

Spatial temporal fishing technologies: specification and estimation

Quinn Weninger	Larry Perruso	Helle Bunzel
Iowa State U	NOAA	Iowa State U

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Problem

$$h_{st} = qE^\alpha X_{st} e^u$$

$$\ln(h_{st}) = \alpha \ln(qE) + \ln(X_{st}) + u$$

$$= \alpha_0 + \alpha \tilde{E}^* + \ln(X_{st}) + u$$

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When X_{st} known to fisherman but not the researcher:

$$\ln(h_{s,t}) = \alpha_0 + \alpha \tilde{E}^*(p, w, R, X_{st}) + \underbrace{\ln(X_{st}) + u}_{\epsilon_{st}}$$

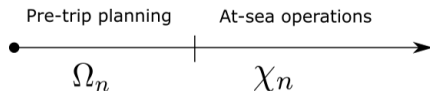
$$\mathbb{E}[\tilde{E}^* \cdot \epsilon_{s,t}] \neq 0$$

Literature:

- ▶ Dual models of multiple-species fishing technologies with/without stock *controls* (e.g., Squires, 1987; Kirkely and Strand, 1988; Weninger, 1998)
- ▶ Zhang and Smith (2011): estimate G-S harvest/stock growth model
- ▶ Ekerhovd and Gordon (2013) - Use virtual population analysis to instrument for unobserved stock

DGP: Trip-level production

1. Stock X_{st} at location s , date t is an unobservable random vector; $F(X|s, t)$ is known (only) to fishermen



2. Fishermen partially control the scale and mix of harvested species; targeting actions chosen during planning phase based on

$$\Omega = \{p, w, F(X|s, t), R\};$$

p - fish price, w - input prices, F - stock distribution, R - regulations

3. Operations stage productivity signal χ_n revealed at sea; harvest scale may respond to χ

Estimation

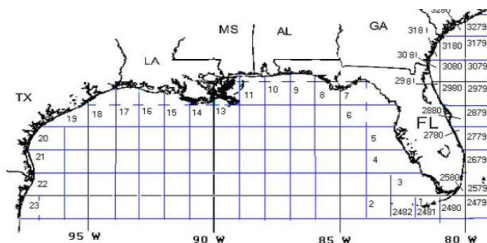
$$C(h, w|X_{st}, k) = \underbrace{\left[1 + \frac{\gamma}{2} \sum_{i=1}^m \left(S_i(h) - \varphi_i(X_{st}) \right)^2 \right]}_A \exp(\beta_0 + \beta_h h) G(w, k|\beta) e^{\chi+u}$$

1. Use a series function approximation to approximate catchability and expected abundance: obtain residual $\hat{\chi} \perp \Omega$

$$\frac{\bar{h}}{\bar{E}} = q(\Omega) \bar{X}(s, t) e^{\chi}$$

2. Use series approximation to *annihilate* A ; exploit timing assumptions and exogenous natural stock variability to consistently estimate β_h and parameters of $G(w, k|\beta)$
3. Use nonlinear GMM IV estimator to consistently estimate β_0 and parameters of A
4. Use block bootstrap to estimate standard errors of parameters

Application to Eastern Gulf of Mexico reef fish:



- ▶ Eight species: red and vermilion snapper, red, gag and OSW groupers, DW grouper, Tilefish, Other species.
- ▶ 9,941 observations on 358 unique vessel operations during 2005-14
- ▶ Trip-level fuel, labor, capital, miscellaneous expenses
- ▶ Landings and regulatory discards
- ▶ Fuel and labor prices, landings prices, quota lease prices (proxy)
- ▶ Regulations: by species, date, gear type, depth, and across fishermen

Results:

Step 1 Parameter Estimates					
Variable	Parm.	Est.	Std. Err.	p-val.	90% c.i.
Red. snap.	β_1	0.060	0.011	<0.001	0.042, 0.079
Verm. snap.	β_2	0.208	0.020	<0.001	0.176, 0.241
Red group.	β_3	0.414	0.025	<0.001	0.366, 0.447
Gag group.	β_4	0.191	0.050	<0.001	0.150, 0.310
O.S.W. group.	β_5	1.036	0.151	<0.001	0.711, 1.194
D.W. group.	β_6	0.299	0.057	<0.001	0.215, 0.398
Tilefish	β_7	0.195	0.161	0.225	-0.120, 0.362
Coast. Pelag.	β_8	0.063	0.033	0.056	-0.002, 0.108
All oth.	β_9	0.397	0.034	<0.001	0.338, 0.446
Red. Group. (long.)	β_3^l	0.044	0.007	<0.001	0.033, 0.037
All Oth. (long.)	β_9^l	0.074	0.010	<0.001	0.059, 0.092
$\ln(w_f)$	β_f	0.299	0.084	<0.001	0.162, 0.436
$\ln(w_l)$	β_l	0.482	0.273	0.078	0.009, 0.932
$\hat{\chi}_n$	β_χ	-0.069	0.013	<0.001	-0.095, 0.054
Vess. length	β_k	0.102	0.012	<0.001	0.082, 0.123
Vess. length sqrd.	β_{kk}	-0.001	0.000	<0.001	-0.001,-0.001

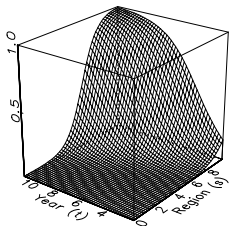
Step 2 Parameter Estimates					
Variable	Parm.	Est.	Std. Err.	p-val.	90% c.i.
Targ. parm.	γ	2.106	1.080	0.051	[0.987, 5.508]
Targ. parm. (LL)	γ_{LL}	1.507	1.739	0.386	[0.090, 3.423]
Con.	β_0	1.813	1.325	0.171	-0.596,4.022
Cons. (HL gear)	β_0^{HL}	-0.346	0.084	< 0.001	-0.453, -0.199
Cons. (TR gear)	β_0^{TR}	-0.797	0.211	< 0.001	-1.089, -0.438
Cons. (LL gear)	β_0^{LL}	1.100	0.337	0.001	-0.087, 0.079
Space	β_s	0.078	0.079	0.322	-0.017, 0.175
Time	β_s	0.118	0.088	0.178	0.071, 0.198
Time sqr.	β_s	-0.045	0.054	0.406	-0.087, 0.079

Reef fish targeting:

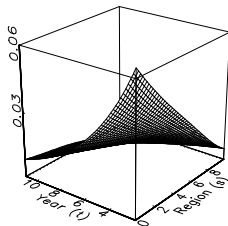
	p_i	$S_i(h)$	$S_i(h_n) - \hat{\varphi}_{in}$	$p_i - \hat{C}_i(\cdot)$
Red. snap.	4.070	0.154	-0.098	3.692
Verm. snap.	2.942	0.136	0.124	2.209
Red group.	3.298	0.222	0.126	2.007
Gag group.	4.470	0.048	0.041	3.873
O.S.W. group.	4.305	0.020	0.008	1.030
D.W. group.	3.639	0.019	0.010	2.228
Tilefish	2.100	0.011	0.003	1.142
All Oth.	1.972	0.391	-0.213	1.190

Results: $\hat{\varphi}'_i$'s

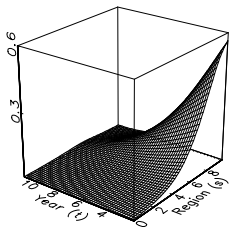
(a) Red Snapper



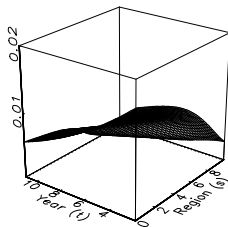
(b) Vermilion Snapper



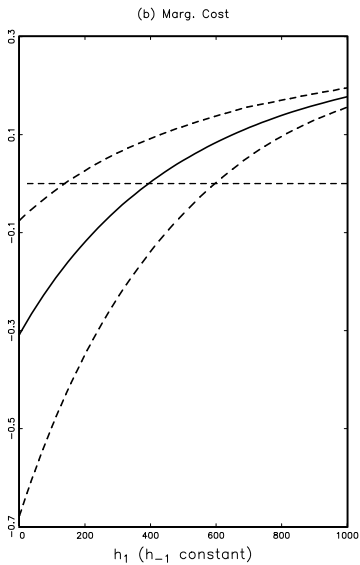
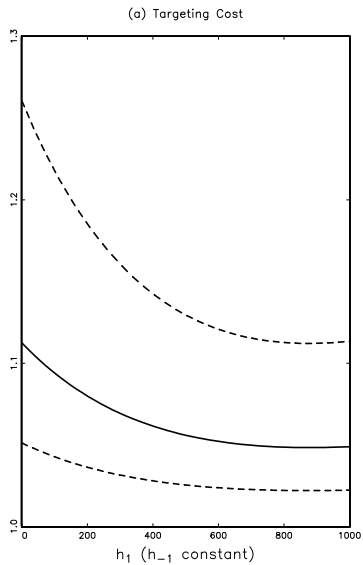
(c) Red Grouper



(d) Gag Grouper



Results: Red snapper targeting



Conclusion

Consistently estimate harvest cost elasticity for a WOD multiple-species technology

Estimations exploit timing of harvest decisions and available information, CPUE stock assessment construct, random fluctuations in marine environment

Present application to the Gulf of Mexico reef fish fishery

Next steps:

Link model to absolute stock abundance and estimate stock-cost elasticity