
	Q3_4	0.089	0.189	0.224	0.636	−0.092	0.235	0.154	0.694
	Q3_5	0.131	0.213	0.379	0.538	0.301	0.257	1.377	0.241
	Q4	−0.673	0.230	8.586	0.003	0.232	0.271	0.733	0.392
	Q5	−0.017	0.075	0.050	0.823	−0.106	0.094	1.285	0.257
	Q6	−0.199	0.183	1.184	0.277	−0.825	0.216	14.531	0.000
	Q7	0.134	0.121	1.222	0.269	−0.178	0.143	1.551	0.213
	Q8	0.571	0.157	13.309	0.000	−0.044	0.197	0.051	0.822
	Q9	−0.052	0.082	0.399	0.528	0.095	0.096	0.975	0.324
	Q12	0.014	0.159	0.007	0.931	0.069	0.200	0.119	0.730
	Q13	0.221	0.094	5.483	0.019	−0.194	0.119	2.648	0.104
	Q14	0.509	0.153	11.091	0.001	−0.248	0.175	1.998	0.157
	Q15	−1.080	0.224	23.297	0.000	−0.228	0.241	0.900	0.343
	DX1	0.160	0.160	1.002	0.317	0.047	0.181	0.068	0.794
	DX2	−0.151	0.046	10.919	0.001	−0.014	0.055	0.063	0.802
	DX6	0.003	0.005	0.388	0.533	−0.010	0.007	2.111	0.146
	DX14	0.200	0.043	21.758	0.000	0.146	0.052	7.813	0.005
	DX15	−0.322	0.104	9.621	0.002	−0.320	0.124	6.626	0.010
	DX16	−0.058	0.043	1.861	0.172	0.052	0.049	1.118	0.290
	DX17	0.020	0.025	0.640	0.424	0.087	0.032	7.569	0.006
	DX18	0.037	0.033	1.230	0.267	−0.082	0.041	3.919	0.048
	[Q1 = 1]	0.113	0.169	0.445	0.505	−0.066	0.193	0.115	0.734
	[Q1 = 2]	0.115	0.175	0.434	0.510	0.443	0.201	4.869	0.027
	[Q1 = 3]	0	–	–	–	0	–	–	–
	[Q10 = 1]	0.488	0.210	5.380	0.020	−0.929	0.256	13.164	0.000
	[Q10 = 2]	0.503	0.400	1.587	0.208	−0.188	0.431	0.191	0.662
	[Q10 = 3]	−0.205	0.453	0.205	0.651	0.561	0.466	1.449	0.229
	[Q10 = 4]	0.763	0.244	9.793	0.002	−0.636	0.283	5.052	0.025
	[Q10 = 5]	−0.021	0.548	0.002	0.969	−0.592	0.547	1.172	0.279
	[Q10 = 6]	−0.111	0.221	0.254	0.615	−0.839	0.265	9.977	0.002
	[Q10 = 7]	0	–	–	–	0	–	–	–
	[Q11 = 1]	−0.463	0.268	2.996	0.083	0.758	0.333	5.193	0.023
	[Q11 = 2]	−0.771	0.301	6.577	0.010	0.181	0.370	0.239	0.625
	[Q11 = 3]	−0.390	0.251	2.410	0.121	0.332	0.309	1.154	0.283
	[Q11 = 4]	0	–	–	–	0	–	–	–
	[DX3 = 1]	−0.835	0.668	1.562	0.211	0.398	1.157	0.118	0.731
	[DX3 = 2]	0.495	0.673	0.540	0.462	0.159	1.166	0.018	0.892

or and seniors +

e = most (+1)	
Wald	Sig
0.016	0.899
3.625	0.057
1.613	0.204
1.455	0.228
0.154	0.694
1.377	0.241
0.733	0.392
1.285	0.257
14.531	0.000
1.551	0.213
0.051	0.822
0.975	0.324
0.119	0.730
2.648	0.104
1.998	0.157
0.900	0.343
0.068	0.794
0.063	0.802
2.111	0.146
7.813	0.005
6.626	0.010
1.118	0.290
7.569	0.006
3.919	0.048
0.115	0.734
4.869	0.027
–	–
13.164	0.000
0.191	0.662
1.449	0.229
5.052	0.025
1.172	0.279
9.977	0.002
–	–
5.193	0.023
0.239	0.625
1.154	0.283
–	–
0.118	0.731
0.018	0.892

Table 10.A3 (*cont.*)

	BWS outcome = least (−1)				BWS outcome = most (+1)			
BWS outcome	Est.	S.E.	Wald	Sig	Est.	S.E.	Wald	Sig
[DX3 = 3]	−1.246	0.675	3.410	0.065	−0.292	1.162	0.063	0.801
[DX3 = 4]	−1.120	0.753	2.210	0.137	0.199	1.189	0.028	0.867
[DX3 = 5]	−0.510	0.675	0.571	0.450	−0.059	1.175	0.002	0.960
[DX3 = 6]	0.163	0.678	0.057	0.811	0.419	1.173	0.127	0.721
[DX3 = 7]	−0.417	0.691	0.363	0.547	0.124	1.183	0.011	0.916
[DX3 = 8]	−0.540	0.749	0.520	0.471	0.340	1.268	0.072	0.788
[DX3 = 9]	−0.867	0.677	1.641	0.200	−0.007	1.171	0.000	0.996
[DX3 = 10]	−3.020	1.272	5.634	0.018	0.890	1.272	0.489	0.484
[DX3 = 11]	−0.907	0.701	1.674	0.196	0.523	1.179	0.197	0.658
[DX3 = 12]	−0.946	0.686	1.901	0.168	0.336	1.183	0.081	0.776
[DX3 = 13]	0	–	–	–	0	–	–	–
[DX5 = 1]	0.696	0.299	5.409	0.020	−0.010	0.322	0.001	0.976
[DX5 = 2]	0.268	0.366	0.538	0.463	−0.530	0.388	1.864	0.172
[DX5 = 3]	0	–	–	–	0	–	–	–
[DX7 = 1]	0.707	0.325	4.726	0.030	0.508	0.400	1.614	0.204
[DX7 = 2]	0.926	0.353	6.871	0.009	1.239	0.415	8.920	0.003
[DX7 = 3]	0.307	0.324	0.897	0.344	0.619	0.402	2.378	0.123
[DX7 = 4]	0	–	–	–	0	–	–	–
[DX8 = 1]	0.198	0.476	0.173	0.677	−0.338	0.482	0.493	0.483
[DX8 = 2]	−0.201	0.524	0.148	0.701	0.546	0.541	1.021	0.312
[DX8 = 3]	−0.826	0.521	2.512	0.113	−0.064	0.557	0.013	0.909
[DX8 = 4]	−0.091	0.443	0.042	0.838	−0.380	0.480	0.6026	0.429
[DX8 = 5]	−0.262	0.440	0.355	0.551	0.125	0.478	0.069	0.793
[DX8 = 6]	−0.644	0.437	2.170	0.141	0.599	0.452	1.753	0.185
[DX8 = 7]	−0.410	0.434	0.894	0.344	0.023	0.460	0.003	0.960
[DX8 = 8]	−1.084	0.480	5.099	0.024	−0.426	0.445	0.917	0.338
[DX8 = 9]	0	–	–	–	0	–	–	–
[DX9 = 1]	1.428	0.404	12.514	0.000	−0.007	0.468	0.000	0.987
[DX9 = 2]	1.894	0.347	29.795	0.000	0.508	0.410	1.534	0.215
[DX9 = 3]	1.214	0.317	14.648	0.000	0.814	0.348	5.472	0.019
[DX9 = 4]	−0.470	0.456	1.061	0.303	0.026	0.535	0.002	0.962
[DX9 = 5]	1.177	0.797	2.178	0.140	0.439	0.624	0.494	0.482
[DX9 = 6]	0.136	0.398	0.118	0.732	0.090	0.540	0.028	0.868
[DX9 = 7]	1.057	0.472	5.010	0.025	0.285	0.460	0.383	0.536
[DX9 = 8]	0	–	–	–	0	–	–	–
[DX10 = 1]	−1.712	0.274	39.107	0.000	−0.769	0.309	6.193	0.013
[DX10 = 2]	−1.147	0.346	10.962	0.001	−0.496	0.365	1.842	0.175
[DX10 = 3]	−1.062	0.259	16.872	0.000	−0.880	0.310	8.073	0.004
[DX10 = 4]	−1.251	0.333	14.090	0.000	−1.426	0.419	11.591	0.001
[DX10 = 5]	−1.169	0.396	8.699	0.003	−0.394	0.464	0.721	0.396
[DX10 = 6]	−0.940	0.241	15.176	0.000	0.070	0.269	0.067	0.795

Table 10.A3 (*cont.*)

		BWS outcome = least (−1)				BWS outcome = most (+1)			
	BWS outcome	Est.	S.E.	Wald	Sig	Est.	S.E.	Wald	Sig
	[DX10 = 7]	0.605	0.406	2.222	0.136	0.715	0.451	2.508	0.113
	[DX10 = 8]	−2.341	0.491	22.732	0.000	−1.163	0.508	5.253	0.022
	[DX10 = 9]	0	–	–	–	0	–	–	–
	[DX11 = 1]	−0.235	0.280	0.707	0.400	−0.197	0.346	0.323	0.570
	[DX11 = 2]	0	–	–	–	0	–	–	–
	[DX12 = 1]	0.206	0.200	1.060	0.303	−0.374	0.241	2.424	0.119
	[DX12 = 2]	0.487	0.229	4.533	0.033	−0.241	0.261	0.853	0.356
	[DX12 = 3]	0	–	–	–	0	–	–	–
	[DX19 = 0]	−0.705	0.173	16.519	0.000	−0.104	0.213	0.241	0.624
	[DX19 = 1]	−0.141	0.195	0.522	0.470	0.069	0.251	0.075	0.784
	[DX19 = 2]	−0.895	0.265	11.401	0.001	−0.273	0.316	0.746	0.388
	[DX19 = 3]	0.607	0.773	0.616	0.432	−1.924	1.105	3.031	0.082
	[DX19 = 4]	−1.836	0.637	8.308	0.004	−0.167	0.671	0.062	0.803
	[DX19 = 5]	0	–	–	–	0	–	–	–
1	Intercept	−2.073	1.124	3.401	0.065	−0.362	1.068	0.115	0.735
	Q3_1	0.055	0.165	0.110	0.740	−0.187	0.156	1.448	0.229
	Q3_2	−0.163	0.176	0.859	0.354	0.198	0.169	1.374	0.241
	Q3_3	0.221	0.108	4.155	0.042	0.085	0.101	0.707	0.400
	Q3_4	−0.184	0.141	1.707	0.191	−0.064	0.130	0.246	0.620
	Q3_5	0.428	0.167	6.548	0.010	0.649	0.156	17.355	0.000
	Q4	−0.179	0.162	1.212	0.271	−0.400	0.150	7.103	0.008
	Q5	0.291	0.057	25.956	0.000	0.153	0.051	8.854	0.003
	Q6	0.424	0.135	9.824	0.002	0.071	0.126	0.322	0.570
	Q7	−0.214	0.090	5.653	0.017	−0.437	0.086	25.998	0.000
	Q8	0.124	0.118	1.094	0.296	0.132	0.108	1.483	0.223
	Q9	0.030	0.060	0.251	0.617	0.185	0.055	11.094	0.001
	Q12	−0.025	0.119	0.044	0.834	0.346	0.109	10.032	0.002
	Q13	0.035	0.072	0.238	0.626	0.107	0.068	2.470	0.116
	Q14	0.006	0.110	0.003	0.954	0.283	0.102	7.744	0.005
	Q15	0.298	0.171	3.026	0.082	0.456	0.165	7.637	0.006
	DX1	0.402	0.115	12.263	0.000	0.051	0.109	0.218	0.640
	DX2	−0.105	0.035	9.298	0.002	−0.146	0.033	19.794	0.000
	DX6	0.008	0.003	7.234	0.007	−0.001	0.003	0.105	0.746
	DX14	−0.167	0.034	23.799	0.000	−0.002	0.031	0.006	0.937
	DX15	0.086	0.075	1.318	0.251	−0.098	0.071	1.927	0.165
	DX16	0.107	0.032	11.350	0.001	0.011	0.029	0.145	0.703
	DX17	−0.023	0.019	1.487	0.223	−0.017	0.017	0.979	0.323
	DX18	−0.025	0.025	0.991	0.319	−0.008	0.023	0.124	0.725
	[Q1 = 1]	0.391	0.126	9.583	0.002	0.070	0.118	0.348	0.555
	[Q1 = 2]	0.706	0.129	29.854	0.000	0.296	0.119	6.209	0.013
	[Q1 = 3]	0	–	–	–	0	–	–	–

Table 10.A3 (*cont.*)

	BWS outcome = least (−1)				BWS outcome = most (+1)			
BWS outcome	Est.	S.E.	Wald	Sig	Est.	S.E.	Wald	Sig
[Q10 = 1]	0.110	0.170	0.420	0.517	−0.337	0.155	4.721	0.030
[Q10 = 2]	0.226	0.297	0.578	0.447	−0.721	0.303	5.657	0.017
[Q10 = 3]	−0.180	0.344	0.274	0.601	−0.530	0.329	2.588	0.108
[Q10 = 4]	0.287	0.191	2.267	0.132	−0.416	0.177	5.510	0.019
[Q10 = 5]	0.241	0.321	0.562	0.454	0.318	0.323	0.973	0.324
[Q10 = 6]	0.147	0.170	0.752	0.386	−0.304	0.158	3.717	0.054
[Q10 = 7]	0	–	–	–	0	–	–	–
[Q11 = 1]	−0.316	0.208	2.316	0.128	0.334	0.185	3.256	0.071
[Q11 = 2]	−0.787	0.224	12.325	0.000	0.455	0.201	5.100	0.024
[Q11 = 3]	−0.102	0.191	0.287	0.592	0.372	0.168	4.914	0.027
[Q11 = 4]	0	–	–	–	0	–	–	–
[DX3 = 1]	−0.296	0.556	0.284	0.594	−1.023	0.546	3.514	0.061
[DX3 = 2]	−0.308	0.566	0.296	0.586	−1.629	0.556	8.594	0.003
[DX3 = 3]	−0.300	0.554	0.294	0.587	−1.308	0.544	5.784	0.016
[DX3 = 4]	0.341	0.580	0.347	0.556	−1.133	0.570	3.951	0.047
[DX3 = 5]	−0.543	0.567	0.917	0.338	−0.908	0.552	2.711	0.100
[DX3 = 6]	−0.356	0.571	0.389	0.533	−0.499	0.561	0.790	0.374
[DX3 = 7]	−0.033	0.568	0.003	0.954	−0.795	0.559	2.025	0.155
[DX3 = 8]	−0.721	0.627	1.325	0.250	−0.863	0.597	2.089	0.148
[DX3 = 9]	−0.105	0.559	0.035	0.851	−1.014	0.549	3.404	0.065
[DX3 = 10]	1.495	0.681	4.823	0.028	−1.053	0.651	2.614	0.106
[DX3 = 11]	−0.832	0.583	2.033	0.154	−1.438	0.569	6.383	0.012
[DX3 = 12]	−0.244	0.564	0.186	0.666	−0.318	0.554	0.329	0.566
[DX3 = 13]	0	–	–	–	0	–	–	–
[DX5 = 1]	−0.020	0.208	0.009	0.923	−0.432	0.192	5.070	0.024
[DX5 = 2]	−0.089	0.246	0.133	0.716	−0.136	0.228	0.357	0.550
[DX5 = 3]	0	–	–	–	0	–	–	–
[DX7 = 1]	0.515	0.242	4.519	0.034	0.654	0.223	8.572	0.003
[DX7 = 2]	0.971	0.259	14.089	0.000	0.637	0.240	7.041	0.008
[DX7 = 3]	0.889	0.240	13.693	0.000	0.501	0.220	5.179	0.023
[DX7 = 4]	0	–	–	–	0	–	–	–
[DX8 = 1]	−0.231	0.311	0.551	0.458	0.276	0.299	0.852	0.356
[DX8 = 2]	0.785	0.360	4.754	0.029	0.519	0.342	2.306	0.129
[DX8 = 3]	−0.073	0.369	0.040	0.842	−0.049	0.349	0.020	0.888
[DX8 = 4]	−0.310	0.313	0.978	0.323	−0.431	0.297	2.102	0.147
[DX8 = 5]	0.248	0.297	0.698	0.403	0.096	0.286	0.113	0.737
[DX8 = 6]	0.298	0.293	1.039	0.308	0.139	0.284	0.240	0.624
[DX8 = 7]	0.633	0.280	5.119	0.024	0.870	0.271	10.345	0.001
[DX8 = 8]	0.104	0.273	0.144	0.705	−0.129	0.273	0.222	0.637
[DX8 = 9]	0	–	–	–	0	–	–	–
[DX9 = 1]	−0.004	0.282	0.000	0.988	0.203	0.264	0.593	0.441

Table 10.A3 (*cont.*)

	BWS outcome = least (−1)				BWS outcome = most (+1)			
BWS outcome	Est.	S.E.	Wald	Sig	Est.	S.E.	Wald	Sig
[DX9 = 2]	0.076	0.247	0.094	0.759	−0.037	0.231	0.026	0.872
[DX9 = 3]	0.394	0.212	3.438	0.064	−0.001	0.204	0.000	0.998
[DX9 = 4]	0.659	0.250	6.941	0.008	0.102	0.250	0.166	0.683
[DX9 = 5]	1.241	0.422	8.632	0.003	0.398	0.400	0.990	0.320
[DX9 = 6]	0.002	0.304	0.000	0.994	0.414	0.284	2.121	0.145
[DX9 = 7]	1.776	0.287	38.298	0.000	0.788	0.271	8.435	0.004
[DX9 = 8]	0	–	–	–	0	–	–	–
[DX10 = 1]	−0.705	0.205	11.812	0.001	−0.104	0.191	0.297	0.586
[DX10 = 2]	0.236	0.240	0.968	0.325	−0.389	0.229	2.891	0.089
[DX10 = 3]	−1.160	0.213	29.587	0.000	−0.247	0.189	1.705	0.192
[DX10 = 4]	0.525	0.230	5.221	0.022	−0.074	0.218	0.116	0.733
[DX10 = 5]	0.409	0.267	2.346	0.126	0.145	0.249	0.341	0.559
[DX10 = 6]	−0.038	0.188	0.042	0.838	0.184	0.177	1.088	0.297
[DX10 = 7]	−0.039	0.330	0.014	0.906	−0.408	0.317	1.664	0.197
[DX10 = 8]	−1.345	0.297	20.436	0.000	−0.882	0.271	10.558	0.001
[DX10 = 9]	0	–	–	–	0	–	–	–
[DX11 = 1]	−0.100	0.235	0.180	0.672	−0.703	0.217	10.528	0.001
[DX11 = 2]	0	–	–	–	0	–	–	–
[DX12 = 1]	−0.093	0.149	0.394	0.530	−0.023	0.138	0.028	0.867
[DX12 = 2]	−0.414	0.164	6.390	0.011	0.041	0.153	0.070	0.791
[DX12 = 3]	0	–	–	–	0	–	–	–
[DX19 = 0]	−0.338	0.122	7.611	0.006	−0.520	0.114	20.703	0.000
[DX19 = 1]	−0.341	0.151	5.134	0.023	−0.253	0.138	3.371	0.066
[DX19 = 2]	−0.800	0.212	14.226	0.000	−1.066	0.199	28.635	0.000
[DX19 = 3]	−1.182	0.473	6.247	0.012	−0.542	0.414	1.716	0.190
[DX19 = 4]	0.592	0.430	1.895	0.169	−1.160	0.409	8.056	0.005
[DX19 = 5]	0	–	–	–	0	–	–	–

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