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## **AJAE Appendix for Dynamic Random Utility Modeling: A Monte Carlo Analysis**

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This technical appendix is intended to provide the reader with a complete illustration of the Monte Carlo results highlighted in our paper. It is divided into three sections. Section one contains a complete set of results for the general model (Equation 16 in the paper) and illustrates how the different metrics of comparison were calculated. Section two contains the results from the welfare analysis discussed within the paper under the five different time horizons assumptions. Section three graphically illustrates a randomly selected cruise trajectory from the general model to visually illustrate how the RUM and DRUM model generate different cruise trajectories within a fishery.

### **Monte Carlo Results for the General Model (Equation 16)**

The following tables contain the complete set of results from the entire set of Monte Carlos conducted and discussed in our paper. Tables 1-6 were generated using 500 Monte Carlo iterations with the number of observations fixed at 4000 for each of the 500 iterations. In order to assure that the number of observations were identical across all the models we varied the number of “cruises” generated. For cruises of length 10 we generated 400 cruises, for 20 we generated 200 and for 40 we generated 100. The distributional assumptions of the data generation process are illustrated in Table 1 of the paper for both the compact fishery (*dist\_scale=1*) and the larger fishery (*dist\_scale=10*). A graphical illustration of these results is contained in the third section of this technical appendix.

Tables 1-6 contain four different metrics of comparison: coefficient bias, root-mean-squared-error (RMSE), within sample predictions and the distance penalty

function. The bias and RMSE were calculated as follows where  $N$  represents the number of Monte Carlo iterations ( $N=500$ ),

$$Bias = \frac{1}{N} \sum_{i=1}^N (\hat{\mathbf{b}}_i) - \mathbf{b}$$

$$RMSE = \sqrt{Bias^2 + Var(\hat{\mathbf{b}})}$$

The within sample predictions was calculated by determining the predicted location in time period  $t$  given an estimated parameter vector, denoted  $\hat{d}_{kt}$ , and seeing whether or not the true site selected (denoted by  $d_{kt}$ ), equaled the predicted. To determine which site was visited, the estimated parameter vector,  $\hat{\mathbf{b}}$ , was used to determine which site possessed the highest probability of selection and selecting it as the site of choice in a given time period for each iteration of the Monte Carlo. Once a site was selected in time period  $t$ , the travel cost matrix  $x_{t+1}^{tc}$  was altered to reflect the current site choice and then used to predict the site choice in time period  $t+1$ . Defining the following binary variable,  $I_b$ , which takes a value of 1 if  $\hat{d}_{kt} \neq d_{kt}$ , the within prediction estimate was determined as follows,

$$Within \% = \frac{1}{N} \sum_{j=1}^N \left( \frac{M - \sum_{t=1}^M I_{jt}}{M} \right) * 100,$$

where  $M$  is the number of data points, 4000, and the subscript  $j$  on  $I_t$  denotes the  $j^{th}$  Monte Carlo iteration from a total of  $N$  runs.

The distance penalty function indicates how far off the true path the estimator predicts a cruise trajectory. Denoting  $D_{jt}$  as the Euclidean distance between the true site selected in time  $t$  for the  $j^{th}$  Monte Carlo iteration and that predicted by the estimator, the distance penalty function is calculated as follows,

$$Dist\_Pen = \frac{1}{N} \sum_{j=1}^N \sqrt{\sum_{t=1}^M D_{jt}} .$$

Note that if the parameter estimates generate site predictions identical to the true cruise trajectory the distance penalty in that time period and iteration of the Monte Carlo is zero,  $D_{jt}=0$ .

### **Monte Carlo Results for Welfare Analysis**

Table 7 illustrates the distributional assumptions of the data generation process used in the Monte Carlo to investigate the compensating variation estimated by the RUM and DRUM assuming a homogeneous and heterogeneous fishery when location 1 is closed. Tables 8-12 contain all the Monte Carlo results for the different assumptions regarding the true time horizon possessed by fisherman. Note that for Tables 8 through 12, the estimated DRUM assumes a time horizon of 20 hauls. All the other metrics of comparison are as defined earlier.

## Graphical Illustration of Cruise Trajectories

Figures 1-4 were generated by randomly selecting one of the 100 cruises simulated in the 40 haul cruise length under both the compact fishery ( $dist\_scale=1$ ) and larger fishery ( $dist\_scale=10$ ) assumptions.<sup>i</sup> Figures 1 and 2 depict the first 20 and last 20 hauls made on the 40 haul cruise assuming a distance scale of 1 for the 20 location model. Figures 3 and 4 depict the same information assuming a distance scale of 10.<sup>ii</sup> In Figures 1 and 2 the vessel behavior is very erratic because for each haul expected revenues dominate the vessel's site choice since travel costs are relatively small. This causes both the static and the DRUM estimator to yield a poor prediction of site selection. In fact the static model slightly outperforms the DRUM estimator by accurately predicting 6 of the true sites whereas the DRUM estimator predicted only 4. This indicates that in a fishery where revenues dominate travel costs, the RUM is comparable to the DRUM model even if the vessel is forward looking. Of course the parameter estimates are still incorrect and biased, which may impact welfare estimates, but the cruise trajectories can be approximated with the RUM model.

When distance becomes relatively more important (Figure 3 and 4), the DRUM trajectory more closely tracks the observed choices, matching the cruise trajectory 37 of 40 hauls, as opposed to 16 of 40 hauls for the static model (RUM). These differences are readily evident in the cruise trajectories illustrated. For instance, the RUM model predicts that the vessel will be operating on the opposite end of the fishery for hauls 4 through 8 whereas the DRUM estimator closely matches the true trajectory. Even when the DRUM misses a prediction, it is much more likely to predict nearer to the optimal trajectory than the RUM. The sites visited in the RUM model represent the myopically

optimal locations, or those locations that possess the highest expected returns today and are not necessarily on the dynamically optimal path. Even though a site may possess advantageous expected returns in the current period, the travel costs one would incur to access other areas in the future are unacceptably high when viewing choices dynamically. The DRUM model captures this behavior and therefore yields a different cruise trajectory than the RUM.

This concludes the technical appendix. Should further clarification be required please contact either author.

Table 1. The 5 Location Model with  $dist\_scale=1$

5 Location Model	$\beta_0$		$\beta_1$		$\beta_2$		Within %	Distance Penalty
	Bias	RMSE	Bias	RMSE	Bias	RMSE		
Cruise = 10								
Static; $d=0$	-0.0104	0.02203	-0.0004	0.01807	0.00422	0.01291	45.22%	64.352
Dynamic; $d=0.85$	-0.0045	0.01861	0.00112	0.01779	-0.0006	0.01208	46.20%	63.280
Dynamic; $d=0.9$	0.00005	0.01786	0.00083	0.01775	0.00016	0.01205	46.26%	63.220
Dynamic; $d=0.95$	0.00494	0.01833	0.00052	0.01771	0.00094	0.01206	46.33%	63.156
Cruise = 20								
Static; $d=0$	-0.0109	0.02176	-0.0001	0.01820	0.00463	0.01306	45.17%	64.354
Dynamic; $d=0.85$	-0.0047	0.01822	0.00106	0.01785	-0.0005	0.01210	46.19%	63.233
Dynamic; $d=0.9$	-0.0002	0.01741	0.00073	0.01780	0.00023	0.01207	46.24%	63.175
Dynamic; $d=0.95$	0.00478	0.01786	0.00039	0.01775	0.00105	0.01209	46.31%	63.117
Cruise = 40								
Static; $d=0$	-0.0112	0.02198	-0.0005	0.01831	0.00496	0.01334	45.05%	64.417
Dynamic; $d=0.85$	-0.0049	0.01825	0.00087	0.01788	-0.0004	0.01230	46.14%	63.227
Dynamic; $d=0.9$	-0.0003	0.01740	0.00053	0.01783	0.00036	0.01227	46.20%	63.165
Dynamic; $d=0.95$	0.00470	0.01783	0.00018	0.01778	0.00120	0.01230	46.27%	63.106



Table 2. The 10 Location Model with  $dist\_scale=1$

10 Location Model	$\beta_0$		$\beta_1$		$\beta_2$		Within %	Distance Penalty
	Bias	RMSE	Bias	RMSE	Bias	RMSE		
Cruise = 10								
Static; $d=0$	-0.0261	0.03981	0.00249	0.01702	-0.0003	0.01021	32.32%	57.983
Dynamic; $d=0.85$	-0.0050	0.02853	0.00056	0.01683	-0.0009	0.01027	32.73%	57.226
Dynamic; $d=0.9$	-0.0005	0.02789	0.00042	0.01682	-0.0007	0.01025	32.75%	57.190
Dynamic; $d=0.95$	0.00431	0.02799	0.00027	0.01682	-0.0005	0.01024	32.77%	57.161
Cruise = 20								
Static; $d=0$	-0.0313	0.04352	0.00275	0.01708	-0.0002	0.01000	32.29%	57.883
Dynamic; $d=0.85$	-0.0053	0.02816	0.00050	0.01685	-0.0009	0.01006	32.77%	57.076
Dynamic; $d=0.9$	-0.0005	0.02742	0.00034	0.01684	-0.0008	0.01005	32.79%	57.047
Dynamic; $d=0.95$	0.00450	0.02753	0.00018	0.01684	-0.0006	0.01003	32.81%	57.020
Cruise = 40								
Static; $d=0$	-0.0334	0.04540	0.00281	0.01717	-0.0002	0.01000	32.29%	57.810
Dynamic; $d=0.85$	-0.0053	0.02806	0.00050	0.01693	-0.0010	0.01009	32.78%	56.987
Dynamic; $d=0.9$	-0.0004	0.02731	0.00033	0.01693	-0.0008	0.01007	32.80%	56.956
Dynamic; $d=0.95$	0.00471	0.02746	0.00017	0.01692	-0.0007	0.01006	32.82%	56.925

Table 3. The 20 Location Model with  $dist\_scale=1$ 

20 Location Model	$\beta_0$		$\beta_1$		$\beta_2$		Within %	Distance Penalty
	Bias	RMSE	Bias	RMSE	Bias	RMSE		
Cruise = 10								
Static; $d=0$	-0.0167	0.02342	-0.0261	0.03041	0.00303	0.01000	20.06%	86.882
Dynamic; $d=0.85$	-0.0032	0.01625	-0.0012	0.01549	0.00022	0.00957	21.18%	84.483
Dynamic; $d=0.9$	-3.1E-6	0.01584	-6.9E-5	0.01543	0.00051	0.00958	21.22%	84.385
Dynamic; $d=0.95$	0.00348	0.01612	0.00106	0.01546	0.00083	0.00960	21.26%	84.301
Cruise = 20								
Static; $d=0$	-0.0186	0.02464	-0.0278	0.0319	0.00303	0.00997	19.91%	86.792
Dynamic; $d=0.85$	-0.0034	0.01583	-0.0015	0.01544	0.00018	0.00952	21.12%	84.166
Dynamic; $d=0.9$	8.1E-6	0.01536	-0.0003	0.01536	0.00048	0.00953	21.17%	84.055
Dynamic; $d=0.95$	0.00365	0.01568	0.00093	0.01537	0.00082	0.00955	21.21%	83.969
Cruise = 40								
Static; $d=0$	-0.0193	0.02492	-0.0289	0.03279	0.00300	0.00982	19.88%	86.751
Dynamic; $d=0.85$	-0.0033	0.01546	-0.0017	0.01546	0.00017	0.00937	21.14%	84.024
Dynamic; $d=0.9$	0.00016	0.01500	-0.0004	0.01535	0.00048	0.00938	21.17%	83.892
Dynamic; $d=0.95$	0.00388	0.01538	0.00080	0.15355	0.00083	0.00940	21.22%	83.795

Table 4. The 5 Location Model with  $dist\_scale = 10$ 

5 Location Model	$\beta_0$		$\beta_1$		$\beta_2$		Within %	Distance Penalty
	Bias	RMSE	Bias	RMSE	Bias	RMSE		
Cruise = 10								
Static; $d=0$	0.31317	0.31318	-0.1322	0.13218	0.32977	0.32978	76.17%	137.856
Dynamic; $d=0.85$	-0.0127	0.02746	0.00063	0.00983	-0.0023	0.02446	93.30%	70.846
Dynamic; $d=0.9$	-0.0023	0.02381	0.00097	0.00984	-0.0023	0.02436	93.54%	69.521
Dynamic; $d=0.95$	0.02264	0.03134	-0.0043	0.01020	0.01158	0.02557	93.54%	69.551
Cruise = 20								
Static; $d=0$	0.31468	0.31469	-0.1333	0.01333	0.33361	0.33362	75.13%	140.965
Dynamic; $d=0.85$	-0.0123	0.02740	0.00066	0.00982	-0.0019	0.02435	93.38%	70.288
Dynamic; $d=0.9$	-0.0021	0.02366	0.00086	0.00970	-0.0021	0.02401	93.66%	68.637
Dynamic; $d=0.95$	0.02322	0.03140	-0.0049	0.01014	0.01246	0.02533	93.60%	69.032
Cruise = 40								
Static; $d=0$	0.31532	0.31533	-0.1338	0.13382	0.33490	0.33491	75.07%	141.203
Dynamic; $d=0.85$	-0.0119	0.02720	0.00023	0.00985	-0.0014	0.02440	93.33%	70.624
Dynamic; $d=0.9$	-0.0017	0.02362	0.00066	0.00977	-0.0015	0.02411	93.68%	68.612
Dynamic; $d=0.95$	0.02390	0.03192	-0.0049	0.01025	0.01322	0.02584	93.65%	68.794

Table 5. The 10 Location Model with  $dist\_scale=10$ 

10 Location Model	$\beta_0$		$\beta_1$		$\beta_2$		Within %	Distance Penalty
	Bias	RMSE	Bias	RMSE	Bias	RMSE		
Cruise = 10								
Static; $d=0$	0.24813	0.24820	-0.1056	0.10560	0.25592	0.25596	78.32%	113.814
Dynamic; $d=0.85$	-0.0111	0.02194	0.00020	0.00741	-0.0011	0.01829	91.10%	69.256
Dynamic; $d=0.9$	-0.0025	0.01882	0.00105	0.00754	-0.0027	0.01855	91.30%	68.322
Dynamic; $d=0.95$	0.01112	0.02120	6.73E-5	0.00738	0.00021	0.01814	91.35%	68.129
Cruise = 20								
Static; $d=0$	0.25136	0.25141	-0.1072	0.10725	0.25815	0.25819	77.38%	116.290
Dynamic; $d=0.85$	-0.0117	0.02298	0.00037	0.00776	-0.0015	0.01898	91.07%	69.237
Dynamic; $d=0.9$	-0.0025	0.01955	0.00094	0.00780	-0.0025	0.01900	91.23%	68.500
Dynamic; $d=0.95$	0.01200	0.02216	-0.0005	0.00760	0.00137	0.01848	91.26%	68.335
Cruise = 40								
Static; $d=0$	0.25461	0.25466	-0.1086	0.10861	0.26148	0.26151	76.64%	118.533
Dynamic; $d=0.85$	-0.0119	0.02263	0.00039	0.00764	-0.0016	0.01870	91.09%	69.136
Dynamic; $d=0.9$	-0.0022	0.01885	0.00083	0.00763	-0.0022	0.01862	91.26%	68.352
Dynamic; $d=0.95$	0.01316	0.02217	-0.0008	0.00743	0.00222	0.01813	91.28%	68.243

Table 6. The 20 Location Model with  $dist\_scale=10$

20 Location Model	$\beta_0$		$\beta_1$		$\beta_2$		Within %	Distance Penalty
	Bias	RMSE	Bias	RMSE	Bias	RMSE		
Cruise = 10								
Static; $d=0$	0.28438	0.28440	-0.1208	0.12076	0.29721	0.29722	61.63%	204.097
Dynamic; $d=0.85$	-0.0086	0.01920	-0.0003	0.00694	2.37E-5	0.01662	87.39%	106.616
Dynamic; $d=0.9$	-0.0025	0.01712	0.00096	0.00703	-0.0025	0.01683	88.01%	103.463
Dynamic; $d=0.95$	0.01881	0.02442	-0.0033	0.00738	0.00914	0.01808	88.04%	103.637
Cruise = 20								
Static; $d=0$	0.28774	0.28775	-0.1222	0.12223	0.29873	0.29874	59.97%	208.679
Dynamic; $d=0.85$	-0.0083	0.01946	-2.0E-5	0.00697	0.00043	0.01700	87.37%	107.175
Dynamic; $d=0.9$	-0.0019	0.01767	0.00070	0.00709	-0.0018	0.01730	88.13%	102.516
Dynamic; $d=0.95$	0.01985	0.02566	-0.0040	0.00782	0.00949	0.01892	88.12%	103.167
Cruise = 40								
Static; $d=0$	0.28945	0.28947	-0.1228	0.12282	0.29984	0.29985	60.04%	208.105
Dynamic; $d=0.85$	-0.0084	0.01940	9.97E-5	0.00694	0.00017	0.01677	87.30%	107.583
Dynamic; $d=0.9$	-0.0021	0.01741	0.00079	0.00698	-0.0021	0.01694	88.04%	102.964
Dynamic; $d=0.95$	0.02020	0.02569	-0.0043	0.00783	0.00964	0.01852	88.04%	103.513

Table 7. Distributional assumptions - Welfare Analysis

	5 – Location Homogenous Fishery		5 – Location Heterogeneous Fishery	
	$\mu$	$s$	$\mu$	$s$
$X_{l,1}$	110	20	80	20
$X_{l,2}$	110	20	60	40
$X_{l,3}$	110	20	60	40
$X_{l,4}$	110	20	60	40
$X_{l,5}$	110	20	80	20

Table 8. Welfare results: True time horizon = 1

Time Horizon – 1 period	Bias $\beta_0$	Bias $\beta_I$	RMSE $\beta_0$	RMSE $\beta_I$	Within %	Distance Penalty	True Welfare	Static Welf.	Dynamic Welf.
Homogeneous									
Dyn(dist=1)	0.00395	0.00044	0.03908	0.01805	91.99%	25.029	23.191	-----	22.622
Stat(dist=1)	0.02119	-0.0222	0.05005	0.02759	91.50%	25.873	23.191	24.306	-----
Dyn(dist=10)	0.24295	-0.2088	0.24304	0.20891	85.26%	107.910	22.482	-----	15.691
Stat(dist=10)	0.33946	-0.3285	0.33947	0.32850	75.07%	139.581	22.482	28.910	-----
Dyn(dist=20)	0.37204	-0.3592	0.37205	0.35922	70.10%	215.162	27.097	-----	12.185
Stat(dist=20)	0.39705	-0.3929	0.39705	0.39288	58.97%	251.535	27.097	34.144	-----
Heterogeneous									
Dyn(dist=1)	0.00367	0.00094	0.04928	0.02254	94.63%	19.692	34.266	-----	36.226
Stat(dist=1)	-0.0131	-0.0181	0.06463	0.02718	94.36%	20.234	34.266	35.100	-----
Dyn(dist=10)	0.19084	-0.1700	0.19112	0.17038	91.24%	78.882	33.545	-----	24.881
Stat(dist=10)	0.33647	-0.3405	0.33648	0.34056	81.97%	113.403	33.545	46.475	-----
Dyn(dist=20)	0.35668	-0.3363	0.35669	0.33627	82.83%	154.744	41.760	-----	22.162
Stat(dist=20)	0.40426	-0.4055	0.40426	0.40554	69.90%	204.804	41.760	56.293	-----

Table 9. Welfare results: True time horizon = 3

Time Horizon – 3 periods	Bias $\beta_0$	Bias $\beta_I$	RMSE $\beta_0$	RMSE $\beta_I$	Within %	Distance Penalty	True Welfare	Static Welf.	Dynamic Welf.
Homogeneous									
Dyn(dist=1)	0.00071	0.00048	0.03899	0.01813	92.00%	25.017	22.836	-----	22.617
Stat(dist=1)	0.01670	-0.0222	0.04807	0.02768	91.49%	25.885	22.836	24.311	-----
Dyn(dist=10)	0.05559	-0.0529	0.05807	0.05555	91.10%	82.734	18.502	-----	14.700
Stat(dist=10)	0.31559	-0.3276	0.31560	0.32759	73.20%	145.019	18.502	29.288	-----
Dyn(dist=20)	0.25099	-0.2427	0.25111	0.24284	84.93%	151.504	19.450	-----	10.910
Stat(dist=20)	0.38827	-0.3964	0.38828	0.39641	55.77%	260.229	19.450	34.674	-----
Heterogeneous									
Dyn(dist=1)	0.00239	0.00101	0.04908	0.02265	94.62%	19.696	33.860	-----	36.221
Stat(dist=1)	-0.0139	-0.0181	0.06440	0.02728	94.35%	20.249	33.860	35.106	-----
Dyn(dist=10)	0.00823	-0.0061	0.02504	0.02472	94.56%	61.059	28.586	-----	24.247
Stat(dist=10)	0.31997	-0.3372	0.31999	0.33717	80.76%	117.278	28.586	46.857	-----
Dyn(dist=20)	0.18804	-0.1806	0.18850	0.18109	92.48%	101.576	31.703	-----	21.00
Stat(dist=20)	0.38986	-0.4038	0.38986	0.40385	66.66%	215.821	31.703	56.771	-----



Table 10. Welfare results: True time horizon = 5

Time Horizon – 5 periods	Bias $\beta_0$	Bias $\beta_I$	RMSE $\beta_0$	RMSE $\beta_I$	Within %	Distance Penalty	True Welfare	Static Welf.	Dynamic Welf.
Homogeneous									
Dyn(dist=1)	0.00072	0.00048	0.03899	0.01813	92.00%	25.017	22.744	-----	22.615
Stat(dist=1)	0.01671	-0.0222	0.04806	0.02768	91.49%	25.885	22.744	24.311	-----
Dyn(dist=10)	0.00550	-0.0047	0.02239	0.02242	92.59%	74.769	17.145	-----	14.642
Stat(dist=10)	0.31385	-0.3269	0.31386	0.32695	72.92%	145.724	17.145	29.289	-----
Dyn(dist=20)	0.12764	-0.1256	0.12876	0.12682	89.95%	123.792	16.428	-----	10.628
Stat(dist=20)	0.38494	-0.3976	0.38494	0.39756	53.33%	207.432	16.428	35.098	-----
Heterogeneous									
Dyn(dist=1)	0.00239	0.00101	0.04908	0.02265	94.62%	19.696	33.722	-----	36.227
Stat(dist=1)	-0.0139	-0.0181	0.06440	0.02728	94.35%	20.249	33.722	35.200	-----
Dyn(dist=10)	0.00197	-0.0009	0.02368	0.02395	94.70%	60.398	26.719	-----	24.229
Stat(dist=10)	0.31984	-0.3375	0.31986	0.33748	80.55%	118.030	26.719	46.907	-----
Dyn(dist=20)	0.04604	-0.0425	0.05278	0.04979	95.03%	80.072	28.355	-----	20.853
Stat(dist=20)	0.38713	-0.4032	0.38714	0.40322	65.85%	217.749	28.355	57.074	-----

Table 11. Welfare results: True time horizon = 10

Time Horizon – 10 periods	Bias $\beta_0$	Bias $\beta_I$	RMSE $\beta_0$	RMSE $\beta_I$	Within %	Distance Penalty	True Welfare	Static Welf.	Dynamic Welf.
Homogeneous									
Dyn(dist=1)	0.00072	0.00048	0.03899	0.01813	92.00%	25.017	22.662	-----	22.615
Stat(dist=1)	0.01671	-0.0222	0.04806	0.02768	91.49%	25.887	22.662	24.311	-----
Dyn(dist=10)	-0.0023	0.00250	0.02252	0.02272	92.90%	72.910	15.494	-----	14.629
Stat(dist=10)	0.31344	-0.3270	0.31346	0.32696	72.88%	145.785	15.494	29.296	-----
Dyn(dist=20)	0.00407	-0.0046	0.03059	0.03109	93.46%	97.194	12.477	-----	10.548
Stat(dist=20)	0.38151	-0.3959	0.38151	0.39586	53.27%	267.987	12.477	34.913	-----
Heterogeneous									
Dyn(dist=1)	0.00239	0.00101	0.04908	0.02265	94.62%	19.696	33.627	-----	36.227
Stat(dist=1)	-0.0139	-0.0181	0.06440	0.02728	94.35%	20.249	33.627	35.100	-----
Dyn(dist=10)	-0.0024	0.00258	0.02429	0.02454	94.82%	59.664	25.012	-----	24.215
Stat(dist=10)	0.31943	-0.3375	0.31944	0.33748	80.53%	118.072	25.012	46.931	-----
Dyn(dist=20)	-0.0035	0.00366	0.03283	0.03281	95.70%	74.931	23.190	-----	20.805
Stat(dist=20)	0.38575	-0.4029	0.38576	0.40287	65.48%	218.889	23.190	57.038	-----

Table 12. Welfare results: True time horizon = 20

Time Horizon – 20 periods	Bias $\beta_0$	Bias $\beta_I$	RMSE $\beta_0$	RMSE $\beta_I$	Within %	Distance Penalty	True Welfare	Static Welf.	Dynamic Welf.
Homo geneous									
Dyn(dist=1)	0.00072	0.00048	0.03899	0.01813	92.00%	25.016	22.605	-----	22.615
Stat(dist=1)	0.01671	-0.0222	0.04806	0.02768	91.49%	25.887	22.605	24.311	-----
Dyn(dist=10)	-0.0023	0.00250	0.02252	0.02271	92.89%	72.915	14.625	-----	14.629
Stat(dist=10)	0.31344	-0.3270	0.31346	0.32697	72.88%	145.784	14.625	29.296	-----
Dyn(dist=20)	-0.0048	0.00450	0.03159	0.03191	93.77%	94.699	10.549	-----	10.548
Stat(dist=20)	0.38145	-0.3958	0.38145	0.39576	53.25%	268.055	10.549	34.912	-----
Heterogeneous									
Dyn(dist=1)	0.00239	0.00101	0.04908	0.02265	94.62%	19.696	33.559	-----	33.577
Stat(dist=1)	-0.0139	-0.0181	0.06440	0.02728	94.35%	20.249	33.559	35.100	-----
Dyn(dist=10)	-0.0023	0.00256	0.02425	0.02453	94.82%	59.666	24.205	-----	24.215
Stat(dist=10)	0.31943	-0.3375	0.31944	0.33748	80.53%	118.072	24.205	46.931	-----
Dyn(dist=20)	-0.0039	0.00411	0.03270	0.03268	95.71%	74.841	20.799	-----	20.804
Stat(dist=20)	0.38575	-0.4029	0.38575	0.40287	65.48%	218.897	20.799	57.040	-----

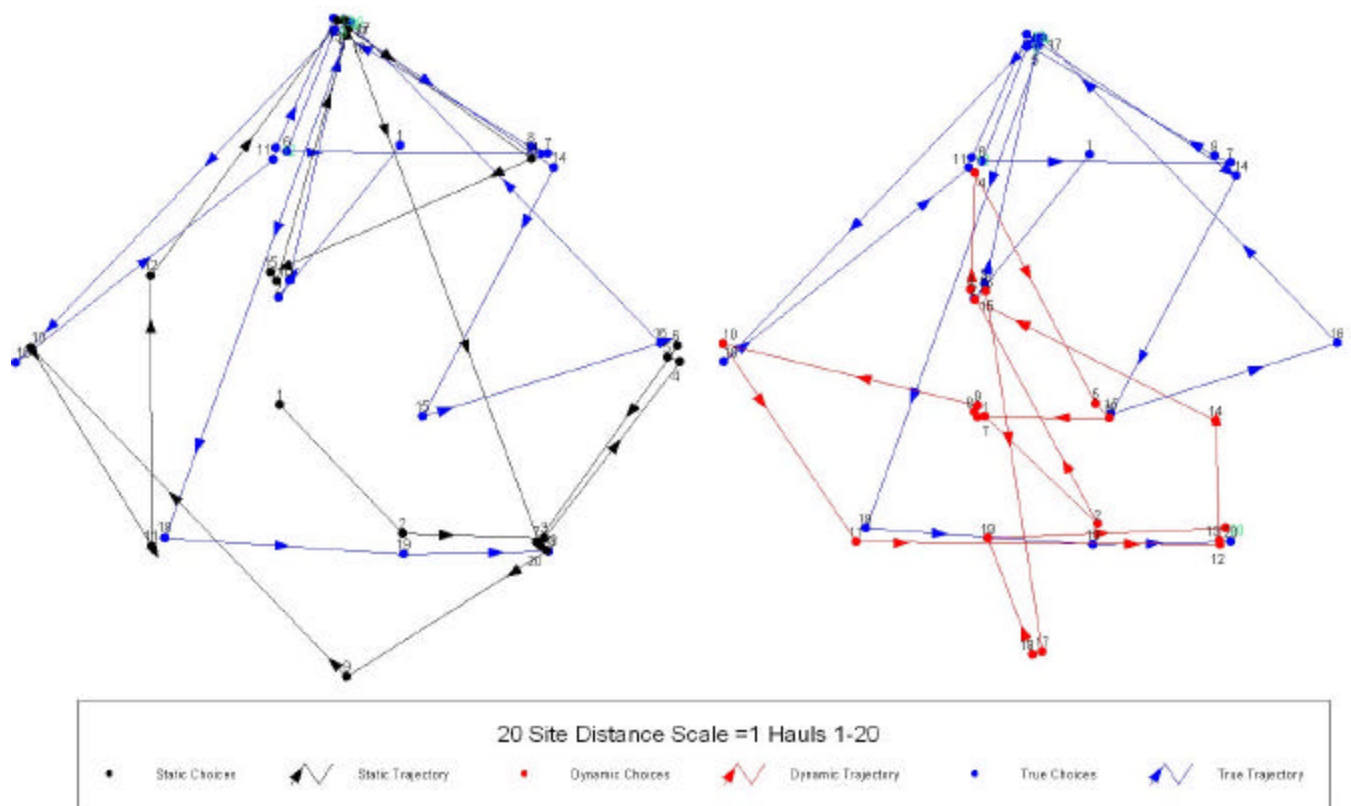


Figure 1. Hauls 1-20 for the 20 location model with  $dist\_scale=1$  (left is the RUM and right is the DRUM estimator)

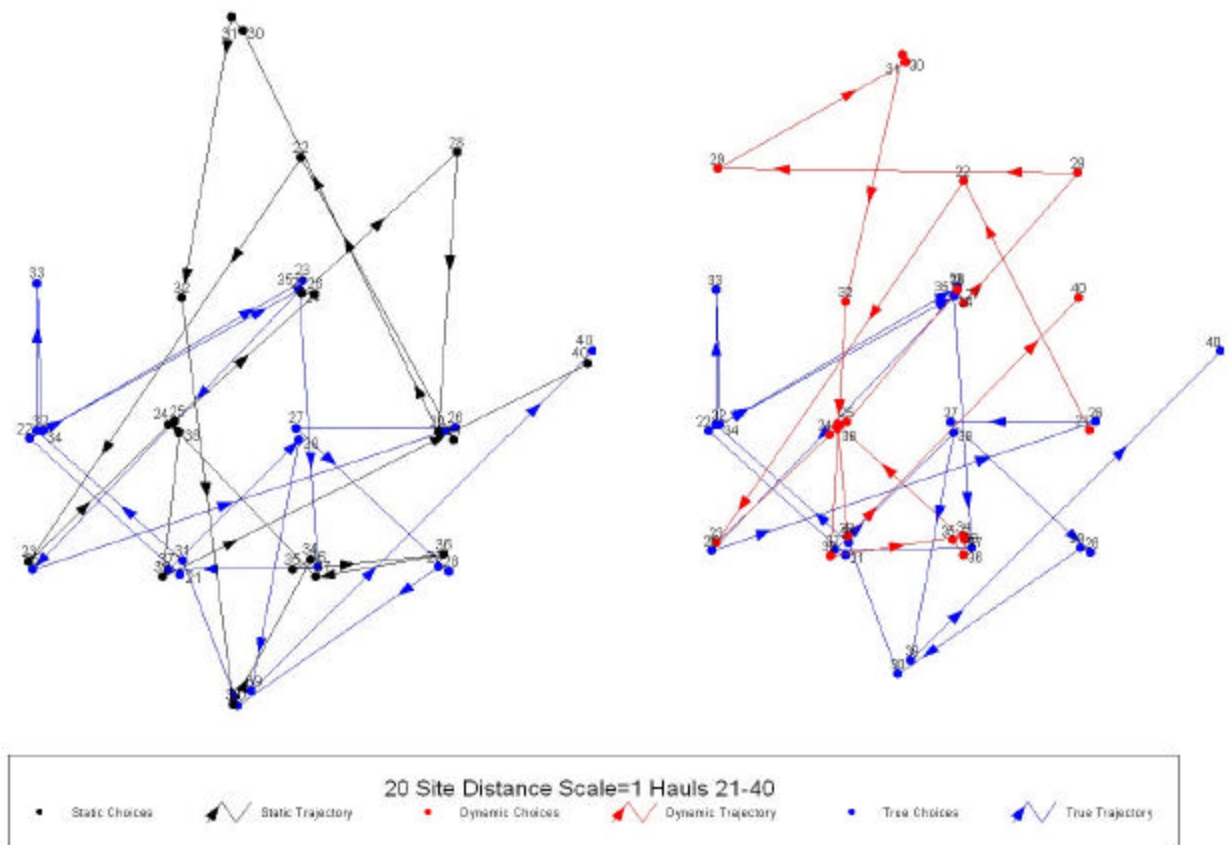


Figure 2. Hauls 21-40 for the 20 location model with  $dist\_scale=1$  (left is the RUM and right is the DRUM estimator)

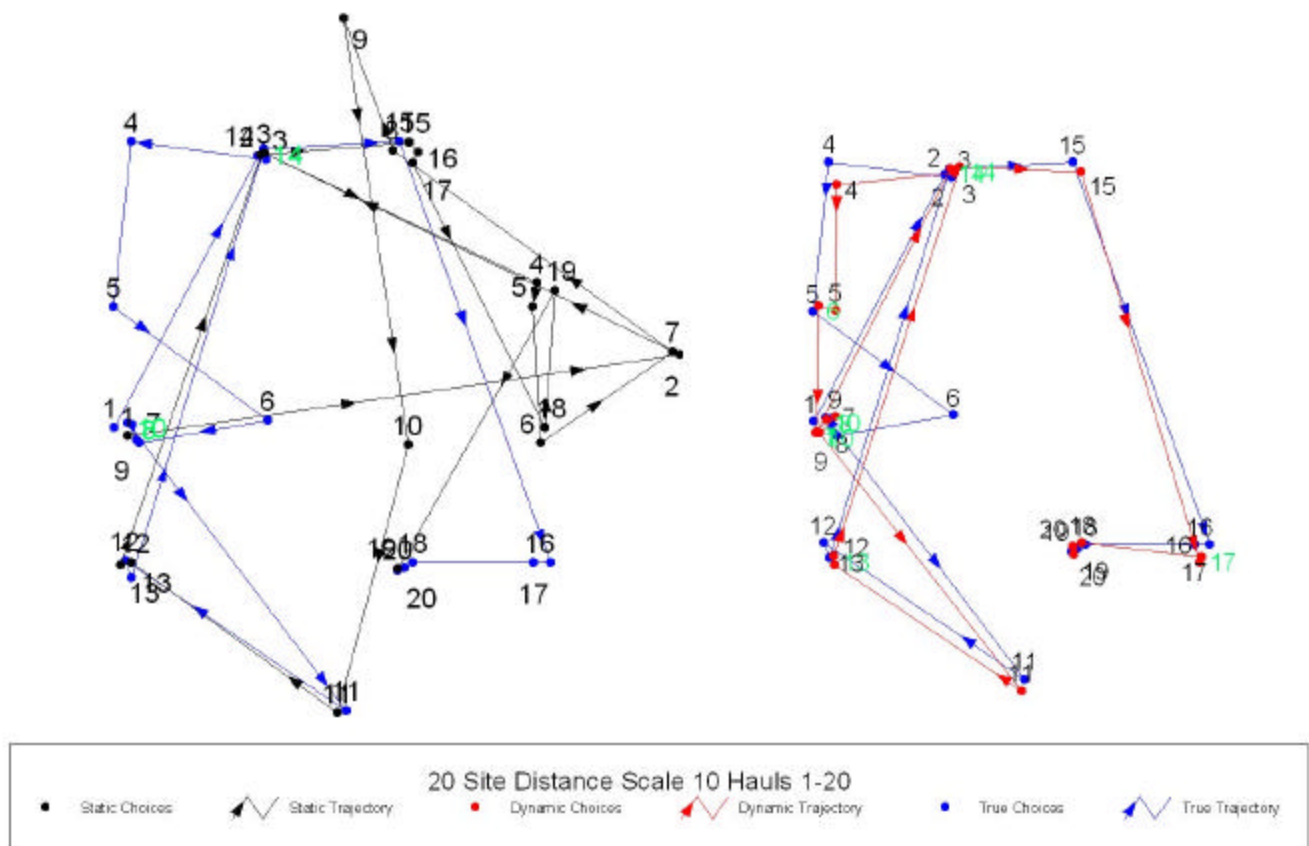


Figure 3. Hauls 1-20 for the 20 location model with  $dist\_scale=10$  (left is the RUM and right is the DRUM estimator)

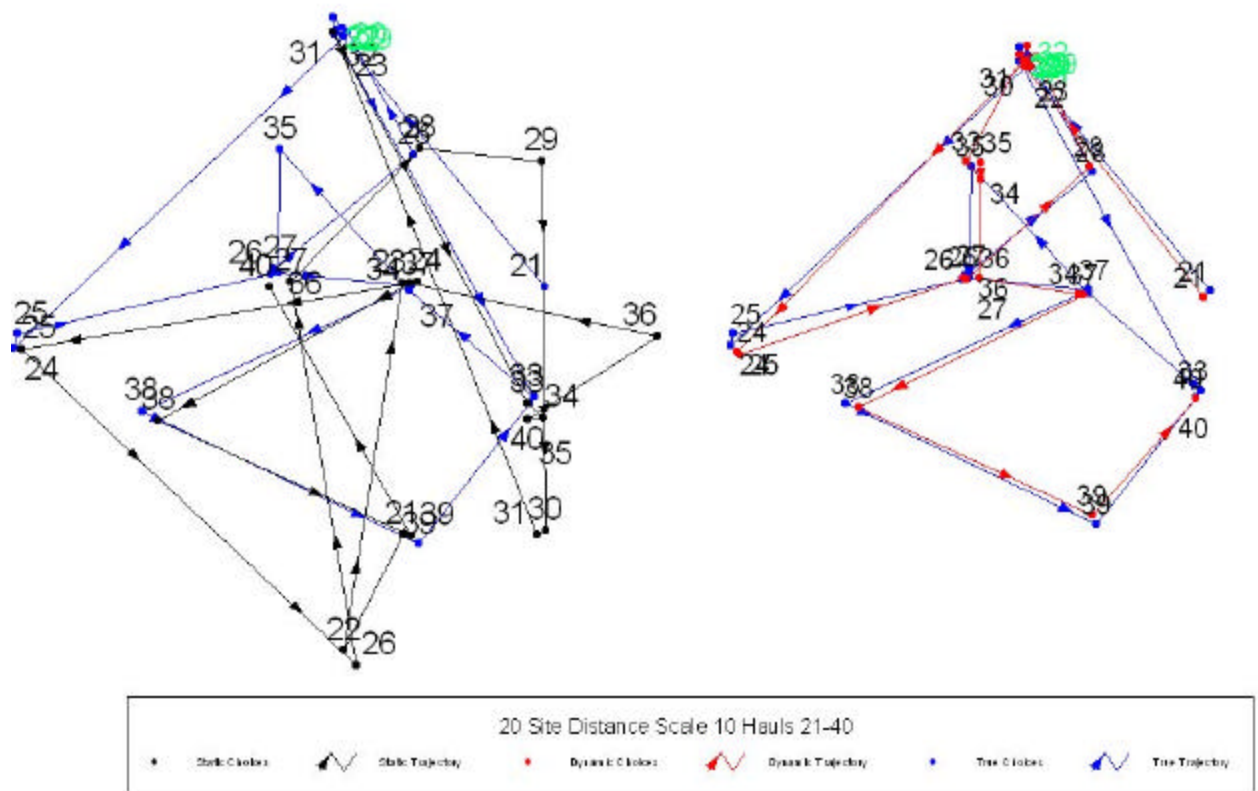


Figure 4. Hauls 21-40 for the 20 location model with  $dist\_scale=10$  (left is the RUM and right is the DRUM estimator)

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<sup>i</sup> This does introduce a degree of “randomness” in the analysis, but we experimented with different random cruises and generated very similar results to those depicted in the figures. These illustrations are indicative of the results we would expect given the differences in the distance penalty metric between the models.

<sup>ii</sup> Our estimator places vessels at zone center points only (corresponding to Figure 3). Predicted points in Figures 4-7 were randomly perturbed slightly to avoid stacking spatial information. This way we are able to completely illustrate the differences in the cruise trajectories without having them stacked upon each other if they predict the same site choice in the same time period.