A. SUPPLEMENTARY TABLES

Table A.1 - Regressions of current catch on monthly and annual abundance measures for the species, market expenses, trip frequencies, and demographic variables by zip code.

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.55995251	0.30007121	1.866
MMREDS	0.36847595	0.23700779	1.555
AREDS	-0.10965756	0.04224035	-2.596
MON	-0.000016971	0.000118226	-0.144
NSWTRIP	0.000788784	0.000874304	0.902
SITETRIP	0.005368462	0,000797330	6.733
PRETIRED	0.85482835	0.72060800	1.186
PSPANISH	0.75937497	0.26831368	2.830
PSPNOENG	0.65719318	0.83394446	0.788
PVIETNAM	-9.52181432	4.10336572	-2.320
PURBAN	-0.18475126	0.06936814	-2.663
PTEXNATV	-0.69407659	0.27218848	-2.550
PFFFISH	4.39061789	1.80245578	2.436
HHLDINC	0.000012134	0.0000073043	1.661

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.32098798	0.96852747	0.331
MMTROUT	0.4602S04S	0.5518182S	0.834
ATROUT	-0.10727163	0.086S9900	-1.239
MON	0.000344210	0.000391106	0.880
NSUTRIP	0.000856360	0.002804431	0.305
SITETRIP	0.008488526	0.0025S5053	3.322
PRETIRED	-2.23625648	2.31717300	-0.965
PSPANISH	2.S0439916	0.909684S9	2.7S3
PSPNOENG	-4.76702938	2.65016291	-1.799
PVIETNAM	-v10.54180776	13.22176053	-0.797
PURBAN	0.007S74193	0.22341404	0.034
PTEXNATV	1.61013946	0.92900808	1.733
PFFFISH	4.43354471	5.80127597	0.764
HHLDINC	0.000016170	0.00002341S	0.691

Table A.1, continued

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	3.30401254	0.98231253	3.364
MMCROAK	-1.23508097	0.45744060	-2.700
ACROAK	0.08828395	0.09482006	0.931
MON	-0.001526458	0.000391878	-3.895
NSWTRIP	-0.006019254	0.002894183	-2.080
SITETRIP	-0.001736803	0.002636454	-0.659
PRETIRED	-3.96485185	2.37842920	-1.667
PSPANISH	-9.44617850	0.91612331	-10.311
PSPNOENG	16.61375283	2.78349049	5.969
PVIETNAM	34.13699452	13.59965826	2.510
PURBAN	1.00645150	0.22970427	4.382
PTEXNATV	4.46549691	0.89550728	4.987
PFFFISH	-26.83794821	5.96099955	-4.502
HHLDINC	-0.000175471	0.000024158	-7.263

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	2.60203861	1.27890185	2.035
MMSAND	0.13525806	0.62965032	0.215
ASAND	0.34725560	0.12388076	2.803
MON	0.003049747	0.000506331	6.023
NSWTRIP	0.000772157	0.003762673	0.205
SITETRIP	0.002321740	0.003427697	0.677
PRETIRED	-6.69928574	3.10020622	-2.161
PSPANISH	-5.S5781967	1.15362653	-4.818
PSPNOENC	8.36237511	3.52678402	2.371
PVIETNAX	-37.14203944	17.67071748	-2.102
PURBAN	1.00236870	0.29815854	3.362
PTEXNATV	1.47548162	1.15738S69	1.275
PFPFISH	18.26459246	7.73754036	2.361
HHLDINC	-0.000122238	0.000031442	-3.888

Table A.1, continued

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.21504911	0.15372003	-1.399
MMBLACK	-0.03098885	0.11983304	-0.259
ABLACK	0.02454022	0.01586489	1.547
MON	-0.000098978	0.000060809	-1.628
NSWTRIP	-0.000610036	0.000452134	-1.349
SITETRIP	0.000872498	0.000411767	2.119
PRETIRED	-0.51376786	0.37191902	-1.381
PSPANISH	-0.88597982	0.13901951	-6.373
PSPNOENC	2.70210744	0.42860428	6.304
PVIETNAM	-0.11057677	2.12731804	-0.052
PURBAN	0.04845612	0.03601018	1.346
PTEXNATV	0.66908968	0.13901599	4.813
PFFFISH	0.23180632	0.93050578	0.249
HHLDINC	-.0000017218	.00000377165	-0.457

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.06836968	0.21828737.	0.313
HMSHEEP	0.12234247	0.15810969	0.774
ASHEEP	-0.04147377	0.03175789	-1.306
MON	0.000139507	0.000087330	1.597
NSWTRIP	0.002547533	0.000636643	4.002
SITETRIP	0.000655088	0.000579990	1.129
PRETIRED	-0.22178639	0.52319454	-0.424
PSPANISH	0.06904953	0.19867934	0.348
PSPNOENC	-0.55274431	0.60979506	-0.906
PVIETNAM	-2.34572452	3.01854217	-0.777
PURBAN	0.02545117	0.05043334	0.505
PTEXNATV	-0.002006479	0.20671267	-0.010
PFFFISH	2.93979145	1.31880893	2.229
HHLDINC	-.0000027911	.00000531521	-0.525

Table A.1, continued

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.01970803	0.32426667	-0.061
MMFLOUND	-0.61281021	0.20575268	-2.978
AFLOUND	-0.15836960	0.03617201	-4.378
MON	-0.000077295	0.000129670	-0.596
NSWTRIP	0.007868546	0.000943887	8.336
SITETRIP	-0.000819604	0.000860134	-0.953
PRETIRED	1.13867584	0.78206752	1.456
PSPANISH	-0.98520829	0.30517406	-3.228
PSPNOENG	2.04588931	0.91854214	2.227
PVIETNAM	1.06771366	4.44847267	0.240
PURBAN	0.16953815	0.07518352	2.255
PTEXNATV	0.63002837	0.30251588	2.083
PFPPISH	-1.23657S29	1.94501820	-0.636
HHLDINC	-.0000037847	.00000789691	-0.479

Table A.2 - Regressions of current catch on major bay and monthly dummy variables

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.05034214	0.07581144	0.664
MJ1	0.09586074	0.16287253	0.589
MJ3	0.47034606	0.09943735	4.730
MJ4	0.41556795	0.12293509	3.380
MJ5	0.19918153	0.08094287	2.461
MJ6	0.19034190	0.07985535	2.384
MJ7	0.39698000	0.09674908	4.103
MJ8	0.87774944	0.08008518	10.960
MN5	0,04357481	0.09756501	0.447
MN6	0.04480128	0.09810146	0.457
MN8	0.20531995	0.08224176	2.497
MN9	0.38649084	0.08346977	4.630
MN10	0.39501347	0.08322912	4.746
MN11	0.26375298	0.10148514	2.599

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	2.02945978	0.24217103	8.380
MJ1	-0.30959043	0.52027779	-0.595
MJ3	0.60509801	0.31764131	1.905
MJ4	1.48200S34	0.39270218	3.774
MJ5	-0.45785320	0,25856281	-1.771
MJ6	-0.23295552	0.25508884	-0.913
MJ7	1.81081777	0.30905394	5.859
MJ8	0.77603162	0.25582300	3.033
MN5	-0.19569724	0.31166034	-0.628
MN6	-0.61720332	0.31337396	-1.970
MN8	-0.37767862	0.26271195	-1.438
MN9	-0.51615104	0.26663468	-1.936
MN10	-0.43755749	0.26586596	-1.646
MN11	-0.08592488	0.32418277	-0.265

Table A.2, continued

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	1.80420655	0.25440856	7.092
MJ1	0.15435967	0.54656879	0.282
MJ3	-1.44501071	0.33369255	-4.330
MJ4	-0.96835590	0.41254645	-2.347
MJ5	-1.22670089	0,27162867	-4.516
MJ6	0.12211734	0.2679791S	0.456
MJ7	-0.80625121	0.32667124	-2.483
MJ8	-1.77502414	0.26875041	-6.605
MN5	-0.52584969	0.32760935	-1.606
MN6	-0.52478913	0.32920957	-1.594
MN8	1.30543161	0,27S98747	4.730
MN9	0.54887768	0.28010843	1.960
MN10	0.24721955	0.27930087	0.885
MN11	-0.73844884	0.34056457	-2.168

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	1.49360615	0.32742378	4.562
Ml	-1.75665494	0.70343395	-2.497
MJ3	-1.55240358	0.42946227	-3.615
MJ4	-1.25885186	0.53094723	-2.371
MJ5	-1.05708742	0.34958605	-3.024
MJ6	-1.56950545	0.34488913	-4.551
MJ7	-2.36323791	0.41785184	-5.656
MJ8	-1.87517327	0.34588174	-5.421
MN5	0.39706249	0.42137579	0.942
MN6	0.32002563	0.42369266	-0.75s
MN8	0.63333692	0.35519583	1.783
MN9	0.43997674	0.36049951	1.220
MN10	0.84778208	0.35946017	2.358
MN11	2.84404560	0.43830655	6.489

Table A.2, continued

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.20731884	0.03932264	5.272
MJ1	-0.02152089	0.08448036	-0.255
MJ3	-0.12508682	0.05157716	-2.425
MJ4	-0.12285552	0.06376521	-1.927
MJ5	-0.15597693	0.04198426	-3.715
MJ6	-0.11956589	0.04142017	-2.887
MJ7	-0.13773178	0.05018278	-2.745
MJ8	-0.15204360	0.04153938	-3.660
MN5	-0.07209143	0.05060600	-1.425
MN6	-0.04345460	0.05088425	-0.854
MN8	-0.01226179	0.04265798	-0.287
MN9	0.02200455	0.04329494	0.508
MN10	0.14766722	0.04317011	3.421
MN11	0,05904913	0.05263933	1.122

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.12359373	0.05514031	2.241
MJ1	-0.19739614	0.11846289	-1.666
MJ3	-0.01479838	0.07232426	-0.205
MJ4	-0.06177563	0.08941499	-0.691
MJ5	-0.07825227	0.05887258	-1.329
MJ6	-0.14568843	0.05808159	-2.508
MJ7	-0.24692556	0.07036899	-3.509
MJ8	-0.15689291	0.05824875	-2.693
MN5	0.05152056	0.07096245	0.726
MN6	-0.007780611	0.07135262	-0.109
MN8	0.03604168	0.05981731	0.603
MN9	-0.004137654	0.06071048	-0.068
MH10	0.05014380	0.06053545	0.828
MN11	0.47535803	0.07381370	6.440

Table A.2, continued

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.82159657	0.08199456	10.020
MJ1	-0.31496533	0.17615627	-1.788
MJ3	-0.30390463	0.10754737	-2.826
MJ4	-0.63615308	0.13296157	-4.784
MJ5	-0.79315402	0.08754450	-9.060
MJ6	-0.79126378	0.08636828	-9.162
MJ7	-0.73886256	0.10463985	-7.061
MJ8	-0.63S85291	0.08661686	-7.341
MN5	0.06951967	0.10552233	0.659
MN6	0.13816270	0.10610253	1.302
MN8	0.15535632	0.08894932	1.747
MN9	0.05658948	0.09027749	0.627
MN10	0.23391866	0.09001721	2.599
MN11	0.78029069	0.10976219	7.109

Table A.3 - Regressions of current catch on monthlv abundance index-, demographic variables, and major bay dummy variables

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.08249090	0.30620085	0.269
MMREDS	0.31460321	0.24591373	1.279
MON	-0.000126631	0.000119475	-1.060
NSWTRIP	0.000997362	0.000871506	1.144
SITETRIP	0.005338593	0.000792004	6.741
PRETIRED	0.40792992	0.72216553	0.565
PSPANISH	0.94774237	0.29027646	3.265
PSPNOENG	-1.92730218	0.94335117	-2.043
PVIETNAM	-6.30008634	4.13511627	-1.524
PURBAN	-0.17926668	0.06960719	-2.575
PTEXNATV	-0.35985526	0.28079594	-1.282
PFFFISH	4.06562241	1.79684467	2.263
HHLDINC	0.000014557	.00000727471	2.001
MJ1	0.22117083	0.16308096	1.356
MJ3	0.41258319	0.10128207	4.074
MJ4	0.29340746	0.11918553	2.462
MJ5	0.11045001	0.08697339	1.270
MJ6	0.14403815	0.08637686	1.668
MJ7	0.36564235	0.09914413	3.688
MJ8	0.80571613	0.09778452	8.240

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.32926072	0.98058040	0.336
MMTROUT	0.72672191	0.51692313	1.406
MON	0.000418306	0.000383818	1.090
NSWTRIP	0.001301984	0.002790464	0.467
SITETRIP	0.009021724	0.002535271	3.558
PRETIRED	-1.40101257	2.31274943	-0.606
PSPANISH	2.38954617	0.93836731	2.546
PSPNOENG	-6.87307423	3.02935838	-2.269
PVIETNAM	-5.11369468	13.24493296	-0.386
PURBAN	-0.08751728	0.22300185	-0.392
PTEXNATV	1.51843888	0.90477954	1.678
PFFFISH	1.66646879	5.76057977	0.289
HHLDINC	0.000014731	0.000023296	0.632
MJ1	-0.12522173	0.51372014	-0.244
MJ3	0.46603374	0.32238217	1.446
MJ4	1.42956747	0.38169115	3.745
MJ5	-0.73896336	0.29216032	-2.529
MJ6	-0.56608140	0.27586664	-2.052
MJ7	1.58614179	0.30245190	5.244
MJ8	0.62707082	0.32306103	1.941

Table A.3. continued

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	2.66756373	1.00525808	2.654
MMCROAK	-3.98638283	0.40759600	-9.780
MON	-0.001477013	0.000392887	-3.759
NSWTRIP	-0.006107054	0.002860786	-2.135
SITETRIP	-0.001945570	0.002599357	-0.748
PRETIRED	-2.84572618	2.37166305	-1.200
PSPANISH	-10.44237560	0.96981335	-10.767
PSPNOENG	21.96652769	3.12265143	7.035
PVIETNAM	42.50799742	13.57571203	3.131
PURBAN	0.88205153	0.22857272	3.859
PTEXNATV	4.60465670	0.92367915	4.985
PFFFISH	-25.60229589	5.90128326	-4.338
HHLDINC	-0.000159420	0.000023899	-6.671
MJ1	-1.32428223	0.52467711	-2.524
MJ3	-1.26997939	0.32994369	-3.849
MJ4	-1.09222587	0.39260972	-2.782
MJ5	-0.23015884	0.28546340	-0.806
MJ6	2.96516199	0.32860335	9.024
MJ7	-0.10117965	0.31440281	-0.322
MJ8	-0.30969034	0.32172324	-0.963

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTINATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	3.49528262	1.33092771	2.626
MMSAND	0.72768171	0.58049126	1.254
MON	0.003208116	0.000516215	6.215
NSWTRIP	0.000111362	0.003769108	0.030
SITETRIP	0.002300422	0.003424049	0.672
PRETIRED	-6.18159589	3.12377497	-1.979
PSPANISH	-4.92447442	1.25551174	-3.922
PSPNOENG	8.32102379	4.07928230	2.040
PVIETNAM	-43.08458320	17.88205173	-2.409
PURBAN	0.98033470	0.30113908	3.255
PTEXNATV	1.59438668	1.21376362	1.314
PFFFISH	20.77898656	7.76855507	2.675
HHLDINC	-0.000125297	0.000031474	-3.981
MJ1	-1.26918171	0.70113740	-1.810
MJ3	-1.80970744	0.44122254	-4.102
MJ4	-1.69999347	0.55660418	-3.054
MJ5	-0.93288233	0.41761009	-2.234
MJ6	-1.51242967	0.37264711	-4.059
MJ7	-1.47083745	0.46585384	-3.157
MJ8	-1.88560063	0.44713447	-4.217

Table A.3, continued

DEP VARIABLE: BUCK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.06527348	0.15959629	-0.409
MMBLACK	-0.03127245	0.12061281	-0.259
MON	-0.000069184	0.000062054	-1.115
NSWTRI	-0.000675180	0.000452805	-1.491
SITETRIP	0.000844350	0.000411388	2.052
PRETIRED	-0.38407660	0.37526227	-1.023
PSPANISH	-0.81824332	“0.15091174	-5.422
PSPNOENG	2.86581250	0.49012528	5.847
PVIETNAM	-1.20317407	2.14842043	-0.560
PURBAN	0.04742877	0.03617276	1.311
PTEXNATV	0.58276254	0.14602230	3.991
PFFFISH	0.39924427	0.93388199	0.428
HHLDINC	-.0000024413	.00000378035	-0.646
MJ1	-0.04210067	0.08343432	-0.505
MJ3	-0.12673404	0.05401686	-2.346
MJ4	-0.15692987	0.06429929	-2.441
MJ5	-0.11390689	0.04643952	-2.453
MJ6	-0.06697295	0.04542878	-1.474
MJ7	-0.10752456	0.04999241	-2.151
MJ8	-0.21494500	0.05137572	-4.184

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.18397633	0.22424085	0.820
MMSHEEP	0.19706534	0.16868340	1.168
MON	0.000146931	0.000087682	1.676
NSWTRIP	0.002501075	0.000638205	3.919
SITETRIP	0.000654810	0.000579796	1.129
PRETIRED	-0.10899880	0.52896178	-0.206
PSPANISH	0.18634607	0.21297531	0.875
PSPNOENG	-0.98841053	0.69064803	-1.431
PVIETNAM	-3.18386372	3.02844868	-1.051
PURBAN	0.02463802	0.05097815	0.483
PTEXNATV	0.03107763	0.20624852	0.151
PFFFISH	2.90768177	1.32049588	2.202
HHLDINC	-.0000038586	.00000532886	-0.724
MJ1	-0.11879970	0.11723539	-1.013
MJ3	-0.08906114	0.07379417	-1.207
MJ4	-0.18881993	0.09180317	-2.057
MJ5	-0.11501370	0.06391136	-1.800
MJ6	-0.16932811	0.06321095	-2.679
MJ7	-0.21894058	0.06971473	-3.141
MJ8	-0.22701709	0.08198620	-2.769

Table A.3. continued

DEP VARIABLE: FLOUND

VARIABLE	PAMMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.21204966	0.33183132	0.639
MMFLOUND	-0.49321815	0.21939866	-2.248
MON	-0.000066724	0.000129246	-0.516
NSWTRIP	0.007551138	0.000943757	8.001
SITETRIP	-0.000819620	0.000857429	-0.956
PRETIRED	1.36027395	0.78225188	1.739
PSPANISH	-0.71324691	0.31584173	-2.258
PSPNOENG	0.81296362	1.02514679	0.793
PVIETNAM	0.52069004	4.47714546	0.116
PURBAN	0.16554232	0.07538672	2.196
PTEXNATV	0.93747057	0.30394040	3.084
PFFFISH	-0.37430053	1.9k690673	-0.192
HHLDINC	-.0000050267	.00000787969	-0.638
MJl	-0.35044016'	0.17397636	-2.014
MJ3	-0.43350722	0.10925459	-3.968
MJ4	-0.80589558	0.12901976	,6.246
MJ5	-0.65223380	0.10370180	-6.290
MJ6	-0.63117761	0.09957913	-6.338
MJ7	-0.55085946	0.10597766	-5.198
MJ8	-0.42631471	0.10855894	-3.927

Table A.4a - Average "Annual" Actual Catch Rates by Sample Respondents (for May-Nov 1987); by Major Bay System

MAJOR	AAREDS	AATROUT	AACROAK	AASAND	AABLACK	AASHEEP	AAFLOUND
1	0.35000	1.44286	1.63571	0.75714	0.214286	0.064286	0.785714
2	0.21942	1.68155	1.92039	1.93689	0.219417	0.172816	0.982524
3	0.70226	2.34292	0.46612	0.19713	0.117043	0.119097	0.603696
4	0.57912	3.36027	0.99663	0.36364	0.090909	0.060606	0.202020
5	0.42059	1.29244	0.75575	1.05586	0.062432	0.118291	0.205915
6	0.45898	1.45691	2.21288	0.63344	0.115265	0.055036	0.236760
7	0.62898	3.56847	1.31051	0.15446	0.057325	0.007962	0.340764
8	1.16386	2.48221	0.33708	0.23034	0.086142	0.014045	0.331461

Table A.4b - OLS Regressions of Actual Individual Catch Rates on Average Rates for Sample Anglers (for each bay and month, MAxxxxxx, and for each bay, AAxxxxxx).

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.12266561	0.29823802	-0.411
MAREDS	0.95085659	0.08092220	11.750
MREDS	-0.05043007	0.12278424	-0.411
MON	-0.000092812	0.000115702	-0.802
NSWTRIP	0.000923382	0.000857973	1.076
SITETRIP	0.005093002	0.000781527	6.517
PRETIRED	0.45725770	0.70551913	0.648
PSPANISH	0.72133204	0.26179804	2.755
PSPNOENG	-1.2285452S	0.82771249	-1.484
PVIETNAM	-4.92451856	4.04183705	-1.218
PURBAN	-0.18016933	"0.06794174	-2.652
PTEXNATV	-0.34731022	0.26481849	-1.312
PFFFISH	2.72013126	1.76799000	1.539
HHLDINC	0.000013987	.00000716232	1.953

Table A.4b, continued

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-1.36523478	0.9&998077	-1.437
MATROUT	0.98197610	0.10033556	9.787
AATROUT	0.006042790	0.14070736	0.043
MON	0.000286035	0,000370669	0.772
NSWTRIP	0.001863515	0.002757012	0.676
SITETRIP	0.008918273	0.002511557	3.551
PRETIRED	-1.43720691	2.26629296	-0.634
PSPANISH	1.43940886	0.84354198	1.706
PSPNOENG	-3.82852658	2.58495718	-1.481
PVIETNAM	-2.07403981	12.94627157	-0.160
PURBAN	-0.07554478	0.21864170	-0.346
PTEXNATV	1.53446304	0.84795042	1.810
PFFFISH	-1.98870119	5.68333396	-0.350
HHLDINC	0.000010671	0.000023018	0.464

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	1.81057461	0.97371072	1.859
MACROAK	0.83774972	0.06864557	12.204
AACROAK	0.11396771	0.13693499	0.832
MON	-0.001215592	0.000383033	-3.174
NSWTRIP	-0.005338101	0.002844955	-1.876
SITETRIP	-0.001572947	0.002590113	-0.607
PRETIRED	-1.90685717	2.34453169	-0.813
PSPANISH	-8.60976875	0.88171963	-9.765
PSPNOENG	18.04502300	2.73232498	6.604
mIETNAM	31.27438S50	13.34679054	2.343
PURBAN	0.82502684	0.22594926	3.651
PTEXNATV	3.72817129	0.87S67771	4.257
PFFFISH	-21.13769899	5.86344930	-3.605
HHLDINC	-0.000159098	0.000023783	-6.690

Table A.4b, continued

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	1.04106408	1.26437786	0.823
MASAND	0.98233478	0.07436923	13.209
AASAND	0.11303100	0.18715312	0.604
MON	0.003017771	0.000497673	6.064
NSWTRIP	-0.001733434	0.003701859	-0.468
SITETRIP	0.000968215	0.003369551	0.287
PRETIRED	-5.89965190	3.04239513	-1.939
PSPANISH	-4.58440729	1.14376694	-4.008
PSPNOENG	7.47884232	3.46885734	2.156
PVIETNAM	-46.01016400	17.40831290	-2.643
PURBAN	0.91626869	0.29301929	3.127
PTEXNATV	1.94350416	1.13489728	1.712
PFFFISH	18.23397447	7.61793262	2.394
HHLDINC	-0.000110765	0.000030901	-3.585

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.29092946	0.15268688	-1.905
MABLACK	0.96665317	0.09114036	10.606
AABLACK	-0.09573732	0.2S278827	-0.379
MON	-0.000071042	0.000060670	-1.171
NSWTRIP	-0.000674880	0.000447214	-1.509
SITETRIP	0.000671392	0.000407375	1.648
PRETIRED	-0.26273281	0.36938636	-0.711
PSPANISH	-0.61890961	0.14299078	-4.328
PSPNOENC	2.06309845	0.43075110	4.790
PVIETNAM	-0.74833926	2.10625389	-0.355
PURBAN	0.04133539	0.03551921	1.164
PTEXNATV	0.53988053	0.13864906	3.894
PFFFISH	0.35225404	0.92028645	0.383
HHLDINC	-5.35967E-07	.00000374053	-0.143

Table A.4b, continued

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.09047019	0.20353089	-0.445
MAWEEP	0.99441736	0.03670434	27.093
AASHEEP	0.04962667	0.31134446	0.159
MON	0.000051587	0.000080557	0.640
NWTRIP	0.002201864	0.000597400	3.686
SITETRIP	0.000382545	0.000544200	0.703
PRETIRED	0.05006948	0.49119093	0.102
PSPANISH	0.01381854	0.18550590	0.074
PSPNOENG	-0.32208556	0.55982006	-0.575
PVIETNAM	-3.32365172	2.82850803	-1.175
PURBAN	0.04434566	0.04734667	0.937
PTEXNATV	0.04907053	0.18406197	0.267
PFFFISH	2.55337512	1.22902375	2.078
HHLDINC	-.0000014707	.00000499508	-0.294

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.61623401	0.31048537	-1.985
MAFmJND	0.97594742	0.05182762	18.831
AAFLOUND	-0.021S3132	0.10986631	-0.196
MON	-0.000030626	0.000124319	-0.246
NSWTRIP	0.006652809	0.000914079	7.278
SITETRIP	-0.001277307	0.000831043	-1.537
PRETIRRD	1.44956602	0.75447296	1.921
PSPANISH	-0.43520381	0.29352799	-1.483
PSPNORNG	0.72106186	0.88677081	0.813
PVIETNAM	-1.86240792	4.30327459	-0.433
PURBAN	0.09270761	0.07250692	1.279
PTEXNATV	0.70903598	0.28266255	2.508
PFFFISH	-0.33088056	1.87895111	-0.176
HHLDINC	-4.07689E-07	.00000763403	-0.053

Table A.4 - OLS Regressions of Actual Individual Catch Rates on “Annual” Average Catch Rates (by bay system, AAxxxxxx)

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.17221294	0.30189259	-0.570
AAREDS	0.88499989	0.09463395	9.352
MON	-0.000142307	0.000117054	-1.216
NSWTRIP	0.001071111	0.000868480	1.233
SITETRIP	0.005384716	0.000790784	6.809
PRETIRED	0.33591552	0.71415935	0.470
PSPANISH	0.82939290	0.26486900	3.131
PSPNOENG	-1.50245838	0.83760654	-1.794
PVIETNAM	-6.08247392	4.09055782	-1.487
PURBAN	-0.17038106	0.06877599	-2.477
PTEXNATV	-0.32388801	0.26808275	-1.208
PFFFISH	4.01044819	1.78637790	2.245
HHLDINC	0.000014969	.00000725031	2.065

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER-0
INTERCEP	-1.46919676	0.95805247	-1.534
MTROUT	0.97625433	0.10071020	9.694
MON	0.000416560	0.000373599	1.115
NSWTRIP	0.001431302	0.002780255	0.515
SITETRIP	0.009029381	0.002533030	3.565
PRETIRED	-1.53660877	2.28566892	-0.672
PSPANISH	2.05603824	0.84838605	2.423
PSPNOENG	-5.2198S591	2.60313817	-2.005
PVIETNAM	-4.62037204	13.05445151	-0.354
PURBAN	-0.07380018	0.22051315	-0.335
PTEXNATV	1.39479051	0.85508754	1.631
PFFFISH	1.56510528	5.72027055	0.274
HHLDINC	0.00001598S	0.000023209	0.689

Table A.4C, continued

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER-0
INTERCEP	2.28572714	0.98589955	2.318
AACROAK	0.91638532	0.12171787	7.529
MON	-0.001416135	0.000387781	-3.652
NSWTRIP	-0.006336075	0.002881682	-2.199
SITETRIP	-0.001620966	0.002624632	-0.618
PRETIRED	-2.73498544	2.37478506	-1.152
PSPANISH	-10.42514263	0.88066463	-11.838
PSPNOENG	22.06274250	2.74857122	8.027
PVIETNAM	35.64921090	13.51980165	2.637
PURBAN	0.87878673	0.22891726	3.839
PTEXNATV	4.15492950	0.88664122	4.686
PFFFISH	-26.48~57430	5.92496424	-4.471
HHLDINC	-0.000177231	0.000024053	-7.368

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	1.41489731	1.28379481	1.102
MSAND	1.08298286	0.17483291	6.194
MON	0.003137767	0.000505358	6.209
NSWTRIP	0.000235592	0.003756601	0.063
SITETRIP	0.002220311	0.003420799	0.649
PRETIRED	-6.59692145	3.08942598	-2.135
PSPANISH	-4.84730866	1.16144683	-4.174
PSPNOENG	7.61299788	3.52299589	2.161
VIETNAM	-43.06236011	17.67862787	-2.436
PURBAN	0.98954192	0.29754040	3.326
PTEXNATV	1.73664712	1.15250486	1.507
PFFFISH	20.49016673	7.73491401	2.649
HHLDINC	-0.000123535	0.000031368	-3.938

Table A.4c, continued

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.26300398	0.15420014	-1.706
AABLACK	0.84957965	0.23893440	3.556
MON	-0.0000732,71	0.000061280	-1.196
NSWTRIP	-0.000649917	0.000451707	-1.439
SITETRIP	0.000826483	0.000411208	2.010
PRETIRED	-0.40638490	0.37285190	-1.090
PSPANISH	-0.70453147	0.14419906	-4.886
PSPNOENC	2.21811495	0.43483440	5.101
PVIETNAM	-1.10922521	2.12716746	-0.521
PUR8AN	0.04450246	0.03587531	1.240
PTEXNATV	0.59054447	0.13996088	4.219
PFFFISH	0.35238792	0.92954552	0.379
HHLDINC	-.0000025102	.00000377348	-0.665

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.03535211	0.21662870	-0.163
AASHEEP	1.14481671	0.32859181	3.484
MON	0.000147038	0.000085663	1.716
NSWTRIP	0.002511729	0.000635759	3.951
SITETRIP	0.000648276	0.000579156	1.119
PRETIRED	-0.16218767	0.52276013	-0.310
PSPANISH	0.14164609	0.19738974	0.718
PSPNOENC	-0.72252764	0.59566819	-1.213
PVIETNAM	-3.27210423	3.01068062	-1.087
PURBAN	0.03013284	0.05039299	0.598
PTEXNATV	0.01242447	0.19591140	0.063
PFFFISH	2.98360822	1.30807122	2.281
HHLDINC	-.0000038444	.00000531597	-0.723

Table A.4C, continued

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	-0.59237667	0.32028494	-1.850
AAFLOUND	0.92591610	0.10075174	9.190
MON	-0.000037291	0.000128243	-0.291
NSWTRIP	0.007522444	0.000941733	7.988
SITETRIP	-0.000864638	0.000856981	-1.009
PRETIRED	1.39301161	0.77828601	1.790
PSPANISH	-0.65905648	0.30254645	-2.178
PSPNOENG	1.15633766	0.91445592	1.265
PVIETNAM	-0.40499133	4.43841383	-0.091
PUR8AN	0.16577954	0.07468882	2.220
PTEXNATV	0.77931103	0.29156099	2.673
PFFFISH	-0.12527303	1.93823814	-0.065
HHLDINC	-.0000051086	0.0000787083	-0.649

Table A.5 - Pretrip Motivation Questions: OLS Regressions

DEP VARIABLE: NOPEOPLE

F-TEST 0.943
OBS 603

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	7.59185247	0.44738621	16.969
TARGR	0.52836370	0.24653310	2.143
TARGT	-0.34403082	0.24382515	-1.411
TARGF	0.47487337	0.47290029	1.004
MJ1	0.64433020	0.41974765	1.535
MJ3	0.84117457	0.46032060	1.827
MJ4	0.23616653	0.44200330	0.534
MJ5	0.34060028	0.46624780	0.731
MJ6	0.27210277	0.50602718	0.538
MJ7	0.27241992	0.54607083	0.499
MJ8	0.46534192	0.41754746	1.114
MN5	-0.04077979	0.38895224	-0.105
MN6	-0.04905820	0.34417911	-0.143
MN8	-0.37063712	0.35045962	-1.058
MN9	0.32841948	0.39216770	0.837
MN10	-0.19742662	0.36166775	-0.546
MN11	-0.09581740	0.44172970	-0.217
WKND	-0.01828012	0.21044572	-0.087

DEP VARIABLE: NOPOLLUT

F-TEST c 791
OBS 429

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	9.28862007	0.32744825	28.367
TARGR	-0.06010503	0.19483745	-0.308
TARGT	0.02721384	0.18658810	0.146
TARGF	-0.18077773	0.37549661	-0.481
MJ1	0.13636153	0.30518053	0.447
MJ3	0.06243266	0.36528564	0.171
MJ4	-0.18281956	0.27396226	-0.667
MJ5	-0.4024S959	0.35735465	-1.126
MJ6	-0.14210375	0.33100665	-0.429
MJ7	0.02401744	0.32870964	0.073
MJ8	0.0802S961	0.27896454	0.288
MN5	-0.007657418	0.31921439	-0.024
MN6	0.08823009	0.32933579	0.268
MN8	0.192079S7	0,25276985	0.760
MN9	0.25429200	0.27247807	0.933
MN10	-0.39582402	0.27040307	-1.464
MN11	-0.28337536	0.32430722	-0.874
WKND	0.10035740	0.19787569	0.507

DEP VARIABLE: DOWHTWNT

F-TEST 1.385
OBS 503

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	7. 709937k8	0.44125530	17.473
TARGR	-0.19641401	0.21523229	-0.913
TARGT	0.10541805	0.21296736	0.495
TARGF	0.26082970	0.39672252	0.657
MJ1	0.80886667	0.48840354	1.656
MJ3	1.33626023	0.43315279	3.085
MJ4	0.77824468	0.43810012	1.776
MJ5	0.80050893	0.42618053	1.878
MJ6	0.48155068	0.40874203	1.178
MJ7	1,08142499	0.43207201	2.503
MJ8	0.89569917	0.46663572	2.005
MN5	0.50210737	0.40968952	1.226
MN6	0.09873351	0.31592841	0.313
MN8	0,60081590	0.37690952	1.594
MN9	-0.13628211	0.31189957	-0.437
MN10	0.002551616	0.35379013	0.007
MN11	0.19458545	0.39803834	0.489
WKND	0.14459588	0.25298011	0.572

DEP VARIABLE: KEEPFISH

F-TEST 2.619
OBS 536

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	8.09163143	0.39754566	20.354
TARGR	-0.63493893	0.28813687	-2.204
TARGT	-0.03000512	0.28608262	-0.105
TARGF	1.16005118	0.51360011	2.259
MJ1	-0.67785857	0.48409302	-1.400
MJ3	-0.89785739	0.42731459	-2.101
MJ4	-0.21607825	0.51354355	-0.421
MJ5	-1.01361087	0.52192311	-1.942
MJ6	-1.04931986	0.49730779	-2.110
MJ7	-0.41688883	0.45091149	-0.925
MJ8	-0.25730722	0.45696247	-0.563
RiNs	-0.14119910	0.54846485	-0.257
MN6	0.22085293	0.39028515	0.566
MN8	-0.63595454	0.36390967	-1.748
MN9	1.45515992	0.48851570	2.979
MN10	0.1882657S	0.36217584	0.520
MN11	-0.67293081	0.44317159	-1.518
WKND	0.21160550	0.26132905	0.810

DEP VARIABLE: OUIETIME

F-TEST 1.579
OBS 482

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	8.33047553	0.58638878	14.206
TARGR	-0.14268653	0.29999957	-0.476
TARGT	-0,18754912	0.30534004″	-0.614
TARGF	0.03336624	0.48896232	0.068
MJ1	-0.73609622	0.69983581	-1.052
MJ3	-0.70451833	0.71501660	-0.985
MJ4	-0.56445054	0.70372958	-0.802
MJ5	-1.14804492	0.69315901	-1″.656
MJ6	-1.34006483	0.68904331	-1.945
MJ7	-0.29360849	0.69167542	-0.424
MJ8	0.04573877	0.74465338	0.061
KN5	-0.81118400	0.47981448	-1.691
MN6	-0.09321641	0.41382943	-0.225
MN8	0.08157845	0.44580404	0.183
MN9	-0.10180406	0.53428639	-0.191
MN10	0.22701246	0.40778226	0.557
MN11	-0.45980224	0.53274809	-0.863
WKND	-0.0S979884	0.32476937	-0.184

DEP VARIABLE: GOODWTHR

F - TEST 2.759
OBS 381

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	7.09707233	0.43106770	16.464
TARGR	-0.48646878	0.32599391	-1.492
TARGT	0.51229235	0.33760558	1.517
TARGF	-1.49302896	0.49194356	-3.035
MJ1	0.40571747	0.49441812	0.821
MJ3	1.09149043	0.56904719	1.918
MJ4	0.72597107	0.44476911	1.632
MJ5	0.48019072	0.58953742	0.815
MJ6	1.23645655	0.46327764	2.669
MJ7	-0.26498057″	0.44679878	-0.593
MJ8	0.22708658	0.46512018	0.488
KN5	-0.31701387	0.38871104	-0.816
MN6	1.28035717	0.60295514	2.123
MN8	0.14411618	0.46022680	0.313
MN9	1.14428728	0.46974240	2.436
MN10	0.49489729	0.43572265	1.136
MN11	0.57428481	0.45843956	1.253
WKND	0.34439790	0.25591639	1.346

DEP VARIABLE : FRNDFMLY

F-TEST 1.233
OBS 406

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	8.54110823	0.46254806	18.465
TARGR	-0.59800573	0.25565774	-2.339
TARGT	0.15487751	0.25328885	0.611
TARGF	0.46287229	0.40689201	1.138
MJ1	0.20963175	0.44760664	0.468
MJ3	0.66950705	0.46462665	1.441
MJ4	0.25996020	0.42541605	0.611
MJ5	0.46650183	0.43289498	1.078
MJ6	0.60614119	0.55775904	1.087
MJ7	-0.09825039	0.43264822	-0.227
MJ8	0,17366924	0.40604008	0.428
MN5	-1.35708719-	0.70293279	-1.931
MN6	0.35442366	0.34017854	1.042
MN8	0.09749444	0.32599378	0.299
MN9	0.15200115	0.39173057	0.388
MN10	0.45811705	0.33971443	1.349
MN11	0.19319351	0.47315411	0.408
WKND	0.13095893	0.23814544	0.550

DEP VARIABLE: ADVNEXCT

F-TEST 1.267
OBS 443

VARIABLE	PARAMETER ESTIMATE “	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	7.25608143	0.61347890	11.828
TARGR	0.23528665	0.31342257	0.751
TARGT	-0.26195517	0.30524996	-0.858
TARGF	-0.14838342	0.47233401	-0.314
MJ1	0.03723037	0.54138594	0.069
MJ3	-0.92314231	0.71890424	-1.284
MJ4	-0.0489124S	0.51960706	-0.094
MJ5	1.01363017	0.56859825	1.783
MJ6	-0.83621541	0.60606846	-1.380
MJ7	0.03118484	0.49129926	0.063
MJ8	0.49056525	0.53133745	0.923
nN5	-0.01289834	0.53358967	-0.024
KN6	0.04472742	0.49114189	0.091
MN8	-0.34816497	0.46015875	-0.757
MN9	-0.55696234	0.54623163	-1,020
MN10	-0.20256002	0.52433722	-0.386
MN11	0.49999921	0.52655699	0.950
WKND	0.44184453	0.26438608	1.671

Table A.S, continued

DEP VARIABLE: PRERELX
F-TEST 1.585
OBS 3722

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0O
INTERCEP	8.78987067	0.13274228	66.218
TARGR	-0.08702046	0.08311952	-1.047
TARGT	-0.02271869	0.08253455	-0.275
TARGF	-0.05306643	0.14142803	-0.375
MJ1	-0.009755689	0.13606929	-0.072
MJ3	-0.25145705	0.14111326	-1.782
MJ4	-0.36764056	0.13622517	-2.699
MJ5	0.03227412	0.14489392	0.223
MJ6	0.008712145	0.14303434	0.061
MJ7	0.05884559	0.13821775	0.426
MJ8	-0.003183858	0.13112852	-0,024
MN5	0.01144559	0.12708450	0.090
MN6	-0.02560113	0.11183769	-0.229
MN8	0.13506010	0.10587769	1.276
MN9	0.01645299	0.12161881	0.135
MN10	0.12827553	0.10739298	1.194
MN11	0.08320163	0.13371926	0.622
WKND	-0.01423466	0.06462206	-0.220

DEP VARIABLE: PRECAT
F - TEST 2.063
OBS 3722

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	6.56236349	0.17428059	37.654
TARGR	0.09004818	0.10912966	0.825
TARGT	0.12237258	0.10836163	1.129
TARGF	0.52153433	0.18568432	2.809
MJ1	0.15331075	0.17864870	0.858
MJ3	-0.17609374	0.18527106	-0.950
MJ4	0.17431650	0.17885337	0.975
MJ5	0.15514299	0.19023478	0.816
MJ6	0.S4007251	0.18779330	2.876
MJ7	0.15005384	0.18146947	0.827
MJ8	0.30449474	0.17216185	1.769.
BINS	-0.10320669	0.16685235	-0.619
HN6	-0.227S5882	0.14683444	-1.550
MN8	0.04694627	0.13900941	0.338
MN9	-0,14802188	0.15967631	-0.927
MN10	-0.10164869	0.14099887	-0.721
MN11	0,05654611	0.17556329	0.322
WKND	0.11237509	0.08484389	1.324

Table A.66- For sample interviewed both before and after fishing trip; demographic, geographic, and seasonal variables and their effects on extent to which "unpolluted natural surroundings are a motivation for going-fishing.

DEP VARIABLE: NOPOLLUT
F-TEST 1.569
OBS 85

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	19.31015380	26.92078701	0.717
HHLDINC	-0.000493022	0.000514831	-0.958
PRETIRED	-42.07217646	41.08032759	-1.024
PTEXNATV	-1.35518067	28.42559659	-0.048
PSPNOENG	6.58063295	39,05040280	0.169
PVIETNA14	-109.12039	406.35400	-0.269
PURBAN	0.18671766	5.03175573	0.037
SITETRIP	0.04004085	0.01082416	3.699
NSWTRIP	0.02132592	0.10230115	0.208
MON	0.005535399	0.01279516	0.433
MJl	-4.17274793	8.7969222S	-0.474
MJ3	-9.84498903	9.81685770	-1.003
MJ4	1.22590283	8.62253424	0.142
MJ5	-2.43125737	8.03930377	-0.302
MJ6	4.13690974	6.64660300	0.622
MJ7	-5.69727465	6.63558981	-0.859
MJ8	-15.01756379	8.27448287	-1.815
MN5	9.44642008	7.95520190	1.187
MN6	4.20898200	7.25488897	0.580
MN8	8.30827846	6.19106440	1.342
MN9	4.44008039	6.23858464	0.712
MN10	0.94326577	5.99986399	0.157
MN11	11.91217331	6.72034145	1.773
WKND	2.07968018	4.75885531	0.437

Table A.7 - Extent to which respondents were able to "Experience Unpolluted Natural Surroundings ." (n-858)

DEP VARIABLE: NOPOLLUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	8.42190686	1.00903630	8.346
HHLDINC	-0.000011214	0.000022673	-0.495
PRETIRED	1.58102890	1.96850152	0.803
PTEXNATV	-0.61188444	0.85289639	-0.717
PSPNOENG	-1.28938826	1.51495547	-0.851
PVIETNAM	19.42599903	11.87295215	1.636
PURBAN	0.08369006	0.19819351	0.422
MJ1	-0.86422020	0.36986443	-2.337
MJ3	0.32246599	0.38965319	0.828
MJ4	0.64005519	0.25369335	2.523
MJ5	1.01771109	0.35532066	2.864
MJ6	0.10662209	0.31278854	0.341
MJ7	0.46076012	0.29608459	1.556
MJ8	0.88094389	0.32441647	2.715
MN3	0.22148059	0.35923225	0.617
MN6	-0.69695574	0.29829741	-2.336
MN8	-0.02393900	0.22370082	-0.107
MN9	-0.18379131	0.27529979	-0.668
MN10	-0.02430656	0.26243870	-0.093
MN11	0.45402552	0.35517060	1.278
WKND	-0.16900558	0,19266161	-0.877

Table A.8 - OLS Regression of "Ability to Enjoy Unpolluted Natural Surroundings" on Measured Water Quality Variables

DEP VARIABLE: NOPOLLUT
F-TEST 4.192
OBS 695

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	7.65156764	1.88693837	4.055
MTURB	0.000064889	0.01043748	0.006
MSAL	0.01185356	0.01791982	0.661
MDO	-0.22131054	0.13894215	-1.593
TRANSP	0.02299990	0.01366888	1.683
DISO	0.26350825	0.10926245	2.412
RESU	0.009595514	0.007438127	1.290
NH4	3.99552741	3.69437706	1.082
NITR	-1.40780844	1.18960581	-1.183
PHOS	0.14529883	1.41691553	0.103
CHLORA	0.009712722	0.02752364	0.353
LOSSIGN	-0.01482662	0.02449996	-0.605
CHROMB	-0.003165001	0.01881366	-0.168
LEADB	-0.04634034	0.01468208	-3.156

Combining Contingent Valuation and Travel Cost Data for the Valuation of Non-market Goods

by

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ABSTRACT

Contingent valuation (CVM) survey methods are now being used quite widely to assess the economic value of non-market resources. However, the implications of these surveys have sometimes met with a degree of skepticism. Here, hypothetical CVM data are combined with travel cost data on actual market behavior (exhibited by the same consumers) to internally validate the implied CVM resource values. We estimate jointly both the parameters of the underlying utility function and its corresponding Marshalllan demand function. Equivalence of the utility functions implied by the two types of data can be tested statistically. Respondent and/or resource heterogeneity can be accommodated readily. A sample of Texas recreational anglers illustrates the technique.

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Combining Contingent Valuation and Travel Cost Data
for the Valuation of Non-market Goods

Economists have long been skeptical about the reliability of consumers' stated intentions, as opposed to their actions in the marketplace. The notion that "actions speak louder than words" underlies much of the criticism of survey methods as a basis for demand forecasting. In some situations, however, market demand activity cannot be directly observed. Surveys and other indirect methods are the only glimpses of demand relationships we have. In these circumstances, it is valuable to explore methods by which researchers can combine survey responses and other available information to formulate the best possible characterization of demand when actual market observations "in the field" are unattainable.

For a wide variety of environmental resources and public goods, the absence of markets makes it extremely difficult to establish a monetary value for access to these commodities. Whenever A proposed change in policy affects the quality or availability of these non-market goods, either explicit or implicit cost-benefit analysis must be undertaken at some point in the decision process. For some time, economists have experimented with alternative methods of eliciting *or* inferring the social value of these non-market goods.

The familiar travel cost method (TCM) popularized by Clawson and Knetsch (1966) has been widely applied in an extensive array of empirical studies. This method interprets variation in travel costs to a particular site where a non-market good is consumed as equivalent to the effect of a per-trip entrance fee to the same location. Subsequent research has provided numerous extensions and qualifications to the original travel cost method.

A somewhat newer, competing approach to valuation involves directly asking individual consumers of the non-market good about its value. A hypothetical market scenario is described to each respondent and their professed behavior under that scenario is recorded. To avoid the connotations of hypotheticality, this has been dubbed the 'contingent valuation method" (m). Despite the potential for a variety of biases in poorly designed CVM surveys (described in detail in surveys by Cummings, Brookshire, and Schulze, 1986, or Mitchell and Carson, 1988) there are still many situations where more realistic methods (such as market simulations or actual market experiments) are prohibitively difficult, and where some of the other potential methods, such as hedonic housing price models or hedonic wage models, are inappropriate, In these cases, it has generally been conceded that CVM surveys, when interpreted cautiously, can provide useful information about the characteristics of demand for a good not presently priced and traded in a real market. The CVM technique has also been widely applied.

Despite the semantic care in naming the CVM, the data it produces have still been criticized as "hypothetical ●nswers to hypothetical questions." Consequently, "external validation" of empirical applications of CVM has received considerable attention in the literature. Some of these compare CVM and TCM; others compare CVM with other valuation methods.

For example, Bishop and Heberlein (1979) and Bishop, Heberlein and Kealy (1983) pit CVM estimates against TCM and the results of simulated market experiments. They conclude that CVM mechanisms produce "meaningful--albeit inaccurate--economic information." CVM and TCM are also compared by Sellar, Stoll and Chavas (1985), who conclude that the two methods do provide comparable estimates of consumer surplus, and that whenever possible, *both* methods should be used in future studies as a validity check on the results.

Schulze, d'Arge and Brookshire (1981) determine that "all evidence obtained to date suggests that the most readily applicable methodologies for evaluating environmental quality--hedonic studies of property values or wages, travel cost, and [CVM] survey techniques--all yield values well within one order of magnitude in accuracy. Such information. . . is preferable to complete ignorance." Brookshire, Thayer, Schulze, and D'Arge (1982) compare CVM estimates with a hedonic property value study. Regarding CVM, they conclude that "[although better accuracy would be highly desirable, in many cases where no other technique is available for valuing public goods, this level of accuracy is certainly preferable to no information for the decision-making process."

Brookshire and Coursey (1987), on the other hand, compare hypothetical non-market CVM responses with market-like elicitation processes (Vernon Smith's public good auction experiments in the laboratory and in the field). Compared to CVM, the marketplace appears to be "a strong disciplinarian" in terms of limiting the tendency for certain types of inconsistencies in valuation responses.

In all these previous studies aimed at external validation of the values for non-market goods produced by CVM, the alternative measures of value were obtained either by indirect methods (the travel cost approach or hedonic wage or rent functions) or by small simulated market experiments. The point estimates of value produced by each technique are generated by completely *separate* models which are sometimes even applied to completely separate samples of data. This makes rigorous statistical comparisons of the different value estimates impossible.

The new joint models introduced in this paper also appeal to the marketplace to "discipline" contingent valuation estimates, while at the same time, the CVM information provides insights into the probable behavior of respondents under conditions which are far removed from the current market scenario. The innovation is that the validation occurs in the context of a *single* joint model applied to a single sample of respondents. Since we collect both CVM and TCM information from each respondent, the joint model can be estimated both with and without restrictions, allowing the consistency of the CVM information and TCM information to be tested in a statistically rigorous fashion.[1]

The new joint models described in this paper will be appropriate for a whole spectrum of non-market resource valuation taska wherever CVM or TCM have been used separately before. For concreteness in this paper, however, we concentrate on an empirical application concerning the non-market demand for access to a recreational fishery. The U.S. Fish and Wildlife Service estimates that economic activity associated with recreational fishing generated $17.3 billion in 1980 and $28.1 billion in 1985, and there are at least 60 million Americans who fish regularly (reported in Forbes, May 16, 1988, pp. 114-120). Recreational fisheries valuation has therefore attracted considerable policy-making interest over the past few years.[2] There are many

[1] The conceptual framework for the econometric implementation is similar to models of discrete/continuous choice employed by Hanemann (1984) and byDubin and McFadden (1984), but in the present case, the discrete choices are purely hypothetical.

[2] Among current related policy issues, for example, is the quantification of the social costs of acid precipitation (which kills fish and decreases the consumer surplus associated with recreational fishing). These costs are

theoretical examinations and empirical attempts at valuation extant.[3] One factor accounting for the proliferation of empirical analyses is the availability of vast quantities of survey data collected regularly for fisheries management purposes.

Section I of this paper develops the logic whereby a discrete-choice direct utility function can be modified into an indirect *utility difference* function (defined over fishing days and a composite of all other goods). Then this function and the corresponding Marshallian demand function for fishing access days can be modeled jointly. Section II describes a sample of CVM and TCM data used to demonstrate this technique. Section III describes alternative stochastic specifications. Section IV provides a general outline of the types of results these models generate. Section V goes into detail regarding the specific empirical results for a basic model and some useful extensions.

I. THE JOINTNESS OF CONTINGENT VALUATION AND TRAVEL COST RESPONSES

A rigorous utility-theoretic tradition in the analysis of "discrete-choice" CVM data was initiated by Hanemann (1984b), who elaborated substantially upon earlier estimation procedures used by Bishop and Heberlein (1979). The discrete choice (or "referendum") format for CVM sumey questions is often argued to be less subject to some of the usual CVM biases than are other fromats. Rather than asking the respondent to place his own specific

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generally considered to be one of the most substantial components of acid rain damages.

[3] To cite only a few of the more recent recreational fisheries studies: McConnell, 1979, Anderson, 1980, Samples and Bishop, undated, McConnell and Strand, 1981, Vaughn and Russell, 1982, Morey and Rowe, 1985, Rowe, Morey, Ross, and Shaw, 1985, Samples and Bishop, 1985, Donnelly, Loomis, Sorg, and Nelson, 1985, Morey and Shaw, 1986, Cameron and James, 1986, 1987, Thomson and Huppert, 1987, Cameron 1988a, Cameron and Huppert, 1988, 1989, Agnello, 1988, and McConnell and Norton, undated.

dollar value on access to the resource, a single threshold value is offered and the respondent is asked to indicate whether his personal valuation is greater or less than this amount.

For the survey available for this study, the referendum CVM question seems *most* easily interpreted as asking whether the respondent would entirely cease to use the resource if the annual access fee ("tax") were equal to T.[4] Let Y be the respondent's income, let q be the current number of trips per year to the recreation site, and let M be the respondent's typical travel costs (i.e. market cost of access and incidental expenses on complementary market goods associated with one trip).[5]

With cross-sectional data, it is convenient to begin by assuming a common utility function wherein access to the recreational resource can be traded off against a composite of all other goods and services, z, for which the price can be normalized to unity. If market goods (travel, etc.) are consumed in fixed proportions with the number of recreation trips, then only the number of trips appears separately in the utility function: $U(z,q) - U(Y-Mq,q)$.

Suppose a respondent to the CVM question indicates that he would continue fishing under the hypothetical two-part tariff with fixed tax T and marginal price M. This implies that his maximum attainable utility when paying the tax and enjoying •ccess exceeds his utility when forgoing all trips

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[4] A possible alternative interpretation of the question Is addressed in Appendix I.

[5] These data do not allow accurate imputation of the opportunity costs of travel time. Rather than invoking a completely arbitrary guess about time costs , we opt to ignore this component while acknowledging that the empirical results will certainly reflect this decision. To the extent that time costs are important, the social values of access implied by the travel cost portion of the model will be underestimated.

and thereby avoiding both the tax and the travel costs associated with each trip:

$$(1) \qquad \Delta U(Y,M,T) = \max_q U(Y-Mq-T,q) - U(Y,0) > 0, \text{ or}$$
$$\Delta V(Y,M,T) = V(Y-T,M) - v(Y) > 0,$$

where U signifies the direct utility function and V the corresponding indirect utility. Crucially, as pointed out by McConnell (1988), the optimal quantity demanded in the first term of the direct utility formulation in (1) would be endogenously determined and is presently unobserved.

The TCM question, however, concerns the respondent's optimal quantity demanded under existing conditions. If the utility surface implied by the discrete-choice CVM response truly describes the configuration of individuals' preferences, then it should also be consistent with the current observed behavior, namely demand for access days in an environment where per-day specific access prices (beyond M) are currently zero.[6] The Marshallian demand function, q(Y,M), corresponding to the same utility function will be given by the maximization of the Lagrangian:

$$(2) \qquad \max_q u(Y-Mq,q) \qquad \text{s. t.} \qquad Y = z + Mq.$$

Theoretically, the utility maximizing decisions of economic agents, whether real or hypothetical, should reflect the same underlying structure of preferences. Conditional on the extent to which the functional form chosen

[6] Except for the hypothetical nature of the discrete choice question in the contingent valuation context, the models used in this paper have much in common with the strategies employed in King (1980) and in Venti and Wise (1984), where consumer choices are modeled explicitly as the result of utility maximization. In contrast, earlier empirical discrete choice/demand models accommodated the choice process in a "reduced form" manner similar to the approaches used in the literature on switching regressions or sample selection.

for U(z,q) is an *adequate* representation of the preferences of individuals in this sample, this supposition will be used to impose parameter constraints across the two parts of the model. Requiring that respondents' professed behavior in a hypothetical context be consistent with their observed behavior in real markets should attenuate the degree of bias due to the hypothetical nature of the CVM question. In turn, the CVM information allows the researcher to "fill in" some information about demand that is not captured by the range of the currently observable demand data and it can temper biases in the travel cost information due to underestimation of the true opportunity costs of access.

One key question to be addressed in this study is whether CVM and TCM data do indeed elicit the same preferences. When parameter constraints are imposed across two models, it is also possible to allow the corresponding parameters to differ, taking on any values the data suggest. This option allows for a rigorous statistical comparison of the different utility configurations implied by the CVH and the TCM data. Contingent on the validity of the assumption of quadratic utility, one can test statistically the hypothesis that the corresponding parameters in the two models are the same. This is implicitly a test of whether professed behavior in the hypothetical market is consistent with observed behavior in a real market. If utility parameter equivalence is rejected, then one might suspect that the contingent valuation technique and/or the travel cost method might be unreliable in this specific application.

Travel cost models seem to enjoy broader acceptance than CVM models, although rudimentary travel cost models like the one employed here can also have serious deficiencies. Fortunately, if the researcher harbors prior opinions regarding the relative or absolute reliability of these two types of information, these priors can be readily incorporated into the estimation process. Consequently, even if parameter equivalence is rejected initially, there will be some recourse.

In addition to these basic issues, this paper describes a number of extensions which demonstrate the flexibility of this model as a prototype for subsequent work in non-market resource valuation.

II. AN ILLUSTRATIVE EXAMPLE

Between May and November of 1987, the Coastal Fisheries Branch of the Texas Department of Parks and Wildlife conducted a major in-person survey of recreational fishermen from the Mexico border to the Louisiana stat. line. The "socioeconomic" portion of the survey is most pertinent here. The specific CVM question asked of respondents was: "If the total cost of all your saltwater fishing last year was ____ more, would you have quit fishing completely?" At the start of each survey day, interviewers randomly chose a starting value from the list $50, $100, $200, $400, $600, $800, $1000, $1500, $2000, $5000, and $20,000. On each subsequent interview, the next value in the sequence was used. Therefore, offered values can be presumed to have no correlation whatsoever with the characteristics of any respondent. In addition to this question, respondents were asked "How much will you spend on this fishing trip from when you left home until you get home?" The survey also established how many trips the respondent made over the last year to all saltwater sites in Texas.[7] Five digit zip codes were collected, which allows establishment of residency in Texas.

[7] Unfortunately, the duration of each trip is unknown, so it must be assumed that the majority are one-day trips, which may or may not be entirely plausible. Here, the term "trip" is used synonymously with "fishing day."

Income data were not collected from each respondent, but the five-digit zip codes allow merging of the data with 1980 Census median household incomes for each zip code. Zip codes cover relatively homogeneous "neighborhoods," at least when compared to income data on the county level, for example. Individuals' consumption patterns tend to conform somewhat to those of their neighbors, so median zip code income may be a better proxy for "permanent" disposable income than actual current self-reported income. There is high variance in median incomes across zip codes, so the Census income variable may actually make a substantial and accurate contribution to controlling for income heterogeneity among the survey respondents.[8]

In other work utilizing the entire dataset (Cameron, Clark, and Stoll, 1988) it has been determined that subsets of individuals in the sample exhibit extreme behavior. The full sample has therefore been filtered somewhat for use in this demonstration study. Since the initial models presume identical underlying utility functions for all individuals, those who report more than sixty fishing trips per year are discarded from the sample. It is relatively likely that these individuals are atypical, since 90% of usable sample reports fewer than this number of days. The median number of trips reported is between eleven and twelve. This research is therefore clearly directed at "typical" anglers.

It is also the case in the full usable sample from the survey that some individuals respond that they would keep fishing if the cost had been $20,000 higher when $20,000 exceeds the median household income of their zip code.

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[8] While the use of group averages instead of individual income information undeniably involves errors-in-variables complications in the estimation process, the distortions may in fact be not much greater than they would be with the use of self-reported income data in an unofficial context. It is well known that many individuals have strong incentives to misrepresent their incomes if they do not perceive a legal requirement to state them correctly.

Since the assignment of value thresholds was completely exogenous, the estimating sample includes only those respondents who were posed values up to and including the $2000 offer. Everyone offered values greater than this was excluded, regardless of their answer to the CVM question.

The final criterion for inclusion in the sample for this study was that a respondent should not report spending more than $100 on this fishing trip. Again, a very large proportion of the sample passes this criterion. When market expenditures are reported to be much larger than this, it seems reasonable to suspect that capital items have been included, so that it would be invalid to treat these costs as “typical” for a single fishing trip. Current expenditures over $2000 were reported by several respondents.

Descriptive statistics for the variables used in this paper are contained in Table I.

III. THE STOCHASTIC SPECIFICATION

It may be helpful to think of the model developed in the following sections as a nonlinear analog to a more familiar econometric model. The conceptual framework is similar to a system of two equations with one right-hand side endogenous variable, cross-equation parameter restrictions, and a non-diagonal error covariance matrix. However, one of the dependent variables is continuous and one is discrete, both equations are highly nonlinear in parameters, and the simultaneity in the model involves an endogenous variable which is not observed directly, but must be counterfactually simulated.

In order to have the option of constraining the coefficients of the utility function (and hence the indirect utility function) as well as those of the corresponding Marshallian demand function to be identical, the discrete choice model and the demand equation must be estimated simultaneously. To fix

Table I

Descriptive Statistics for the Variables
(n - 3366)

Acronym	Description	Mean	Std. dev.
Y	median household income for respondent's S-digit zip code (in $10,000)" (1980 Census scaled to reflect 1987 income; factor=1.699)	3.1725	0.6712
M	current trip market expenditures, assumed to be average for all trips (in $10,000)	0.002915	0.002573
T	annual lump sum tax proposed in CVM scenario (in $10,000)	0.05602	0.04579
~	reported total number of salt water fishing trips to sites in Texas over the last year	17.40	16.12
I	indicator variable indicating that respondent would choose to keep fishing, despite tax T	0.8066	0.3950
PVIET	proportion of population in respondent's 5-digit zip code claiming Vietnamese ancestry	0.002497	0.006217

[a] Dollar-denominated quantities l re expressed in $10,000 units throughout the study, so that squared income and squared net income do not become too large, resulting in extremely small probit coefficient estimates which thwart the optimization algorithm.

ideas, it is helpful to begin by considering the two components of the joint model completely separately, ignoring any potential error correlation.

A. A Separate CVM Choice Model

The decision to work within the framework of direct, rather than indirect, utility functions buys easy characterization of the shapes of consumer indifference curves. Under the hypothetical CVM scenario, the respondent is asked to choose between ceasing to use the resource and paying no lump-sum tax, or continuing to consume a revised optimal quantity of access $q(y-T,M)$ at a new lower net income. Unless one can assume that there is no income effect, $q(Y-T,M)$ will probably be less than the current optimal quantity, $q(Y,M)$. But if, for the initial exposition, it is temporarily assumed that the income elasticity of demand for access is zero, one can begin by considering how the CVM component of the joint model should be estimated.

It will be convenient to model the discrete choice elicited by the CUM question using conventional maximum likelihood probit (rather than logit) techniques, where the underlying distribution of the implicit dependent variable, the true utility difference, is presumed to be Normal. Since $\Delta U(Y,M,T)$ in equation (1) can at best be only an approximation, assume that for the i^{th} observation $\Delta U_i - \Delta U_i^* + \epsilon_i$, where ϵ_i is • random error term distributed $N(0, \sigma^2)$. ΔU_i^*, the systematic portion of the utility difference on the right hand side of equation (1) will be represented in what follows as $f(x_i,\beta)$.

In conventional probit models, AU~ is unobserved, but if ΔU_i is “large” (i.e. $\Delta U_i > 0$), one observes an indicator variable, I_i (the “yes/no” response), taking on a value of one. Otherwise, this indicator takes the value zero. In constructing the likelihood function for this discrete response variable, the following algebra is required:

(3) $$\Pr(I_i - 1) - \Pr (\Delta U_i > 0) - \Pr (\epsilon_i > - f(x_i, \beta)).$$

Since ϵ_i has standard error u, dividing through by a will create a standard normal random variable, Z, with cumulative density function Φ.

(4) $$\begin{aligned} \Pr(\epsilon_i > - x_i'\beta) & - \Pr (Z > - f(x_i,\beta)/\sigma) \\ & - \Pr (Z < f(x_i,\beta)/\sigma) \\ & - \Phi (f(x_i,\beta)/\sigma), \end{aligned}$$

by the symmetry of the standard normal distribution.

At best, in cases where $f(x_i,\beta)$ is linear-in-parameters, the vector β can only be identified up to a scale factor, since it only ever appears in ratio to u. (However, this is quite acceptable, because the solutions to the consumer's utility maximization problem are invariant to monotonic transformations of the utility function.) The probability of observing $I_i - 0$ is just the complement of $\Pr(I_i - 1)$, namely $1 - \Phi (f(x_i,\beta)/\sigma)$, so the log-likelihood function for n observations will be:

(5) $$\log L - \Sigma_i I_i \log [\Phi (f(x_i,\beta)/\sigma)] + (1 - I_i) \log (1 -[\Phi (f(x_i,\beta)/\sigma)] \}$$

If $f(x_i,\beta)$ was linear in β, and if q(Y-T,M) could be observed or assumed to be equal to q(Y,M), this separate discrete choice model could readily be estimated by any number of maximum likelihood routines in packaged statistical programs (such u SAS or SHAZAM). For compatibility with what follows, however, when q(Y-T,H) is made endogenous, this application requires a general MLE algorithm. (In this paper, the GQOPT nonlinear function optimization package is used). The endogenous demands, q(Y-T,M) will be functions of the same parameters appearing in (5). When the formulas for these demands are substituted into $f(x_i,\beta)$, these functions will usually no longer be linear functions of the β parameters.

B. A Separate Demand Model

The systematic portion of the TCM Marshallian demand function resulting from the optimization problem in (2) will be denoted by $g(x_i,\beta)$. In estimating this model separately, one might assume that $q_i = g(x_i,\beta) + \eta_i$, where η_i $N(0, \upsilon^2)$. This suggests that nonlinear least squares (by maximum likelihood) is an appropriate estimation method.

The log-likelihood function associated with the demand model is therefore:

$$(6) \qquad \log L = -(n/2)\log(2\pi) - n \log \upsilon - (1/2)\, \Sigma_i \{ [q_i - g(x_i,\beta)]/\upsilon \}^2$$

Again, there exist packaged computational routines to estimate such nonlinear models, but this application requires a general function optimization program to allow for subsequent constrained **joint** estimation of this model and the utility difference model.

C. Constrained Joint Estimates, Independent Errors

To impose the requirement that the two decisions (one real and one hypothetical) reflect the identical underlying utility function, the CVM and TCM models must be estimated simultaneously. With independent errors, it is simple to combine the two specifications by summing the two separate log-likelihood functions and constraining the corresponding β_j coefficients in each component to be the same:

$$(7) \quad \log L = -(n/2)\log(2\pi) - n \log \upsilon - (1/2)\, \Sigma_i \{ [q_i - g(x_i,\beta)]/\upsilon \}^2$$
$$+ \Sigma_i \left(I_i \log [\Phi (f(x_i,\beta)/\sigma)] + (1 - I_i) \log (1 - [\Phi (f(x_i,\beta)/\sigma)]) \right).$$

D. Constrained Joint Estimates, Correlated Errors

Realistically, unobservable factors which affect respondents' answers to the CVM discrete choice question are simultaneously likely to affect their actual number of fishing days demanded. To accommodate the influence of unmeasured variables, one can allow for a correlation, ρ, between the ϵ_i error terms in the discrete choice model and the η_i error terms in the demand model.[9] Assume that these errors have a bivariate normal distribution, BVN(0, 0, σ^2, υ^2, ρ).

In empirical discrete/continuous choice models, it is frequently more convenient not to work directly with the joint distribution of the errors. Instead, one can take advantage of the fact that the joint density can be represented equivalently as the product of a conditional density and a marginal density. In order to derive the model with nonzero ρ, one can exploit the fact that for a pair of standardized normal random variables, say W_1 and W_2, the conditional distribution of W_2, given $W_1 - w_1$, is univariate Normal with mean (ρ w_1) and variance ($1 - \rho^2$).

When allowing for nonzero values of ρ, then, the term $\Phi(f(x_i,\beta)/\sigma)$ in the discrete-choice portion of equation (7) will be replaced by:

$$\Phi\left([(f(x_i,\beta)/\sigma) + \rho Z_i] \,/\, (1 - \rho^2)^{1/2} \right) \tag{8}$$

where $Z_i - [q_i - g(x_i,\beta)]/\upsilon$, the standardized fitted error in the demand function, evaluated at the current parameter values. Clearly, if $\rho - 0$, this model collapses to the model with independent errors described in the previous section.

IV. AN EXPLICIT FUNCTIONAL FORM AND CLASSES OF RESULTS

The basic model proposed in this paper (and its variants) uses a quadratic direct utility specification for $U(z,q)$. Other discrete/continuous

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9 If the estimated value of the error correlation, p, is substantial and statistically significant, one probably ought to generalize the specification, if possible, to accommodate systematic heterogeneity across respondents. Section V will address this issue.

modeling exercises have begun with an indirect utility function, since commodity prices (rather than quantities) are more plausibly assumed to be exogenous for the typical consumer. In the present context, however, we desire to maintain the geometric intuition behind direct utility functions and their associated indifference tunes.[10] We have selected the quadratic form for the direct utility function because of its simplicity and because a number of other familiar specifications are unsuitable for the derivation of associated Marshallian demand functions (also discussed in Appendix II).

For identical consumers, the simplest quadratic direct utility specification is:

$$(9) \qquad U(z,q) = \beta_1 z + \beta_2 q + \beta_3 z^2/2 + \beta_4 zq + \beta_5 q^2/2$$

Under the current scenario for the respondent, consumption of the Hicksian composite good z is (Y - Mq) and q will be non-zero for anyone being interviewed, so the utility function in (9) is really a function of Y and q.[11]

$$(9a) \qquad u(Y,q) = \beta_1 (Y-Mq) + \beta_2 q + \beta_3 (Y-Mq)^2/2 + \beta_4 (Y-Mq)q + \beta_5 q^2/2.$$

The specific form of the utility difference which dictates a respondent's answer to the CVM question will be linear in the same parameters as U:

$$(10) \qquad \Delta U(Y,M,T) = f(x_i,\beta) = \beta_1 ([Y-Mq-T] - Y) + \beta_2 q + \beta_3 ([Y-Mq-T]^2 - Y^2)/2 + \beta_4 [Y-Mq-T]q + \beta_5 (q)^2/2.$$

[10] A quadratic indirect utility version of the model is discussed in Appendix II. Unfortunately, the calibrated model does not satisfy the regularity conditions for valid indirect utility functions.

[11] In-person CVM surveys typically sample only current users of the resource. When access price increases (or simply positive access prices) are being contemplated, this does not pose much of a problem. However, when projected scenarios involved improved resource attributes, one must really survey potential users as well as current users to elicit an accurate measure of aggregate demand responsiveness.

The first order conditions for the Lagrangian in equation (2) yield a corresponding Marshallian demand for q of:

$$(11) \qquad q(Y,M - g(x_1,\beta) = [\ \beta_2 + \beta_4\ Y - \beta_1\ M - \beta_3\ Y\ (M)\ ]\ /$$
$$[2\beta_4\ (M) - \beta_3\ M^2 - \beta_5\ ].$$

Since every additive term in both the numerator and denominator of this expression contains a multiplicative β coefficient, the demand function is of course invariant to the scale of the β vector. Consequently, it is necessary to adopt some normalization of the demand function parameters (for example, $\beta_2 = 1$, an entirely arbitrary and inconsequential choice). Thus the form of the demand function actually estimated will be:

$$(12) \qquad q(Y,M) - [\ 1 + (\beta_4{*})\ Y - (\beta_1{*})\ (M) - (\beta_3{*})\ Y\ (M)\ 1\ /$$
$$[\ 2(\beta_4{*})(M) \cdot (\beta_3{*})\ (M)^2 \cdot \beta_5{*}\ ]\ .$$

where $\beta_j{*} - \beta_j/\beta_2$. This demand function is highly non-linear in M.

Crucially, when we endogenize the q in equation (10) by substituting the formulas for q(Y-T,M) based on the calibrated demand models in (11) or (12), we are effectively converting the direct utility specification into an indirect utility specification! But if the indirect utility function V(Y-T,M) - U(Y-T,q(Y-T,M)) were to be written out in full, it would be a complex and unappealing formula. Instead, we will describe our results in terms of the implied direct utility function U(z,q).

The central empirical results in this study •re the estimates of the β parameters of the assumed underlying quadratic direct utility function. All of the economically interesting empirical measurements in this paper are derived from this calibrated utility function. Throughout, the empirical utility function should exhibit properties which are consistent with economic intuition about plausible shapes for these functions.

First, the derivatives of the underlying direct utility function are:

$$(13)\qquad \partial U/\partial z = \beta_1 + \beta_3 z + \beta_4 q \qquad \partial^2 U/\partial z^2 = \beta_3$$
$$\partial U/\partial q = \beta_2 + \beta_4 z + \beta_5 q \qquad \partial^2 U/\partial q^2 = \beta_5$$
$$\partial^2 U/\partial z \partial q = \beta_4$$

The marginal utilities of the composite good z and of access days q will depend on the local values of z and q. Whether or not each marginal utility is increasing or decreasing will be revealed by the signs of β_3 and β_5.

If both β_3 and β_5 are negative, the fitted utility function will be globally concave, and a globally optimal combination of z and q will be implied. The budget constraint will be binding unless the implied global optimum is attainable inside the budget set. The formulas for the global optimum will be strictly in terms of the estimated coefficients:

$$(14)\qquad q^{mull} = [-\beta_2 + (\beta_1\ \beta_4/\beta_3)\ ]\ /\ [\beta_5 - (\beta_4^2/\beta_3)\ ]$$
$$z^{max\ U} = (-\beta_1 - \beta_4 q^*)/\beta_3$$

Admissible fitted quadratic utility functions are not necessarily strictly concave, however. The bundle at which both marginal utilities go to zero may correspond to a saddle point of the complete fitted utility function. But only quasi-convexity in the positive orthant is required. To assess compliance with this regularity condition, one can easily examine the configuration of the fitted utility function's indifference curves.

An indifference curve through any arbitrarily chosen bundle (z′,q′) can be identified by first determining the level of utility this bundle represents:

$$(15) \qquad u' - \beta_1 z' + \beta_2 q' + \beta_3 z'^2/2 + \beta_4 Z'q' + \beta_5 q'^2/2.$$

To find all other bundles (z,q) which provide utility U', one merely sets up the quadratic formula for z:

$$(16) \qquad (\beta_3/2)z^2 + (\beta_1 + \beta_4 q)z + [\beta_2 q + (\beta_5/2)q^2 - u'] - 0$$

Plots of empirical indifference curves are highly intuitive and relatively novel and will be used throughout the discussion to highlight the differences in estimated preference structures.

Once the corresponding Marshallian demand function has been calibrated by joint estimation of the utility parameters, we are usually curious about the implied price and income derivatives:

$$(17) \qquad dq/dM- \left[-(2\beta_4 M-\beta_3 M^2-\beta_5)(\beta_1+\beta_3 Y) - 2(\beta_2+\beta_4 Y-\beta_1 M-\beta_3 MY)(\beta_4-\beta_3 M) \right] / [2\beta_4 M-\beta_3 M^2-\beta_5]^2$$

$$\partial q/\partial Y = [\beta_4-\beta_3 M] / [2\beta_4 M-\beta_3 M^2-\beta_5]^2 \ .$$

From the demand curves, policy makers are also sometimes interested in estimates of the resonation price. One simply sets q - 0 in equation (11) and solves the resulting quadratic formula for (M). Given the current level of M, the reservation level of any additional potential per-day access charge can readily be determined.

One of the ultimate empirical objectives of this research concerns estimation of the total social value of recreational access to this fishery. One measure of value is the equivalent variation, E, which can be viewed as the fixed tax which would make these anglers just indifferent between paying the tax and continuing to fish, or not paying the tax and forgoing their fishing opportunities. Algebraically, E is given by the equation $\max_q U(Y-Mq-E,q) - U(Y,0)$.

But completely depriving everyone of access to the resource is an extremely drastic proposition. So we also consider the equivalent variation formulas that give the social costs of limiting access to a proportion α of current (fitted) access levels, where $0 < \alpha < 1$. The equivalent variation for such partial restrictions is given by $\max_q U(Y-Mq-E,q) - U(Y-\alpha Mq,\alpha q)$. Letting $D - (2\beta_4 M - \beta_3 M^2 - \beta_5)$, $R - (\beta_2+\beta_4 Y-\beta_1 M-\beta_3 MY)/D$ and $S - (\beta_4-\beta_3 M)/D$, the value of E is the solution of the quadratic formula:

$$
\begin{aligned}
(18)\quad 0 - {} & [\,(\beta_3/2)(MS-1)^2 - \beta_4 S(MS-1) + (\beta_5/2)S^2\,]\,E^2 \\
& + [\,\beta_1(MS-1) - \beta_2 S + \beta_3(Y-MR)(MS-1) + \beta_4(R(MS-1) - (Y-MR)S) - \beta_5 RS\,]\,E \\
& + [\,-\beta_1(1-\alpha)MR + \beta_2(1-\alpha)R + (\beta_3/2)\{(Y-MR)^2 - (Y-\alpha MR)^2\} \\
& + \beta_4\{(Y-MR)R - (y-\alpha MR)(\alpha R)\} + (\beta_5/2)(1-\alpha^2)R^2\,].
\end{aligned}
$$

When a-0, the formula produces the equivalent variation for a complete loss of access. While it would be desirable to compute Taylor's series approximations to the standard errors of the value of E computed from the estimated β parameters, this would clearly be a daunting task.

An alternative measure of value (the compensating variation, C) asks what amount of money would have to be given to a respondent who has been denied some or all of his access in order to leave him equally well off as before the intervention. Algebraically, this C is given by $\max_q U(Y-Hq,q) - U(Y+C,0)$. For a complete loss of access, C is the root of the quadratic formula:

$$
\begin{aligned}
(19)\quad 0 - {} & -(\beta_3/2)\,C^2 - (\beta_1 + \beta_3 Y)\,C \\
& -\beta_1 Mq + \beta_2 q + (\beta_3/2)[\,(Y-Mq)^2 - Y^2] + \beta_4(Y-Mq)q + (\beta_5/2)q^2.
\end{aligned}
$$

A general formula for partial loss of access could easily be devised, but this paper will ‘focus on the equivalent variations.

V. SPECIFIC EMPIRICAL ESTIMATES

A. The Basic Model

The “basic model” constrains the quadratic direct utility parameters and the corresponding parameters in the Marshallian demand function for fishing days *to* be identical. The model initially assumes equal reliability of the two types of information (CVM and actual market demand), and allows the post-tax quantity demanded in the discrete choice model to be determined endogenously according to the same demand function. The model also allows for correlated errors in the two decisions. The pair of columns in Table II give these results (the second pair of columns will be discussed later). Both the estimated quadratic direct utility function parameters and the corresponding implied (normalized) Marshallian demand parameters ●re provided.

The utility function implied by these parameter estimates is globally concave, with a slightly positively sloped principal axes for the ellipses that form its level tunes. (The relevant lower left portions of these curves are interpreted as indifference curves). Of course, the quadratic form is merely a local approximation to the true utility function. Nevertheless, if the entire surface of the true utility function was quadratic, the apparent global optimum of that function would be located at 28.4 fishing days and $289,823 in median zip code income (compared to sample means of 17.4 fishing days and $31,725 in income). Thus the utility function is well-behaved in the relevant region. At the means of the data, the two marginal utilities are positive. The implied price elasticity of demand at the means of the data is -0.074 and the income elasticity is 0,078, although these elasticities change substantially with deviations away from the sample mean values. To establish

Table II

Fitted Quadratic Direct Utility Parameters
(with and without parameters constrained to be identical
for CVM and TCM portions of model)

Parameter	Constrained @ Point Est.	Constrained @ Implied $\beta^* = \beta/\beta_2$	Unconstrained βs Point Est. (Asymp. t-ratio)	Unconstrained βs Implied $\beta^* = \beta/\beta_2$
β_1 (z)	3.309 (8.237)[a]	27.76	1.276[b] (0.7457)	0.04530
β_2 (q)	0.1192 (19.55)	1.0	28.17 (2.573)	1.0
β_3 ($z^2/2$)	-0.1167 (-1.836)	-0.9790	1.498 (2.834)	0.05318
β_4 (zq)	0.002579 (2.006)	0.02164	2.263 (2.147)	0.08033
β_5 ($q^2/2$)	-0.006837 (-22.80)	-0.05736	-502.3 (-1.311)	-17.83
$\beta_1^* = \beta_1/\beta_2$	-		75.89 (5.756)	
$\beta_2^* = \beta_2/\beta_2$	-		1.0 -	
$\beta_3^* = \beta_3/\beta_2$	-		-10.89 (-2.428)	
$\beta_4^* = \beta_4/\beta_2$	-		-0.01749 (-0.9029)	
$\beta_5^* = \beta_5/\beta_2$	-		-0.04739 (-14.97)	
v	16.01 (81.98)		15.97 (82.04)	
ρ	0.2315 (9.086)		0.2505 (9.749)	
max Log L	-15708.17		-15640.61[c]	

[a] Asymptotic t-ratios in parentheses.

[b] CVM utility parameters do not satisfy regularity conditions.

[c] Likelihood ratio test statistic for four parameter restrictions - 115.12. Equivalence of utility parameters is soundly rejected.

a visual benchmark for this basic model, for an individual with mean income and travel costs, an indifference curve for the empirical quadratic utility function, the budget constraint through $(\mu_Y, 0)$, and the fitted maximum attainable Indifference cume are shown in Figure 1.

Using the basic constrained model that assumes one common utility function for all respondents, it is possible to use equation (18) to compute fitted values for the equivalent variation (either for 'each respondent, or at the means of the data). Across the 3366 respondents in this sample, the fitted values of E for a complete loss of access appear in the first row of Table III (a - 0).[12] Over the estimating sample, the average point estimate for the equivalent variation for a complete loss of access is $3451 (or, alternatively, at the means of the data, it is $3423). Minimum and maximum values in the sample are also provided.

Table III also gives the model's estimates for the equivalent variation associated with successively smaller restrictions on days of access (α denotes the proportion of current consumption to which each individual's access days are restricted).[13] For an across-the-board 10% reduction in fishing days, for example, the average calculated utility loss by these respondents would be only $35, although values as high as $52 and as low as $19 can obtain, due solely to different incomes and travel costs faced by different respondents.

The main policy interest in equivalent variations for partial restrictions on access stems from the need to make optimal allocations of finite fish stocks between recreational" anglers and commercial harvesters. If

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[12] For the single individual with average characteristics in Figure 1, this quantity would be determined by taking the parallel downward shift in the budget constraint which would leave the new constraint just tangent to the lower indifference curve.

[13] The computed equivalent variation, plotted as a function of a, is convex when viewed from below.

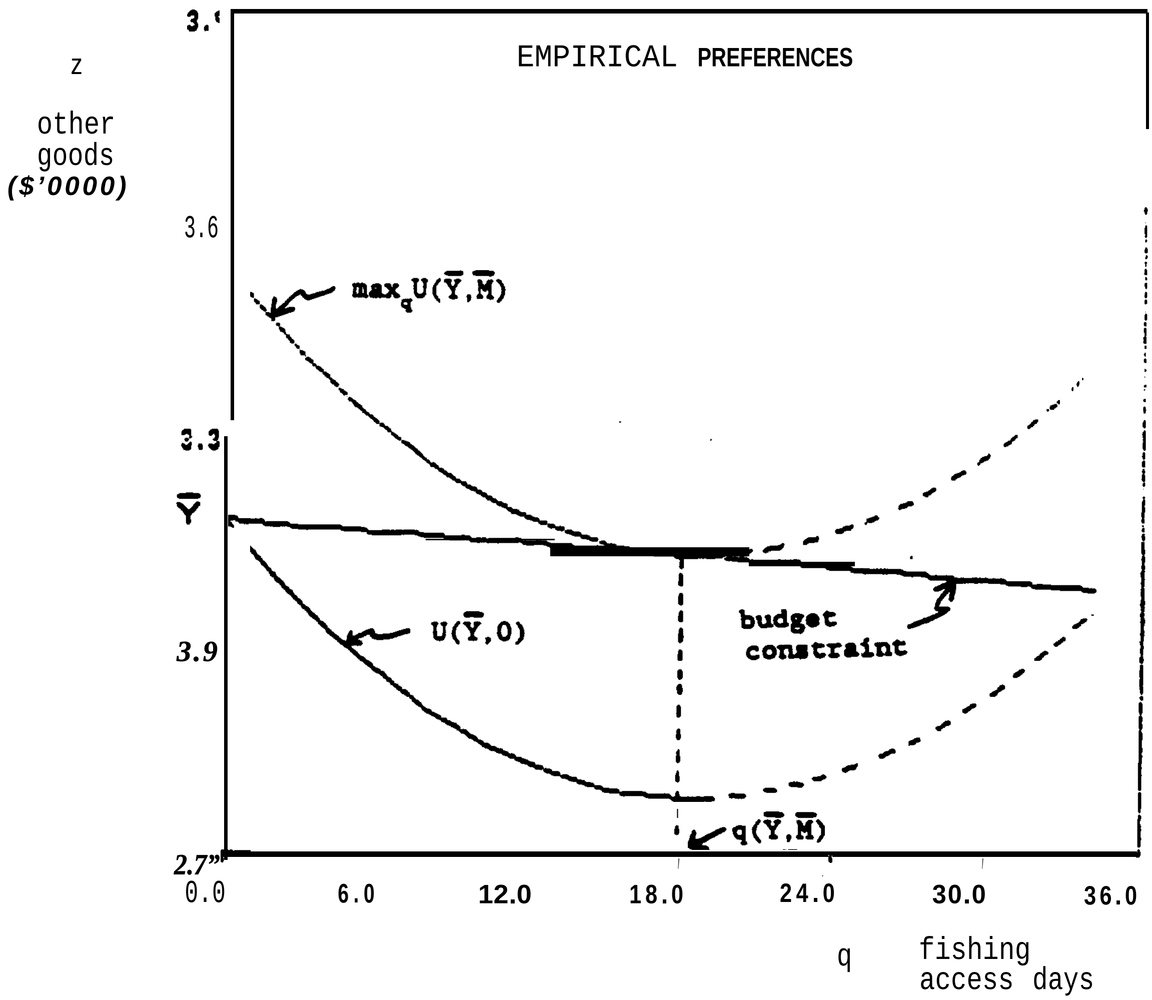

Figure 1 - Indifference curves at optimum and at zero access days, for respondent with mean income and travel costs.

Table III

Fitted Individual Equivalent and Compensating Variation Estimates[a] for the Basic (Constrained) Model (Table II)

Valuation Measure:	mean	max	min
Equivalent Variation			
a - 0.0[b]	$ 3451	$ 5132	$ 1857
α - 0.1	2799	4166	1505
a - 0.2	2214	3298	1190
a - 0.3	1697	2529	912
a - 0.4	1248	1861	670
a - 0.5	867	1294	465
a - 0.6	555	829	298
a - 0.7	313	467	168
a - 0.8	139	207	75
a - 0.9	35	52	19
Compensating Variation			
a - 0.0	$ 3560	$ 5361	$ 1899

[a] Since the same utility function is presumed for all respondents, individual variations in these quantities stem solely from differences in income and travel costs.

[b] For access days restricted to the fraction a of fitted current access days.

faced with a proposal to cut back on recreational access, it would be necessary to quantify the social losses co recreational anglers, compare these losses to the anticipated gains accruing to commercial harvesters, and then to argue that such a. redistribution of the catch would result in a potential Pareto improvement.[14]

The final row of Table III provides, for comparison, the corresponding compensating variation for a complete loss of access (i.e. for α - 0 only). As is typical, the compensating variation for the loss is larger than the equivalent variation for the same loss. Here, however, the difference is largely an artifact of the quadratic form chosen for the utility function. The concentric ellipses which form the level tunes of a globally concave utility function can be expected to have this “relationship.

B. Different Preferences Implied by Real versus Contingent Data

We require both a constrained and an unconstrained specification if we plan to use a formal likelihood ratio test statistic to determine whether the utility parameters implied by the CVM data alone are consistent with those estimated jointly using both CVM and TCM data. The constrained specification (the basic model just described) appears in the first pair of columns in Table II.

For the unconstrained model, the demand information necessary *to* compute the endogonous quantity in the CVM discrete choice model is calculated using only the utility function parameters for the CVM portion of the model. We therefore allow the discrete choice CVM model exclusively to imply values for

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1' In a richer specification, with enough shift variables to more closely capture the variations in quantity demanded, it would be an interesting exercise to assess total aggregate losses due to restrictions of access to specific numbers of days. The present data are not appropriate for simulating these policy changes.

β_1, β_2, β_3, β_4, and β_5. The observed TCM demand decisions will imply separate values for β_1*, β_3*, β_4*, and β_5*.

The second pair of columns in Table II displays results for an unconstrained model corresponding to the first pair of columns in the same table. The point estimates do not bode well for the consistency of the preferences elicited by the two types of responses. First of all, it is especially unsettling to note that the quadratic direct utility function implied by the CVM data alone does not even conform *to the* regularity conditions expected of a valid utility function. At the means of the data, the implied marginal utility from an additional access day is negative; there is also increasing marginal utility with respect to the composite good. The TCM quadratic direct utility parameters, however, are thoroughly acceptable. (The only link between the two submodels is the estimated error correlation, P.)

Nevertheless, there must still be some information about preferences in the CVM data, and the recorded responses on these su~eys dictate these particular parameter values. We can certainly still compare the maximized value of the log-likelihood in the constrained and unconstrained models in order to assess whether the imposition of cross-equation parameter restrictions is tenable. A likelihood ratio test for the set of four parameter restrictions embodied in the "basic" model soundly rejects these restrictions.[15] For this quadratic specification, the CVM- and TCM-elicited preference functions are different.

[15] It may be suspected that the TCM estimates systematically understate the true value of access (due to underestimates of the actual opportunity costs of access) and that the CVM estimates systematically overscace the true value of access (due to the incentives embodied in the way the question was posed). If data deficiencies make it too implausible to force compatibility of these responses with a common underlying set of preferences, the researcher would of course be free to report the two types of value estimates separately.

For a respondent with mean characteristics, Figure 2 shows the empirical indifference curves passing through the bundle (0,Y) for (i.) the "basic" constrained model and (ii.) the demand portion of the unconstrained model. The greater curvatrue of the indifference curve for the restricted parameters implies that E (the equivalent variation) based on the joint model, will be substantially larger than E based on observed TCM market demand behavior alone. For the unrestricted TCM demand parameters, the fitted equivalent variation at the means of the data is only $1686 (versus about $3451 for the constrained model).

The implied inverse demand functions corresponding to the different sets of preferences implied by the joint model and by the unconstrained TCM model are shown in Figure 3. When the CVM responses and observed TCM demand behavior are constrained to reflect the same set of quadratic preferences, the reservation price is about $409. The unrestricted TCM demand behavior implies a much lower reservation price. Thus the CVM (i.e. hypothetical market) scenario does seem to invite respondents to overstate the strength of their demand for resource access, as one might suspect (and/or the TCM indirect market data understates the strength of demand).

C. *Differing Reliability for Real versus Contingent Data*

The basic model (with or without the utility parameters constrained across the two sub-models) reflects the presumption that the decisions which respondents claim they would make under the hypothetical scenario proposed in the CVM question deserve to be treated as equally credible when compared to their actual market behavior regarding number of fishing days demanded. This need not be the case.

In other research on CVM (Cameron and Huppert, 1988), Monte Carlo techniques were used to demonstrate the wide range of referendum CVM value

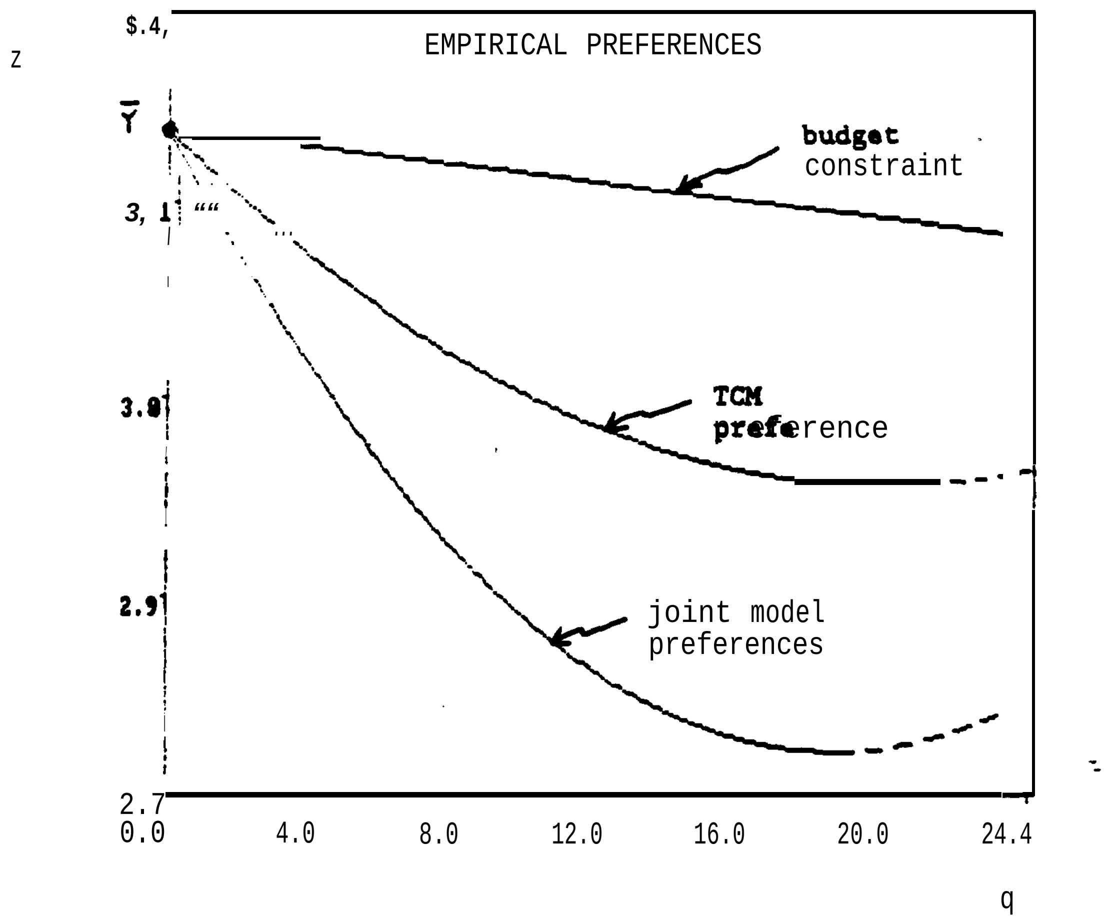

Figure 2 - $U(\bar{Y},0)$ for respondent with mean travel costs, according to constrained joint modal preference parameters and according to TCM portion of model with separate sets of preference parameters (CVM parameters fail to satisfy regularity conditions and are not shown).

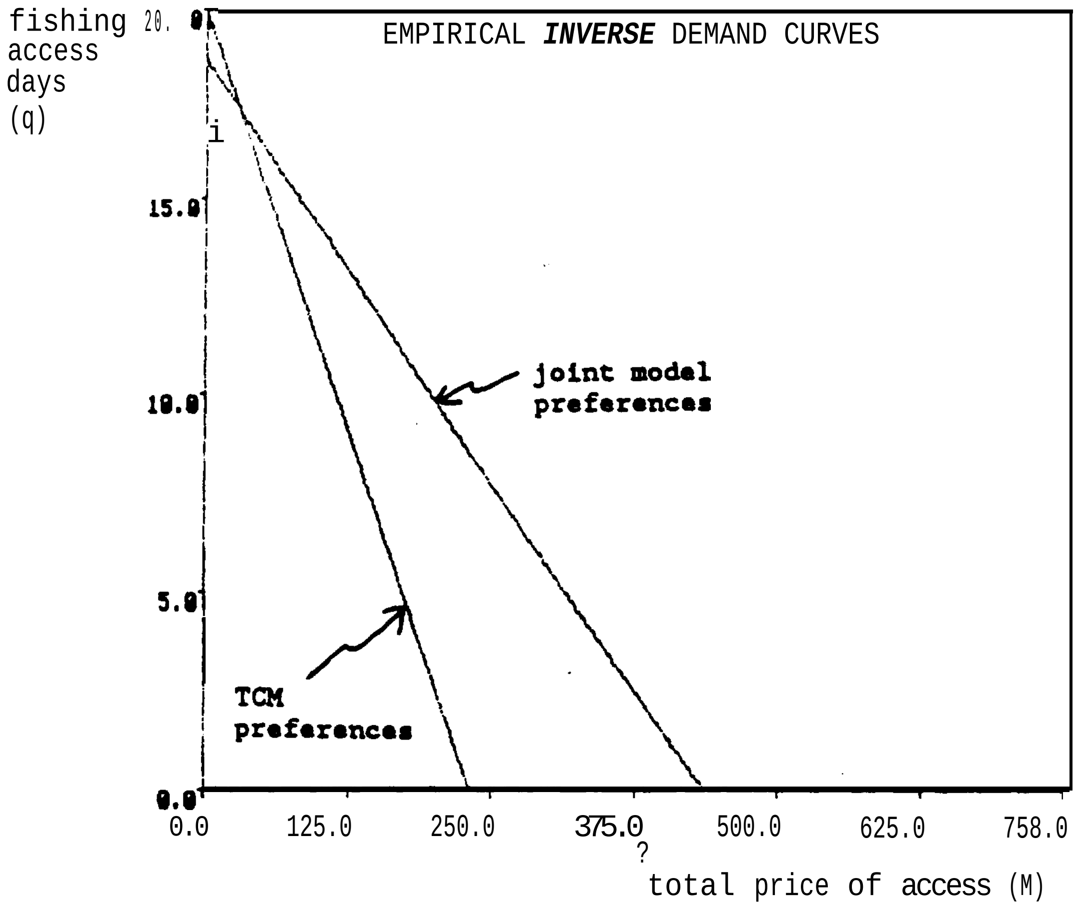

Figure 3 - Inverse demand curves corresponding to constrained joint modal preference parameters, and according to TCM parameters from unconstrained model, for respondent with mean income and travel costs. (CVM parameters do not satisfy regularity conditions and are not shown.)

estimates which can result simply as an artifact of the arbitrary assignment of the threshold values on the questionnaires. One conclusion in that study was that researchers should probably insist on vastly larger samples for referendum CVM data, in order to offset the inefficiencies in estimation which result from the highly diffuse information in referendum responses. By itself, this property of referendum data might be sufficient to warrant a discounting of its credibility when it is combined with "point" information from the same sized sample.

Fortunately, researchers are free to use their own prior opinions to adjust the relative credibility of each type of information. This can be done in an ad hoc fashion, by employing non-unitary weights on the respective terms in the log-likelihood function (see Appendix IV). Alternately, it can be done more rigorously, by making assumptions about the variances of the distributions of the estimated β parameters around the "true" mean of the β vector.[16]

In the discussion that follows, we assume that CVM data are presumed to be *less* reliable than travel cost data, since this has been a typical sentiment among researchers in this area. However, the demand information inferred from the travel cost data is *also* likely to be unreliable, especially since TCM applications often assume that the opportunity cost of access is constant as access days increase. If opportunity costs rise, as they most likely do, TCM will underestimate the implicit value of access, perhaps severely.[17] Also recall that we do not impute an arbitrary value of travel

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[16] We owe this helpful suggestion to Ed Learner.

[17] If increasing opportunity costs of access can be captured in the data, there exist econometric strategies for dealing with non-linear budgets sets which could undoubtedly be adapted to this type of problem. (See Hausman, 1985.)

time in this study. Depending upon the relative qualities of the two types of data, then, appropriate discounting of each type of information can be decided ex ante.

*Utilizing Explicit Priors on the Distributions of β and β**

Let β continue to denote the utility parameter estimates derived from the CVM data, and let ~" be the utility parameter estimates from the TCM data. Let β^T signify the true but unknown utility parameter vector. (Without loss of generality, we can normalize the second element, β_2, to unity in all three cases.) Now assume that conditional on the true β^T, β and β^* are statistically independent and that the elements of β/β^T are distributed $N(1,\sigma^2)$ and the elements of β^*/β^T are distributed $N(1,\sigma^{*2})$. (These us are distinct from the unidentifiable probit regression variance employed in section III.)

The researcher is free to make prior assumptions about the magnitudes and relative sizes of σ^2 and 0*², and this prior information can be incorporated into the log-likelihood function in (7) as follows. Note that β^T, β and β^* are now all estimated separately, so the parameter space is increased. The additional log-likelihood term will be:

(20) -n $\log 2\pi$ - n(log σ + log u*)

" (1/2) Σ ($[(\beta/\beta^T)-1]^2/\sigma^2 + [(\beta^*/\beta^T)-1]^2/\sigma^{*2}$).

Maximization of the augmented log-likelihood with respect to the vectors of variables β, β^*, β^T, v, and P, given preselected values of σ^2 and o● 2 will yield, for the model with identical consumers, fifteen distinct parameter estimates.[18]

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[18] It is not possible to optimize this likelihood function also with respect to σ and σ*. The algorithm will drive these values to zero.

What are the consequences for our ultimate estimates of the equivalent" variation for a complete loss of access? In Table IV, the first column, reproduced from Table II, reflects an implicit assumption that σ - σ^* - 0. (The implied Marshallian demand parameters corresponding to the CVM portion of the model are given in the second column.) Nothing is "tying together" the two sets of estimates for the utility parameters, so they are very different indeed.

In contrast, for arbitrarily selected standard errors a - 1.0 and o^* - 1.0, the third column of Table IV displays the revised estimates of β and β^*, along with the additional, separate, estimates of the true β^T. (The fourth column again shows the Marshallian demand parameters impliedby the CVM L3 estimates.) Ultimately, of course, we are interested in the value implications of the estimates. *At* the means of the data, these "tree" β^T parameters imply en equivalent variation for a complete loss of access of $3378 (which is very little different from the $3423 ●t the means of the data for the basic model),

To illustrate a more-extreme case, we also include another pair of columns in Table IV. In this case, the assumed standard error of β/β^T (for the CV M parameters) is increased to 3.0. A standard error this large would seem to discredit the CVM data substantially. The assumption of poorer-quality information has the anticipated effect upon the precision of the three sets of utility parameters in the model. The asymptotic t-ratios for all of the different β parameters drop substantially, with the coefficients on z* and zq becoming insignificant in all three cases. However, the resulting equivalent variation according to β^T shrinks only to $3124.

To assess the sensitivity of the parameter estimates and the welfare implications to different assumptions about the distributions of β and β^*

Table IV

Joint Models with Separate CVM and TCM Parameters
(CVM end TCM discounted by disproportionate variances)

	no σ, σ^*, β^T		σ_1 - 1.0 σ_2 - 1.0		σ_1 - 3.0 σ_2 - 1.0	
Parameter	Point Est.	Implied β^*	Point Est.	Implied β^*	Point Est.	Implied β^*
β_1 (z)	1.276 (0.7457)	0.04530	3.421 (8.361)	28.11	3.930 (2.989)	30.07
β_2 (q)	28.17 (2.573)		0.1217 (16.67)	1.0	0.1307 (13.18)	1.0
β_3 ($z^2/2$)	1.498 (2.834)	0.05318	-0.1383 (-1.883)	-1.136	-0.2572 (-0.5393)	-1.968
β_4 (zq)	2.263 (2.147)	0.08033	0.002157 (1.909)	0.01772	0.002038 (0.7828)	0.01559
β_5 ($q^2/2$)	-502.3 (-1.311)	-17.83	-0.007072 (-14.36)	-0.05811	-0.007873 (-6.875)	-0.06024
$\beta_1^*-\beta_1/\beta_2$	[illegible]5.89 (5.756)		28.48 (9.323)		32.56 (2.679)	
$\beta_2^*-\beta_2/\beta_2$	1.0 -		1.0 -		1.0 -	
$\beta_3^*-\beta_3/\beta_2$	-10.89 (-2.428)		-1.135 (-1.846)		-1.945 (-0.5421)	
$\beta_4^*-\beta_4/\beta_2$	-0.01749 (-0.9029)		0.02069 (1.793)		0.01561 (0.7751)	
$\beta_5^*-\beta_5/\beta_2$	-0.04739 (-14.97)		-0.05714 (-25.74)		-0.05596 (-14.74)	
$\beta_1^T-\beta_1^T/\beta_2^T$			28.30 (9.484)		32.33 (2.707)	
$\beta_1^T-\beta_1^T/\beta_2^T$			1.0 -		1.0 -	
$\beta_3^T-\beta_3^T/\beta_2^T$			-1.136 (-1.845)		-1.947 (-0.5418)	
$\beta_4^T-\beta_4^T/\beta_2^T$			0.02068 (1.794)		0.01560 (0.7751)	
$\beta_5^T-\beta_5^T/\beta_2^T$			-0.05763 (-23.35)		-0.05641 (-13.87)	
u	15.97 (82.04)		16.01 (81.95)		16.00 (81.87)	
P	0.2505 (9.749)		0.2317 (9.120)		0.2331 (9.090)	

(relative to β^T), one can perform a grid search across different values of a and $\sigma*$ to produce a range of values for the "true" β^T coefficients and for the implied equivalent variations. These are summarized in Table V. (Since these functions are extremely expensive to optimize, we provide results only for combinations of σ and $\sigma*$ where σ > a*. It seems likely, a priori, that the CVM data are at least as noisy as the TCM data, although both may be questionable.) The implied equivalent variations, EV, for each set of error assumptions, appear in bold print, implying a surprising robustness of the value estimates to differing reliabilities of the two types of data.

What conclusion is implied? A very wide range of different assumptions can be made about the relative reliability of CVM and TCM data, without producing too much difference in the ultimate welfare implications of the fitted preference functions. This result should be greatly reassuring, although it is conditional upon the maintained hypotheses of quadratic direct utility and has been demonstrated for this one sample only.

D. Accommodating Respondent and/or Resource Heterogeneity

The models described above have presumed that these respondents are homogeneous on all dimensions other than income, Y, proposed tax, T, number of fishing days, q, and typical market expenditures, M. It is a simple matter, however, to relax this assumption.

For example, one can explore the effects of allowing the utility parameters to vary continuously with the level of a sociodemographic variable. In the ad hoc valuation models explored in Cameron, Clark, and Stoll (1988), it was found-that the Census proportion of people in the respondent's zip code who report themselves as being of Vietnamese origin, PVIET, seemed to be

Table V

Results of Grid Search across Different Error Assumptions
For the Distribution of the CVM and the TCM Parameter Vectors

Contingent Valuation Information:		Travel Cost Information: U*- 0.5	1.0	1.5	2.0	2.5	3.0
o	-						
0.5	al;	27.90					
	β_{3T}	-1.021					
	β_{4T}	0.02139					
	β_{5}	-0.05742					
EV at means:[a]		$3412					
1.0	β_{1T}	28.15	28.30				
	β_{3T}	-1.070	-1.134				
	β_{4T}	0.02108	0.02070				
	β_{5}	-0.05735	-0.05763				
EV at means:		$3395	$3378				
1.5	β_{1T}	28.64	28.75	29.01			
	β_{3T}	-1.177	-1.224	-1.335			
	β_{4T}	0.02043	0.02013	0.01944			
	β_{5}	-0.05720	-0.05750	-0.0S796			
EV at means:		$3364	$3348	$3320			
2.0	β_{1T}	29.39	29.53	29.74	30.10		
	β_{3T}	-1.331	-1.391	-1.482	-1.636		
	β_{4T}	0.01967	0.01910	0.01852	0.01852		
	β_{5}	-0.05698	-0,05725	-0.05773	-0.05773		
EV at means:		$3317	$3300	$3272	$3233		
2.5	β_{1T}	30.53	30.64	30.84	31.10	31.51	
	β_{3T}	-1.s66	-1.614	-1.702	-1.820	-1.998	
	β_{4T}	0.01802	0.01770	0.01712	0.01633	0.01516	
	β_{5}	-0.05665	-0.05692	-0.05738	-0.05805	-0.05892	
EV at means:		$3245	$3229	$3202	$316S	$3116	
3.0	β_{1T}	32.17	32.32	32.51	32.77	32.96	33.08
	β_{3T}	-1.887	-1.945	-2.025	-2.142	-2.247	-2.347
	β_{4T}	0.01600	0.01561	0. 01S06	0.01427	0.01350	0.01270
	β_{5}	-0.05617	-0.05642	-0.05686	-0.05769	-0.05840	-0.05963
EV at means:		$3141	$3125	$3099	*$3062*	$3019	$2970

[a] The values for EV may or may not be statistically significantly different. They are the solutions of the elaborate quadratic formulas given in equation (18) in the body of the paper.

influential in a wide range of models.[19] Allowing this variable to shift the parameters of the quadratic utility function, one can replace the constant β_j by the varying parameter $(\beta_j + \gamma_j PVIET_i)$ for j - 1,...,5. Table VI demonstrates that the PVIET variable does indeed make a statistically significant difference to the overall fit of the model and to the parameters of the utility function.[20] Individually, only γ_5, reflecting the additional curvature of the utility function with respect to fishing access days, is statistically significantly different from zero. However, the whole set of shift terms is jointly significant according to the likelihood ratio test statistic value of 28.40 (where $X^2_{.05}(5)$ - 11.07).

A visual display of the effect on preferences of allowing for heterogeneity with respect to the PVIET variable is displayed in Figure 4. As benchmark levels, PVIET=0 and PVIET=.02 are selected. (Maximum PVIET in the sample 1s 0.0649). Other than this distinction, the indifference tunes pertain to individuals both having the overall sample's mean income and travel costs .

The higher the proportion of individuals of Vietnamese ancestry in the respondent's zip code, the greater the cu~ature of the indifference tunes, and the larger the implied equivalent variation for a loss of access to the fishery. Current optimal numbers of days are similar for the two representative anglers, so the large discrepancy between the vertical intercepts of the two empirical indifference curves suggests that while the two socioeconomic groups exhibit similar current behavior, they respond

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[19] This is consistent with anecdotal evidence which suggests than many people in this socioeconomic group supplement their diets with "recreationally-caught" fish.

[20] Both the income and PVIET variables are certainly measured with a degree of error due to reliance on Census zip code means. With specific data at the individual level, the following results would certainly be somewhat different,

Table VI

Jointly Estimated Model;
Heterogeneous Utility Function
(varies with proportion Vietnamese)

Coefficient and Variable	Estimate (asy. t-ratio)
β_1 (z)	2.897 (2.761)
β_2 (q)	0.1195 (14.87)
β_3 ($z^2/2$)	0.1210 (0.3711)
β_4 (zq)	0.003829 (1.800)
β_5 ($q^2/2$)	-0.007125 (-21.84)
γ_1 (zPVIET)	96.64 (0.7534)
γ_2 (qPVIET)	-0.08279 (-0.09106)
γ_3 (z^2PVIET/2)	-58.89 (-1.467)
γ_4 (zqPVIET)	-0.3573 (-1.395)
γ_5 (q^2PVIET/2)	0.08352 (6.583)
u	15.95 (81.93)
ρ	0.2302 (8.971)
Max. logL	-15693.97[a]

[a] Compare to basic model in Table II.

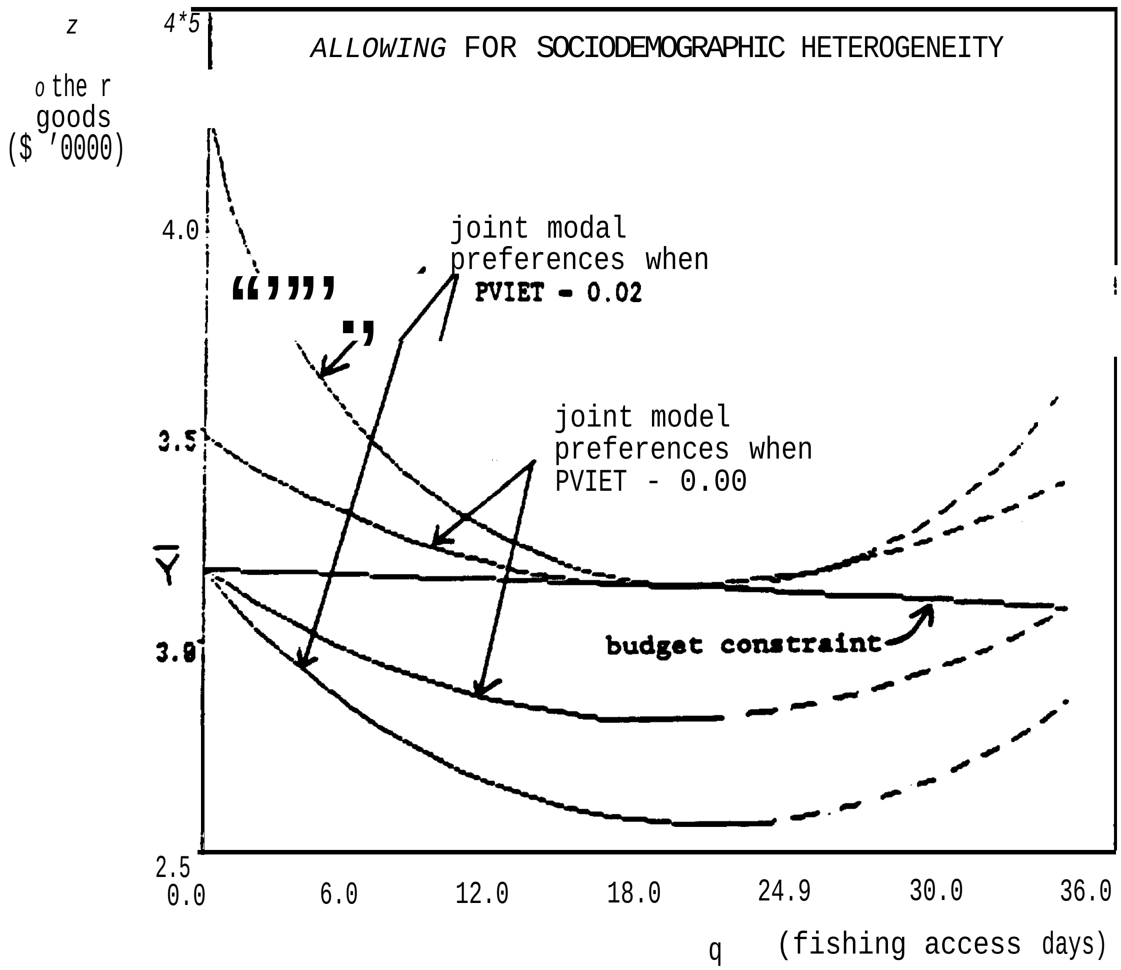

Figure 4 - Systematic variation in preferences when utility parameters are allowed to vary linearly with the zip code proportion of census respondents of Vietnamese origin. Plotted for respondent with mean income and travel costs.

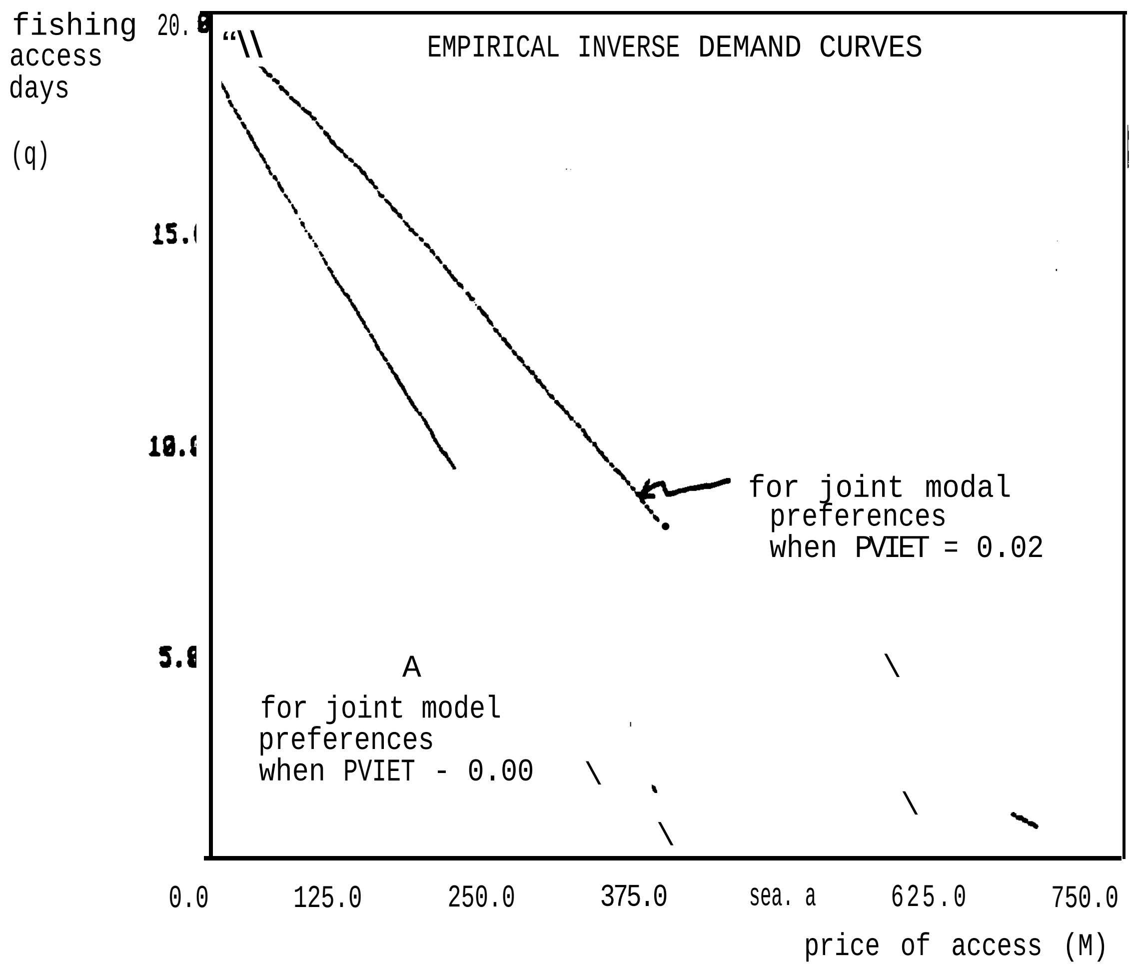

Figure 5 - Differences in empirical demand curves according to proportion Vietnamese for two respondents with otherwise identical income and travel costs.

systematically differently to the hypothetical CVM question. Respondents from zip codes with higher proportions of population with Vietnamese ancestry are more inclined to claim that they would continue to fish despite substantial annual access fees. Figure 5 shows how these different preferences translate into systematically different inverse demand curves. The demand curve for the PVIET - 0.02 group is situated considerably further out than that for the PVIE - 0 group.

What is the policy significance of the finding that preferences for fishing access can vary across sociodemographic groups? Different preferences imply that any policy measure the government might contemplate will have distributional consequences. This will be true whether the policy affects real incomes or the relative price of access or if it consists of access restrictions. Distributional effects can be of critical importance in policy-making.

Ethnic differences are just one of a variety of sources of heterogeneity which could be recognized explicitly in resource valuation models of this type. For models intended to allow simulation of specific policy measures, it will also be important to incorporate dimensions of heterogeneity which can be affected by these policy actions. For example, individual values for access to a recreational fishery are affected not only by angler characteristics, but also by attributes of the resource in question. In one illustration, for a subsample of this dataset, we have addressed the effects on social value of respondent's perceptions about pollution levels (Cameron, 1988b). Not surprisingly, deteriorating environmental quality reduces the demand for access and diminishes the social value of the resource. Likewise, improvements increase social value. This type of model can be used to simulate anticipated social benefits' accruing to recreational anglers if government or private expenditures are devoted to cleanup efforts.

We have also supplemented a subset of the survey data used here with independently gathered data on the abundance of the primary gamefishing target species (Cameron, 1988c). The experiment reveals that gamefish abundance makes intuitively plausible and statistically significant differences in preferences and therefore in the social value of the resource. This type of model can be used to simulate the social benefits to recreational anglers as a consequence of fish stock depletions or enhancement programs.[21]

VI. CONCLUSIONS AND CAVEATS

A fully utflicy-theoretic *specification* distinguishes this analysis from much earlier empirical work on the valuation of non-market resources. By concentrating on identifying the underlying preference structure for access days versus all other goods and services, theoretically sound measures of access values (equivalent and compensating variations) can readily be produced.

Several features of the "basic" model should be emphasized. First, it starts from an assumption of quadratic direct utility, presumed to explain the hypothetical contingent valuation responses. Second, the associated non-linear Marshallian demand functions are employed to explain the observed demand decisions by the respondents (a "travel cost" type of model). Third, the corresponding parameters in the utility and the demand functions are

[21] For our three examples of how respondent and resource heterogeneity can be accommodated in this prototype model, we have assumed that these sources of heterogeneity are mutually orthogonal, so that they may be entered individually and separately. For sufficiently large surveys, the complexity of these heterogeneous models is limited only by the variables upon which data have been collected and by computing capacity. Very elaborate models can potentially be accommodated.

constrained to be identical. Fourth, the quantity demanded under the CVM scenario is fully endogenized. And finally, unobservable attributes of respondents are allowed to affect both types of responses simultaneously through a non-zero (estimated) error correlation.

The “basic model” forms a minimal prototype for models in a wide range of applications in resource valuation. However, this paper has also described a variety of important extensions --potentially very relevant to subsequent researchers. “Prior” assumptions about the relative qualities of the hypothetical CVM questions and the “real” travel cost data can be used to” modify the influence of each of these responses during joint estimation the utility parameters, Examples have also demonstrated that it is straightforward to allow the parameters of the quadratic preference structure to vary systematically with the levels of (exogenous) respondent or resourco attributes.

To review the central empirical findings (for these data, in combination with the assumption of quadratic preferences), the “basic model” yields a sample average fitted equivalent variation of $3451 for a complete loss of access to the fishery. In contrast if ccess days for each individual were restricted by only 10%, the average equivalent variation would be only $35. The implications of the model for small local variations are probably more reliable, although in this case, the complete loss is explicitly “within the range of the data” because of the information extracted from the CVM responses.

Some caveats should be emphasized. Tho sample for this application was consciously trimmed along a number of dimensions. Most notably, anyone who reported fishing more than 60 days per year was dropped from the sample. When attempting to fit a single utility function to an entire sample, the assumption of identical preferences must be at least roughly tenable. People who fish more than 60 days per year probably have fundamentally different preferences. With enough detailed information about the exogenous sociodemographic attributes of these individuals that might account for these differences, one could accommodate broad heterogeneity. This survey, however, provides little such information. In order to highlight the capabilities of the model (without obscuring the relationships due to unrecognized heterogeneity), it is necessary *to* disenfranchise some extremely avid anglers. Consequently, if these average values are scaled up to the population of anglers, the total will underestimate the true value of the fishery. Fortunately, with more detailed surveys (and future generations of computing hardware and software), more comprehensive models will certainly be practicable.

From a policy standpoint, it is also critical to emphasize that in many applications, the benefits computed for the group of resource users represented by the survey sample will comprise only a portion of the total social benefits generated by the resource. Non-consumptive use of the resource will often be substantial: option and existence value can sometimes be larger by orders of magnitude than the user values implied by survey such as the one analyzed in this study. The dollar measures of benefits produced here, for example, are only a lower bound on the total social benefits enjoyed by residents of Texas, the rest of the United States, the continent, or the entire world.

Methodologically, this research has demonstrated that it is indeed *feasible,* and probably highly desirable, to employ referendum contingent valuation data in the context of a fully utility-theoretic model whenever the quality of the data justify such an effort. These results also demonstrate that forcing contingent valuation utility parameter estimates to be consistent with observed demand behavior can have a substantial effect on the estimated preference structure, the implied demand functions, and ultimately on the apparent social value of the resource or public good.

It has also been demonstrated that jointly estimating the discrete/continuou8 choices of respondents *without* parameter constraints allows a rigorous statistical check of the consistency of the hypothetical CVM responses with demonstrated real market decisions (conditional on the functional form chosen for utility). The implications of this dimension of the problem are being explored in greater depth in some follow-up research. Previous validation studies have typically relied on entirely separate models for CVM data and other types of data, such as travel cost information or market experiments. This earlier strategy allows comparisons of *point* estimates of value, but precludes any statistical assessments of the degree of similarity between the results. In contrast, the joint models presented here permit standard likelihood ratio tests. For this sample, the hypothetical CVM data and the obsemed TCM data appear to imply sharply different sets of preferences if completely independent sets of utility parameters are estimated. In other applications, however, consistent responses under the real and hypothetical scenarios may be readily accepted. Such a finding would reinforce the credibility of contingent valuation procedures in those contexts.

When CVM and TCM data are combined in the estimation process, in order to exploit all of the information available, it has been demonstrated that the researcher can systematically accommodate into the estimation process any prior opinion regarding the relative reliability of the two types of data. It is possible to like the two source of preference information without forcing the implied utility function to be exactly identical.

In sum, this research demonstrates the value of combining both contingent valuation and travel data whenever possible. Pooling of these two types of valuation information allows the advantages of each technique to temper the disadvantages of the other. Making the underlying preference structure of consumers the core of the analysis facilitates joint modeling of the two decisions. It also allows a rigorous assessment of the probable responses of individual consumers under a wide range of simulated counterfactual scenarios, and permits welfare estimates which are consistent with neoclassical macroeconomic theory.

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APPENDIX I

An *Alternative Interpretation of the Contingent Valuation Question*

In this study, an alternative interpretation of the CVM question is conceivably possible. Perhaps respondents think of the access fee T as implicitly reflecting a price change at their current consumption level, q(y,M), rather than a lump sum tax. They may interpret the question as asking whether or not they would choose non-zero access days if the price per day went from M to M+(T/q(Y,M)). In this case, the the CVM question would seem to be asking respondents whether their post-price change optimal consumption of access days would be positive. (I.e. if their optimal number of access days was negative, their highest utility would correspond to zero access days, providing that preferences are well-behaved.) The results reported in this paper have emphasized the "lump sum tax" interpretation, but some results for the alternative "price change" interpretation are provided here for comparison, since the interpretation *does* affect the resulting estimates of resource value.

Rather than the *utility-difference* underlying the discrete response in equation (5),this projected optimal consumption level would "drive" the discrete choice portion of the model. A "yes" response implies that the respondent's optimal consumption of access days under the hypothesized scenario is positive. A "no" would mean that optimal consumption would actually b. negative, but zero days are the fewest which can be consumed. The "yes/no" response thus provides censored information regarding the magnitude of optimal quantity demanded. Unlike conventional probit models, where the location of the distribution is unknown (and therefore set arbitrarily to zero), the "threshold" in this case is exactly ***zero days.*** *AS* above, $\mathbf{g}(\mathbf{x}_i,\boldsymbol{\beta})$ will be adopted as the generic representation for the MarshallIan demand function corresponding to the quadratic utility model, where the variables x_i include income and the "price" of a day of access. As in Section III, υ can be used as the same (constant) standard error of the conditional distribution of quantities demanded. The magnitude of υ can be inferred from observed consumption under current prices, so the conditional dispersion of the unobservable dependent variable in the CVM model is "known" (in contrast to the conventional probit situation).

Providing, then, that it is reasonable to assume that real and hypothetical behavior are derived from the identical set of underlying preferences, the discrete responses to the CVM question can be used to supplement the estimation of the underlying demand parameters. Specifically, the expression (f(xL,~)/a) in equations (5) and (7) will be replaced by $g(x_i^*, \beta)/\upsilon$, where x_i^* includes current actual income, but price M is replaced by the hypothesized (M+T/q(Y,M)).

One difference under this interpretation of the CVM question is that this specification no longer allows identification of the individual utility parameters (PI through β_5, up to the scale factor, a, of the unobservable dispersion in the latent variable driving the CVM response). Only the demand parameters, PI*, β_3*, β_4*, and β_5* and v can be identified. Fortunately, the utility function is invariant to the scale of the parameters and arbitrarily setting β_2 "- 1 will result in exactly the same implications in terms of optimizing behavior.

The demand parameter estimates for the utility function under this fundamentally different interpretation of the CVM question appur in Table 1.1. It is not surprising that the point estimates differ systematically from their counterparts in the body of the paper.

For this version of the joint model, the marginal utilities at the means of the data are positive; the price elasticity of demand for access days is about -0.035; the income elasticity is 0.11. The implied global optimum is 20.2 access days and $78212 in median household income.

While the fitted utility function under this interpretation is completely plausible from a theoretical standpoint, the implications of this model are quite a bit different from the "lump-sum tax" interpretation. The sample mean of the fitted equivalent variations for a complete loss of resource access, according *to* these preferences, is markedly higher, at $7386 (with standard deviation $2244). Clearly, subsequent surveys will have to be very careful in conveying to respondents exactly what type of scenario is intended, since the interpretation of the question can make almost an order of magnitude difference in the results.

Table 1.1

Model with CVM Question Interpreted as Price Change

Parameter	Point Estimate (asymp. t-ratio)
β_1^* (z)	19.80 (5.366)
β_2^* (q)	1.000
β_3^* ($z^2/2$)	-2.613 (-2.573)
β_4^* (zq)	0.03155 (1.726)
β_5^* ($q^2/2$)	-0.06163 (-18.23)
υ	16.18 (86.75)
ρ	0.08754 (3.080)
Max. LogL	-15708.12

APPENDIX II

Alternative Direct and Indirect Utility Specifications

Other linear-in-parameters functions that have been widely used empirically include tha translog and tha generalized Leontief specifications. The translog is quadratic in the logarithms of the arguments, but it is critical for the basic model in this paper that *direct* utility levels be defined and non-zero when consumption of one commodity (namely, recreation days) goes to zero. This disqualifies the ordinary translog model, since this function is only defined over strictly positive quantities of each good.[22]

The generalized Leontief specification satisfies the boundary requirements, and is generally considered to be a more "flexible" functional form than the quadratic. However, while a generalized Leontief *indirect* utility function can readily be differentiated to yield Marshallian demands, this similar functional form for the *direct* utility function yields Marshallian demands which are prohibitively complex.

Empirical research on consumer decisions has sometimes employed the Stone-Geary utility function and its corresponding "linear expenditure system" demand equations. This specification may at first seem attractive, but it too is only appropriate when one is considering interior consumer optima. In this case, the utility function would be:

(11.1) $$u(z,q) - (z - \beta_1)^{\beta_2} (q - \beta_3)^{\beta_4}$$

The corresponding demand for fishing days will be given by:

[22] One could, of course, shift the utility surface one unit towards the origin along the dimension of each good by adding ona to each quantity within the functional form for the translog direct utility. However, when the direct utility function, rather than the indirect utility function, takes on a translog functional form, the associated Marshallian demand functions are awkward to derive; they are even more awkward if the function Is additively shifted.

$$q = \beta_3 + (\beta_4/p)\,[Y - \beta_1 - \beta_3\, p] \tag{11.2}$$

where the price of the composite good, z, has again been normalized to unity.

This utility function is not linear in parameters, so initial estimates cannot be obtained via a conventional maximum likelihood probit package. But there is a bigger problem, stemming from the necessity of considering utility levels for zero days of access. In particular, the systematic portion of the utility difference function, which would form the non-linear "index" function for the discrete choice *portion* of the model, would take the following form:

$$AU - [(Y-M-T) - \beta_1]^{\beta_2}\, [q - \beta_3]^{\beta_4} - [\,Y - \beta_1\,]^{\beta_2}\, [\,-\beta_3\,]^{\beta_4} \tag{11.3}$$

The problem for estimation stems from the last term. The coefficient β_4 is often fractional. Attempting to take the β_4-root of a negative number can be expected to create difficulties. Furthermore, the usual interpretation of β_3 is that is represents "subsistence" consumption levels of commodity q, so negative values of the parameter itself are unlikely to result, or to be defensible intuitively, if they do. As expected, in attempts to estimate this model using the data employed in the rest of this study, the algorithm persistently failed.

The quadratic form is a useful local approximation to any arbitrary surface. Why not then expand to third-order terms? Several of the quantities of interest which are derived from the calibrated model necessitate solving the fitted utility function for the value of one of its arguments. The standard formula for computing quadratic roots is straightforward to use. The formulas for the roots of cubic equations are considerably less easy. (See CRC, 1981, p.9.) However, continuing empirical research explores such forms, since the results for quadratic utility specifications suggest that a higher degree of parametrization might be supported.[23]

Contemporaneous work by Huppert (1988) employs an alternative strategy in the context of a standard simultaneous equations model. He begins with a simple functional form (log-linear) for the Marshallian demand specification and accepts the corresponding (unnamed) functional form for the underlying utility function. Huppert's payment card contingent valuation responses are treated as a continuous variable, so that the joint estimation of the utility and demand parameters can be accomplished via standard packaged simultaneous non-linear least squares algorithms.

It is interesting to compare the results derived using a quadratic direct utility function (and implicitly its associated indirect utility function) with those derived for a model that begins with an *indirect* utility function which is quadratic in prices and income. This will imply a very different function form for the direct utility function.

If indirect utility, V, is quadratic in the price of z, the price of q (i.e. M), and income Y, the terms in the unitary price of z will be absorbed into a constant and into the coefficients on M and Y. The effective functional form will be:

$$(11.4) \quad . \qquad V(M,Y) = \alpha_1 M + \alpha_2 Y + \alpha_3 M^2/2 + \alpha_4 MY + \alpha_5 Y^2/2.$$

The corresponding Marshallian demand for q is given by application of Roy's Identity:

---

23 The data appear to support cubed terms in z and q, but the optimization algorithm cannot seem to settle upon coefficients for the second-order interaction terms, z2q and zq^2. The two cubed terms do make a statistically significant improvement in the log-likelihood. function for the model.

$$q(Y, M) = -(\partial V/\partial M)/(\partial V/\partial Y) = (-\alpha_1 - \alpha_3 M - \alpha_4 Y)/(\alpha_2 + \alpha_4 M + \alpha_5 Y), \quad (11.5)$$

or, normalizing α_2 to unity:

$$q(Y,M) = (-\alpha_1^* - \alpha_3^* M - \alpha_4^* Y)/(1 + \alpha_4^* M + \alpha_5^* Y). \quad (11.6)$$

The respondent will decide to pay lump sum tax T and continue fishing if $V(M,Y-T) > V(Y)$, i.e., if

$$\Delta V(Y,M,T) = f(x_i,\beta) = \alpha_1 M + \alpha_2(-T) + \alpha_3 M^2/2 + \alpha_4 M(Y - T) + \alpha_5 [(Y-T)^2 - Y^2]/2 > 0. \quad (11.7)$$

The equivalent variation, E, which would leave the respondent indifferent between fishing and not fishing is given by the quadratic root E of:

$$\alpha_5/2\, E^2 - [\alpha_2 + \alpha_4 M + \alpha_5 Y]\, E + [\alpha_1 M + \alpha_3 M^2/2 + \alpha_4 MY] = 0. \quad (11.8)$$

The joint model can be set up as in the text of the paper, except now we have $f(x_i,\beta) = \Delta V(Y,M,T)$ and $g(x_i,\beta)$ is replaced by the Marshallian demand formula derived in this section.

The indirect utility approach has the distinct advantage that it does not require endogenous determination of post-tax quantity demanded, $q(Y-T,M)$. However, the direct utility specification corresponding to this representation of preferences is prohibitively awkward to derive, so the intuitive advantages of standard indifference curve diagrams are beyond our reach.

Nevertheless, it is straightforward to estimate the joint model of indirect utility differences and the corresponding Marshallian demands. We have done so. The parameter estimates appear in Table 11.1.

Unfortunately, while the direct utility approach used in the body of the paper easily satisfies the regularity conditions for a valid utility function, this is not the case for the quadratic indirect utility specification used here. $V(M,Y)$ should be nonincreasing in M and nondecreasing in Y. At the means of the data, however, the parameters given in Table 11.1 produce a value of 97.87 for $\partial V/\partial M$ and a value of -5.653 for $\partial V/\partial Y$. As a consequence of these irregularities, the values we compute for the equivalent variation associated with a loss of access are nonsensical. In other applications, however, the indirect utility approach (possibly using alternative functional forms) may prove to be satisfactory, or even preferable, to the direct utility model, especially if it 1s deemed unnecessary to provide empirical indifference tunes as a visual aid.

Table 11.1

Quadatic Indirect Utility Specification

Parameter	Point Estimate (asymp. t-ratio)
β_1* (M)	75.50 (6.642)
β_2* (y)	-4.123 (-6.667)
β_3* ($M^2/2$)	-4936.81 (-8.237)
β_4* (MY)	11.59 (3.374)
β_5* ($Y^2/2$)	-0.4929 (-2.624)
v	15.97 (82.04)
ρ	0.2043 (8.506)
Max. LogL	-15957.66

APPENDIX III

Estimates in the absence of travel cost data

In some applications, M may be measured accurately and may be relativel constant across fishing days, but in other cases, it may not. Sometimes, the researcher may be better off ignoring the questionable information on M, and using a simpler "Engel curve" model as opposed to a "demand function" (where equation numbers indicate revisions of the original specification):

$$(1') \qquad AU = U(Y - T, q^1) - U(Y, 0) > 0.$$

If the data on M are excluded, z will be identically Y.

$$(10') \qquad \Delta U(Y,T) - \beta_1 ([Y-T] - Y\} + \beta_2 q^1 + \beta_3 ([Y-T]^2 - Y^2)/2 + \beta_4 [Y-T]q^1 + \beta_5 (q^1)^2/2.$$

$$(11') \qquad q(Y) = [1 + (\beta_4*) Y] / [- \beta_5*].$$

$$(17') \qquad \partial q/\partial p - [\beta_5(\beta_1-\beta_3 Y) - 2\beta_4(\beta_2+\beta_4 Y) 1 / [\beta_5]^2$$

$$\partial q/\partial Y - -\beta_4/\beta_5.$$

In order to appreciate the benefits of joint estimation with income data and numbers of trips but in the absence of travel costs as proxy data for prices, one can consider the estimates of the utility function parameters when the data on M in this sample are ignored. Table 111.1 displays these results. At the means of the data, these fitted parameters imply a utility function with positive marginal utility from other goods, but very slightly negative marginal utility from access days. This implies that the utility function in this case is not globally concave. The saddle point of the utility function is located at 12.25 access days and $-47348. Nevertheless, the level curves are still convex to the origin. At the means of the data, the price elasticity of demand for access days is -0.125 and the income elasticity is 0.0682.

Figure 111.1 shows the effects on the fitted preference function of ignoring travel costs in the estimation phase. As benchmarks, this figure includes the “basic” indifference curve for a typical respondent (curve E) as well as the indifference tune based on the CVM portion (curve A) and the *demand* portion (curve D) of the unrestricted model. Here, however, attention should be focused on the indifference curve for a model similar to the basic model except that the available data on travel costs are ignored (curve A). Even this very “thin” information about market demand pulls the parameter estimates a long way away from the unrestricted CVM estimates depicted by cunre A. Still, it is not clear in this application that the resulting (much smaller) equivalent variation estimates will be superior to those generated by the CVM portion of the unrestricted model.

Table 111.1

Jointly Estimated Model Ignoring Travel Costs (i.e. M - O; Only Engel Curves from Observed Demand Employed)

β_1 (z)	3.586 (1.342)
β_2 (q)	0.1259 (13.19)
β_3 ($z^2/2$)	0.7711 (0.9538)
β_4 (zq)	0.005329 (2.058)
β_5 ($q^2/2$)	-0.008213 (-22.46)
u	16.12 (81.85)
P	0.2343 (9.076)
log L	-15679.17

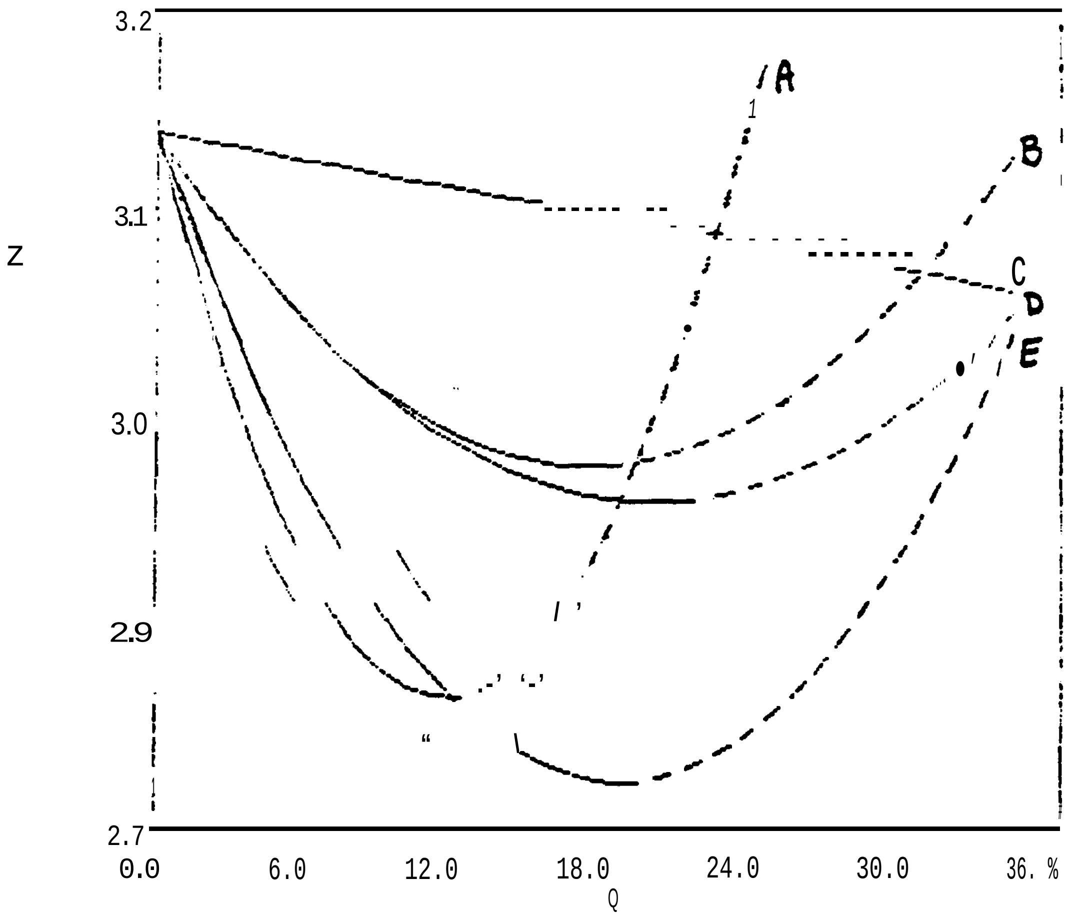

Figure III.1 - For respondent with mean income and travel costs, effects of ignoring travel costs during estimation of utility parameters by modified basic model: actual budget constraint (C), indifference curve from basic model (E), indifference curve from the CV portion of the unrestricted model (A), indifference curve from demand portion of unrestricted model (D), and indifference curve from model estimated without travel cost (using only Engel curve information) (B).

APPENDIX IV

An Ad Hoc Reweighing Scheme

Researchers who work with maximum likelihood estimation of models using sample data are by now very familiar with reweighing procedures for scaling the influence of different observations to allow the sample to more nearly reflect the proportions of each types of person in the entire population. Each observation in the sample is represented by one additive term in the log-likelihood function, each bearing an implicit unit weight. Non-unit weights, based on cross-tabulations performed on the population and on the sample, are computed by calculating the ration of population proportions to sample proportions in each cell of the cross-tabulation. Respondents who represent undersampled groups in the population then have their contribution to parameter estimation scaled up; oversampled respondents are given weights of less than unity to decrease their influence on the final parameter estimates.

If CVM and TCM responses are treated •s equally credible, the two terms in the log-likelihood function in (7) corresponding to each type of information each receive an implicit unit weight. Fortunately, the dismantling of the joint normal error distribution into a conditional times a marginal error distribution leaves the error correlation, ρ, determined entirely within the discrete choice CVM portion of the likelihood function. It see,ms feasible, therefore, to "undo" the CVM and TCM terms in the likelihood function and to scale the influence of each type of information in determining the final parameter estimates.

If, for example, intuition suggests that the available CVM information is only half as reliable as the "real" travel cost information, one might change the weights on the CVM terms in the log-likelihood function to 2/3 and those on the TCM demand terms to 4/3 (so that the weights still sum to two).

This ratio of the weights will be designated as a "reliability" factor of .5 for the CVM information.

Given the maintained hypothesis of a quadratic utility function, one can ask just how small the weight on the CVM information would have to become before LR tests could just fail to reject the null hypothesis of parameter equivalence for the two models. For equal unit weights (relative weight - 1.0) the results for the constrained and unconstrained models from Table II are reproduced in Table IV.1. The second pair of columns in that table show the consequences of decreasing the relative weight on the CVM information. The relative reliability of the CVM information has been. decreased to 0.1 and it is still possible to reject the hypothesis of common utility parameters. It would therefore be quite a "stretch" to bring the utility implications of the hypothetical CVM responses into line with observed demand behavior in this particular application.

Still, the observed demand behavior might itself be misleading if the true opportunity costs of access are poorly proxied by travel costs. It may be inappropriate to expect the preferences implied by the two types of value information to be identical. Likewise, the simple quadratic utility function and homogeneous preferences may be too restrictive. Therefore, this finding does not necessarily refute the equivalence of the true preferences underlying these two types of responses.[24]

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24 We have extendad the specification of the direct utility function to include cubic terms in z and q. The data are not rich enough to support separate parameters for the terms z2q or zq^2. For the new "basic" model with seven utility parameters, the maximized value of the log-likelihood function is -15699.41. For the corresponding "unrestricted" model with separate CVM and TCM parameters,convergence has not been attained after several hundred iterations, but the log-likelihood function has been driven ●s high as -15631.95, which is more than adequate to reject the restrictions.

Table IV.1

Joint Models with Separate CVM and TCM Parameters
(CVM and TCM equally credible; CVM discounted by weighting;
CVM discounted by disproportionate variances)

Parameter	Rel.wt. - 1.0[a]		Rel.wt. - 0.1	
	Basic Model	Unconstr. Mode 1	Basic Model	Unconstr. Model
β_1 *(z)*	3.909 (8.237)	1.276 (0.7457)	7.840 (6.385)	1.290 (0.2952)
β_2 (q)	0.1192 (19.55)	28.17 (2.573)	0.1399 (12.64)	39.43 (0.9207)
β_3 $(z^2/2)$	-0.1167 (-1.836)	1.498 (2.834)	-1.036 (-2.986)	1.494 (1.111)
β_4 (zq)	0.002579 (2.006)	2.263 (2.147)	-0.001093 (-0.6008)	3.157 (0.8039)
β_5 $(q^2/2)$	-0.006837 (-22.80)	-502.3 (-1.311)	-0.007060 (-13.47)	-983.3 (-0.4689)
$\beta_1^*=\beta_1/\beta_2$	-	75.89 (5.756)	-	76.03 (7.703)
$\beta_2^*=\beta_2/\beta_2$		1.0		1.0
$\beta_3^*=\beta_3/\beta_2$		-10.89 (-2.428)	-	-11.88 (-3.567)
$\beta_4^*=\beta_4/\beta_2$	-	-0.01749 (-0.9029)	-	-0.02129 (-1.495)
$\beta_5^*=\beta_5/\beta_2$		-0.04739 (-14.97)		-0.04721 (-20.09)
υ	16.01 (81.98)	15.97 (82.04)	15.98 (110.5)	15.97 (110.6)
P	0.2315 (9.086)	0.2505 (9.749)	0.2324 (4.030)	0.2495 (4.166)
max Log L	-15708.17	-15640.61[b]	-25938.13	-25920.04[c]

[a] "Rel. wt." is the size of the weight on the hypothetical CVM information relative to the weight on the observed demand behavior.

[b] LR test for hypothesis of same ~ parameters for CVM and TCM utility functions is 115.12 (when the 5% critical value of the X^2 test statistic is 9.49 and the 1% critical value is 13.28).

[c] LR test for same β parameters is 36.1; still rejects hypothesis.

APPENDIX V

Implementing These Prototype Models in Other Applications

The illustration in this paper pertains to the valuation of a particular recreational fishery. However, the joint model developed here is potentially applicable to the valuation of any non-market good where consumers would have to incur varying travel costs in order to engage in the process of consumption. Individually, the travel cost method and the contingent valuation methods each have shortcomings. Implications drawn from their combined evidence ere likely to be much more robust.

While relatively good, the data used in this paper are still less then ideal. The specific implications of the fitted models described here must be judged accordingly. But this research has provided vital groundwork for future studies.

First, the sampling procedures used in the gathering of the data employed in this study were not ideal. In particular, rotating sites for the survey were chosen, and virtually everyone who passed during the 10 a.m. to 5 p.m. period was interviewed. This precludes “outgoing” surveys for avid anglers who may be out well before 10 a.m. , although many of these anglers would be intercepted upon their return. A more serious problem is that we cannot identify respondents who have been interviewed more than once. At best, we have a reasonable sample of fishing trips, not anglers, so the estimated preferences may be biased towards those of frequent anglers. This problem cannot be remedied with this data set.

It would be highly desirable to have individual-specific measures of income (and other sociodemographic variables). Census zip code means are helpful, but much information is lost in using group averages as proxies for the true variables. If at all possible, the survey instrument should elicit these data for each respondent.

The contingent valuation question should be phrased so as to make it clear whether the hypothesized change is intended to be a lump-sum change in income (as modeled in the body of this paper), or a change in relative prices (as explored in Appendix I). This information is vital to the utility-theoretic formulation of the estimating model,and great care must be taken to ensure that the CVM question is completely unambiguous.

The present survey asks about travel costs for the current fishing day. What the model requires is *typical* costs for a *typical* fishing trip, or better yet, enough information *to* construct the actual schedule of opportunity costs as they increase with number of access days. This would make the travel cost portion of the model more reliable. The current model also must presume that individuals fish most of the time at the same location. Much more sophisticated analyses will be required in order to introduce site choice modeling into this framework.[25]

Respondents could be asked specifically about how sure they are concerning their hypothetical responses to the CVM and travel cost questions. This information could be incorporated into the weighting scheme for the auto-validation of the CVM data.

Optton and existence values cannot be captured with the current data set. Selection problems in the assessment of recreation demand have received considerable attention recently (e.g. Smith, 1988). A random sample of households in the target population could be contracted by telephone. If they do not currently consume access days, quantity demanded will simply be zero.

2S At present, site choice modeling has been pursued in a largely atheoretic multiple discrete choice framework. Blending the two approaches have to wait for further computer software and hardware innovations.

Travel costs to relevant sites could still be elicited and appropriate CVM questions could be formulated to allow extension of this modeling framework to non-use demands.