

## Response to Desvousges, Mathews and Train

John Whitehead, September 29, 2017

DMT consider the problem to be the contingent valuation method (CVM) and “inadequate response to cost” instead of their execution of their study. The nonparametric willingness to pay (WTP) estimation approach used in DMT yields small standard errors that allow rejection of adding-up but this is an artifact of pooling bids from non-monotonically decreasing bid curves as my parametric analysis shows.<sup>1</sup> In other fields of economics pooling of bids is negatively described as data cleaning when the data does not fit the theory. Data pooling is legitimate CVM practice when the goal is to produce lower bound nonparametric WTP estimates for natural resource damage assessment. Data cleaning should not be considered a valid research method when the goal is conducting validity tests as in DMT (2012).

Whenever bids are pooled using dichotomous choice data, the researcher implicitly acknowledges that something went wrong with the execution of the study or with the CVM itself. It might be that (a) bid subsamples are too low to generate enough power to conduct the statistical test, (b) bids are poorly designed, (c) survey respondents took little care in answering the valuation questions or (d) survey respondents are irrational or inconsistent.

The DMT data suffers from problem (a) but not likely (b) since DMT claim that they used the same surveys developed by Chapman et al. (2009). Based on my own recent experience it is likely that (c) is a problem in DMT (2012). In the past several years I have conducted no less than four separate stated preference surveys with the same opt-in panel vendor used by DMT.<sup>2</sup> In each instance, I have encountered similar problems. Inexpensive opt-in samples are useful for split-sample experimental analyses but any broad generalizations should be done with the caveat that the data quality is low and errors are likely.

There is substantial evidence in the contingent valuation literature to reject (c) and (d) when the data is high quality. But, readers unfamiliar with the contingent valuation method literature should see the Appendix to this response where I conduct a similar analysis with the Chapman et al. (2009) data with sample sizes adjusted downward to match the DMT sample size. Higher quality data tends to avoid the “inadequate response to cost” problem.

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<sup>1</sup> See Whitehead (ECON Journal Watch 2017) for another example of inappropriate use of the Turnbull estimator.

<sup>2</sup> See Bake et al. (Public Opinion Quarterly 2010) for a report on data quality and opt-in panels. Opt-in panel samples tend to be more expensive than Amazon Mechanical Turk and less expensive than probability-based online panels such as the GfK Knowledge Panel.

## Appendix. Contrast with Chapman et al. (2009)

The parametric WTP estimates in DMT (2012) exhibit significant variability. The wide ranges are due to the nonmonotonicity of the DMT data over the cost amounts. The high variability of results is in contrast to dichotomous choice CVM data that is monotonically decreasing in the cost amount. To illustrate I apply the bid curve probabilities from Table 6.27 of Chapman et al. (2009) to the sample sizes of DMT (2012). The data problems in DMT (2012) are further exposed by comparison with results using the simulated Chapman et al. (2009) data.

Chapman et al. (2009) field base and scope treatments which are called the whole and second scenarios in DMT (2012). Chapman et al. (2009) use a probability-based sample and in-person interviews. DMT (2012) use an online opt-in sample and an online survey. Both of these features of Chapman et al. (2009) tend to result in higher quality data.

Chapman et al.'s (2009) sample sizes are much larger,  $n = 1093$  and  $n = 544$  than those used by DMT (2012) for the same scenarios ( $n = 166$  and  $n = 152$ ). In order to create the yes/no data with similar sample sizes I multiply the sub-sample sizes from the DMT study to the percentage yes responses from Chapman et al. (2009) and round to the nearest integer (Table A-1). The "simulated" percentage yes responses differ slightly from those in the Chapman et al. (2009) data due to the small sample sizes and rounding. But, the basic pattern of results is similar.

The simulated bid curve for the whole scenario (i.e., "base" scenario in Chapman et al. 2009) is non-monotonically decreasing in only one cost amount. The simulated bid curve for the second scenario (i.e., scope scenario) is monotonically decreasing. Both of the simulated bid curves are steep relative to the DMT bid curves for the same scenarios. The overall simulated percentage yes responses is similar in the whole scenario but 43% higher in the simulated second scenario compared to the DMT data.

While the bid curves are very different the simulated Chapman et al. (2009) data produces a Turnbull WTP estimate, \$188, similar to that produced by the DMT data, \$200, for the whole scenario. The simulated Chapman et al. (2009) data produces a Turnbull estimate different than that produced by the DMT (2012) data for the second scenario. The Turnbull mean WTP estimate is \$139 with the simulated data compared to \$84 with the DMT data.

In Table A-2 I present regression models similar to those in Table 5. Each of the regression coefficients is statistically different from zero except for the second constant in the linear logit model.

The WTP estimates calculated from the regression models in Table A-2 are presented in Table A-3. The mean WTP estimates for the whole scenario range from \$228 to \$291. The median WTP estimate from the log linear model is \$170. The mean WTP estimates for the second scenario range from \$64 to \$228 with a median of \$48 in the log-linear model. As in Table 5, the

lower end of the range is from the linear logit model that allows negative WTP and the upper end of the range is from same model that constrains WTP to be positive.

Comparing these results to those in Table 6, the range of estimates is much narrower with the higher quality simulated Chapman et al. (2009) data. The ratios of the WTP range to WTP midpoint are 58% and 665% for whole and second scenario from the DMT data. The ratios of the WTP range to WTP midpoint from the simulated data is 24% and 112% for whole and second scenario in the simulated Chapman et al. (2009) data. As this comparison shows, the flatter the bid curve the wider the range of potential WTP estimates that could be used for hypothesis testing.

Table A-1. Simulated Dichotomous Choice CVM Data from Chapman et al. (2009) Bid Curves

Cost	<u>Base = Whole</u>			
	Simulated		<u>% Yes</u>	
	Yes	N	Simulated	Chapman et al.
10	20	24	83	82
45	22	31	71	70
80	16	26	62	60
125	16	26	62	62
205	12	28	43	44
405	11	31	36	34
Total	97	166	58	58
Cost	<u>Scope = Second</u>			
	Simulated		<u>% Yes</u>	
	Yes	N	Simulated	Chapman et al.
10	17	24	71	71
45	13	28	46	48
80	10	23	43	41
125	11	28	39	39
205	8	24	33	31
405	7	25	28	29
Total	66	152	43	43

Table A-2. Dichotomous Choice Probability Models with Chapman et al. (2009) Simulated Data

Intercept	Linear Logit			Log Linear Logit		
	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat
Whole	1.070	0.254	4.21	3.23	0.78	4.14
Second	0.226	0.247	0.92	1.86	0.69	2.70
Slope	Coefficient	S.E.	t-stat	Coefficient	S.E.	t-stat
Whole	-0.005	0.001	-3.76	-0.63	0.16	-3.87
Second	-0.004	0.001	-2.56	-0.48	0.15	-3.17
$\chi^2$		29.85			35.79	
McFadden R <sup>2</sup>		0.07			0.08	
Sample size		318			318	

Table A-3. Willingness to Pay Estimates with Chapman et al. (2009) Simulated Data

	Linear Logit						Log Linear Logit		
	Mean WTP			Mean WTP > 0			Median WTP > 0		
	WTP	S.E.	t-stat	WTP	S.E.	t-stat	WTP	S.E.	t-stat
Whole	228	40	5.66	291	54	5.43	170	49	3.48
Second	64	54	1.18	228	66	3.44	48	19	2.55