

Internet Appendix to  
Estimation of Sample Selection Models with Spatial  
Dependence

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# Contents

Tables A1 through A4 present the simulation results not shown in the paper.

The Theoretical Appendix presents the proofs to the propositions presented in the paper.

## Appendix Tables

Table A1. Simulation Results for N=625, 25% Sample Selection

(δ, γ, ρ)		BIAS					RMSE				
		OLS	KP-SAE	Heckit	Spheck-E	Spheck-O	OLS	KP-SAE	Heckit	Spheck-E	Spheck-O
(0,0,0.5)*	$\beta_0$	0.303	0.304	-0.024	-0.064	-0.069	0.326	0.327	0.258	0.377	0.305
	$\beta_1$	0.013	0.012	-0.007	-0.007	-0.012	0.161	0.163	0.160	0.162	0.180
	$\beta_2$	-0.210	-0.211	0.018	0.050	0.040	0.253	0.255	0.212	0.350	0.245
	$\rho$			0.036	0.090	-0.003			0.374	0.524	0.360
	$\gamma$		-0.044		-0.045	-0.039		0.186		0.191	0.196
(0.25,0.25,0.5)	$\beta_0$	0.308	0.314	-0.022	-0.053	-0.066	0.332	0.343	0.266	0.364	0.322
	$\beta_1$	0.011	0.007	-0.008	-0.010	-0.016	0.164	0.186	0.164	0.162	0.181
	$\beta_2$	-0.212	-0.219	0.016	0.035	0.034	0.256	0.273	0.215	0.339	0.251
	$\rho$			0.040	0.089	0.000			0.384	0.546	0.400
	$\gamma$		0.026		0.031	0.038		0.156		0.158	0.165
(0.5,0.5,0.5)	$\beta_0$	0.321	0.357	-0.025	-0.077	-0.069	0.353	0.440	0.293	0.426	0.347
	$\beta_1$	0.016	0.004	-0.003	-0.006	-0.013	0.172	0.341	0.171	0.164	0.183
	$\beta_2$	-0.218	-0.267	0.014	0.052	0.036	0.270	0.423	0.234	0.352	0.262
	$\rho$			0.060	0.073	-0.035			0.418	0.562	0.381
	$\gamma$		0.104		0.112	0.118		0.155		0.161	0.168
(0.75,0.75,0.5)	$\beta_0$	0.371	0.678	0.006	-0.419	-0.163	0.425	1.300	0.376	1.067	0.715
	$\beta_1$	0.013	-0.241	-0.006	-0.005	-0.014	0.187	1.647	0.188	0.162	0.181
	$\beta_2$	-0.233	-0.541	-0.013	0.206	0.092	0.302	1.506	0.263	0.709	0.445
	$\rho$			0.059	0.296	-0.057			0.482	1.055	0.603
	$\gamma$		0.132		0.146	0.149		0.144		0.159	0.163
(0,0.75,0.5)	$\beta_0$	0.332	0.578	0.036	-0.306	-0.094	0.397	1.304	0.322	0.887	0.544
	$\beta_1$	0.016	-0.167	-0.002	-0.002	-0.003	0.181	1.841	0.181	0.156	0.168
	$\beta_2$	-0.234	-0.498	-0.026	0.143	0.054	0.302	1.634	0.254	0.610	0.370
	$\rho$			-0.017	0.137	-0.154			0.379	0.888	0.466
	$\gamma$		0.159		0.171	0.174		0.165		0.178	0.182
(0.25,0.75,0.5)	$\beta_0$	0.341	0.643	0.018	-0.293	-0.066	0.403	1.332	0.317	0.873	0.475
	$\beta_1$	0.008	-0.280	-0.012	-0.007	-0.015	0.186	1.854	0.186	0.157	0.174
	$\beta_2$	-0.235	-0.503	-0.013	0.146	0.039	0.300	1.616	0.242	0.635	0.333
	$\rho$			0.025	0.148	-0.167			0.386	0.876	0.393
	$\gamma$		0.155		0.167	0.171		0.162		0.174	0.180
(0.75,0.25,0.5)	$\beta_0$	0.307	0.309	-0.025	-0.039	-0.075	0.331	0.337	0.319	0.373	0.400
	$\beta_1$	0.012	0.011	-0.005	-0.007	-0.015	0.167	0.180	0.166	0.164	0.186
	$\beta_2$	-0.188	-0.191	0.013	0.022	0.033	0.242	0.252	0.232	0.319	0.280
	$\rho$			0.017	0.039	-0.009			0.455	0.547	0.479
	$\gamma$		-0.031		-0.025	-0.018		0.159		0.160	0.166
(0,0,0.75)*	$\beta_0$	0.459	0.460	-0.030	-0.055	-0.143	0.473	0.474	0.256	0.306	0.333
	$\beta_1$	0.023	0.023	-0.006	-0.007	-0.014	0.148	0.150	0.146	0.148	0.166
	$\beta_2$	-0.321	-0.323	0.020	0.035	0.064	0.348	0.350	0.211	0.314	0.247
	$\rho$			0.051	0.089	0.047			0.366	0.438	0.373
	$\gamma$		-0.047		-0.047	-0.039		0.183		0.186	0.191
(0.25,0.25,0.75)	$\beta_0$	0.465	0.473	-0.032	-0.058	-0.152	0.479	0.489	0.263	0.334	0.344
	$\beta_1$	0.022	0.017	-0.007	-0.008	-0.016	0.152	0.167	0.150	0.148	0.166
	$\beta_2$	-0.322	-0.331	0.022	0.037	0.065	0.349	0.363	0.214	0.331	0.252
	$\rho$			0.060	0.097	0.066			0.376	0.480	0.410
	$\gamma$		-0.005		-0.002	0.007		0.155		0.156	0.161
(0.5,0.5,0.75)	$\beta_0$	0.485	0.530	-0.039	-0.095	-0.177	0.503	0.569	0.286	0.429	0.428
	$\beta_1$	0.027	0.011	-0.002	-0.004	-0.013	0.158	0.269	0.155	0.148	0.164
	$\beta_2$	-0.327	-0.384	0.024	0.066	0.078	0.358	0.466	0.225	0.345	0.283
	$\rho$			0.095	0.107	0.065			0.412	0.568	0.483
	$\gamma$		0.058		0.067	0.071		0.132		0.139	0.143
(0.75,0.75,0.75)	$\beta_0$	0.573	0.914	0.005	-0.500	-0.275	0.600	1.232	0.355	1.035	0.743
	$\beta_1$	0.023	-0.186	-0.006	-0.007	-0.015	0.169	1.231	0.169	0.145	0.163
	$\beta_2$	-0.352	-0.752	-0.008	0.217	0.129	0.393	1.318	0.252	0.686	0.448
	$\rho$			0.126	0.372	-0.032			0.472	1.064	0.624
	$\gamma$		0.102		0.129	0.127		0.123		0.148	0.148
(0,0.75,0.75)	$\beta_0$	0.496	0.812	0.051	-0.416	-0.185	0.538	1.360	0.319	0.945	0.567
	$\beta_1$	0.025	-0.237	-0.003	-0.002	-0.006	0.170	1.717	0.169	0.144	0.152
	$\beta_2$	-0.351	-0.659	-0.038	0.180	0.079	0.399	1.665	0.250	0.624	0.366
	$\rho$			-0.028	0.131	-0.214			0.366	0.893	0.509
	$\gamma$		0.159		0.181	0.182		0.165		0.188	0.189
(0.25,0.75,0.75)	$\beta_0$	0.497	0.802	0.022	-0.490	-0.219	0.535	1.295	0.312	0.996	0.609
	$\beta_1$	0.035	-0.175	0.005	0.004	0.000	0.174	1.614	0.171	0.143	0.155
	$\beta_2$	-0.355	-0.688	-0.026	0.166	0.090	0.400	1.549	0.236	0.649	0.374
	$\rho$			0.019	0.245	-0.181			0.369	0.990	0.492
	$\gamma$		0.151		0.173	0.175		0.157		0.181	0.183
(0.75,0.25,0.75)	$\beta_0$	0.463	0.465	-0.038	-0.054	-0.165	0.477	0.479	0.313	0.355	0.423
	$\beta_1$	0.020	0.019	-0.005	-0.006	-0.015	0.154	0.158	0.152	0.151	0.170
	$\beta_2$	-0.283	-0.285	0.021	0.033	0.066	0.317	0.319	0.230	0.303	0.281
	$\rho$			0.029	0.055	0.058			0.441	0.515	0.521
	$\gamma$		-0.164		-0.161	-0.154		0.232		0.232	0.231

Note: Simulation results are based on 500 replications. \* In these models with no spatial dependence Heckit is theoretically consistent.

Table A2. Simulation Results for N=625, 40% Sample Selection

(δ, γ, ρ)		BIAS					RMSE				
		OLS	KP-SAE	Heckit	Spheck-E	Spheck-O	OLS	KP-SAE	Heckit	Spheck-E	Spheck-O
(0,0,0.5)*	$\beta_0$	0.443	0.443	-0.018	-0.026	-0.072	0.464	0.464	0.327	0.366	0.408
	$\beta_1$	0.016	0.017	-0.010	-0.010	-0.015	0.182	0.184	0.181	0.184	0.209
	$\beta_2$	-0.268	-0.268	0.010	0.015	0.023	0.311	0.312	0.240	0.288	0.284
	$\rho$			0.021	0.026	-0.007			0.337	0.363	0.356
	$\gamma$		-0.050		-0.049	-0.045		0.190		0.194	0.201
(0.25,0.25,0.5)	$\beta_0$	0.447	0.453	-0.019	-0.025	-0.074	0.469	0.478	0.339	0.361	0.412
	$\beta_1$	0.019	0.015	-0.007	-0.006	-0.013	0.189	0.206	0.188	0.186	0.209
	$\beta_2$	-0.272	-0.278	0.007	0.012	0.020	0.318	0.330	0.247	0.284	0.288
	$\rho$			0.026	0.023	-0.006			0.352	0.365	0.362
	$\gamma$		-0.043		-0.036	-0.031		0.167		0.167	0.174
(0.5,0.5,0.5)	$\beta_0$	0.467	0.500	-0.023	-0.083	-0.102	0.493	0.553	0.370	0.550	0.497
	$\beta_1$	0.012	-0.001	-0.014	-0.010	-0.019	0.193	0.310	0.193	0.183	0.202
	$\beta_2$	-0.275	-0.316	0.011	0.048	0.040	0.327	0.431	0.262	0.377	0.330
	$\rho$			0.054	0.071	0.005			0.387	0.527	0.417
	$\gamma$		0.001		0.013	0.019		0.129		0.132	0.138
(0.75,0.75,0.5)	$\beta_0$	0.530	0.753	0.009	-0.312	-0.124	0.573	1.147	0.468	0.985	0.724
	$\beta_1$	0.011	-0.124	-0.015	-0.010	-0.014	0.206	1.237	0.208	0.181	0.197
	$\beta_2$	-0.284	-0.540	-0.007	0.132	0.055	0.355	1.241	0.306	0.580	0.393
	$\rho$			0.095	0.188	-0.060			0.494	0.843	0.509
	$\gamma$		0.069		0.087	0.092		0.107		0.121	0.128
(0,0.75,0.5)	$\beta_0$	0.493	0.683	-0.002	-0.334	-0.108	0.545	1.200	0.417	0.999	0.574
	$\beta_1$	0.022	-0.037	-0.007	-0.004	-0.005	0.216	1.419	0.217	0.182	0.196
	$\beta_2$	-0.300	-0.558	0.000	0.183	0.056	0.368	1.395	0.305	0.650	0.373
	$\rho$			0.060	0.113	-0.124			0.398	0.745	0.379
	$\gamma$		0.100		0.117	0.122		0.120		0.136	0.144
(0.25,0.75,0.5)	$\beta_0$	0.499	0.699	-0.014	-0.370	-0.121	0.549	1.199	0.418	1.030	0.576
	$\beta_1$	0.018	-0.036	-0.011	-0.007	-0.014	0.222	1.376	0.223	0.185	0.204
	$\beta_2$	-0.303	-0.582	0.005	0.212	0.064	0.369	1.401	0.293	0.655	0.367
	$\rho$			0.080	0.156	-0.106			0.417	0.782	0.376
	$\gamma$		0.092		0.109	0.115		0.117		0.132	0.140
(0.75,0.25,0.5)	$\beta_0$	0.426	0.427	-0.007	-0.015	-0.076	0.448	0.452	0.400	0.417	0.472
	$\beta_1$	0.005	0.003	-0.015	-0.015	-0.019	0.178	0.189	0.179	0.178	0.201
	$\beta_2$	-0.229	-0.229	0.002	0.002	0.020	0.288	0.294	0.264	0.295	0.295
	$\rho$			-0.004	0.002	-0.018			0.431	0.439	0.430
	$\gamma$		-0.077		-0.068	-0.063		0.184		0.182	0.191
(0,0,0.75)*	$\beta_0$	0.666	0.666	-0.033	-0.034	-0.176	0.677	0.678	0.320	0.323	0.419
	$\beta_1$	0.032	0.032	-0.007	-0.007	-0.014	0.166	0.166	0.161	0.166	0.186
	$\beta_2$	-0.405	-0.405	0.018	0.015	0.053	0.429	0.430	0.234	0.246	0.267
	$\rho$			0.038	0.037	0.053			0.325	0.332	0.349
	$\gamma$		-0.053		-0.052	-0.046		0.196		0.200	0.203
(0.25,0.25,0.75)	$\beta_0$	0.671	0.679	-0.036	-0.043	-0.194	0.683	0.692	0.331	0.346	0.443
	$\beta_1$	0.033	0.028	-0.006	-0.005	-0.014	0.171	0.181	0.166	0.165	0.184
	$\beta_2$	-0.406	-0.414	0.020	0.021	0.059	0.432	0.442	0.239	0.272	0.279
	$\rho$			0.047	0.046	0.069			0.341	0.352	0.371
	$\gamma$		-0.076		-0.069	-0.064		0.185		0.184	0.186
(0.5,0.5,0.75)	$\beta_0$	0.700	0.742	-0.038	-0.067	-0.198	0.714	0.766	0.355	0.400	0.456
	$\beta_1$	0.030	0.013	-0.009	-0.006	-0.015	0.178	0.249	0.174	0.165	0.183
	$\beta_2$	-0.414	-0.464	0.018	0.031	0.060	0.443	0.519	0.252	0.281	0.281
	$\rho$			0.083	0.069	0.081			0.376	0.422	0.402
	$\gamma$		-0.051		-0.038	-0.036		0.145		0.143	0.145
(0.75,0.75,0.75)	$\beta_0$	0.793	1.039	-0.013	-0.369	-0.259	0.816	1.211	0.453	0.973	0.773
	$\beta_1$	0.025	-0.104	-0.015	-0.011	-0.014	0.186	0.874	0.185	0.162	0.177
	$\beta_2$	-0.422	-0.714	0.009	0.175	0.102	0.464	1.051	0.290	0.582	0.418
	$\rho$			0.170	0.212	-0.014			0.490	0.802	0.560
	$\gamma$		0.024		0.056	0.056		0.094		0.112	0.115
(0,0.75,0.75)	$\beta_0$	0.728	0.972	0.000	-0.353	-0.205	0.759	1.357	0.395	0.860	0.541
	$\beta_1$	0.041	-0.026	-0.002	-0.003	-0.003	0.201	1.424	0.198	0.162	0.173
	$\beta_2$	-0.445	-0.776	-0.003	0.162	0.074	0.486	1.445	0.282	0.510	0.324
	$\rho$			0.071	0.002	-0.210			0.374	0.581	0.378
	$\gamma$		0.114		0.142	0.145		0.129		0.156	0.161
(0.25,0.75,0.75)	$\beta_0$	0.744	1.017	-0.022	-0.421	-0.229	0.774	1.352	0.400	0.984	0.623
	$\beta_1$	0.039	-0.056	-0.005	-0.005	-0.010	0.206	1.323	0.203	0.165	0.181
	$\beta_2$	-0.448	-0.804	0.013	0.219	0.096	0.486	1.411	0.285	0.635	0.372
	$\rho$			0.113	0.091	-0.164			0.400	0.713	0.426
	$\gamma$		0.096		0.125	0.130		0.119		0.146	0.151
(0.75,0.25,0.75)	$\beta_0$	0.635	0.635	-0.025	-0.031	-0.183	0.647	0.648	0.386	0.395	0.500
	$\beta_1$	0.021	0.020	-0.010	-0.012	-0.018	0.162	0.164	0.160	0.161	0.179
	$\beta_2$	-0.343	-0.343	0.009	0.007	0.050	0.379	0.380	0.254	0.265	0.287
	$\rho$			0.005	0.014	0.040			0.411	0.426	0.441
	$\gamma$		-0.192		-0.180	-0.174		0.260		0.255	0.256

Note: Simulation results are based on 500 replications. \* In these models with no spatial dependence Heckit is theoretically consistent.

Table A3. Simulation Results for the Selection Equation, 25% Sample Selection

		N=324						N=625						N=900					
		BIAS			RMSE			BIAS			RMSE			BIAS			RMSE		
( $\delta, \gamma, \rho$ )		Heckit	Sp Heck- I	Sp Heck- O	Heckit	Sp Heck- I	Sp Heck- O	Heckit	Sp Heck- I	Sp Heck- O	Heckit	Sp Heck- I	Sp Heck- O	Heckit	Sp Heck- I	Sp Heck- O	Heckit	Sp Heck- I	Sp Heck- O
(0,0,0.5)*	$\alpha_0$	-0.008	-0.021	-0.240	0.195	0.355	0.329	0.005	0.003	-0.212	0.138	0.241	0.263	-0.002	-0.006	-0.216	0.120	0.170	0.252
	$\alpha_1$	0.016	0.055	0.069	0.279	0.651	0.350	-0.004	0.011	0.029	0.195	0.455	0.228	0.003	0.017	0.031	0.171	0.315	0.191
	$\alpha_2$	0.022	0.052	0.076	0.281	0.410	0.335	0.004	0.009	0.036	0.201	0.262	0.220	0.003	0.004	0.031	0.152	0.184	0.176
	$\delta$		-0.057	-0.055		0.313	0.301		-0.049	-0.055		0.199	0.201		-0.016	-0.016		0.153	0.150
(0.25,0.25, 0.5)	$\alpha_0$	-0.009	-0.030	-0.256	0.199	0.351	0.349	0.006	0.012	-0.223	0.144	0.266	0.279	-0.002	0.000	-0.224	0.122	0.176	0.263
	$\alpha_1$	0.007	0.083	0.098	0.275	0.650	0.397	-0.014	0.012	0.046	0.196	0.466	0.262	-0.006	0.028	0.044	0.172	0.330	0.224
	$\alpha_2$	0.019	0.073	0.104	0.281	0.437	0.365	0.000	0.028	0.062	0.200	0.271	0.252	0.000	0.006	0.051	0.152	0.208	0.199
	$\delta$		-0.041	-0.073		0.322	0.338		0.020	-0.006		0.215	0.215		0.046	0.020		0.167	0.160
(0.5,0.5, 0.5)	$\alpha_0$	0.005	0.009	-0.264	0.206	0.374	0.378	0.019	0.038	-0.231	0.160	0.275	0.302	0.010	0.042	-0.233	0.128	0.202	0.281
	$\alpha_1$	-0.033	0.104	0.118	0.273	0.663	0.472	-0.052	0.028	0.051	0.205	0.446	0.299	-0.043	0.032	0.047	0.176	0.324	0.243
	$\alpha_2$	-0.021	0.028	0.100	0.277	0.458	0.415	-0.040	0.009	0.054	0.204	0.288	0.257	-0.038	-0.014	0.044	0.148	0.232	0.219
	$\delta$		-0.089	-0.198		0.405	0.495		0.017	-0.057		0.284	0.286		0.083	-0.012		0.193	0.208
(0.75,0.75, 0.5)	$\alpha_0$	0.012	0.117	-0.224	0.252	0.487	0.403	0.043	0.166	-0.169	0.192	0.394	0.294	0.026	0.177	-0.175	0.164	0.380	0.274
	$\alpha_1$	-0.160	-0.110	-0.030	0.305	0.719	0.444	-0.157	-0.153	-0.080	0.252	0.519	0.320	-0.143	-0.190	-0.097	0.226	0.459	0.266
	$\alpha_2$	-0.127	-0.235	-0.079	0.293	0.562	0.450	-0.159	-0.303	-0.144	0.244	0.497	0.330	-0.143	-0.306	-0.133	0.205	0.463	0.261
	$\delta$		-0.402	-0.588		0.612	0.838		-0.418	-0.635		0.586	0.837		-0.386	-0.572		0.510	0.745
(0,0.75, 0.5)	$\alpha_0$	-0.019	0.055	-0.250	0.199	0.460	0.363	-0.014	0.114	-0.216	0.143	0.376	0.283	-0.015	0.122	-0.211	0.120	0.326	0.261
	$\alpha_1$	0.006	0.073	0.126	0.284	0.737	0.430	0.006	-0.025	0.063	0.200	0.507	0.264	0.011	-0.041	0.051	0.172	0.387	0.214
	$\alpha_2$	0.034	-0.045	0.091	0.277	0.545	0.413	0.021	-0.125	0.031	0.195	0.443	0.271	0.016	-0.147	0.025	0.159	0.398	0.220
	$\delta$		0.314	0.106		0.517	0.591		-0.313	0.094		0.457	0.512		0.336	0.178		0.425	0.445
(0.25,0.75, 0.5)	$\alpha_0$	-0.026	0.077	-0.252	0.199	0.454	0.370	-0.009	0.118	-0.218	0.138	0.361	0.280	-0.013	0.122	-0.213	0.120	0.319	0.257
	$\alpha_1$	0.007	0.052	0.122	0.277	0.712	0.436	-0.006	-0.047	0.056	0.189	0.498	0.261	-0.003	-0.039	0.040	0.172	0.396	0.220
	$\alpha_2$	0.026	-0.088	0.069	0.274	0.557	0.436	0.008	-0.120	0.035	0.192	0.431	0.274	0.014	-0.156	0.024	0.156	0.399	0.202
	$\delta$		0.077	-0.141		0.418	0.590		0.070	-0.162		0.343	0.554		0.099	-0.083		0.275	0.435
(0.75,0.25, 0.5)	$\alpha_0$	0.050	0.032	-0.190	0.256	0.389	0.340	0.064	0.053	-0.161	0.206	0.270	0.268	0.045	0.052	-0.171	0.170	0.199	0.244
	$\alpha_1$	-0.153	-0.079	-0.072	0.297	0.636	0.374	-0.160	-0.133	-0.117	0.255	0.419	0.268	-0.154	-0.149	-0.124	0.229	0.313	0.229
	$\alpha_2$	-0.136	-0.098	-0.068	0.302	0.379	0.338	-0.168	-0.139	-0.123	0.257	0.284	0.252	-0.147	-0.145	-0.113	0.209	0.222	0.208
	$\delta$		-0.586	-0.601		0.670	0.686		-0.540	-0.551		0.578	0.585		-0.506	-0.523		0.530	0.544
(0,0,0.75)*	$\alpha_0$	-0.008	-0.018	-0.218	0.194	0.334	0.312	0.006	0.006	-0.186	0.140	0.250	0.245	-0.003	-0.007	-0.191	0.119	0.172	0.230
	$\alpha_1$	0.017	0.054	0.058	0.277	0.605	0.357	-0.005	0.003	0.004	0.194	0.454	0.227	0.003	0.017	0.010	0.170	0.324	0.186
	$\alpha_2$	0.018	0.044	0.055	0.280	0.381	0.329	0.004	0.011	0.018	0.203	0.251	0.226	0.003	0.006	0.013	0.152	0.173	0.164
	$\delta$		-0.049	-0.050		0.322	0.324		-0.053	-0.050		0.212	0.202		-0.017	-0.019		0.152	0.150
(0.25,0.25, 0.75)	$\alpha_0$	-0.008	-0.013	-0.234	0.197	0.339	0.339	0.007	0.012	-0.198	0.145	0.263	0.265	-0.002	-0.001	-0.199	0.122	0.182	0.243
	$\alpha_1$	0.008	0.052	0.092	0.272	0.599	0.431	-0.014	0.007	0.036	0.195	0.467	0.293	-0.005	0.021	0.026	0.172	0.342	0.228
	$\alpha_2$	0.016	0.073	0.106	0.281	0.400	0.409	-0.001	0.020	0.053	0.201	0.268	0.283	0.000	0.008	0.033	0.152	0.192	0.209
	$\delta$		-0.060	-0.083		0.331	0.367		-0.007	-0.013		0.218	0.230		0.025	0.014		0.166	0.158
(0.5,0.5, 0.75)	$\alpha_0$	0.004	0.023	-0.252	0.206	0.361	0.391	0.021	0.042	-0.221	0.161	0.277	0.318	0.009	0.042	-0.221	0.129	0.207	0.279
	$\alpha_1$	-0.032	0.072	0.153	0.273	0.617	0.555	-0.054	0.045	0.113	0.205	0.469	0.441	-0.041	0.039	0.090	0.176	0.338	0.329
	$\alpha_2$	-0.022	0.020	0.139	0.277	0.413	0.522	-0.042	0.007	0.112	0.205	0.289	0.408	-0.037	-0.013	0.086	0.148	0.212	0.296
	$\delta$		-0.082	-0.169		0.380	0.494		0.035	-0.026		0.240	0.334		0.077	0.031		0.198	0.239
(0.75,0.75, 0.75)	$\alpha_0$	0.015	0.159	-0.192	0.250	0.485	0.402	0.046	0.228	-0.145	0.195	0.432	0.311	0.031	0.259	-0.141	0.164	0.440	0.275
	$\alpha_1$	-0.153	-0.126	-0.036	0.301	0.680	0.455	-0.156	-0.177	-0.077	0.249	0.520	0.380	-0.146	-0.237	-0.101	0.225	0.515	0.347
	$\alpha_2$	-0.120	-0.267	-0.101	0.285	0.540	0.447	-0.153	-0.335	-0.155	0.242	0.500	0.391	-0.145	-0.362	-0.158	0.206	0.494	0.321
	$\delta$		-0.341	-0.555		0.546	0.821		-0.306	-0.587		0.491	0.818		-0.280	-0.547		0.422	0.751
(0,0.75, 0.75)	$\alpha_0$	-0.033	0.106	-0.230	0.198	0.465	0.359	-0.024	0.158	-0.188	0.145	0.409	0.274	-0.022	0.193	-0.171	0.120	0.393	0.233
	$\alpha_1$	0.017	0.031	0.134	0.282	0.673	0.486	0.013	-0.046	0.055	0.195	0.511	0.307	0.014	-0.098	0.021	0.168	0.439	0.216
	$\alpha_2$	0.050	-0.112	0.084	0.279	0.545	0.475	0.031	-0.194	0.003	0.197	0.466	0.310	0.024	-0.240	-0.020	0.165	0.446	0.234
	$\delta$		0.358	0.109		0.509	0.605		0.343	0.038		0.441	0.537		0.308	0.082		0.393	0.466
(0.25,0.75, 0.75)	$\alpha_0$	-0.032	0.125	-0.221	0.198	0.474	0.353	-0.020	0.220	-0.169	0.143	0.452	0.255	-0.017	0.225	-0.161	0.118	0.429	0.228
	$\alpha_1$	0.006	0.002	0.098	0.279	0.682	0.426	-0.003	-0.125	0.011	0.187	0.552	0.248	0.005	-0.143	0.009	0.170	0.472	0.220
	$\alpha_2$	0.042	-0.133	0.055	0.272	0.547	0.453	0.021	-0.242	-0.026	0.196	0.493	0.292	0.015	-0.252	-0.033	0.162	0.459	0.240
	$\delta$		0.107	-0.147		0.393	0.612		0.112	-0.214		0.317	0.571		0.078	-0.143		0.268	0.487
(0.75,0.25, 0.75)	$\alpha_0$	0.044	0.034	-0.171	0.253	0.365	0.328	0.064	0.059	-0.136	0.208	0.268	0.253	0.044	0.046	-0.151	0.169	0.200	0.229
	$\alpha_1$	-0.150	-0.109	-0.100	0.298	0.567	0.363	-0.160	-0.141	-0.138	0.254	0.404	0.289	-0.153	-0.149	-0.143	0.229	0.308	0.239
	$\alpha_2$	-0.132	-0.098	-0.082	0.299	0.363	0.362	-0.170	-0.150	-0.146	0.258	0.275	0.267	-0.147	-0.145	-0.131	0.208	0.215	0.213
	$\delta$		-0.692	-0.696		0.764	0.773		-0.668	-0.67									

Table A4. Simulation Results for the Selection Equation, 40% Sample Selection

		N=324						N=625						N=900					
		BIAS			RMSE			BIAS			RMSE			BIAS			RMSE		
( $\delta, \gamma, \rho$ )		Heckit	Spheck- I	Spheck- O	Heckit	Spheck- I	Spheck- O	Heckit	Spheck- I	Spheck- O	Heckit	Spheck- I	Spheck- O	Heckit	Spheck- I	Spheck- O	Heckit	Spheck- I	Spheck- O
(0,0,0.5)*	$\alpha_0$	-0.010	-0.027	-0.251	0.190	0.259	0.340	0.011	0.010	-0.207	0.140	0.172	0.259	-0.003	-0.003	-0.216	0.116	0.129	0.248
	$\alpha_1$	0.009	0.041	0.046	0.253	0.408	0.316	-0.012	-0.012	0.003	0.183	0.264	0.203	0.006	0.004	0.015	0.156	0.199	0.166
	$\alpha_2$	0.021	0.032	0.057	0.255	0.296	0.292	-0.007	-0.003	0.009	0.182	0.194	0.200	0.005	0.010	0.021	0.146	0.150	0.158
	$\delta$		-0.057	-0.054		0.286	0.284		-0.051	-0.047		0.195	0.190		-0.006	-0.007		0.141	0.134
(0.25,0.25, 0.5)	$\alpha_0$	-0.005	-0.035	-0.267	0.196	0.272	0.371	0.020	0.013	-0.210	0.146	0.181	0.267	0.005	0.006	-0.215	0.119	0.132	0.250
	$\alpha_1$	0.002	0.058	0.060	0.249	0.429	0.335	-0.018	-0.006	0.009	0.183	0.282	0.214	-0.006	-0.008	0.009	0.152	0.192	0.162
	$\alpha_2$	0.015	0.041	0.071	0.257	0.314	0.317	-0.023	-0.011	0.006	0.185	0.193	0.208	-0.004	0.004	0.019	0.143	0.148	0.156
	$\delta$		-0.066	-0.089		0.282	0.295		-0.038	-0.055		0.189	0.187		-0.004	-0.025		0.138	0.128
(0.5,0.5, 0.5)	$\alpha_0$	0.031	-0.025	-0.300	0.208	0.304	0.462	0.043	0.015	-0.237	0.160	0.238	0.338	0.031	0.015	-0.245	0.133	0.173	0.317
	$\alpha_1$	-0.046	0.078	0.095	0.252	0.486	0.460	-0.048	0.020	0.031	0.186	0.349	0.288	-0.040	0.012	0.036	0.161	0.251	0.250
	$\alpha_2$	-0.023	0.029	0.101	0.252	0.354	0.435	-0.054	-0.014	0.018	0.188	0.273	0.268	-0.039	-0.007	0.036	0.150	0.216	0.253
	$\delta$		-0.093	-0.163		0.348	0.422		-0.014	-0.081		0.237	0.263		0.032	-0.035		0.171	0.161
(0.75,0.75, 0.5)	$\alpha_0$	0.115	0.110	-0.234	0.275	0.460	0.500	0.140	0.163	-0.170	0.238	0.391	0.358	0.120	0.160	-0.162	0.201	0.336	0.295
	$\alpha_1$	-0.156	-0.029	0.010	0.296	0.597	0.438	-0.167	-0.099	-0.043	0.245	0.438	0.334	-0.150	-0.092	-0.063	0.219	0.324	0.250
	$\alpha_2$	-0.134	-0.171	-0.021	0.279	0.512	0.488	-0.160	-0.192	-0.078	0.240	0.426	0.348	-0.149	-0.208	-0.101	0.206	0.385	0.269
	$\delta$		-0.366	-0.526		0.614	0.813		-0.264	-0.423		0.493	0.685		-0.242	-0.369		0.480	0.583
(0,0.75, 0.5)	$\alpha_0$	-0.017	0.010	-0.343	0.192	0.398	0.493	0.002	0.031	-0.295	0.139	0.318	0.399	-0.006	0.032	-0.282	0.116	0.284	0.362
	$\alpha_1$	0.010	0.116	0.159	0.254	0.589	0.452	-0.004	0.076	0.105	0.185	0.425	0.355	0.011	0.067	0.091	0.158	0.352	0.295
	$\alpha_2$	0.026	-0.049	0.118	0.261	0.504	0.472	0.004	-0.050	0.070	0.180	0.399	0.314	0.007	-0.043	0.060	0.147	0.372	0.282
	$\delta$		0.407	0.219		0.614	0.619		0.470	0.268		0.638	0.595		0.528	0.349		0.622	0.537
(0.25,0.75, 0.5)	$\alpha_0$	-0.014	0.002	-0.362	0.199	0.400	0.534	0.014	0.040	-0.279	0.142	0.290	0.365	0.001	0.052	-0.280	0.124	0.290	0.348
	$\alpha_1$	0.003	0.126	0.177	0.251	0.581	0.489	-0.014	0.071	0.094	0.179	0.379	0.310	0.001	0.046	0.085	0.158	0.363	0.268
	$\alpha_2$	0.025	-0.044	0.142	0.262	0.510	0.525	-0.016	-0.068	0.042	0.186	0.397	0.285	0.000	-0.058	0.051	0.153	0.354	0.244
	$\delta$		0.155	-0.008		0.502	0.590		0.216	0.047		0.481	0.522		0.286	0.110		0.464	0.454
(0.75,0.25, 0.5)	$\alpha_0$	0.138	0.112	-0.116	0.287	0.325	0.317	0.144	0.141	-0.079	0.242	0.256	0.217	0.125	0.124	-0.095	0.204	0.208	0.204
	$\alpha_1$	-0.157	-0.104	-0.100	0.295	0.452	0.370	-0.168	-0.162	-0.149	0.247	0.300	0.253	-0.153	-0.149	-0.137	0.221	0.241	0.230
	$\alpha_2$	-0.142	-0.123	-0.095	0.290	0.309	0.319	-0.163	-0.156	-0.143	0.244	0.245	0.243	-0.153	-0.148	-0.135	0.211	0.214	0.221
	$\delta$		-0.619	-0.633		0.683	0.704		-0.577	-0.590		0.607	0.617		-0.548	-0.562		0.565	0.577
(0,0,0.75)*	$\alpha_0$	-0.011	-0.029	-0.232	0.190	0.247	0.334	0.010	0.012	-0.179	0.140	0.167	0.236	-0.003	0.001	-0.185	0.116	0.126	0.222
	$\alpha_1$	0.009	0.049	0.038	0.253	0.399	0.336	-0.012	-0.016	-0.021	0.183	0.243	0.203	0.007	-0.002	-0.008	0.156	0.185	0.163
	$\alpha_2$	0.022	0.029	0.044	0.255	0.279	0.294	-0.007	-0.003	-0.011	0.182	0.188	0.197	0.004	0.007	-0.001	0.146	0.149	0.156
	$\delta$		-0.057	-0.049		0.293	0.320		-0.055	-0.052		0.201	0.206		-0.002	-0.003		0.141	0.137
(0.25,0.25, 0.75)	$\alpha_0$	-0.006	-0.034	-0.257	0.196	0.261	0.391	0.020	0.021	-0.183	0.146	0.178	0.248	0.005	0.007	-0.191	0.119	0.137	0.242
	$\alpha_1$	0.003	0.053	0.067	0.249	0.394	0.387	-0.017	-0.016	-0.010	0.182	0.261	0.214	-0.006	-0.010	-0.006	0.152	0.189	0.177
	$\alpha_2$	0.016	0.040	0.073	0.255	0.296	0.358	-0.022	-0.017	-0.011	0.185	0.192	0.216	-0.004	0.001	0.006	0.143	0.154	0.192
	$\delta$		-0.098	-0.098		0.298	0.334		-0.068	-0.070		0.203	0.217		-0.025	-0.032		0.138	0.157
(0.5,0.5, 0.75)	$\alpha_0$	0.031	-0.012	-0.299	0.206	0.296	0.477	0.044	0.027	-0.252	0.159	0.225	0.370	0.032	0.023	-0.257	0.133	0.170	0.370
	$\alpha_1$	-0.041	0.062	0.119	0.251	0.466	0.511	-0.050	0.000	0.072	0.187	0.319	0.361	-0.040	0.004	0.070	0.160	0.234	0.328
	$\alpha_2$	-0.026	0.019	0.116	0.251	0.331	0.470	-0.055	-0.021	0.064	0.183	0.227	0.337	-0.040	-0.019	0.070	0.148	0.174	0.331
	$\delta$		-0.092	-0.139		0.326	0.433		-0.021	-0.034		0.212	0.271		0.025	0.007		0.162	0.195
(0.75,0.75, 0.75)	$\alpha_0$	0.121	0.129	-0.234	0.277	0.443	0.535	0.137	0.174	-0.197	0.235	0.387	0.440	0.120	0.183	-0.184	0.201	0.355	0.391
	$\alpha_1$	-0.155	-0.039	0.034	0.293	0.540	0.509	-0.163	-0.084	0.005	0.242	0.429	0.434	-0.149	-0.103	-0.023	0.218	0.334	0.366
	$\alpha_2$	-0.132	-0.172	-0.006	0.280	0.459	0.525	-0.159	-0.201	-0.054	0.238	0.412	0.429	-0.150	-0.220	-0.071	0.207	0.368	0.382
	$\delta$		-0.260	-0.413		0.497	0.720		-0.148	-0.317		0.373	0.591		-0.125	-0.280		0.324	0.518
(0,0.75, 0.75)	$\alpha_0$	-0.023	0.040	-0.342	0.195	0.391	0.530	-0.001	0.078	-0.281	0.138	0.312	0.402	-0.011	0.091	-0.264	0.116	0.291	0.369
	$\alpha_1$	0.017	0.093	0.185	0.257	0.552	0.533	-0.003	0.028	0.109	0.186	0.386	0.391	0.015	-0.003	0.090	0.159	0.329	0.343
	$\alpha_2$	0.030	-0.084	0.118	0.258	0.473	0.521	0.007	-0.094	0.064	0.178	0.374	0.352	0.010	-0.099	0.054	0.148	0.326	0.312
	$\delta$		0.424	0.273		0.633	0.647		0.475	0.284		0.650	0.624		0.458	0.297		0.621	0.594
(0.25,0.75, 0.75)	$\alpha_0$	-0.021	0.034	-0.347	0.199	0.396	0.542	0.012	0.091	-0.284	0.142	0.304	0.427	0.001	0.106	-0.267	0.120	0.310	0.396
	$\alpha_1$	0.006	0.093	0.176	0.253	0.539	0.515	-0.014	0.027	0.119	0.182	0.381	0.412	-0.001	-0.001	0.093	0.156	0.337	0.368
	$\alpha_2$	0.032	-0.072	0.129	0.262	0.495	0.559	-0.013	-0.117	0.055	0.185	0.384	0.389	-0.003	-0.119	0.047	0.145	0.346	0.330
	$\delta$		0.222	0.046		0.484	0.584		0.259	0.070		0.494	0.559		0.263	0.096		0.484	0.504
(0.75,0.25, 0.75)	$\alpha_0$	0.136	0.121	-0.094	0.286	0.312	0.306	0.145	0.146	-0.054	0.242	0.258	0.206	0.125	0.124	-0.070	0.204	0.206	0.186
	$\alpha_1$	-0.158	-0.124	-0.122	0.294	0.400	0.353	-0.168	-0.171	-0.170	0.247	0.290	0.261	-0.153	-0.153	-0.158	0.221	0.236	0.236
	$\alpha_2$	-0.140	-0.127	-0.109	0.290	0.303	0.330	-0.163	-0.159	-0.162	0.244	0.248	0.251	-0.153	-0.148	-0.152	0.211	0.212	0.223
	$\delta$		-0.713	-0.710		0.770	0.781		-0.693	-0.692	</								

# Theoretical Appendix



The parameter estimate of the sample selection model with SAE dependence is obtained from the solution to equation (11) in the paper, where  $g_N(\theta) = \frac{1}{N} z_N' \tilde{u}_N(\theta)$ . Denote  $g(\theta) \equiv \lim_{n \rightarrow \infty} E[g_n(\theta)]$ . Then, the unknown parameter vector  $\theta_0$  satisfies  $\lim_{n \rightarrow \infty} E[g_N(\theta_0)] = 0$ . Further, define the objective function as  $Q_N = g_N'(\theta) M_N g_N(\theta)$ , where  $M_N \xrightarrow{p} M$ , and  $Q = g'(\theta) M g(\theta)$ .

The proof of all three propositions follow closely Pinkse and Slade (1998). The main difference is that some extra conditions have to be verified for the additional moments stacked in  $g_N(\theta)$  and the estimated inverse-Mills ratio (IMR).

## Assumptions

**A1**  $\theta_0$  is in the interior of the parameter space  $\Theta$ , which is a compact set.

**A2**  $Q$  is uniquely minimized at  $\theta_0$

**A3** The vector valued function  $g(\theta)$  is continuous.

**A4** The density of observations in any region whose area exceeds a fixed minimum is bounded.

**A5** The elements of  $z_N$  are uniformly bounded.<sup>1</sup>

**A6** Let  $d_{ij}$  denote the distance between location  $i$  and  $j$ , then

$$\begin{aligned} \sup_{Nij} |cov(y_{1i}, y_{1j})| &\leq \alpha(d_{ij}), \\ \sup_{Nij} |cov(y_{2i}, y_{2j})| &\leq \alpha(d_{ij}) \text{ and} \\ \alpha(d) &\rightarrow 0 \text{ as } d \rightarrow \infty. \end{aligned}$$

**A7** The moments  $var(u_{ij}) = \sigma_1^2 \sum_j [\omega_{ij}^1]^2$ ,  $var(u_{2i}) = \sigma_2^2 \sum_j [\omega_{ij}^2]^2$ , and  $E[u_{1i}, u_{2i}] = \sigma_{12} \sum_j \omega_{ij}^1 \omega_{ij}^2$  are uniformly bounded, bounded away from zero, and boundedly differentiable (with respect to  $\theta$ ).

**A8** As  $N \rightarrow \infty$ ,  $M_N \xrightarrow{p} M$  for some positive definite matrix  $M$ .

**A9** As  $d \rightarrow \infty$ ,  $d^2 \alpha(dd^*) / \alpha(d^*) \rightarrow 0$ , for all fixed  $d^* > 0$ .

**A10** The area in which the observations are located grows at a rate of  $\sqrt{N}$  in both directions.

**A11**  $\Psi_1(\theta_0) = \lim_{N \rightarrow \infty} E\{N g_N(\theta_0) g_N'(\theta_0)\}$  and  $\Psi_2(\theta_0) = [\partial g'(\theta_0) / \partial \theta] M [\partial g(\theta_0) / \partial \theta']$  are positive definite matrices.

**A12** Let  $\rho_{Nij}(\theta)$  be the covariance between  $\frac{u_{Ni}}{\sqrt{var(u_{Ni})}}$  and  $\frac{u_{Nj}}{\sqrt{var(u_{Nj})}}$ . For some fixed  $N^* > 0$ ,  $\rho_{Nij}(\theta)$  is boundedly differentiable, uniformly in  $\theta \in \Theta$ ,  $N > L$ , and  $i \neq j$ .

**A13**  $|\rho_{Nij}(\theta)|$  is boundedly away from one from below, uniformly in  $\theta \in H(\theta_0)$ ,  $N > N^*$ , and  $i \neq j$ , with  $H(\theta_0)$  some neighborhood of  $\theta_0$ .

---

<sup>1</sup> $\lambda(\delta, \gamma)$  is an element of  $z_N$  which will be shown below to be uniformly bounded, as well as its first derivative.

**A14** As  $N \rightarrow \infty$ ,  $\frac{1}{N} \sum_{ij} |\rho_{Nij}(\theta)|$  is uniformly bounded in  $\theta \in H(\theta_0)$ .

A discussion of the implications of these assumptions can be found in Pinkse and Slade (1998).

### Proof of Proposition 1

By assumption A2,  $Q$  is uniquely minimized at  $\theta_0$ . Thus, we only need to establish that  $Q_N$  converges uniformly to  $Q$  over the parameter space  $\Theta$ .

To show that  $Q_N$  converges uniformly to  $Q$  over  $\Theta$ , it suffices to show that

(a)  $Q_N \xrightarrow{p} Q$  at all  $\theta \in \Theta \iff g_N(\theta) \xrightarrow{p} g(\theta)$  at all  $\theta \in \Theta$ .

(b)  $Q_N$  is stochastically equicontinuous and  $Q$  is continuous on  $\Theta \iff g_N(\theta) \xrightarrow{p} g(\theta)$  is stochastically equicontinuous.

For (a), note that  $g(\theta) \equiv \lim_{N \rightarrow \infty} E[g_N(\theta)]$ , that is,  $E[g_N(\theta)] \xrightarrow{p} g(\theta)$ . If  $g_N(\theta) \xrightarrow{p} E[g_N(\theta)]$ , then  $g_N(\theta) \xrightarrow{p} g(\theta)$ , so we show the former.

Define the functions

$$\tau_{1i}(\psi_i(\theta)) \equiv \sqrt{\sum_j (\omega_{ij}^1)^2 \cdot \phi(\psi_i(\theta)) / \{\Phi(\psi_i(\theta)) [1 - \Phi(\psi_i(\theta))]\}}$$

such that  $\tilde{u}_{1i}(\theta) = \tau_{1i}(\psi_i(\theta)) (y_i - \Phi(\psi_i(\theta)))$ .

Let  $\tau_i(\psi_i(\theta)) \equiv (\tau_{1i}(\psi_i(\theta))', \mathbf{1})$  where  $\mathbf{1}$  is a conformable vector of ones such that  $\tilde{u}_N(\theta) = ((\tau_1(\psi(\theta)) (y - \Phi(\psi(\theta))))', \mathbf{1}u'_{2N}(\theta))'$ .

Then,

$$\begin{aligned} & \lim_{n \rightarrow \infty} E |g_N(\theta) - E[g_N(\theta)]|^2 \\ &= \lim_{n \rightarrow \infty} \frac{1}{N^2} \sum_{ij} z_i' \tau_{Ni} \tau_{Nj} z_j \text{cov}[y_i, y_j] \\ &\leq \lim_{N \rightarrow \infty} \frac{1}{N^2} C \sum_{ij} \alpha(d_{ij}) \quad \text{by assumptions A5-A7} \\ &= 0 \end{aligned}$$

since  $\alpha(d_{ij}) \rightarrow 0$  as  $d \rightarrow \infty$  by assumption A6. Therefore, since  $g_N(\theta) \xrightarrow{p} E[g_N(\theta)]$  then  $g_N(\theta) \xrightarrow{p} g(\theta)$ .

For (b), given that by assumption A3  $g(\theta)$  is continuous, we need to show that  $g_N(\theta)$  is stochastically equicontinuous.

Using the mean value theorem for  $\theta^*$  between  $\theta$  and  $\tilde{\theta}$  we rewrite

$$g_N(\theta) - g_N(\tilde{\theta}) = \frac{1}{N} z_N' \{ \tilde{u}_N - \tilde{u}_N(\tilde{\theta}) \} = \frac{1}{N} z_i' \frac{\partial \tilde{u}_{Ni}(\theta^*)}{\partial \theta'} (\theta - \tilde{\theta}).$$

Following Andrews(1992), stochastic equicontinuity is implied by

$$\sup_{\theta \in \Theta} \left| \frac{1}{N} \sum_i z_i' \frac{\partial \tilde{u}_{Ni}(\theta)}{\partial \theta'} \right| = Op(1).$$

Recall that  $\tau_i(\psi(\theta)) \equiv (\tau_{1i}(\psi(\theta))', \mathbf{1})'$  with  $\tau_{1i}(\psi_i(\theta)) \equiv \sqrt{\sum_j (\omega_{ij}^1)^2} \cdot \phi[\psi_i(\theta)] / \Phi[\psi_i(\theta)] \{1 - \Phi(\psi_i(\theta))\}$ .

Similarly, define  $h_i(\theta) \equiv ((y_i - \Phi(\psi_i(\theta)))', \tilde{u}_{2i}(\theta)')'$ , such that  $u_{Ni}(\theta) = \tau_i(\psi_i(\theta)) h_i(\theta)$  and the derivative becomes:

$$\frac{\partial \tilde{u}_{Ni}(\theta)}{\partial \theta'} = \left[ \frac{\partial \tau_i(\psi_i(\theta))}{\partial \theta} h_i(\theta) - \frac{\partial h_i(\theta)}{\partial \theta} \tau_i(\psi_i(\theta)) \right] \frac{\partial \psi_i(\theta)}{\partial \theta}$$

where

$$\begin{aligned} \frac{\partial \tau_i(\psi_i(\theta))}{\partial \theta} &= \frac{\partial}{\partial \theta} \left[ \begin{array}{c} \tau_{1i}(\psi_i(\theta))' \\ \mathbf{1} \end{array} \right] = \left[ \begin{array}{c} \frac{\partial}{\partial \theta} \left[ \sqrt{\sum_j (\omega_{ij}^1)^2} \cdot \frac{\phi[\psi_i(\theta)]}{\Phi[\psi_i(\theta)] \{1 - \Phi(\psi_i(\theta))\}} \right]' \\ \mathbf{0} \end{array} \right] \\ \frac{\partial h_i(\theta)}{\partial \theta} &= \frac{\partial}{\partial \theta} \left[ \begin{array}{c} [y_1 - \Phi[\psi_i(\theta)]]' \\ [y_2 - \beta_0 - x'_{2i} \beta_1 - \mu \lambda_i(\delta, \gamma)]' \end{array} \right] = \left[ \begin{array}{c} [-\Phi[\psi_i(\theta)]]' \\ - \left[ 1 - x'_{2i} - \mu \frac{\partial \lambda_i(\delta, \gamma)}{\partial \theta} - \lambda_i(\delta, \gamma) \right]' \end{array} \right] \\ \frac{\partial \psi_i(\theta)}{\partial \theta} &= \frac{\partial}{\partial \theta} \left[ \frac{\alpha_0 + x'_{1i} \alpha_1}{\sqrt{\sum_j [\omega_{ij}^1(\theta)]^2}} \right] \\ &= \left[ \sqrt{\sum_j [\omega_{ij}^1(\theta)]^2} (1 + x'_{1i}) - (\alpha_0 + x_{1i} \alpha_1) \frac{\partial \sqrt{\sum_j [\omega_{ij}^1(\theta)]^2}}{\partial \theta} \right] \cdot \left[ \sum_j [\omega_{ij}^1(\theta)]^2 \right] \end{aligned}$$

Then the task is to show that each of the parts of  $\frac{\partial \tilde{u}_{Ni}(\theta)}{\partial \theta'}$  is bounded uniformly. Following Pinkse and Slade (1998), we first establish

$$\sup_{y_i \in 0,1; t \in \mathbb{R}, y_2 \in \mathbb{R}} \left| \frac{\partial \tau(t)}{\partial t} h(t) - \frac{\partial h(t)}{\partial t} \tau(t) \right| < \infty$$

for which it is enough to show (i)  $\frac{\partial \tau(\theta)}{\partial \theta}$  and (ii)  $\frac{\partial h(\theta)}{\partial \theta} \tau(\theta)$  are bounded uniformly in  $t$ .

For (i), given that the only non-zero components of  $\frac{\partial \tau(\theta)}{\partial \theta}$  are those of  $\frac{\partial \tau_1(t)}{\partial \theta}$ , we concentrate on those. These components are the same as in Pinkse and Slade (1998) setup and thus their same arguments apply. Note that:

$$\begin{aligned} \frac{\partial \tau_1(\theta)}{\partial \theta} &= \left\{ \frac{1}{\Phi(t)} \left[ \frac{\phi(t)}{1 - \Phi(t)} \left\{ \frac{\phi(t)}{1 - \Phi(t)} - t \right\} \right] - \frac{\phi^2(t)}{\Phi^2(t) (1 - \Phi(t))} \right\} \cdot \sqrt{\sum_j (\omega_{ij}^1)^2} + \\ &\quad \frac{\partial}{\partial \theta} \left[ \sqrt{\sum_j (\omega_{ij}^1)^2} \right] \cdot \frac{\phi[t]}{\Phi[t] \{1 - \Phi(t)\}} \end{aligned}$$

and (using assumption A7) the only places it can be unbounded are at  $\pm\infty$ . Since the expression is an even function, it suffices to check  $t \rightarrow \infty$ . Define  $\Upsilon(t) = \frac{\phi(t)}{1-\Phi(t)}$  and rewrite the above expression as:

$$\frac{\partial \tau_1(t)}{\partial t} = \frac{(\Upsilon(t) - t)^2 + t(\Upsilon(t) - t) - \phi(t)(\Upsilon(t) - t)/\Phi(t) - t\phi(t)/\Phi(t)}{\Phi(t)} \cdot \sqrt{\sum_j (\omega_{ij}^1)^2} + \frac{\partial}{\partial \theta} \left[ \sqrt{\sum_j (\omega_{ij}^1)^2} \right] \cdot \frac{\Upsilon(t)}{\Phi(t)}$$

and noting that as  $t \rightarrow \infty$ ,  $\Phi(t) \rightarrow 1$  and  $t\phi(t) \rightarrow 0$ , and that

$$1 - \Phi(w) = \int_w^\infty \phi(t) dt = \int_w^\infty \frac{t\phi(t)}{t} dt = \frac{\phi(w)}{w} \left\{ 1 + \frac{1}{w^2} + O(w^{-4}) \right\}$$

as  $w \rightarrow \infty$ , the remaining term is

$$\Upsilon(t) - t = \frac{t}{1 + 1/t^2 + O(t^{-4})} - t = \frac{1}{t} + O(t^{-3})$$

as  $t \rightarrow \infty$ .

Thus, analyzing

$$\frac{[\frac{1}{t} + O(t^{-3})]^2 + t[\frac{1}{t} + O(t^{-3})] - \phi(t)[\frac{1}{t} + O(t^{-3})]/\Phi(t) - t\phi(t)/\Phi(t)}{\Phi(t)} \rightarrow 1$$

and hence, together with assumption A7,  $\frac{\partial \tau_1(\theta)}{\partial \theta}$  is bounded.

For (ii), that is,  $\frac{\partial h(t)}{\partial \theta} \tau(t)$ , recall that

$$\frac{\partial h(t)}{\partial t} = \begin{bmatrix} [-\phi(t)]' \\ -\left[1 - x_2' - \mu \frac{\partial \lambda(\delta, \gamma)}{\partial \theta} - \lambda(\delta, \gamma)\right]' \end{bmatrix} \text{ and } \tau(t) = \begin{bmatrix} \tau_1(t)' \\ \mathbf{1} \end{bmatrix}$$

and note it can be written as

$$\frac{\partial h(t)}{\partial t} \tau(t) = \begin{bmatrix} -\phi(t) \tau_1(t) \\ -\left[1 - x_2' - \mu \frac{\partial \lambda(t)}{\partial t} - \lambda(t)\right] \end{bmatrix} = \begin{bmatrix} -\phi(t) \frac{1}{\Phi(t)} [\Upsilon(t) - t + t] \cdot \sqrt{\sum_j (\omega_{ij}^1)^2} \\ -\left[1 - x_2' - \mu \frac{\partial \lambda(t)}{\partial t} - \lambda(t)\right] \end{bmatrix}.$$

The first component,  $\phi(t) \frac{1}{\Phi(t)} [\Upsilon(t) - t + t] \cdot \sqrt{\sum_j (\omega_{ij}^1)^2}$  is bounded by the same arguments above:  $\Phi(t) \rightarrow 1$ ,  $(\Upsilon(t) - t) = t^{-1} + O(t^{-3})$  and  $\phi(t) \rightarrow 0$ . So that it remains to check that the second component is bounded:  $\left[1 - x_2' - \mu \frac{\partial \lambda(t)}{\partial t} - \lambda(t)\right]$ .

$$\text{Take } \lambda(t) = \frac{\sum_j \omega_{ij}^1 \omega_{ij}^2}{\sum_j [\omega_{ij}^1]^2} \cdot \frac{\phi(t)}{\{1-\Phi(t)\}} = \frac{\sum_j \omega_{ij}^1 \omega_{ij}^2}{\sum_j [\omega_{ij}^1]^2} \Upsilon(t).$$

Since  $\Upsilon(t) = \frac{1}{1/t + 1/t^3 + (1/t)O(t^{-4})}$  as  $t \rightarrow \infty$  and by assumption A7,  $\lambda(t)$  is bounded.

Taking  $\frac{\partial \lambda(t)}{\partial t} = \frac{\sum_j \omega_{ij}^1 \omega_{ij}^2}{\sum_j [\omega_{ij}^1]^2} \cdot \frac{\partial \Upsilon(t)}{\partial t}$ , by assumption A7 the first term is bounded, while using results above, the second term:

$$\begin{aligned} \frac{\partial}{\partial t} \left[ \frac{\phi(t)}{1 - \Phi(t)} \right] &= \frac{\{1 - \Phi(t)\} \phi(t) (-t) - \phi(t) (-\phi(t))}{[\{1 - \Phi(t)\}]^2} = \frac{\phi^2(t) - \phi(t)t(1 - \Phi(t))}{[\{1 - \Phi(t)\}]^2} \\ &= \frac{\phi^2(t)}{\phi^2(t) [1/t + 1/t^3 + (1/t)0 \cdot (t^{-4})]^2} - \frac{[1/t + 1/t^2 + 0 \cdot (t^{-4})]}{[1/t + 1/t^3 + (1/t)0 \cdot (t^{-4})]^2} \end{aligned}$$

and thus  $\frac{\partial}{\partial t} \Upsilon(t)$  is bounded and therefore  $\frac{\partial \lambda(t)}{\partial t}$  is bounded and the expression  $\frac{\partial h(t)}{\partial t}$  is also bounded.

Note also that the term  $h(t) = \left[ \begin{array}{c} y_1 - \Phi(t) \\ [y_2 - \beta_o - x'_2 \beta_1 - \mu \lambda(t)] \end{array} \right]$  is also bounded as  $\Phi(t) \rightarrow 1$  and  $\lambda(t)$  is bounded.

By assumption A5 the elements of  $z_N$  are bounded and thus for some constant  $C$ :

$$\sup_{\theta \in \Theta} \left| \frac{1}{N} \sum_i z_i' \frac{\partial \tilde{u}_{Ni}(\theta)}{\partial \theta'} \right| \leq C \sup_{\theta \in \Theta} \frac{1}{N} \sum_{i=1}^N \left\| \frac{\partial \psi_i(\theta)}{\partial \theta} \right\|.$$

Finally, checking  $\frac{\partial \psi_i(\theta)}{\partial \theta}$  with previous results,

$$\frac{\partial \psi_i(\theta)}{\partial \theta} = \left[ \sqrt{\sum_j [\omega_{ij}^1(\theta)]^2} (1 + x'_{2i}) - (\alpha_0 + x'_{1i} \alpha_1) \frac{\partial \sqrt{\sum_j [\omega_{ij}^1(\theta)]^2}}{\partial \theta} \right] \cdot \left[ \sum_j [\omega_{ij}^1(\theta)]^2 \right].$$

Since  $x_{1i}$  is bounded by A5 and the terms in the sums are also bounded by A7, then  $\sup_{\theta \in \Theta} \frac{1}{N} \sum_{i=1}^N \left\| \frac{\partial \psi_i(\theta)}{\partial \theta} \right\|$  is bounded by A6 and A1. *QED*

## Proof of Proposition 2

The first order conditions based on the objective function  $Q_N = g_{N'}(\theta) M_N g_N(\theta)$  are given by  $\frac{\partial Q_N(\hat{\theta})}{\partial \theta} = 0$ . Using the mean value theorem for  $\theta^*$  between  $\hat{\theta}$  and  $\theta_0$  we can write:

$$\left( \hat{\theta}_{GMM} - \theta_0 \right) = \left[ \frac{\partial^2 Q_N(\theta^*)}{\partial \theta \partial \theta'} \right]^{-1} \frac{\partial Q_N(\theta_0)}{\partial \theta} \quad (1)$$

The expression that corresponds to the second derivative of the objective function  $Q_N$  can be written as:

$$\frac{\partial^2 Q_N(\theta)}{\partial \theta \partial \theta'} = \frac{2}{N^2} \left[ \sum_{i=1}^N \frac{\partial^2 \tilde{u}_{Ni}(\theta)}{\partial \theta \partial \theta'} z_i' M_N z_j \tilde{u}_{Nj}(\theta) + \sum_{i=1}^N \frac{\partial \tilde{u}_{Ni}(\theta)}{\partial \theta} z_i' M_N z_j \frac{\partial \tilde{u}_{Nj}(\theta)}{\partial \theta'} \right].$$

We start by analyzing the convergence properties of this second derivative of the objective function. The following lemma will be useful.

**Lemma 1** (Pinkse and Slade (1998) Lemma A3)

For any  $\tilde{\theta}$  consistent for  $\theta_0$ , i.e.  $\tilde{\theta} \xrightarrow{p} \theta_0$  :

$$(a) \quad \frac{\partial g_N(\tilde{\theta})}{\partial \theta'} \xrightarrow{p} \frac{\partial g(\theta_0)}{\partial \theta'}$$

$$(b) \quad g_N(\tilde{\theta}) \xrightarrow{p} g_N(\theta_0)$$

Proof:

(a) Need to show that for  $\omega$  such that  $\|\omega\| = 1$ ,

$$\omega' \left[ \frac{\partial g_N(\tilde{\theta})}{\partial \theta'} - \frac{\partial g_N(\theta_0)}{\partial \theta'} \right] \xrightarrow{p} 0$$

as  $\lim_{N \rightarrow \infty} \frac{\partial g_N(\theta_0)}{\partial \theta'} = \frac{\partial g(\theta_0)}{\partial \theta'}$  follows from  $g_N(\theta_0) \xrightarrow{p} g(\theta_0)$  and A3.

Setting  $\bar{z}_i = \omega' z_i$  and using the mean value theorem, the above expression can be written as

$$= \frac{1}{N} \sum_{i=1}^N \bar{z}_i \left[ \frac{\partial \tilde{u}_{Ni}(\tilde{\theta})}{\partial \theta'} - \frac{\partial \tilde{u}_{Ni}(\theta_0)}{\partial \theta'} \right] = (\tilde{\theta} - \theta_0)' \frac{1}{N} \sum_{i=1}^N \bar{z}_i \frac{\partial^2 \tilde{u}_{Ni}(\theta^*)}{\partial \theta \partial \theta'}$$

where  $\theta^*$  is between  $\tilde{\theta}$  and  $\theta_0$ .

Analyzing the last expression,  $\frac{1}{N} \sum_{i=1}^N \bar{z}_i \frac{\partial^2 \tilde{u}_{Ni}(\theta^*)}{\partial \theta \partial \theta'}$  is bounded since by A5  $\bar{z}_i$  is uniformly bounded (including  $\lambda(\delta, \gamma)$ , which was shown in the proof of proposition 1) and  $\frac{\partial^2 \tilde{u}_{Ni}(\theta^*)}{\partial \theta \partial \theta'}$  is also bounded. Therefore, since  $\tilde{\theta} \xrightarrow{p} \theta_0$ ,  $(\tilde{\theta} - \theta_0) \xrightarrow{p} 0$  and thus

$$\omega' \left[ \frac{\partial g_N(\tilde{\theta})}{\partial \theta'} - \frac{\partial g_N(\theta_0)}{\partial \theta'} \right] \xrightarrow{p} 0 \blacksquare$$

(b) The proof is analogous to part (a).

Now returning to analyzing the second derivative of  $Q_N(\theta)$ , note that  $\sum_{j=1}^N z_j \tilde{u}_{Nj}(\theta) = op(N)$  from (a) in the proof of proposition 1. Furthermore, by lemma 1  $g_N(\theta^*) \xrightarrow{p} g_N(\theta_0)$  and also  $\frac{1}{N} \sum_{i=1}^N \frac{\partial^2 \tilde{u}_{Ni}(\theta^*)}{\partial \theta \partial \theta'} z_i' \omega$  is bounded in probability in probability  $\forall \|\omega\| = 1$ . Then, the first term inside the square brackets will vanish asymptotically.

Considering the remaining term of  $\frac{\partial^2 Q_N(\theta)}{\partial\theta\partial\theta'}$ , looking at  $\frac{1}{N}\sum_{i=1}^N z_i \frac{\partial \tilde{u}_{Ni}(\tilde{\theta})}{\partial\theta'}$ , it will converge in probability to  $\frac{\partial g(\theta_0)}{\partial\theta'}$  by lemma 1. Finally, since  $M_N \xrightarrow{p} M$  by A8,  $\frac{\partial^2 Q_N(\theta^*)}{\partial\theta\partial\theta'} \xrightarrow{p} \left[ \frac{\partial g'(\theta_0)}{\partial\theta} \right] M \left[ \frac{\partial g(\theta_0)}{\partial\theta'} \right] \equiv \Psi_2(\theta_0)$ .

Now we turn to the term  $\frac{\partial Q_N(\theta_0)}{\partial\theta}$  in equation (1), which is equal to  $\frac{\partial Q_N(\theta_0)}{\partial\theta} = 2\frac{\partial g'_N(\theta_0)}{\partial\theta} M_N g_N(\theta_0)$  and it follows from previous results that  $\frac{\partial g'_N(\theta_0)}{\partial\theta} \xrightarrow{p} \frac{\partial g'(\theta_0)}{\partial\theta}$ .

The remaining task is to show that  $g_N(\theta_0) \rightarrow N(0, \Psi_1(\theta_0))$ . To do this, we follow again closely Pinkse and Slade (1998)'s strategy and employ Berenstein (1927) blocking method using McLeish (1974) central limit theorem for dependent processes in Davison's (1994, chapter 24).

Start by defining  $Y_{0N} = \omega' \{E[Ng_N(\theta_0)g'_N(\theta_0)]\}^{-\frac{1}{2}} \sqrt{N}g_N(\theta_0) = \frac{1}{\sqrt{N}}\sum_{t=1}^N A_{Nt}$  for implicitly defined  $A_{Nt}$  and  $\forall \|\omega\| = 1$ , and thus the task is to show  $Y_{0N} \xrightarrow{d} N(0, 1)$ .

Following Davison (1994, chapter 24), split the region in which the observations are located into  $a_N$  areas of size  $c_1\sqrt{b_N} \times c_2\sqrt{b_N}$  each, where  $a_N$  and  $b_N$  are integers such that  $a_N b_N = N$ .

Without loss of generality, set  $c_1 = c_2 = 1$  and let  $a_N$  and  $b_N$  be such that  $\alpha(b_N)a_N \rightarrow 0$  and  $N^{l-(\frac{1}{2})}b_N < 1$  uniformly in  $N$  for some fixed  $0 < l < \frac{1}{2}$ .

Define the set of indices  $\Lambda_{Nj}$  that correspond to observations in area  $j$ . By assumption, a number  $c > 0$  exists such that  $\max_j |\Lambda_{Nj}| < Cb_N$ , where  $|\cdot|$  applied to sets denotes the

cardinality of that set. Define  $D_{Nj} = \frac{1}{\sqrt{N}} \sum_{t \in \Lambda_{Nj}} A_{Nt}$  such that  $Y_{0N} = \sum_{j=1}^{a_N} D_{Nj}$ .

Following Davison's (1994) theorem 24.1, McLeish's (1974) CLT requires that the following conditions hold.

- (a)  $T_{Na_N} = \prod_{j=1}^{a_N} (1 + i\lambda D_{Nj})$  is uniformly integrable in  $N > N^*$  for some fixed  $N^*$  and  $\lambda > 0$ .
- (b)  $E[T_{Na_N}] - 1 \rightarrow 0$
- (c)  $\sum_{j=1}^{a_N} D_{Nj}^2 - 1 \xrightarrow{p} 0$
- (d)  $\max_j |D_{Nj}| \xrightarrow{p} 0$

Before establishing each of these conditions, we note that for sufficiently large  $N$ ,  $A_{Nt}$  is bounded, since  $\Psi_1(\theta_0)$  is positive definite (p.d.) and thus  $E[Ng_N(\theta_0)g'_N(\theta_0)]$  is p.d. and its inverse is bounded. We establish each of the above conditions in turn.

- (a) It needs to be shown that for some fixed  $N^*$ ,

$$\sup_{N > N^*} E|T_{Na_N} I\{|T_{Na_N}| > K\}| \rightarrow 0 \text{ as } K \rightarrow \infty$$

where  $I$  is an indicator function.

Following Pinkse and Slade (1998), we begin by showing that  $P \left[ \sup_{N > N^*} |T_{Na_N}| > K \right] = 0$

for some  $K > 0$  which will imply the above condition.

Note that

$$\begin{aligned} P \left[ \sup_{N > N^*} |T_{Na_N}| > K \right] &= P \left[ \sup_{N > N^*} \left| \prod_{j=1}^{a_N} (1 + i\lambda D_{Nj}) \right| > K \right] \\ &\leq P \left[ \sup_{N > N^*} \prod_{j=1}^{a_N} (1 + \lambda^2 D_{Nj}^2)^{\frac{1}{2}} > K \right] \\ &= P \left[ \sup_{N > N^*} \prod_{j=1}^{a_N} (1 + \lambda^2 D_{Nj}^2)^{\frac{1}{2}} > K \mid \sup_{N > N^*} N^l |D_{Nj}| \leq C \right] \cdot P \left[ \max_j N^l |D_{Nj}| \leq C \right] + \\ &\quad P \left[ \sup_{N > N^*} \prod_{j=1}^{a_N} (1 + \lambda^2 D_{Nj}^2)^{\frac{1}{2}} > K \mid \sup_{N > N^*} N^l |D_{Nj}| > C \right] \cdot P \left[ \sup_{N > N^*} N^l |D_{Nj}| > C \right] \\ &\leq P \left[ \sup_{N > N^*} \prod_{j=1}^{a_N} (1 + \lambda^2 D_{Nj}^2)^{\frac{1}{2}} > K \mid \sup_{N > N^*} N^l |D_{Nj}| \leq C \right] + P \left[ \sup_{N > N^*} N^l |D_{Nj}| > C \right] \end{aligned}$$

with  $C$  a uniform upper bound to the  $A_{Nt's}$ . Nothing that the first summand is bounded by  $\sup_{N > N^*} I \{ (1 + \lambda^2 C N^{-2l})^{a_N/2} > K \}$  which is zero for sufficiently large  $K$ , and that the

second summand is bounded by  $P \left[ \sup_{N > N^*, l} N^{l - (\frac{1}{2})} b_N |A_{Nt}| > C \right] = 0$  since  $N^{l - (\frac{1}{2})} b_N < 1$  by

construction. Therefore,  $P \left[ \sup_{N > N^*} |T_{Na_N}| > K \right] = 0$  for some  $K > 0$ , which in turn implies  $\sup_{N > N^*} E |T_{Na_N} I \{ |T_{Na_N}| > K \}| \rightarrow 0$  as  $K \rightarrow \infty$  and thus condition (a) holds.

(b) From Davison (1994) we can write  $T_{Na_N} = (i\lambda) \sum_{j=1}^{a_N} D_{Nj} T_{N,j-1}$ . Then, it is enough to show that the  $\max_j |E [D_{Nj} T_{N,j-1}]| = o(a_N^{-1})$ .

Writing  $T_{N,j-1} = \prod_{k \in \Xi_{Nj1}} (1 + i\lambda D_{Nk}) \cdot \prod_{k \notin \Xi_{Nj1}} (1 + i\lambda D_{Nk}) = \prod_{k \in \Xi_{Nj1}} (1 + i\lambda D_{Nk}) T_{RNj}$  where  $T_{RNj}$  is implicitly defined and  $\Xi_{Nj1}$  is the set of blocks adjacent to block  $j$ .

Thus,  $T_{N,j-1} = (i\lambda) \sum_{\gamma \in \Gamma_{Nj}} \left( \prod_{k \in \Xi_{Nj1}} D_{Nk}^{\gamma_k} \right) T_{RNj}$  with  $\Gamma_{Nj}$  the set of vectors of size equal to  $|\Xi_{Nj1}|$  whose elements are all either zero or one. Because the number of elements in  $\Gamma_{Nj}$  is finite, it is enough to show that  $\max_{j, \gamma} \left| E \left[ D_{Nj} T_{RNj} \prod_{k \in \Xi_{Nj1}} D_{Nk}^{\gamma_k} \right] \right| = o(a_N^{-1})$ . To show this, we show that (i)  $\max_j |E [D_{Nj} T_{RNj}]| = o(a_N^{-1})$  and (ii)  $\max_{j \neq k} |E [D_{Nj} D_{Nk} T_{RNj}]| = o(a_N^{-1})$ .

For (i), note that the observations in  $T_{RNj}$  are located at least a distance  $b_N^{\frac{1}{2}}$  away from those in  $D_{Nj}$  by construction. Therefore,  $\max_j |E [D_{Nj} T_{RNj}]|$  is bounded by  $C_1 \max_j E |D_{Nj} T_{RNj}| \alpha(\sqrt{b_N})$  for large  $C_1 > 0$  given the conditions on the covariances and that  $E [D_{Nj}] = 0$ . Using the properties of the constructed  $a_N$ ,  $b_N$  and the properties of  $\alpha$  in A6:



$C_1 \max_j E |D_{Nj} T_{RNj}| \alpha(\sqrt{b_N}) = o\left(N^{-\frac{1}{2}} b_N \alpha(\sqrt{b_N})\right) = o\left(a_N^{-\frac{1}{2}} b_N^{-\frac{1}{2}} \alpha(\sqrt{b_N})\right) = o(a_N^{-1})$   
for large  $N$ , as required.

For (ii),  $\max_{j \neq k} |E[D_{Nj} D_{Nk} T_{RNj}]| \leq \max_{j \neq k} N^{-\frac{1}{2}} b_N |E[D_{Nj} T_{RNj}]|$  by the boundedness property of the  $A_{N' s}$ . The maximum is thus of order  $O\left(N^{-\frac{1}{2}} b_N a_N^{-1}\right)$  which is  $o(a_N^{-1})$ . Repeating the argument for the remaining elements in  $\Gamma_{Nj}$  completes the proof.

Therefore, condition (b)  $E[T_{Na_N}] \rightarrow 1$  is demonstrated.

(c) We start by showing that  $\sum_{j=1}^{a_N} (D_{Nj}^2 - E[D_{Nj}^2]) \xrightarrow{p} 0$

Take  $\sum_{i,j=1}^{a_N} E\{(D_{Nj}^2 - E[D_{Nj}^2])(D_{Ni}^2 - E[D_{Ni}^2])\} \leq C_2 \sum_{l=0}^{C_1 \sqrt{a_N}} (l+1) \alpha(\sqrt{b_N} l) \max_i E[D_{Ni}^4]$

where  $C_1, C_2 > 0$  are sufficiently large constants, and the inequality is a result of the conditions on the covariances and locations in assumptions A6 and A9. The right hand side of the inequality is of order  $O(N^{-2} b_N^3 a_N)$  since it follows from the conditions in A6 and A9 that  $\max_i E[D_{Ni}^4]$  is bounded by

$$\frac{1}{N^2} \max_i \sum_{t_1, t_2, t_3, t_4 \in \Lambda_{N_i}} |E[A_{Nt_1} A_{Nt_2} A_{Nt_3} A_{Nt_4}]| \leq$$

$$C_1 \frac{1}{N^2} \max_i \sum_{t_1, t_2, t_3, t_4 \in \Lambda_{N_i}} \{\alpha(d_{t_1, t_2}) + \dots + \alpha(d_{t_3, t_4})\} \leq C_2 \frac{1}{N^2} b_N^2 \max_i \sum_{t_1, t_2 \in \Lambda_{N_i}} \alpha(d_{t_1, t_2}) \leq$$

$$C_4 \frac{1}{N^2} b_N^2 \max_i \sum_{t_1 \in \Lambda_{N_i}} \sum_{l=0}^{C_3 b_N^{1/2}} l \alpha(l) \text{ for some } C_1, C_2, C_3, C_4 > 0, \text{ and since } \sum_{l=0}^{\infty} l \alpha(l) \text{ is bounded}$$

by A6, the last term is of order  $O(N^{-2} b_N^3 a_N)$ .

Finally,  $C_2 \sum_{l=0}^{C_1 \sqrt{a_N}} (l+1) \alpha(\sqrt{b_N} l) \max_i E[D_{Ni}^4] = O(N^{-2} b_N^3 a_N) = o(1)$  as  $n \rightarrow \infty$  by the

properties of  $a_N$  and  $b_N$ . Thus we have shown that  $\sum_{j=1}^{a_N} (D_{Nj}^2 - E[D_{Nj}^2]) \xrightarrow{p} 0$  and condition

(c) can be written as:  $\sum_{j=1}^{a_N} D_{Nj}^2 - 1 = \sum_{j=1}^{a_N} E[D_{Nj}^2] - 1 + op(1)$  which can be further rewritten

as  $\sum_{j=1}^{a_N} E[D_{Nj}^2] - 1 + op(1) = E[Y_{0N}^2] - 1 - \sum_{i \neq j} E[D_{Ni} D_{Nj}] + op(1)$ .

To check the order of convergence we need only to analyze the term  $\sum_{i \neq j} E[D_{Ni} D_{Nj}]$ . For this it is enough to analyze  $\max_i \sum_{i \neq j} |E[D_{Ni} D_{Nj}]|$  since each of the summations over  $i$  and  $j$  contain terms with  $a_N$  or  $a_{N-1}$ . Take  $\Xi_{Nil}$  as previously defined, then, for some  $C_1 > 0$ ,  $\max_i \sum_{i \neq j} |E[D_{Ni} D_{Nj}]|$  can be bounded by

$$\max_i \sum_{l=1}^{C_1 \sqrt{a_N}} \sum_{j \in \Xi_{Nil}} |E[D_{Ni} D_{Nj}]| \leq \max_i \sum_{j \in \Xi_{Nil}} |E[D_{Ni} D_{Nj}]| + \max_i \sum_{l=2}^{C_1 \sqrt{a_N}} \sum_{j \in \Xi_{Nil}} |E[D_{Ni} D_{Nj}]| \quad (2)$$

and we analyze each of the terms in the right-hand side .

For the first term, note that  $\max_{i \neq j} |E[D_{Ni}D_{Nj}]| = \max_{i \neq j} \left| \frac{1}{N} \sum_{t \in \Lambda_{Ni}, s \in \Lambda_{Nj}} E[A_{Nt}A_{Ns}] \right|$   
 $\leq \max_{i \neq j} C_1 \frac{1}{N} \sum_{t \in \Lambda_{Ni}, s \in \Lambda_{Nj}} \alpha(d_{ts})$  for some large  $C_1 > 0$ , by the boundedness of  $A_{Nt}$ 's and A6.

Consider adjacent blocks for which dependence will be typically stronger, then, by A9 and A6, the number of  $(t, s)$  combinations within distance  $d$  is bounded by  $C_2 b_N^{1/2} d^2$  for some  $C_2 > 0$ . Letting  $C_3 = C_2 C_1$  the expression is bounded by  $C_3 \max_{i \neq j} \frac{1}{N} b_N^{1/2} \sum_{d=0}^{C_4 \sqrt{b_N}} d^2 \alpha(d)$  for some  $C_4 > 0$  and since by A9  $d^2 \alpha(d) \rightarrow 0$  the expression is  $o\left(\frac{1}{N} b_N\right)$  and thus  $\max_{i \neq j} |E[D_{Ni}D_{Nj}]| = o\left(\frac{1}{N} b_N\right)$  or  $o(a_N^{-1})$  (since  $n = a_N b_N$ ), and so is the first term in (2).

For the second term, first note that by the boundedness of  $A_{Nt}$  and  $E[A_{Nt}] = 0$ :  $\max_{j \in \Xi_{Ni}} \max_{t \in \Lambda_{Ni}} \max_{s \in \Lambda_{Nj}} |E[A_{Nt}A_{Ns}]| = O(\alpha(\sqrt{b_N}(l-1)))$  uniformly in  $l$ . Therefore, the second term is

bounded by  $C_2 \max_i \sum_{l=2}^{C_1 \sqrt{a_N}} \frac{1}{N} |\Xi_{Ni}| |\Lambda_{Ni}| |\Lambda_{Nj}| \alpha(\sqrt{b_N}(l-1)) \leq$

$C_3 \frac{1}{N} b_N^2 \sum_{l=1}^{C_1 \sqrt{a_N}} l \alpha(\sqrt{b_N} l) = o\left(\frac{1}{N} b_N \sum_{l=1}^{C_1 \sqrt{a_N}} l \alpha(l)\right) = o(a_N^{-1})$ . The second-to-last equality

is due to  $\frac{\alpha(ts)}{\alpha(s)} = o(t^2)$  as  $t \rightarrow \infty$  and the last one due to the boundedness of the sum

$$\sum_{l=1}^{C_1 \sqrt{a_N}} l \alpha(l).$$

Finally, since  $\max_i \sum_{i \neq j} |E[D_{Ni}D_{Nj}]|$  is  $o(a_N^{-1})$  and thus  $\sum_{i \neq j} E[D_{Ni}D_{Nj}]$  is  $o(1)$ , condition (c) is demonstrated.

(d) Using the boundedness of  $A_{Nt}$ ,

$\max_j |D_{Nj}| = \max_j \left| \frac{1}{\sqrt{N}} \sum_{t \in \Lambda_{Nj}} A_{Nt} \right| \leq \frac{1}{\sqrt{N}} |\Lambda_{Nj}| \max_t |A_{Nt}| = Op\left(\frac{1}{\sqrt{N}} b_N\right) = op(1)$  by the construction of  $b_N$ .

Since conditions (a)-(d) are satisfied under the current assumptions,  $Y_{0N} \xrightarrow{d} N(0, 1) \iff g_N(\theta_0) \xrightarrow{d} N(0, \Psi_1(\theta_0))$  which concludes the proof of proposition 2. *QED*

### Proof of Proposition 3

$\Psi_{2N}(\hat{\theta}_{GMM}) \xrightarrow{p} \Psi_2(\theta_0)$  follows from the fact that  $\frac{\partial g_N(\hat{\theta}_{GMM})}{\partial \theta'} \xrightarrow{p} \frac{\partial g(\theta_0)}{\partial \theta'}$  by part (a) of Lemma 1, by the consistency of  $\theta_{GMM} \xrightarrow{p} \theta_0$ ; and by A8 which assumes  $M_N \xrightarrow{p} M$

To show that  $\Psi_{1N}(\hat{\theta}_{GMM}) \xrightarrow{p} \Psi_1(\theta_0)$  we can show that  $\Psi_{1N}(\hat{\theta}_{GMM}) \xrightarrow{p} \Psi_{1N}(\theta_0)$  as we did in Lemma 1.

Note that

$$\begin{aligned}
\Psi_{1N}(\theta_0) &= \frac{1}{N} \sum_{ij} \tau_{Ni}(\theta_0) \tau_{Nj}(\theta_0) z_i z_j' \left\{ \Phi_2(\psi_i(\theta_0), \psi_j(\theta_0), \rho_{Nij}(\theta_0)) - \Phi_2(\psi_i(\theta_0), \psi_j(\theta_0), 0) \right\} \\
&= \frac{1}{N} \sum_{ij} \tau_{Ni}(\theta_0) \tau_{Nj}(\theta_0) z_i z_j' \rho_{Nij}(\theta_0) \frac{\partial \Phi_2(\psi_i(\theta_0), \psi_j(\theta_0), \rho_{Nij}(\theta_0^*))}{\partial \rho} \quad (3)
\end{aligned}$$

where  $\tau(\cdot)$  is as defined in the proof of proposition 1,  $\Phi_2$  stands for the bivariate normal distribution, and the second equality follows from the mean value theorem for  $\theta^*$  between  $\hat{\theta}_{GMM}$  and  $\theta_0$ .

First consider the partial derivative term and show that it is bounded. Take the following bivariate normal distribution.

$$\Phi_2(a, b, \rho) = \int_{-\infty}^b \int_{-\infty}^a \frac{1}{2\Pi(1-\rho)^{1/2}} \exp\left\{-\frac{1}{2(1-\rho^2)}(t^2 - 2\rho ts + s^2)\right\} dt ds$$

and make the following change of variable from  $t$  to  $u = (t - \rho s)(1 - \rho^2)^{-1/2}$ . Integrating over  $u$  and differentiating with respect to  $\rho$  yields:

$$\frac{\partial \Phi(a, b, \rho)}{\partial \rho} = \frac{1}{\sqrt{2\Pi}} \int_{-\infty}^b \left\{ -s(1 - \rho^2)^{-1/2} + (a - \rho s) \rho (1 - \rho^2)^{-3/2} \right\}$$

$\rho$  assumed in A12 - A14, is bounded.

Repeating the application of the mean value theorem with respect to  $\theta$  in (3), using the boundedness of the above partial derivative and the fact that  $\hat{\theta}_{GMM} \xrightarrow{p} \theta_0$  yields the result that  $\Psi_{1N}(\hat{\theta}_{GMM}) \xrightarrow{p} \Psi_{1N}(\theta_0)$  and thus  $\Psi_{1N}(\hat{\theta}_{GMM}) \xrightarrow{p} \Psi_1(\theta_0)$ . *QED*

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