Establishing Causality in Coupled Human-Natural Systems
Insights from Numerical Modeling of Fisheries

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3 Days MESSH Keynote Address Part 2

Sète, France

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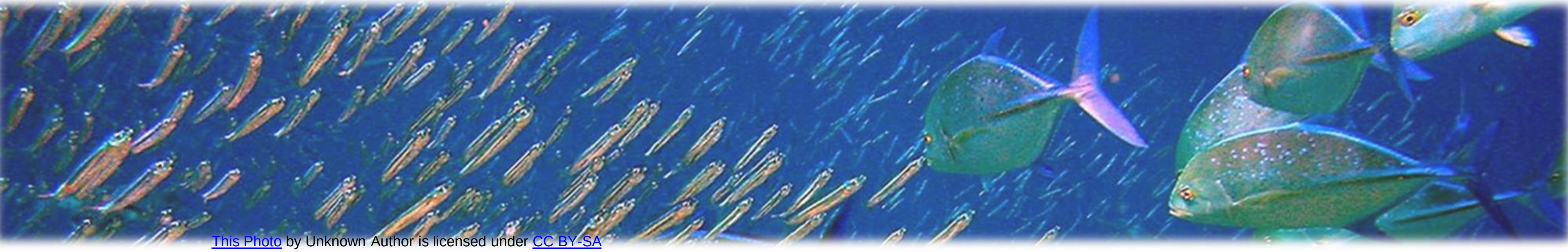


Overarching Theme

Bioeconomic modeling is necessary for empirical analysis of fisheries data

- **Models prevent us from drawing spurious inferences**
- **Models guard against bad policy decisions based on spurious inferences**

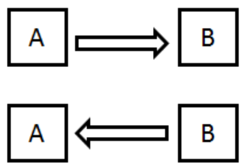
Outline

1. Background – coupled systems and the credibility revolution
2. Some relevant statistical challenges with nonlinear systems
3. Treated units as coupled pairings and empirical implications
4. Numerical experiments with feedbacks and statistical interference
   - Impacts of hypoxia on a fishery
   - Effects of Marine Protected Areas
   - Effects of a gear restriction

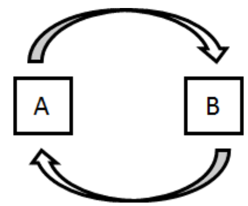
1. BACKGROUND

The Fishery as a Coupled Human-Natural System

Feedbacks, interactions, and couplings

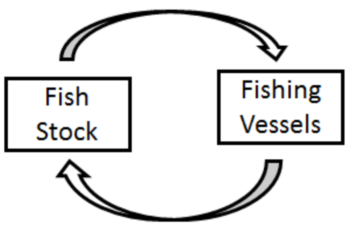


a. Interactions

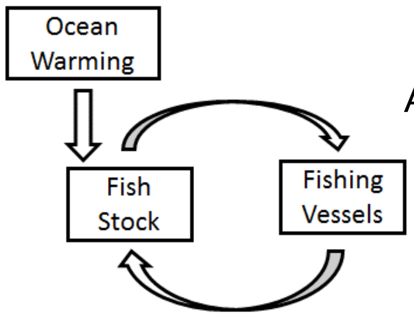


b. Feedback

a “two-way feedback is a more specific concept than ‘bi-directional causality’ or ‘joint determination/ simultaneity’ because it implies a causal sequence *in time* that has implications for the dynamics of both the human and natural systems.”
Abbott, Sanchirico, Smith *MRE* 2018



c. The fishery as a coupled human-natural system



d. A fishery with a bioeconomic feedback and a climate change interaction.

NatAcSciEngMed 2018

Note: “Coupled human-natural system” often used interchangeably with social-ecological system (SES)

The Credibility Revolution

Angrist, J.D. and Pischke, J.S., 2010. The credibility revolution in empirical economics: How better research design is taking the con out of econometrics. *Journal of Economic Perspectives*, *24*(2), pp.3-30.

- Focus on research design, more (big) data, and clear econometric identification of causal effects
- How much does "treatment" with A cause outcome B to change? Need to know what would have happened to B in the absence of treatment with A (the counterfactual)
- Statistical models of observational data attempt to generate properties that resemble those of randomized experiments (with treated units and control units for comparison)
- "Critics of design-driven studies argue that in pursuit of clean and credible research designs, researchers seek good answers instead of good questions. We briefly respond to this concern, which worries us little."

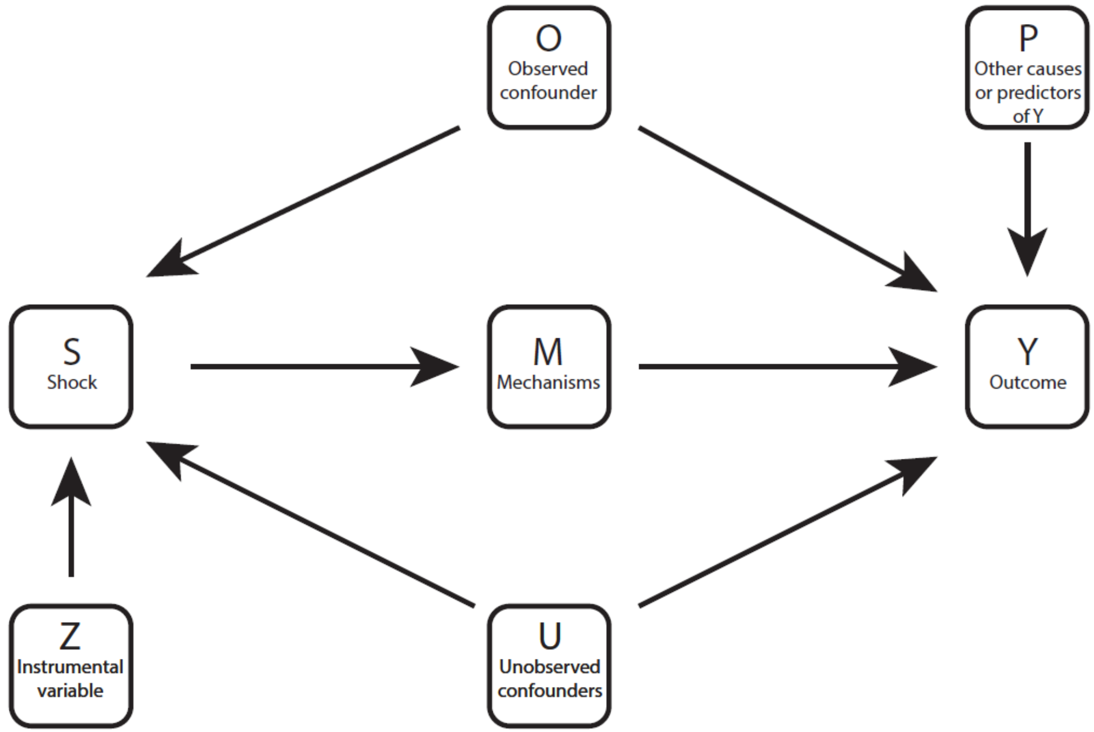
Why should interdisciplinary mathematical modelers of fisheries care about causal inference statistics?

- Effects of ecological disturbances and technological disasters
  - Ocean warming and catches / fish stocks
  - Oil spill and fishery / fish stocks
  - Hurricanes and fishery infrastructure
- Policy evaluation
  - Effects of catch shares on catches / stocks
  - Effects of Marine Protected Areas (marine reserves) on catches / fish stocks
- To answer these questions, you need to know the counterfactual – what would have happened in the absence of the shock or intervention
- Policy-makers, general science journals, and the media like causal inference studies because conclusions are easy to understand
- Despite the "credibility revolution" in economics, they (the statisticians and econometricians) are likely to get the wrong answers in coupled human-natural systems in the absence of modeling

Examples of Purely Empirical Causal Inference Studies of Fisheries

- Effects marine reserves on reef fish catches Smith, Zhang, and Coleman *CJFAS* 2006
- Effects of catch shares on "collapse" Costello, Gaines, and Lynham *Science* 2008
- Spillover effects of catch shares (on adjacent region fisheries) Cunningham, Bennear, and Smith *Land Econ* 2016
- Catch shares and safety at sea Pfeiffer and Gratz *PNAS* 2016
- Catch shares slow the race to fish Birkenbach, Kaczan, and Smith *Nature* 2017
- Spillover benefits of Marine Protected Areas Medoff, Lynham and Raynor *Science* 2022

Directed Causal Graph that Depicts Causal Relationship of S on Y and Confounding Variables.



Ferraro, Sanchirico, and Smith *PNAS* 2019

2. ESTIMATION PROBLEMS IN NONLINEAR SYSTEMS

Problems

- Nonlinear dynamics can lead to multiple equilibria, path dependence, and other forms of complexity

Even simple models can lead to complex behaviors

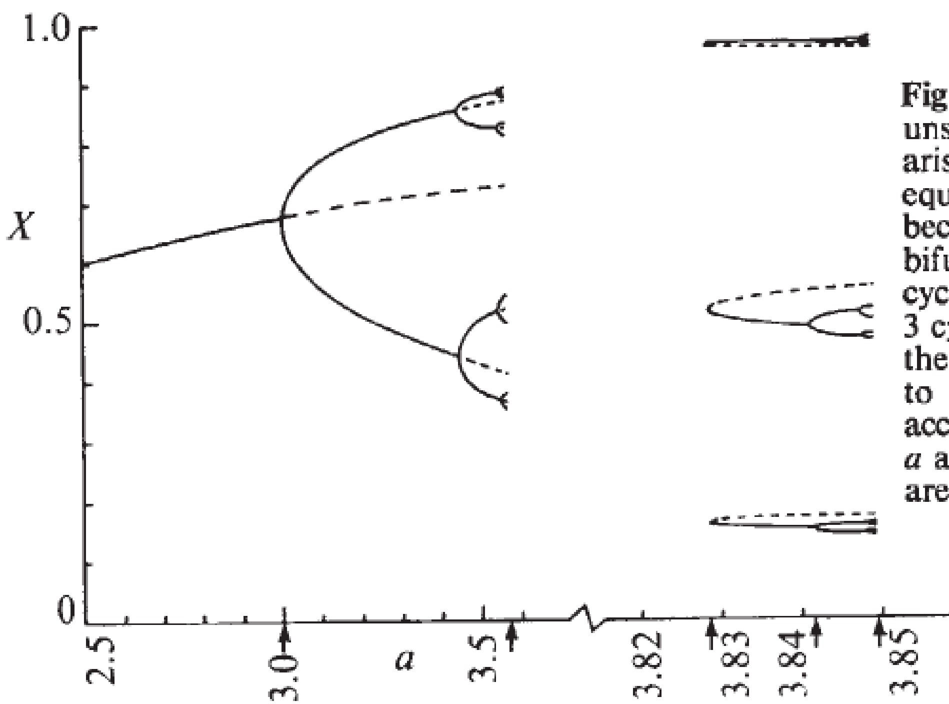


Fig. 4 This figure illustrates some of the stable (———) and unstable (— — — —) fixed points of various periods that can arise by bifurcation processes in equation (1) in general, and equation (3) in particular. To the left, the basic stable fixed point becomes unstable and gives rise by a succession of pitchfork bifurcations to stable harmonics of period 2^n; none of these cycles is stable beyond $a = 3.5700$. To the right, the two period 3 cycles appear by tangent bifurcation: one is initially unstable; the other is initially stable, but becomes unstable and gives way to stable harmonics of period 3×2^n, which have a point of accumulation at $a = 3.8495$. Note the change in scale on the a axis, needed to put both examples on the same figure. There are infinitely many other such windows, based on cycles of higher periods.

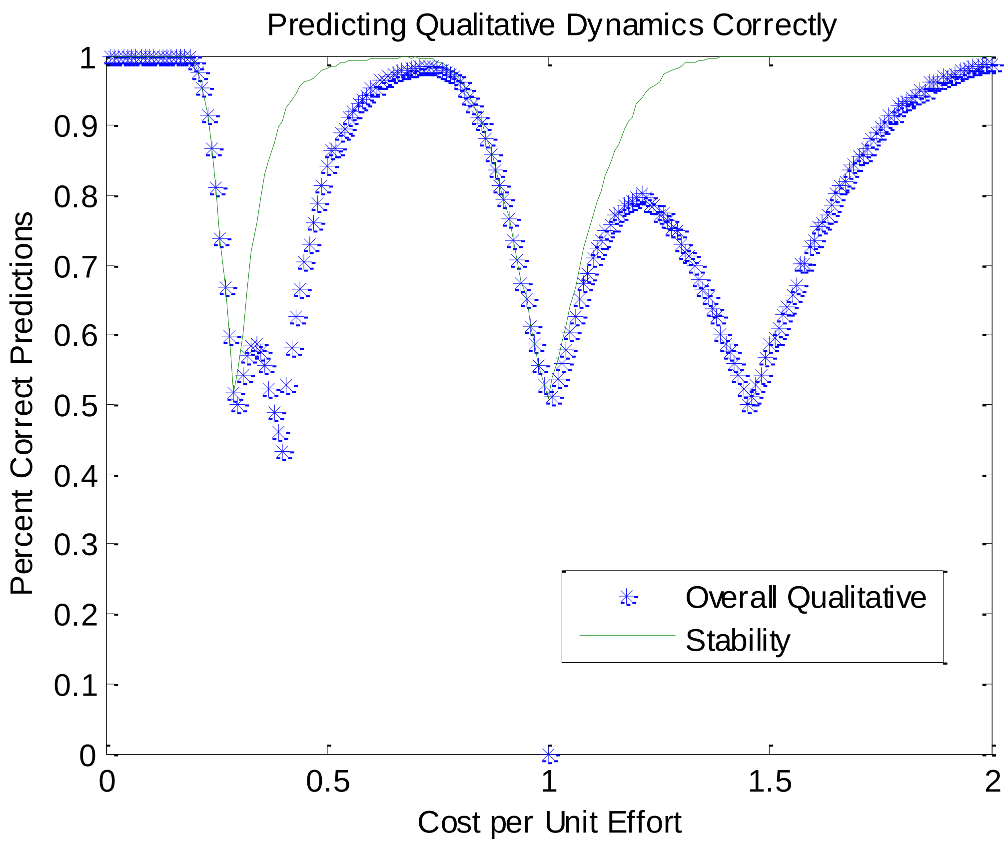
May, Robert M. "Simple mathematical models with very complicated dynamics." *Nature* 261, no. 5560 (1976): 459-467.

Problems

- Nonlinear dynamics can lead to multiple equilibria and path dependence
  - Implication: a small change in “treatment” or “history” could lead to qualitative difference in outcome
  - Huge challenge to external validity (the applicability of empirical findings to other settings)

Econometrically recovering system properties hardest when closest to a change

- Dynamic open access with critical depensation
- Varying cost parameter and recovering qualitative properties
- From left to right, linearized system goes: Stable Node, Unstable Node, Unstable Focus, Center, Stable Focus, Stable Node



Smith *MRE* 2008

3. TREATED UNITS AS COUPLED PAIRINGS

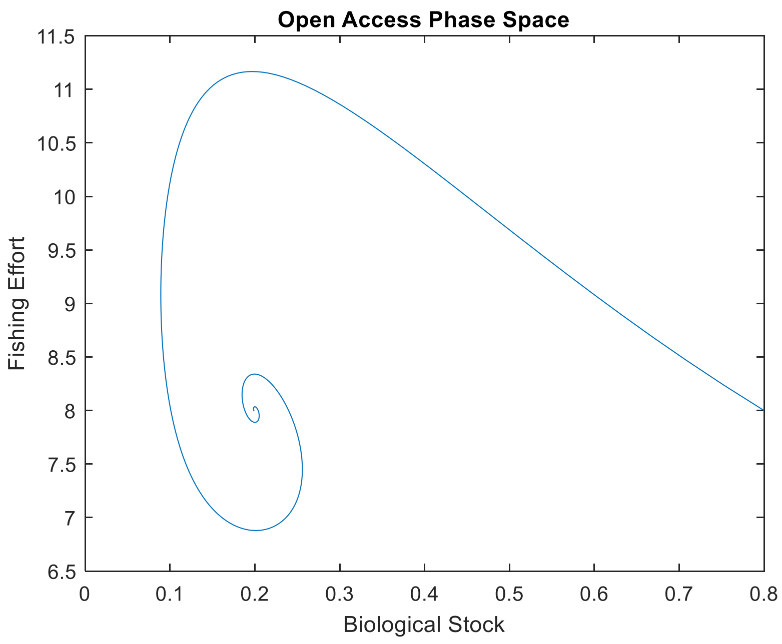
Problems

- Nonlinear dynamics can lead to multiple equilibria and path dependence
- In coupled system, treated units are coupled pairings that trace out a causal sequence
  – Counterfactuals must account for both human and natural components (challenge to matching and initial conditions)

Recall Dynamic Open Access

V. Smith *AER* (1968) and *JPE* (1969)

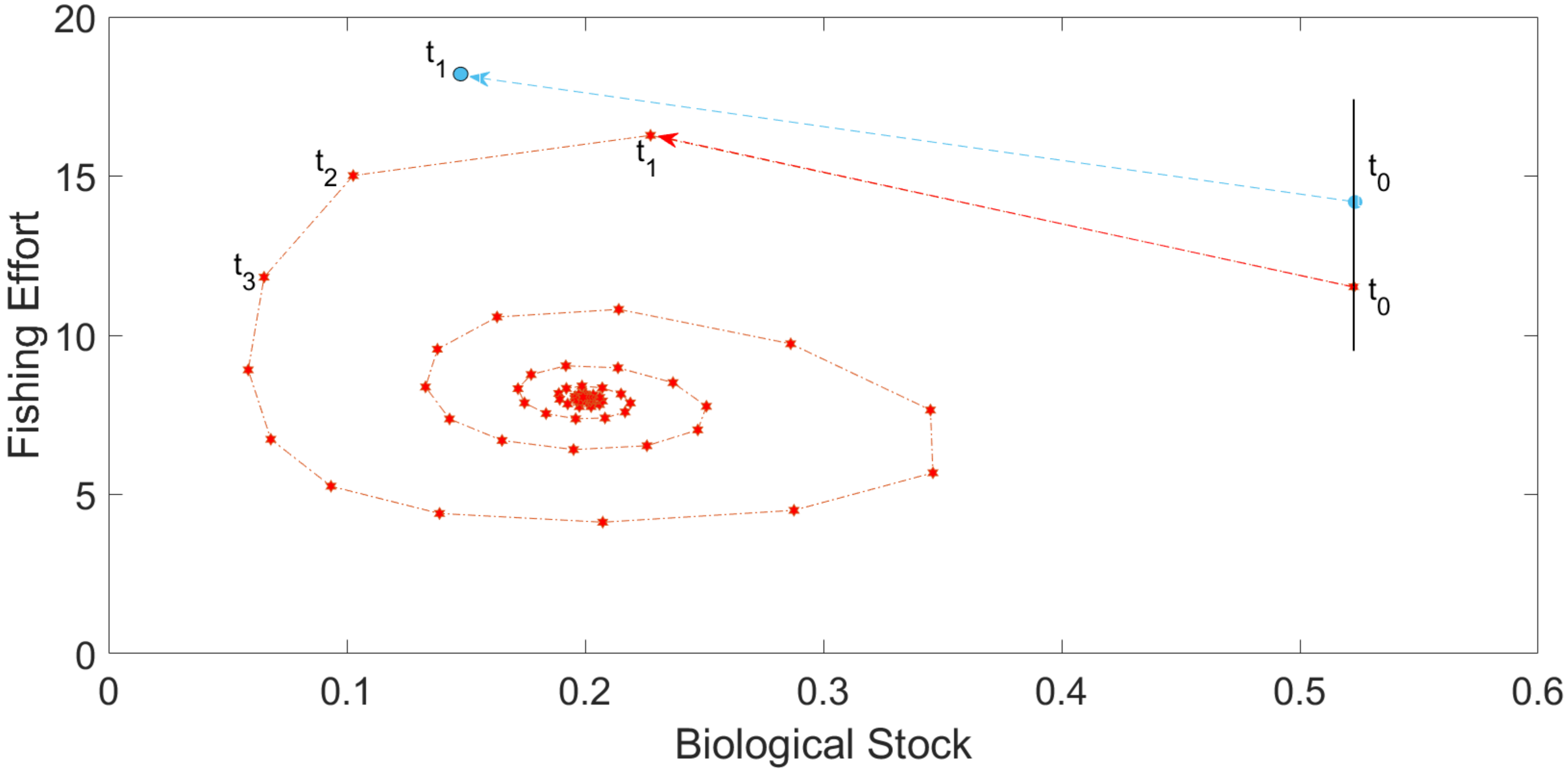
- Models stocks dynamics
- Models entry/exit based on Gordon zero-rent equilibrium
- 2 ODEs
- Stable focus in continuous time



$$\dot{x}(t) = rx(t)\left[1 - \frac{x(t)}{k}\right] - qE(t)x(t)$$

$$\dot{E}(t) = \gamma\left[pqE(t)x(t) - cE(t)\right]$$

Treated units are coupled pairings of ecological and social attributes of the CHANS.

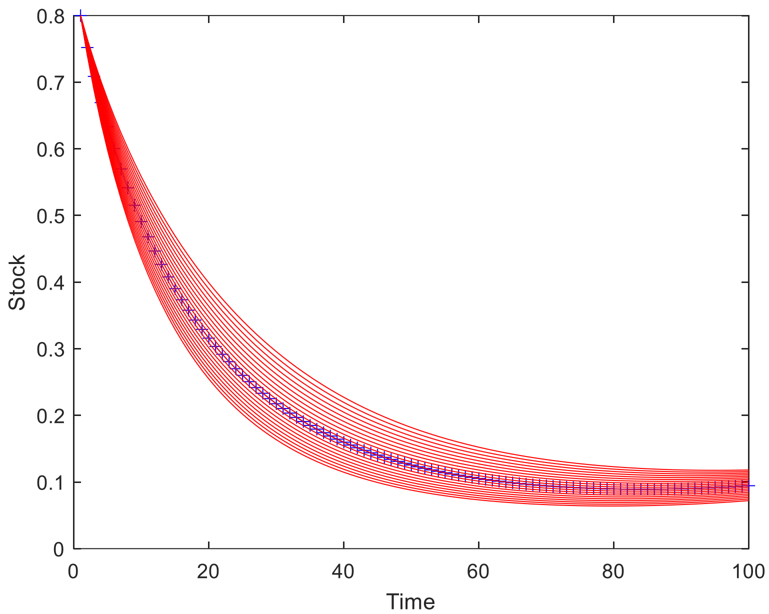


Ferraro, Sanchirico, and Smith *PNAS* 2019

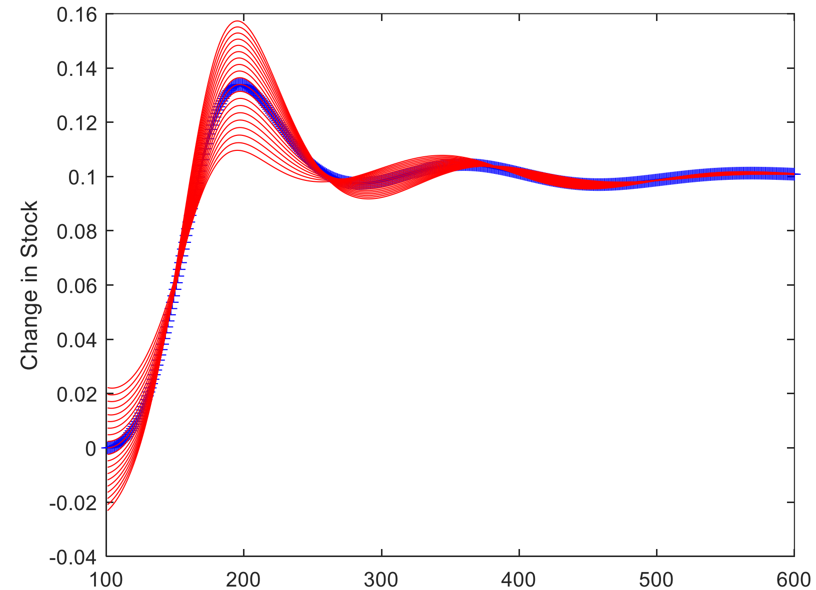
Treated Dynamic Open Access Fishery

Double Carrying Capacity (e.g., clean up pollution)

Varying Initial Conditions



Pre-treatment



Post-treatment

All parameters are the same. Treated fishery in blue, control fisheries in red have initial effort +/- 20%.

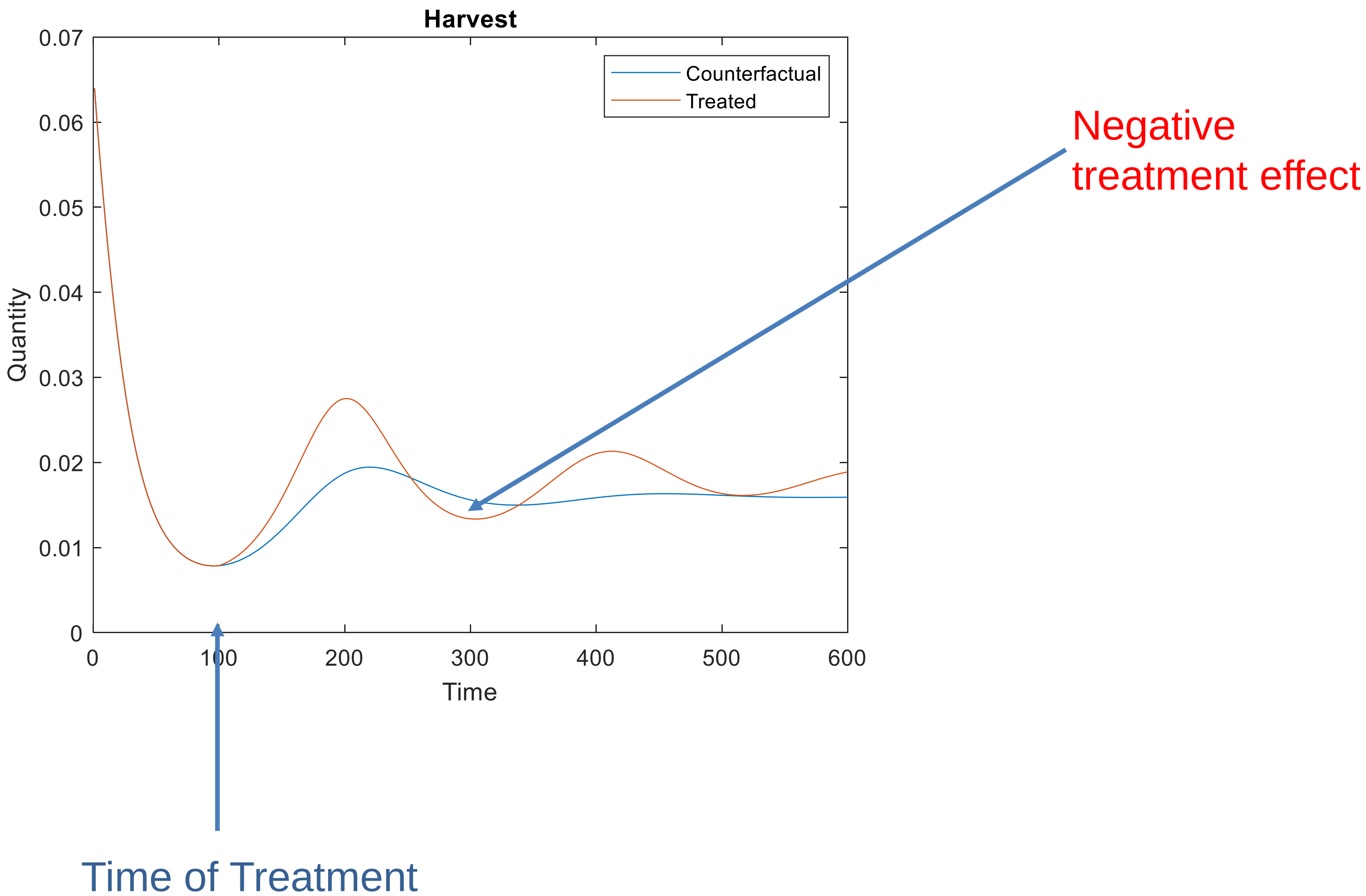
Ferraro, Sanchirico, and Smith *PNAS* 2019

Problems

- Nonlinear dynamics can lead to multiple equilibria and path dependence
- In coupled system, treated units are coupled pairings that trace out a causal sequence
  - Counterfactuals must account for both human and natural components (challenge to matching and initial conditions)
  - Time of measurement influences conclusion (positive or negative effect)

Treated Dynamic Open Access Fishery

Time of Measurement Matters



4. NUMERICAL EXPERIMENTS WITH FEEDBACKS AND STATISTICAL INTERFERENCE

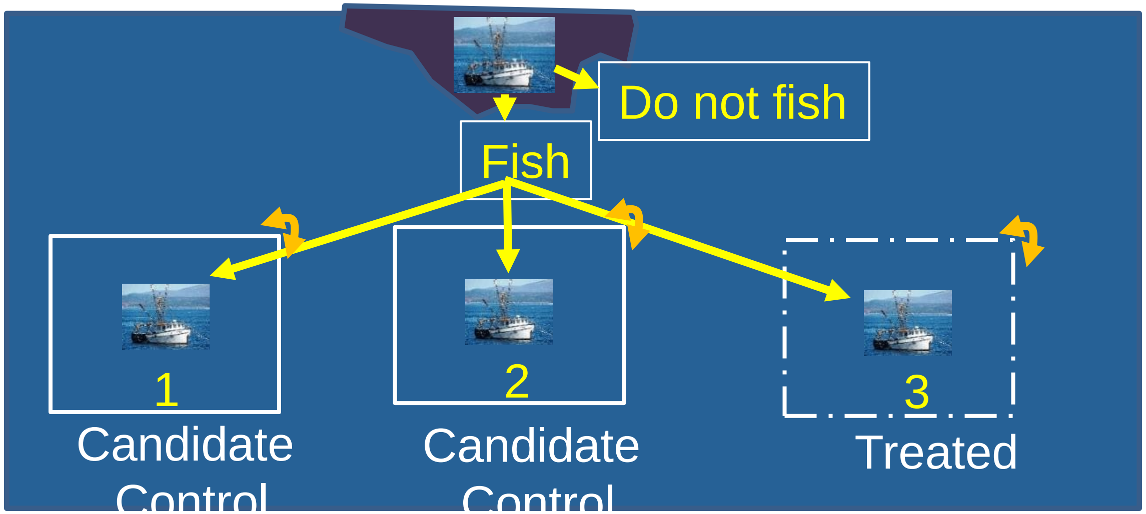
Problems

- Nonlinear dynamics can lead to multiple equilibria and path dependence
- In coupled system, treated units are coupled pairings that trace out a causal sequence
- In spatial-dynamic systems, human mobility can violate Stable Unit Treatment Value Assumption

SIMULATED DATA EXPERIMENTS TO EXPLORE SUTVA (NON-INTERFERENCE) VIOLATIONS IN PROGRAM EVALUATION OF ENVIRONMENTAL SHOCKS AND POLICY INTERVENTIONS

Ferraro, Sanchirico, and Smith *PNAS* 2019

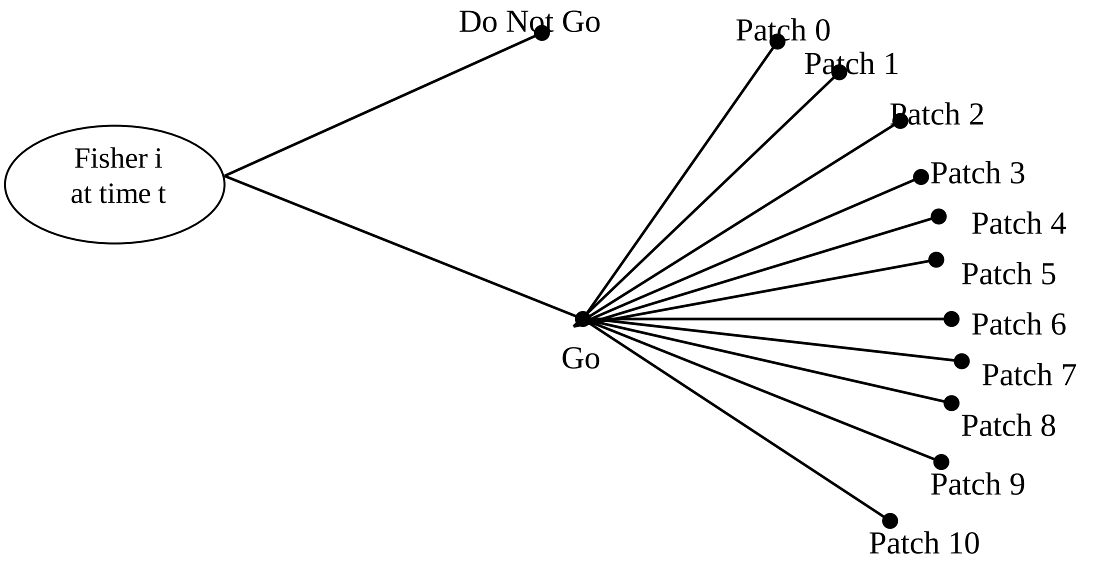
Choice Structure and Experimental Design



Ferraro, Sanchirico, and Smith *PNAS* 2019

Empirical Support for Spatial Discrete Choice Model Structure

- New England Groundfish Holland and Sutinen *Land Econ* 2000
- Sea urchin fishery Smith *Land Econ* 2002; Smith and Wilen *JEEM* 2003
- Alaskan pollock Haynie and Layton *JEEM* 2010
- Reef fish Zhang and Smith *EnvResEcon* 2011
- Gulf of Mexico shrimp Smith et al. *PNAS* 2017



The Model

(1) $$X_{jt+1} = X_{jt} + r_j X_{jt}\left(1 - {X_{jt}}\big/{K_j}\right) + d_{jj} X_{jt} + \sum_{k \neq j} d_{kj} X_{kt} - \sum_{i=1}^{N} H_{ijt}$$

(2) $$H_{ijt} = q_i E_{ijt} X_{jt} \eta_{ijt}$$

(3) $$\pi_{ijt} = \begin{cases} \alpha + \varepsilon_{ijt},\ if\ \ j = 0 \\ \phi_R p \bar{H}_{ijt} - c - \phi_D z_{ij} + \varepsilon_{ijt} \end{cases}$$

(4) $$E_{ijt} = \begin{cases} 1,\ if\ \ \pi_{ijt} = \arg\max\left\{\pi_{i0t}, \pi_{i1t}, \pi_{i2t}, \ldots \pi_{iJt}\right\} \\ 0,\ otherwise \end{cases}$$

(5) $$\eta_{ijt} = \exp(\xi),\ \ \xi \sim N(0, \sigma^2)$$

(6) $$\varepsilon_{ijt} = \psi \ln(-\ln(u_{ijt})),\ \ u_{ijt} \sim U(0,1)$$

Simulating the Model

- **Simulate the Model**

1. Specify production shocks
2. Specify payoff shocks
3. Specify initial stock conditions
4. Fishers form expected harvests from equation 2
5. Fishers compute choice-specific payoffs from expected harvests and equation 3 and payoff shocks in equation 6
6. Fishers make decisions as in equation 4
7. Decisions feed into equation 2 for each fisher along with production shocks from equation 5
8. Harvests are aggregated across fishers and fed into equation 1
9. Stocks are updated in equation 1
10. Repeat steps 4-9 until the end of the simulation

- **Run causal inference econometrics on simulated data**

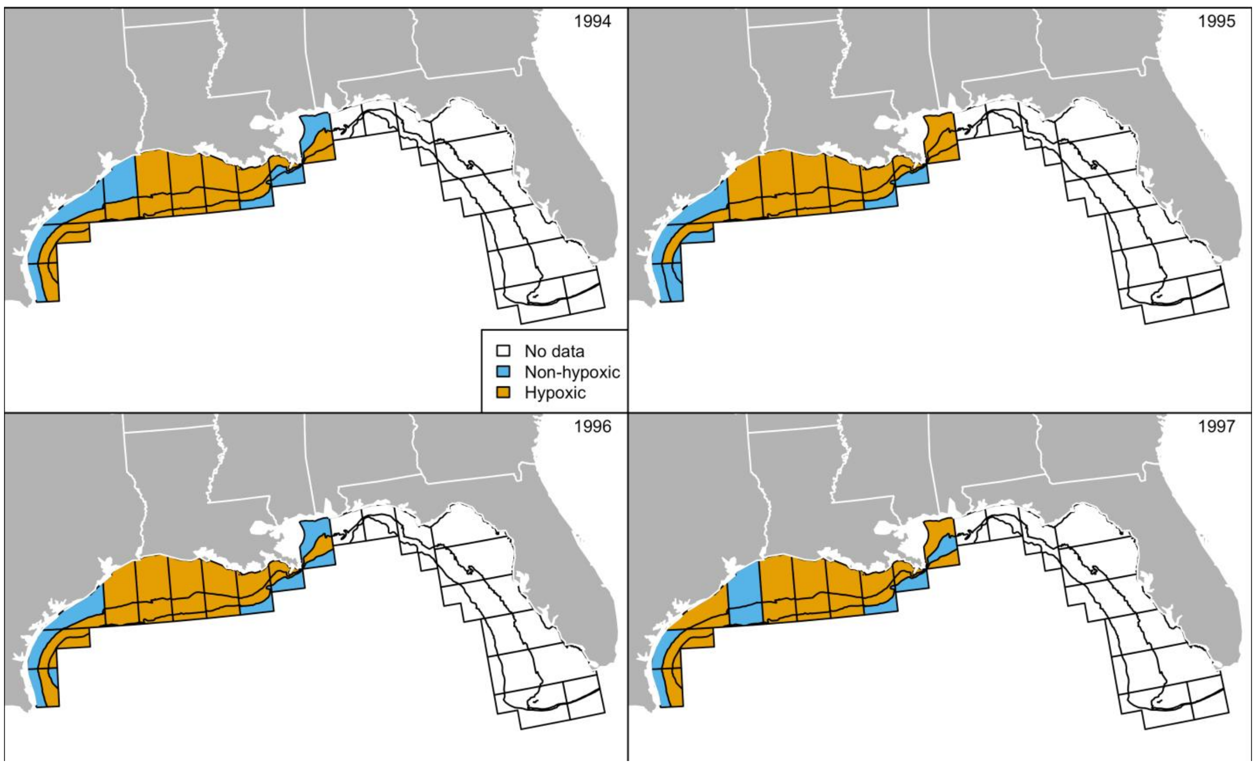
- **Compare estimated treatment effect to true treatment effect**

NUMERICAL EXPERIMENT 1

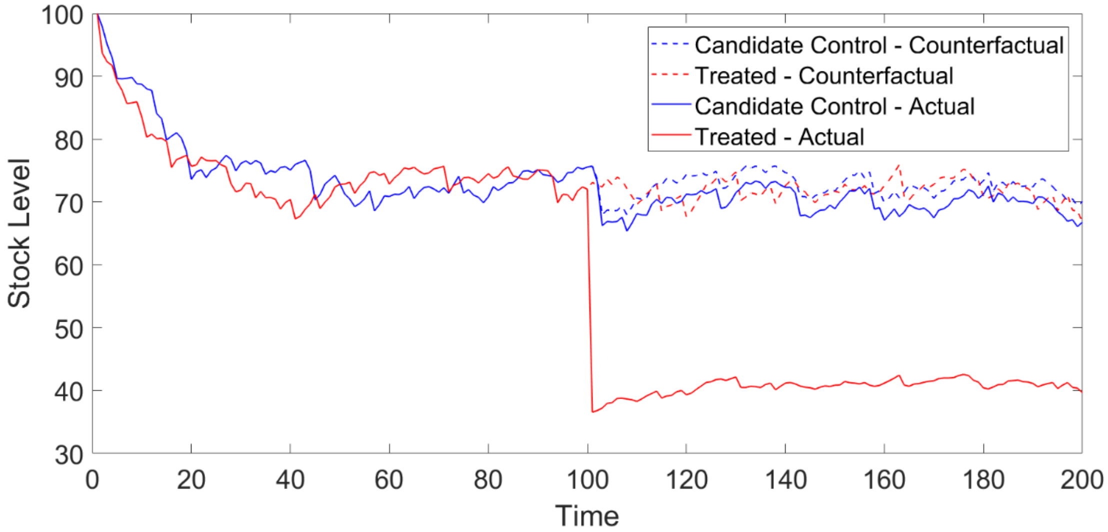
HOW DOES HYPOXIA AFFECT THE UNDERLYING FISH STOCK?

Difference-in-differences (BACI) Finds **No Effects on Catches**

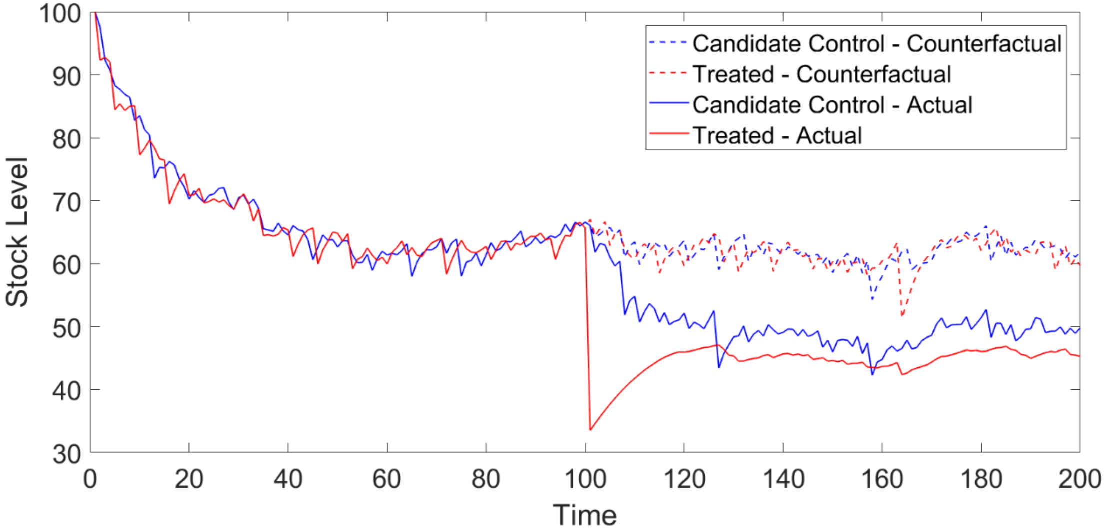
Smith et al. *PNAS* 2017



Interference: Low Versus High Mobility

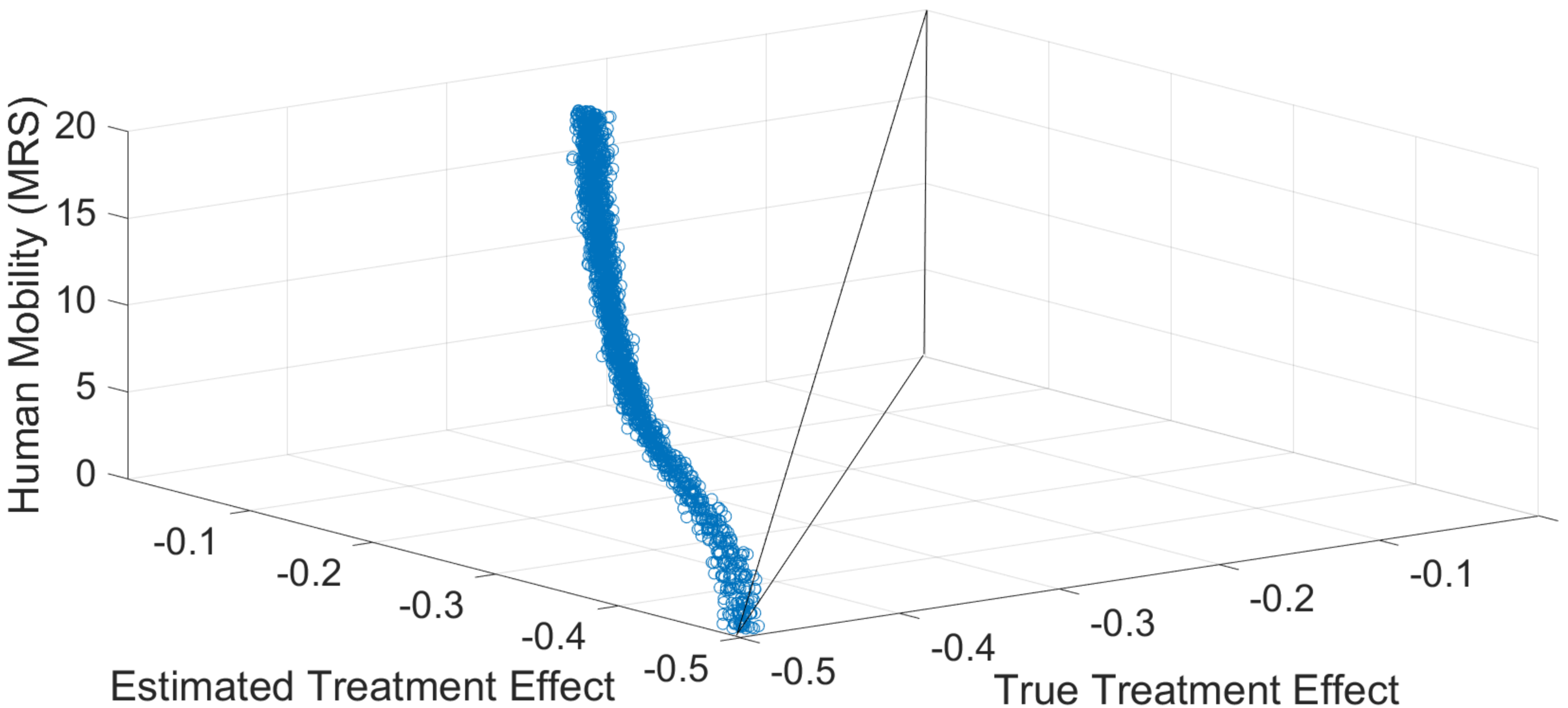


Low Mobility
The candidate control zone tracks the counterfactual treated zone



High Mobility
The candidate control zone tracks the counterfactual treated zone

Mobility Biases the Estimated Treatment Effect Downward



Insights so far

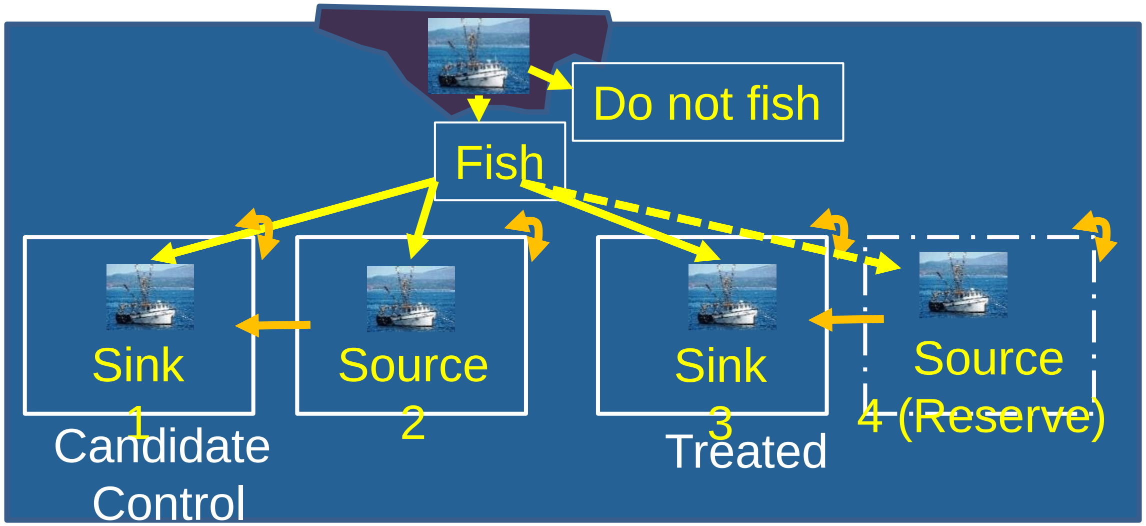
- Unbiased only at extremely low levels of mobility (fishers basically do not switch fishing grounds and choose to stay in the treated area or not fish)
- Downward bias worsens as mobility increases
- Mobility also affects the true treatment effect size

NUMERICAL EXPERIMENT 2

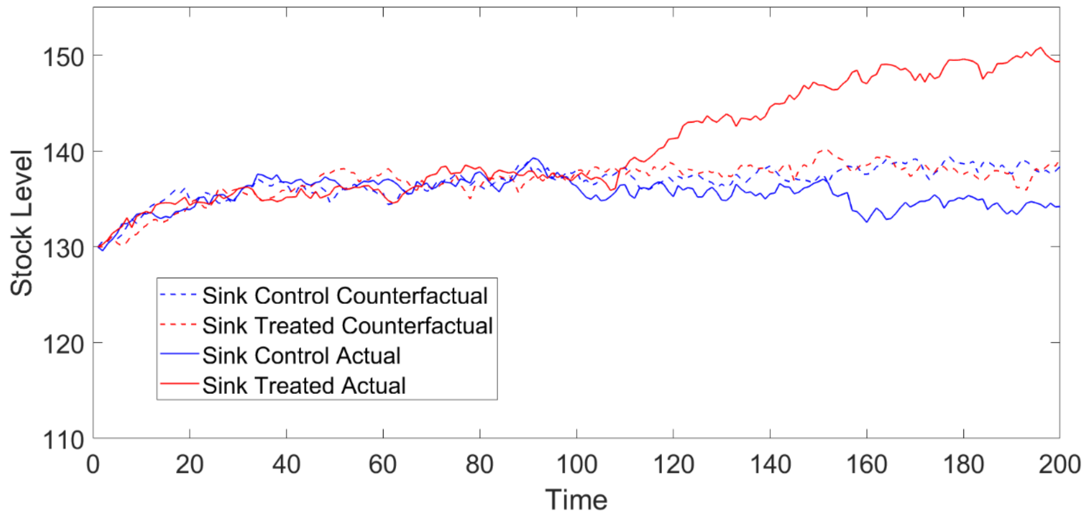
HOW DOES CREATION OF A MARINE PROTECTED AREA IN A SOURCE AFFECT THE UNDERLYING FISH STOCK IN CORRESPONDING SINK?

Experimental Design

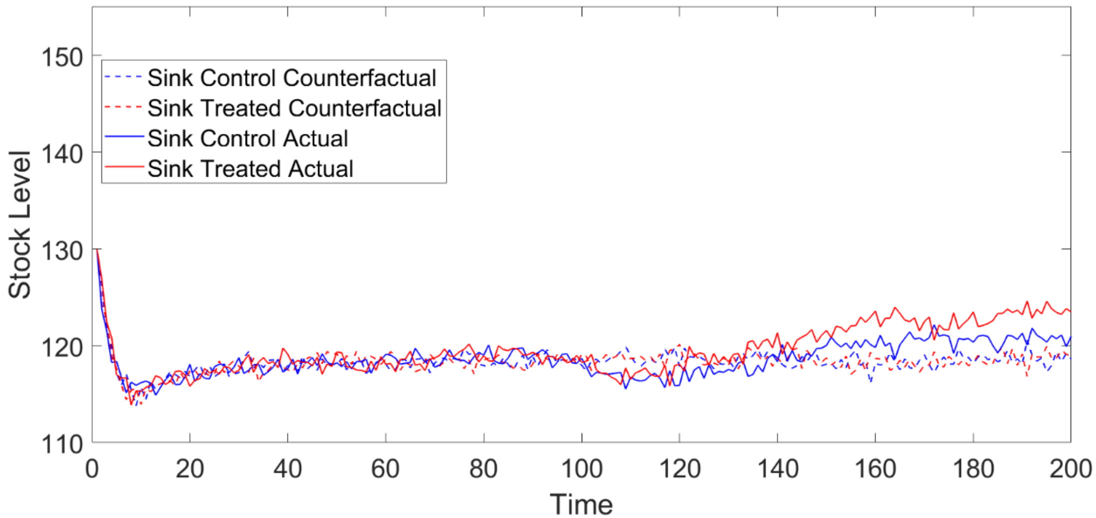
Compare Paired Sink/Source with Treatment to Paired Sink/Source without Treatment



Interference: Low Versus High Mobility

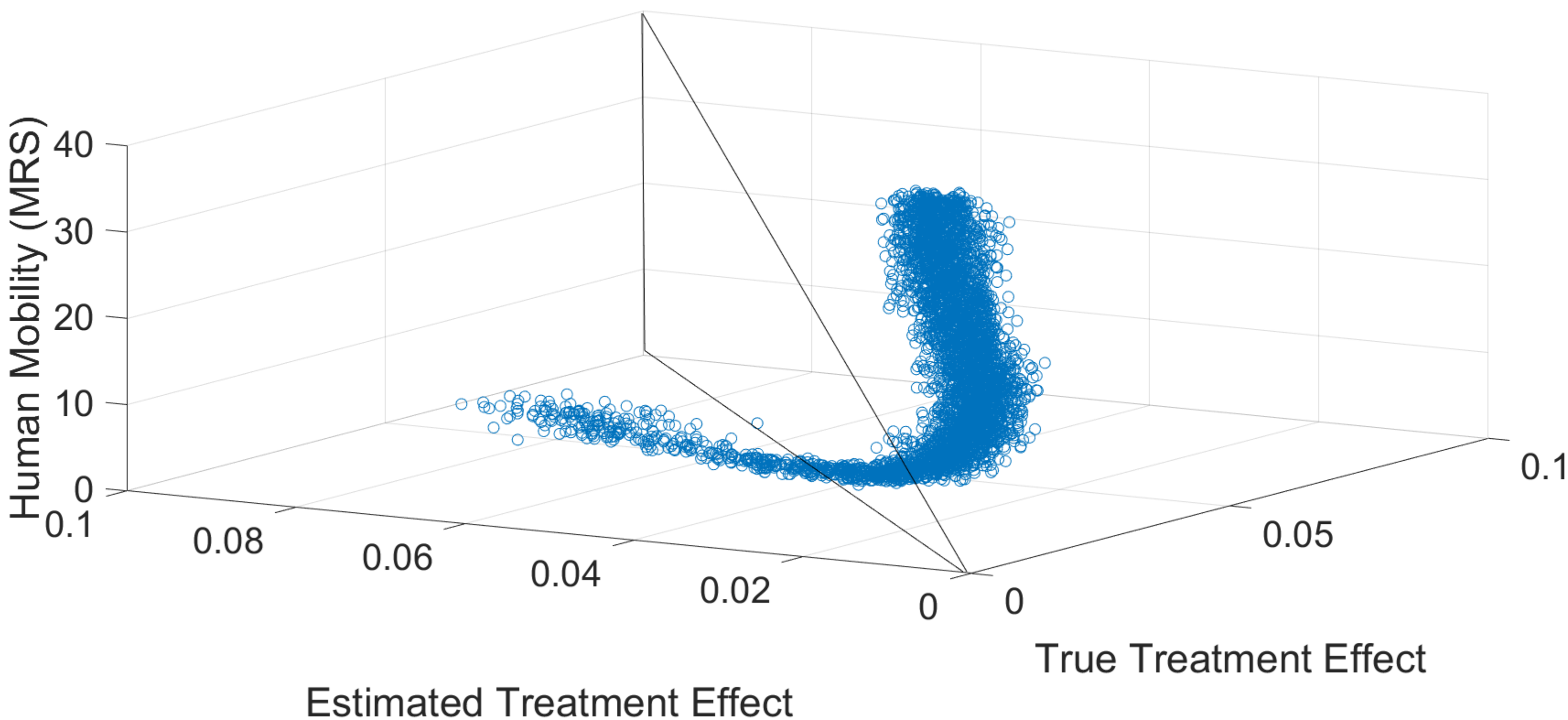


Low Mobility
Upward bias in the estimated treatment effect



High Mobility
Downward bias in the estimated treatment effect

Mobility Biases the Estimated Treatment Effect (Both Upward and Downward, Depending)

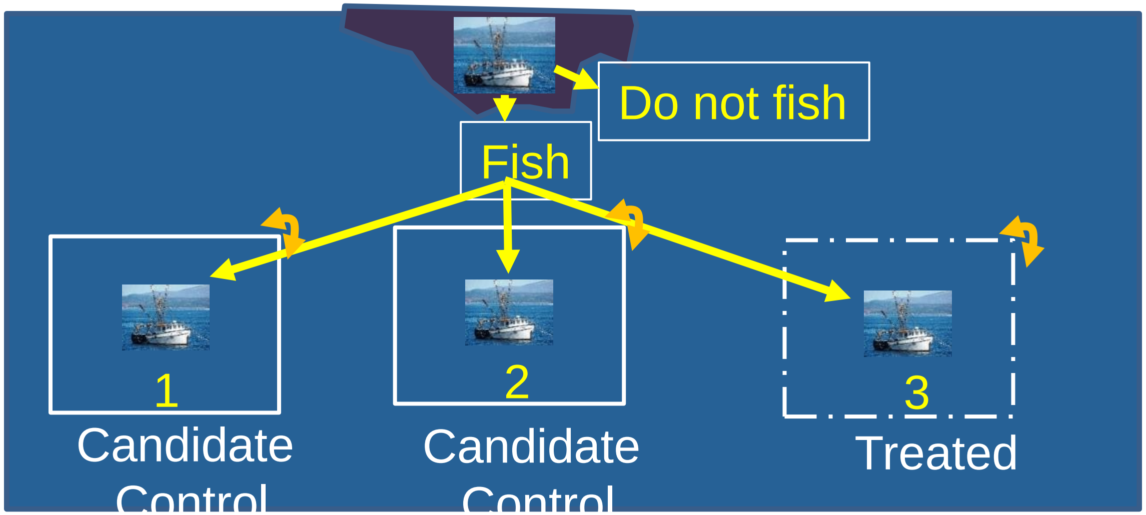


Additional Insight

- Ecological dispersal acts as a compounding source of interference in addition to human mobility

NUMERICAL EXPERIMENT 3
HOW DOES A GEAR RESTRICTION IN ONE ZONE AFFECT THE FISH STOCK?

Based on Schlüter, Brelsford, Ferraro, Orach, Qiu, Smith, In Prep, 2023



Mobility affects true treatment effect size

REMOVED FIGURES THAT ARE UNPUBLISHED (IN PREP)

Pre-restriction Exploitation: Modest

Pre-restriction Exploitation: High

Mobility can induce upward or downward bias, depending on pre-treatment exploitation level

REMOVED FIGURES THAT ARE UNPUBLISHED (IN PREP)

Pre-restriction Exploitation: Modest

Pre-restriction Exploitation: High

Additional Insights

- Effect of mobility on true treatment effect size is non-monotonic and depends on pre-treatment exploitation level
- Estimated treatment effect could be upper or lower bound, depending on the degree of exploitation
- Treatment can increase stocks in untreated areas (due to compensatory effects)!

Discussion

- Models prevent us from drawing spurious inferences
  - Plausible causal inference statistical designs get the wrong answers in some cases
  - These problems cannot be diagnosed without models of the coupled system
  - Models inform what effect size to expect, which has helps to power studies

- Models guard against bad policy decisions based on spurious inferences

- Models still useful for all of the other things that they do as well, e.g. *ex ante* policy analysis, deriving optimal policy, etc.



Thank You!



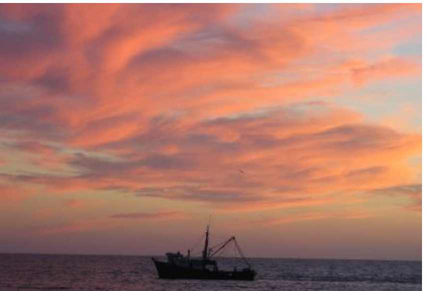

EXTRAS – COULD DISCUSS SOME IF TIME

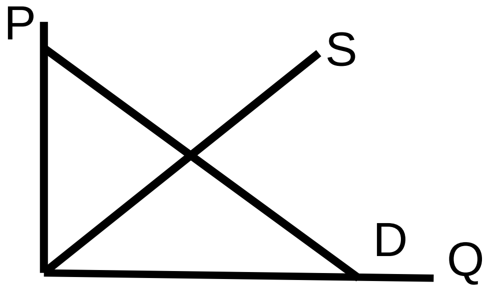
Seafood Prices Reveal Impacts of a Major Ecological Disturbance

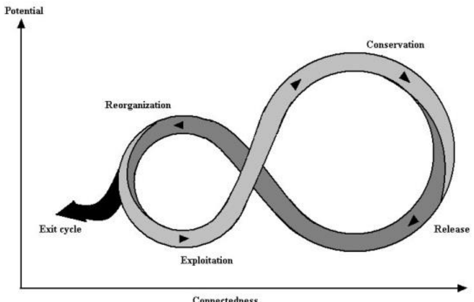
The Case of the Gulf of Mexico Dead Zone

Thanks to NOAA Grant #NA09NOS3780235

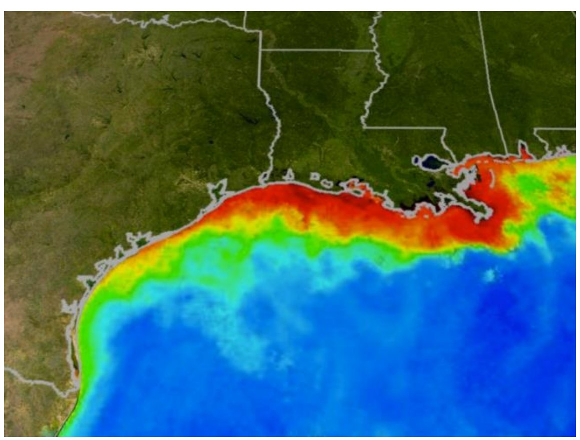
Smith, Martin D., et al. "Seafood prices reveal impacts of a major ecological disturbance." *Proceedings of the National Academy of Sciences* 114.7 (2017): 1512-1517.

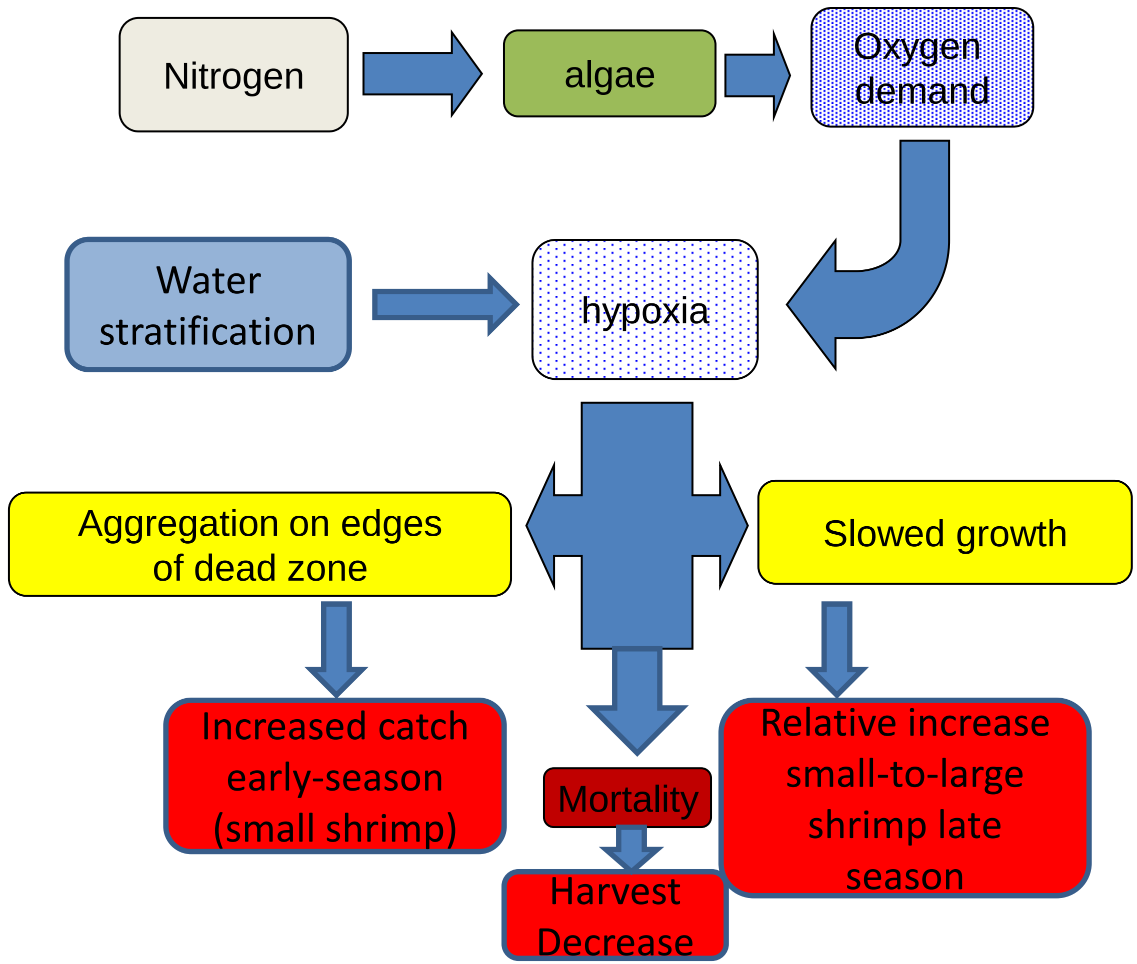






Does the Gulf of Mexico "dead zone" harm the shrimp fishery?



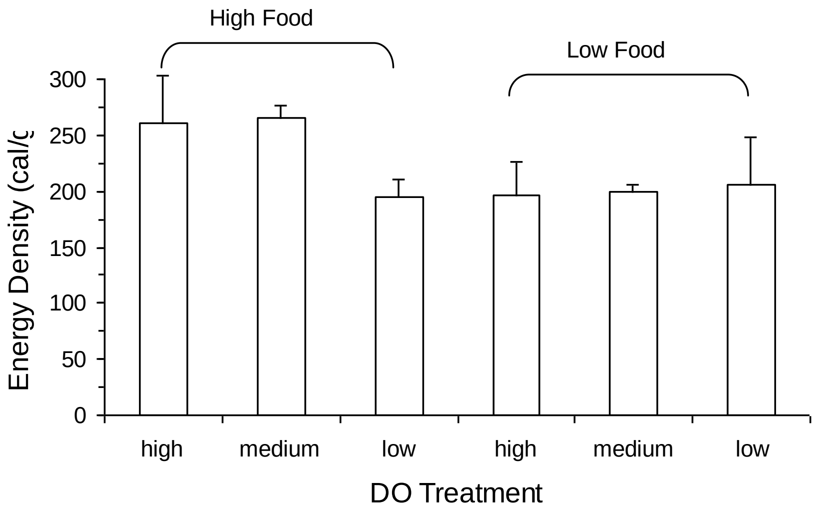


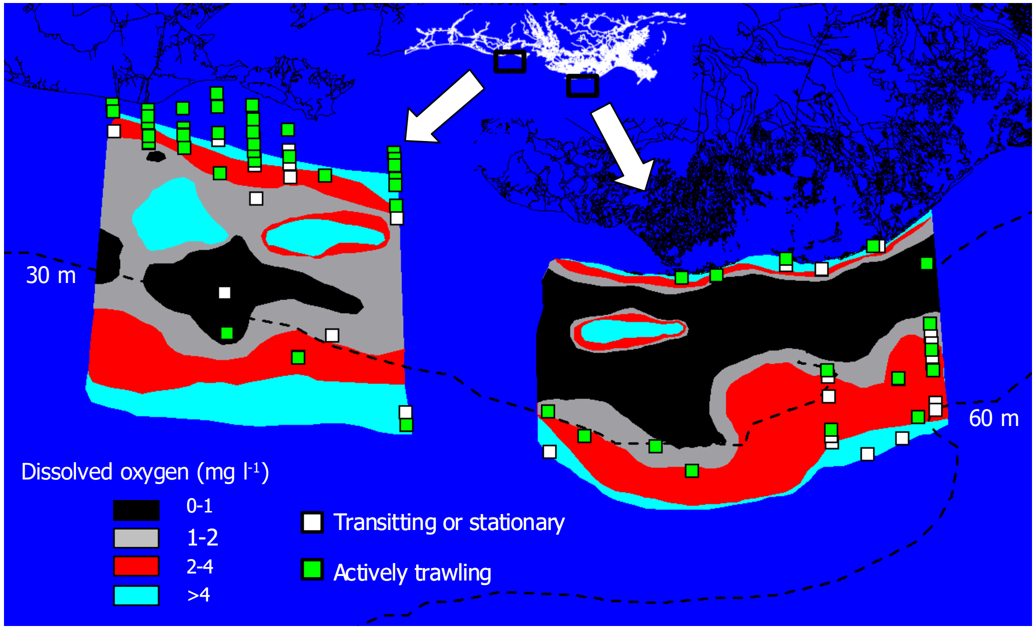
Example: Effects of hypoxia on brown shrimp catches in the Gulf of Mexico

1. NAÏVE DIFFERENCE-IN-DIFFERENCES

Naïve difference-in-differences (LIKE BACI)

- Clear predictions from marine ecology about effects of hypoxia on shrimp growth
  - **More small and fewer large!**

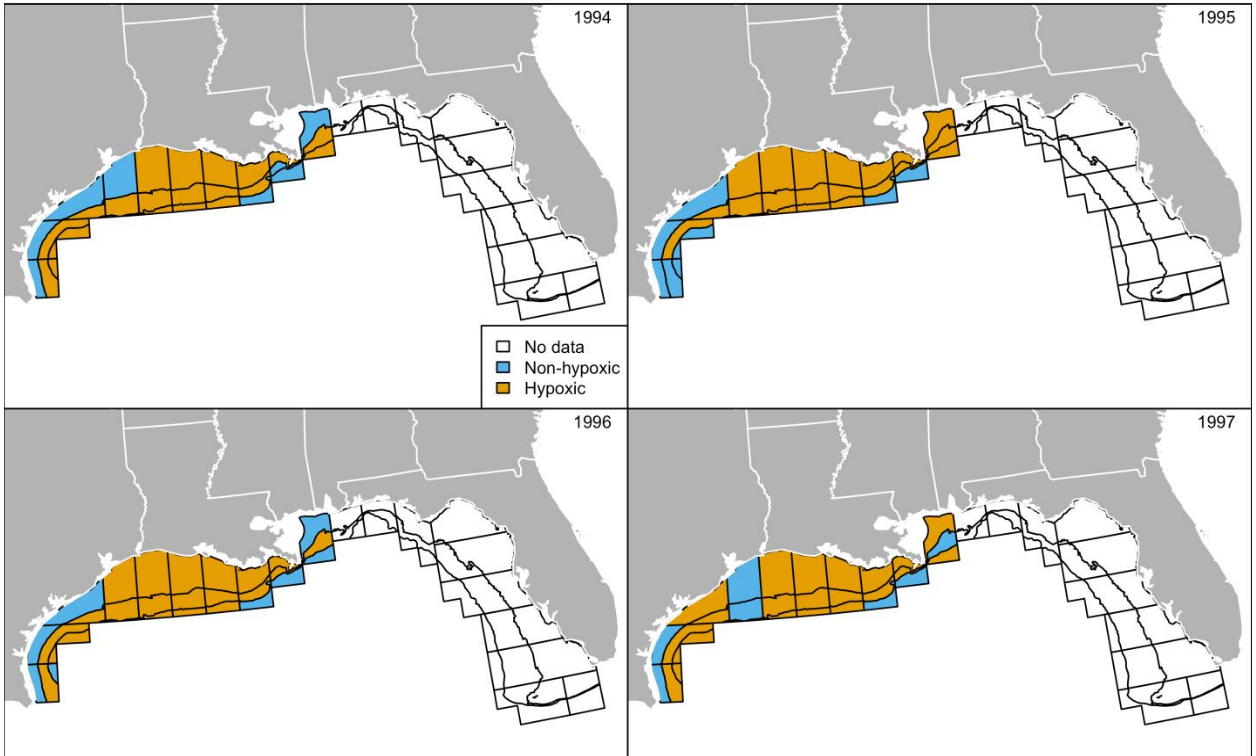




Source: J.K. Craig, 2012

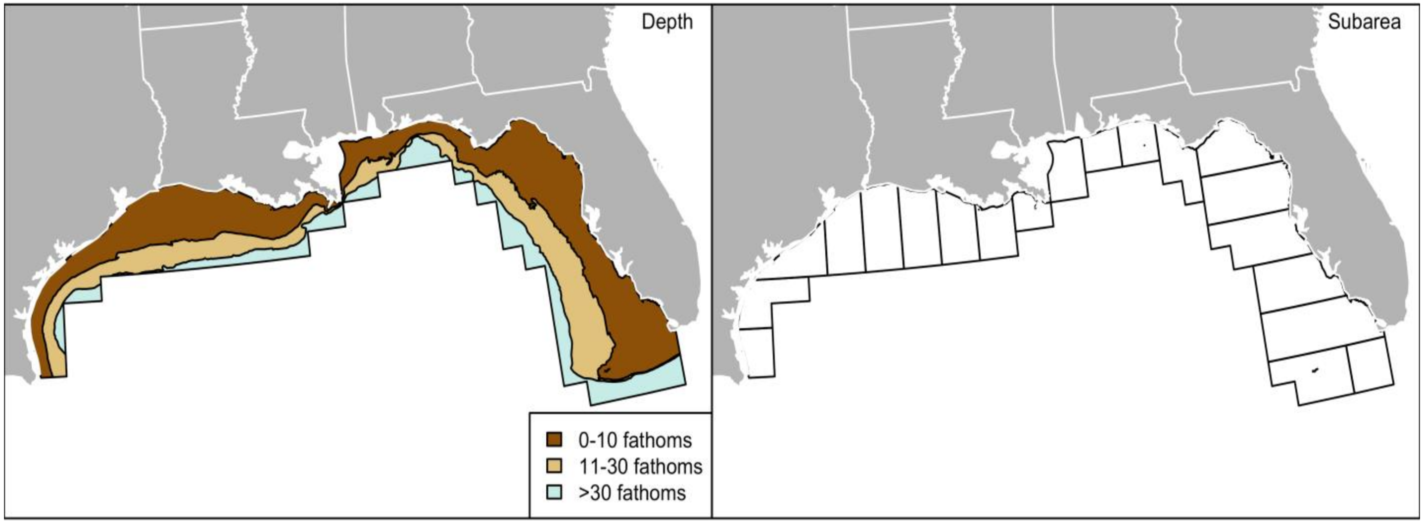
Naïve difference-in-differences

- Clear predictions from marine ecology about effects of hypoxia on shrimp growth
- Exogenous spatio-temporal variation in hypoxia



Naïve difference-in-differences

- Clear predictions from marine ecology about effects of hypoxia on shrimp growth
- Exogenous spatio-temporal variation in hypoxia
- Spatio-temporal and size-based resolution of shrimp catches



Naïve difference-in-differences

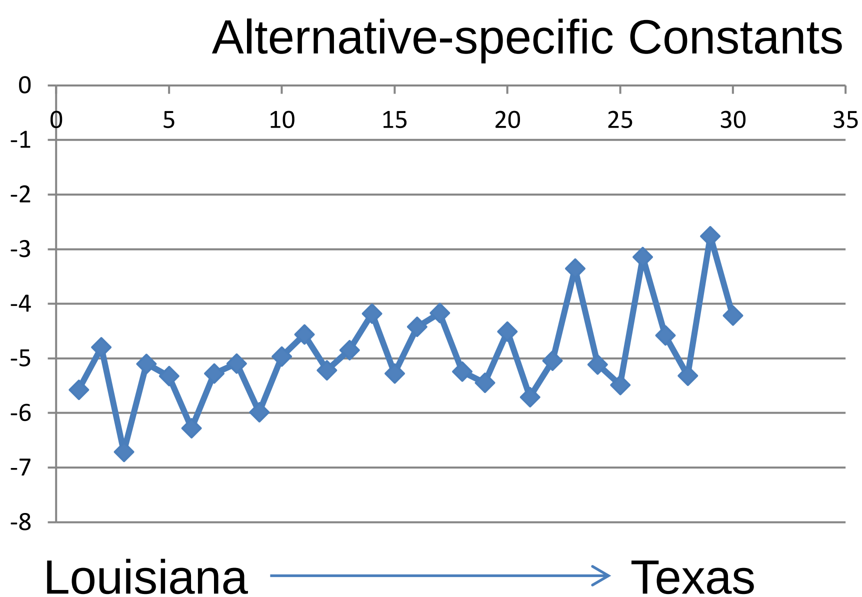
- Clear predictions from marine ecology about effects of hypoxia on shrimp growth
- Exogenous spatio-temporal variation in hypoxia
- Spatio-temporal and size-based resolution of shrimp catches
- Sounds like a straightforward natural experiment!

Identification Strategy

- Compare catches in zones “treated” with hypoxia to catches in other zones before and after “treatment”
- Condition catches on fishing effort
  - Smith, Zhang, and Coleman (2006)
- Instrument for time- and zone-specific fishing effort
  - 31-choice conditional logit on stratified random sample

Effort Conditional Logit Restults

Covariate	Estimate	St. Error	t-statistic
Wave Height (j,t)	-2.220	0.042	-52.46
Shrimp Price (t)	8.951	0.211	42.43
Diesel Price (t)	-15.618	0.455	-34.30
Expected Revenue (j,t)	$\boxed{0.257}$	0.004	66.36
Expected Catch (j,t)	0.178	0.004	44.39
Distance (i,j)	$\boxed{-42.359}$	0.121	-350.14



Diff-in-diff Estimates – Large Shrimp

Covariates	Filtered	All	Filtered	All	Filtered	All	Filtered	All
Contemporaneous Hypoxia	0.392**	0.153	0.497***	0.257	0.366**	0.248	0.371*	0.276
	(2.525)	(0.743)	(2.935)	(1.373)	(2.078)	(1.218)	(1.992)	(1.237)
Hypoxia lag 1			-0.132	-0.0538	-0.0303	-0.136	-0.138	-0.203
			(-1.030)	(-0.291)	(-0.185)	(-0.571)	(-0.764)	(-0.767)
Hypoxia lag 2			-0.0319	-0.149	-0.0467	-0.131	0.0555	-0.124
			(-0.266)	(-0.899)	(-0.272)	(-0.584)	(0.266)	(-0.443)
Hypoxia lag 3			0.0275	0.0367	0.126	0.192	0.0370	0.214
			(0.171)	(0.213)	(0.815)	(0.965)	(0.187)	(0.942)
Hypoxia lag 4					-0.281	-0.139	-0.194	0.0117
					(-1.454)	(-0.874)	(-0.755)	(0.0503)
Hypoxia lag 5					0.150	-0.266	0.0126	-0.312
					(0.815)	(-1.544)	(0.0548)	(-1.271)
Hypoxia lag 6					-0.00223	0.163	0.170	0.132
					(-0.0129)	(0.833)	(0.648)	(0.396)
Hypoxia lag 7							-0.166	0.0258
							(-0.717)	(0.0827)
Hypoxia lag 8							0.137	0.212
							(0.459)	(0.676)
Hypoxia lag 9							-0.210	-0.0775
							(-0.830)	(-0.356)
Hypoxia lag 10							0.134	-0.116
							(0.874)	(-0.473)
Hypoxia lag 11							-0.203	0.304
							(-0.944)	(1.108)
Hypoxia lag 12							0.170	0.0892
							(0.808)	(0.328)
Predicted Effort	3.060***	6.636***	3.015***	6.534***	2.845***	6.671***	2.958***	6.658***
	(3.152)	(3.915)	(3.085)	(4.023)	(2.839)	(3.888)	(2.852)	(4.062)
Yearly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subarea/Depth Zone Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yearly and Subarea/Depth Zone Interaction Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly and Subarea/Depth Zone Interaction Fixed Effect:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Diff-in-diff Estimates – Large Shrimp

Null Results!

Covariates	Filtered	All	Filtered	All
Contemporaneous Hypoxia	0.392**	0.153	0.497***	0.257
	(2.525)	(0.743)	(2.935)	(1.373)
Hypoxia lag 1			-0.132	-0.0538
			(-1.030)	(-0.291)
Hypoxia lag 2			-0.0319	-0.149
			(-0.266)	(-0.899)
Hypoxia lag 3			0.0275	0.0367
			(0.171)	(0.213)

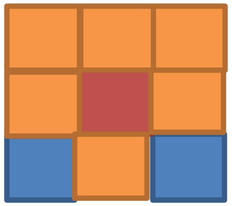
Diff-in-diff Estimates – Small Shrimp

Null Results!

Covariates	Filtered	All	Filtered	All
Contemporaneous Hypoxia	-0.0615	-0.113	-0.104	-0.0141
	(-0.401)	(-0.721)	(-0.546)	(-0.113)
Hypoxia lag 1			0.0587	-0.00465
			(0.410)	(-0.0291)
Hypoxia lag 2			-0.00289	-0.240
			(-0.0214)	(-1.436)
Hypoxia lag 3			-0.0395	0.0223
			(-0.249)	(0.147)

2. SPATIAL-DYNAMIC BIOECONOMIC SIMULATION

Spatial-dynamic Bioeconomic Simulation



Space as (3 x 3) Grid with stochastic hypoxia (worse in middle)

$N_{0,j,y} = \widetilde{N}(1 + \varepsilon_{j,y})\theta_j$ Recruitment

$N_{t,j,y} = N_{0,j,y} e^{\sum_s -m_s + \sum_s -f_s}$ Survival

$m_t = \beta(L_t)^\rho$ Natural Mortality

$f_t = qE_t$ Fishing Mortality

$L_t = L_\infty(1 - e^{-\delta t})$ Growth

$w_t = \omega(L_t)^\gamma$ Allometric (length to weight)

$H_t = \dfrac{f_t}{f_t + m_t}(1 - e^{-f_t}) w_t N_t$ Harvest

Hypoxia Adjustments

$\widetilde{m_t} = (1 + \Delta_m) m_t$

$\widetilde{q_t} = (1 + \Delta_q) q$

$\widetilde{\delta_t} = (1 - \Delta_\delta) \delta$

$N_{a,t,j,y}$ Now adding cohorts!

Based on Smith et al., *MRE* 2014

Spatial-dynamic Bioeconomic Simulation

$$U_{ijt} = v_{itj} + \eta_{ijt}$$

Random Utility Maximization

$$v_{itj} = \begin{cases} \alpha, & for\ \ j = 0 \\ p_t h_{ijt} - c - \phi l_{ij}, & for\ \ j = 1, 2, 3, \ldots J \end{cases}$$

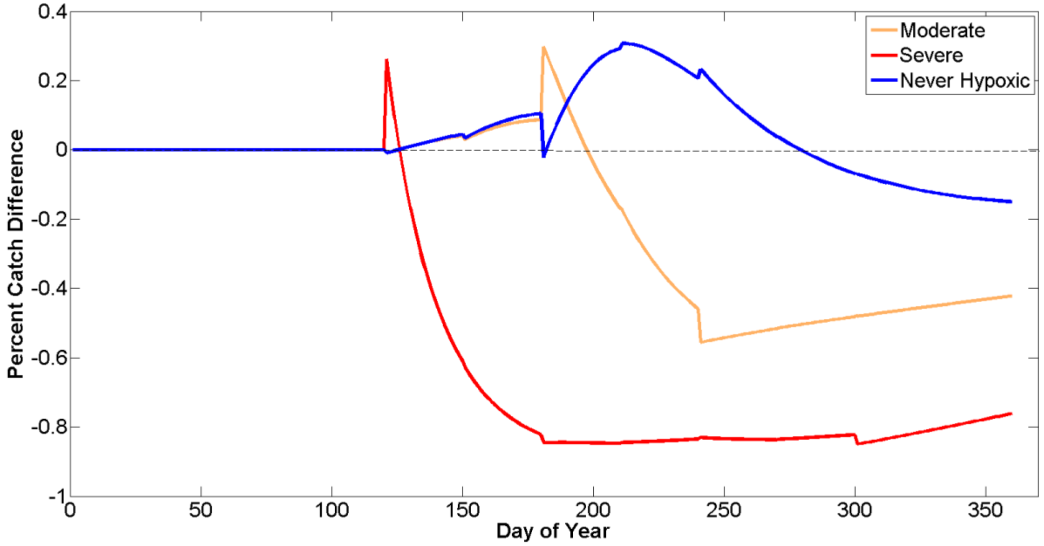
$$p_t = \overline{p_t} + \varphi w_t$$

Weight-based Prices

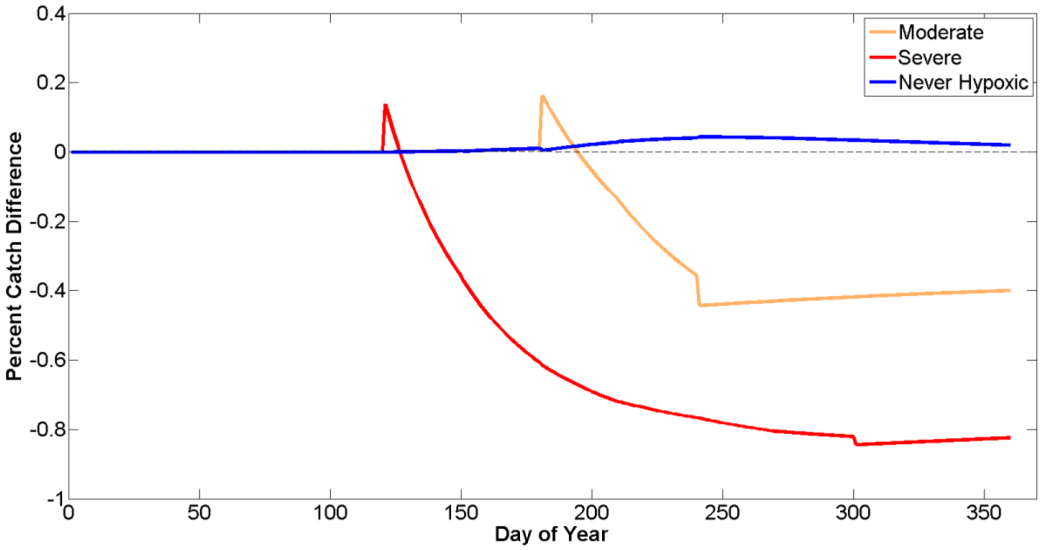
$$E_{t,j} = I\left(\frac{e^{v_{i,t,j}}}{\sum_{k=0}^{J} e^{v_{i,t,k}}}\right)$$

Effort (closes the model)

Diagnosing Treatment-Control Contamination (Violations of SUTVA)



Major Contamination



Minor Contamination

3. EVALUATING EVIDENCE OF TREATMENT-CONTROL CONTAMINATION

Evidence of SUTVA Violations

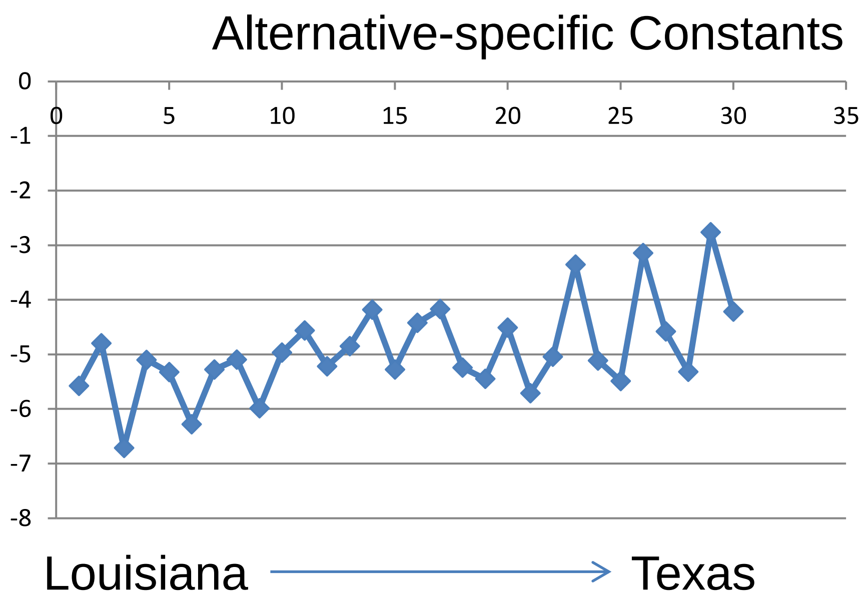
- Conditional logit model (sorting behavior)
- Panel effort models: controlling for two-way fixed effects, hypoxia explains
  - Contemporaneous effort
  - Temporally lagged effort
  - Spatially lagged effort

Contemporaneous	36.786**
Lag 1	26.68
Lag 2	-55.858**
Lag 3	-23.673
Lag 4	46.084**
Lag 5	-5.795
Lag 6	-78.416***
spatial.lag	9.851*

- Pattern resembles conjugate pair

Effort Conditional Logit Restults

Covariate	Estimate	St. Error	t-statistic
Wave Height (j,t)	-2.220	0.042	-52.46
Shrimp Price (t)	8.951	0.211	42.43
Diesel Price (t)	-15.618	0.455	-34.30
Expected Revenue (j,t)	0.257	0.004	66.36
Expected Catch (j,t)	0.178	0.004	44.39
Distance (i,j)	-42.359	0.121	-350.14



Marginal Rates of Substitution indicate SUTVA violations are major

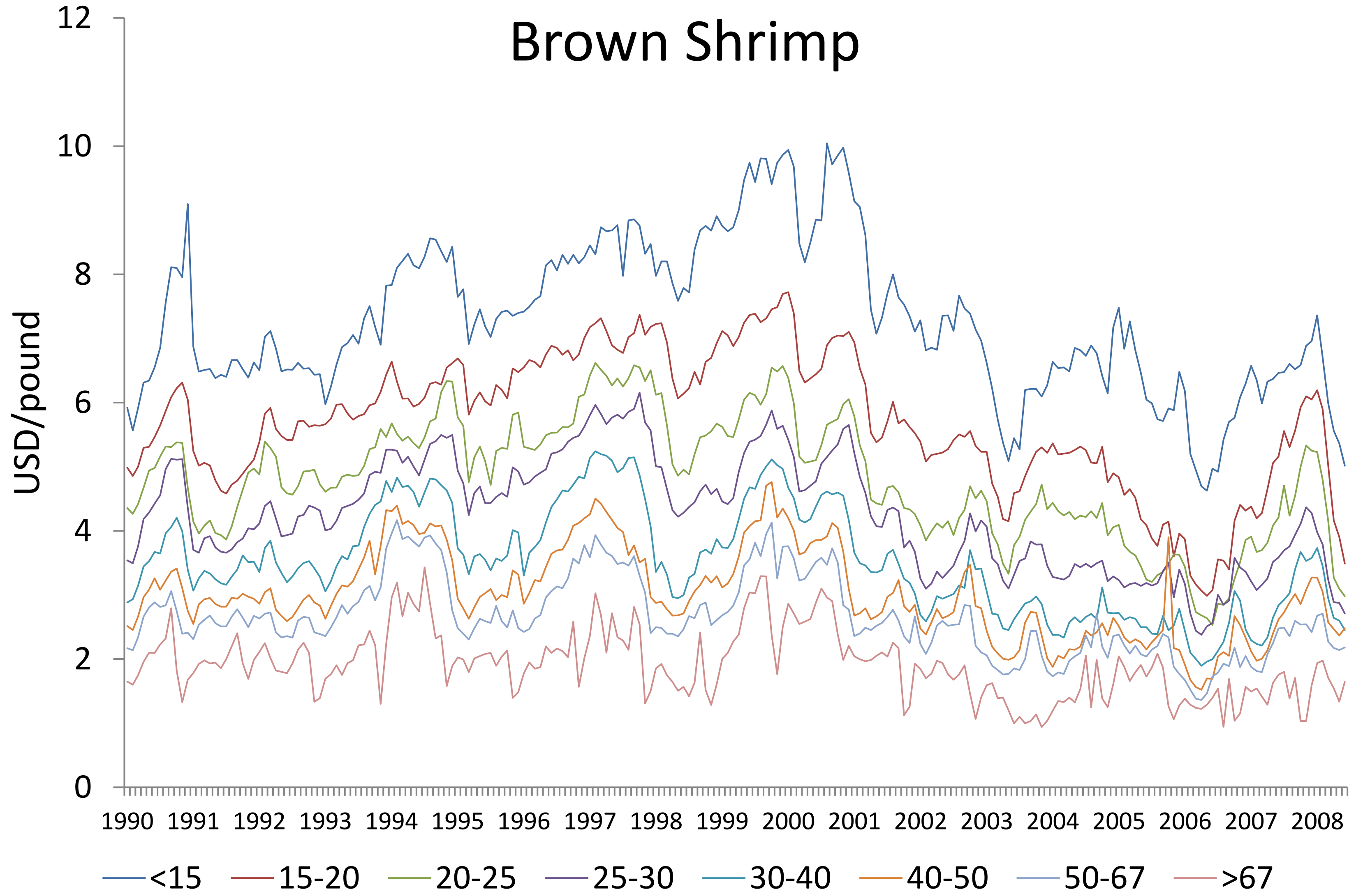
- MRS of Distance for Expected Revenue
  - Simulation (Major) 4 km/$ - very responsive
  - Simulation (Minor) 40 km/$ - unresponsive

- Empirical estimate 0.4 km/$ - extremely responsive

- Treatment/control contamination likely introduces severe bias in diff-in-diff estimates

4. TIME SERIES ANALYSIS OF SHRIMP PRICES – LET THE MARKET REVEAL THE ECOLOGICAL DISTURBANCE

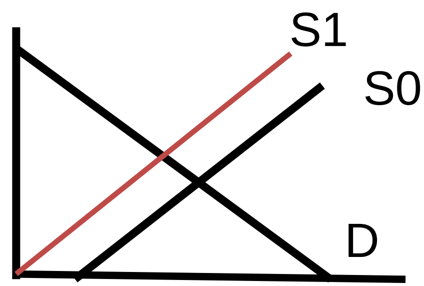
Shrimp Sold by Size Class (#/pound)

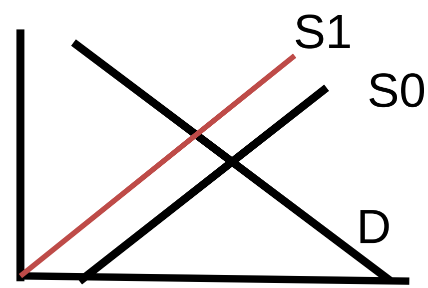


Econ 1 Intuition for Regime Shift Detection

Small Shrimp | **Large Shrimp**

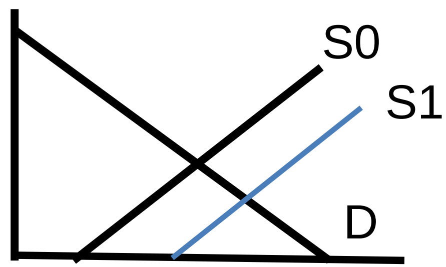
Ordinary Recruitment Shock

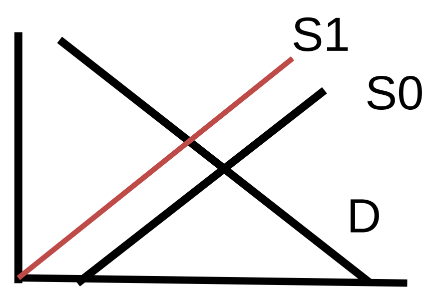




P_S	+
P_L	+
P_S/P_L	?

Hypoxia Shock





P_S	-
P_L	+
P_S/P_L	-

Key assumption: markets determine what a meaningful supply shift is

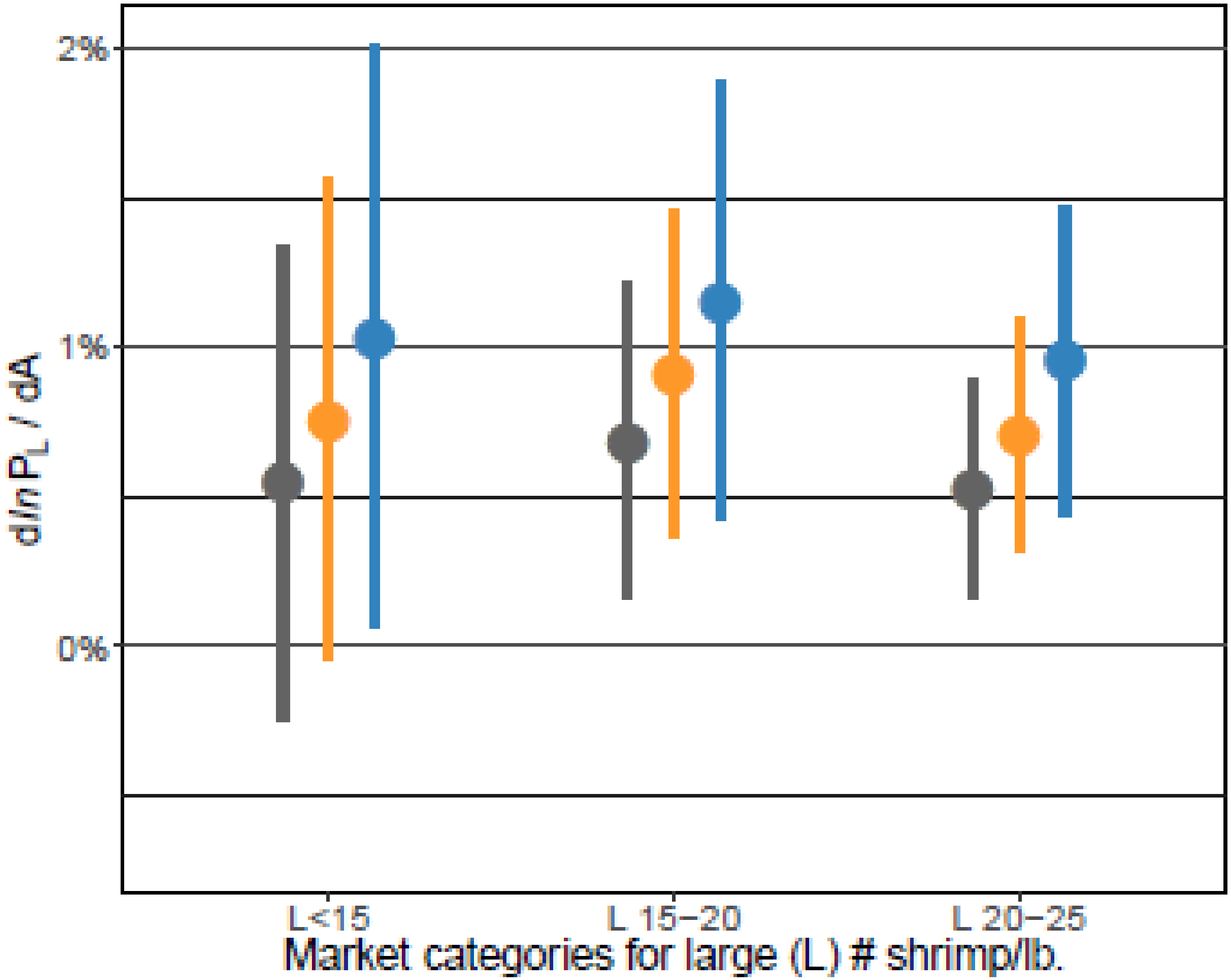
Law of One Price (LOP) in the shrimp market

$$P_L = \alpha \left(P_S \right)^{\gamma} \qquad \gamma = 1$$

- ln (price) series non-stationary in levels but stationary in 1st difference (ADF and KPSS tests)
- Series are cointegrated (bivariate Johansen tests)
- Fail to reject null of LOP in eight of nine pairwise comparisons
- Implications of LOP
  - If holds, then regress relative prices on hypoxia (and other covariates)
  - If does not hold, regress large price on small price (and other coavariates)
  - We do both – January 1990 through March 2010
- Covariates: sea surface temperature, fuel price, monthly dummies

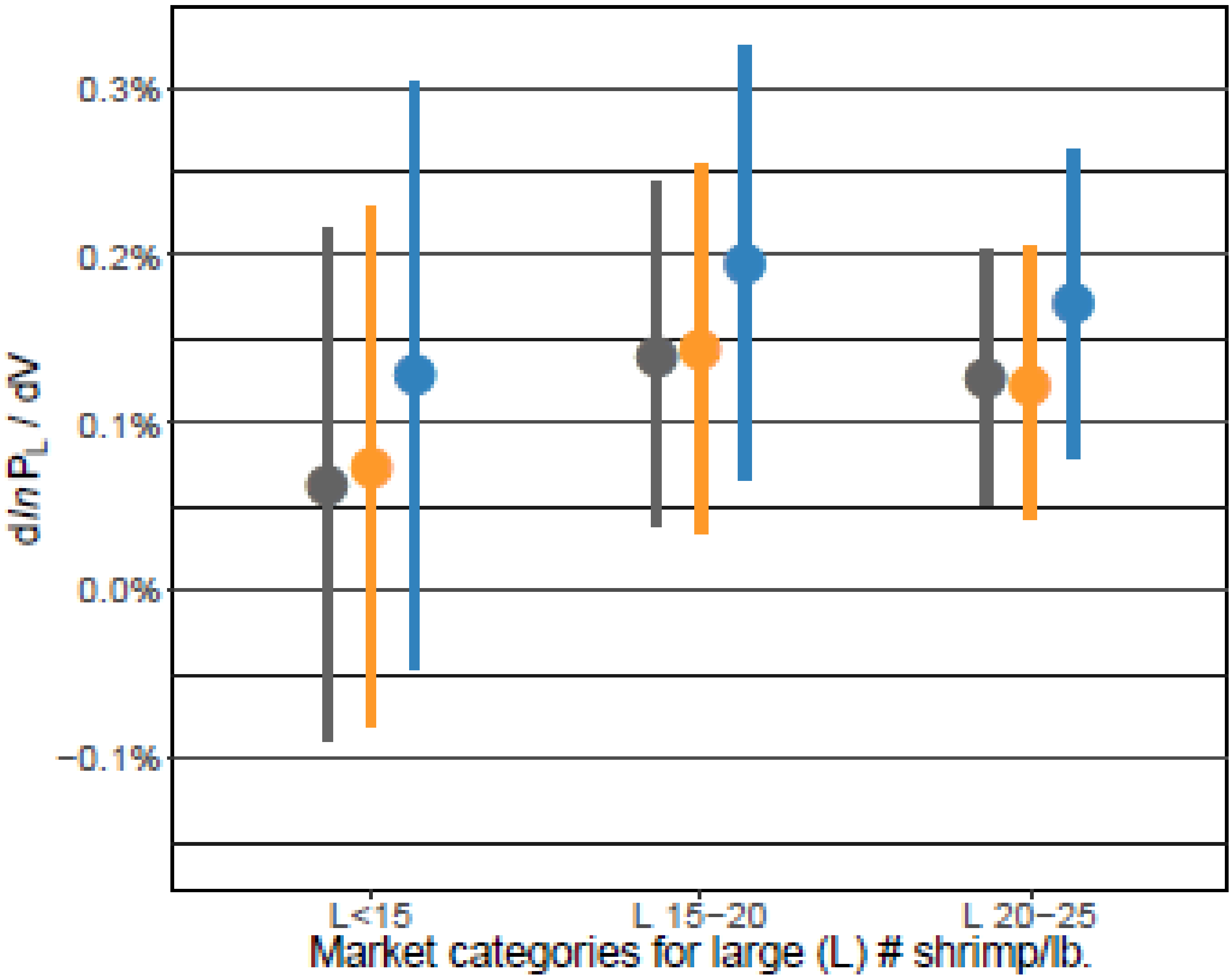
Hypoxia causes **increase** in price of large shrimp conditioning on small

Areal Extent (2.0 mg/l)



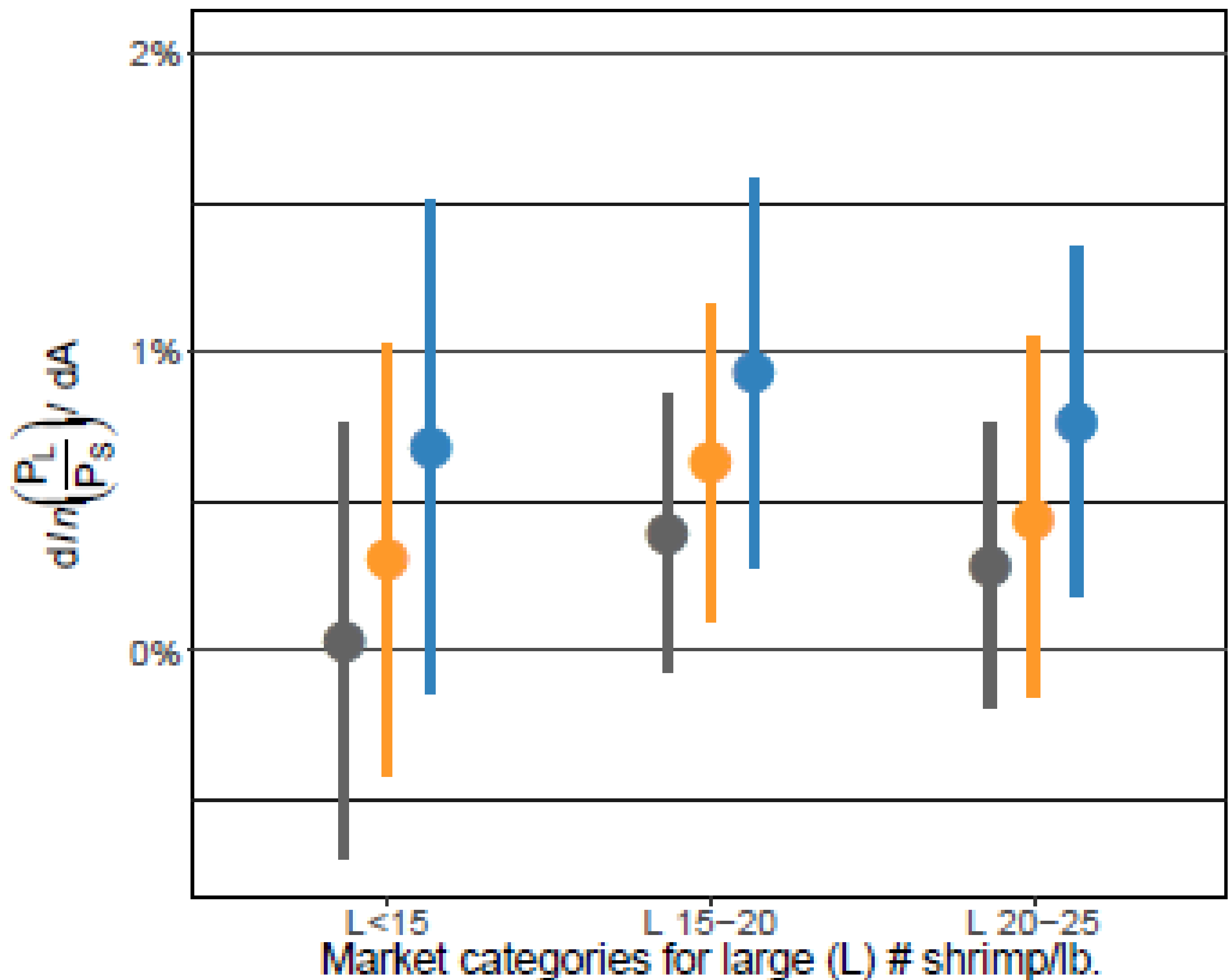
Hypoxia causes **increase** in price of large shrimp conditioning on small

Volumetric Extent (2.0 mg/l)



Hypoxia causes **increase** in relative price of large-to-small shrimp

Areal Extent (2.0 mg/l)



Supporting evidence and robustness checks

- Two interpolation schemes
- Areal extent: 1.5 mg/l, 2.0 mg/l, 2.5 mg/l
- Volumetric extent 2.0 mg/l
- Models with relative price (LOP) and conditioning on small shrimp price
- Fuel prices negative effect on large shrimp prices (due to growth overfishing)
- Removing first or last 24 months (not in paper)
- Models with difference subsets of covariates (not in paper)
- Regime-shift models using mixing distribution (not in paper)

Conclusions

- Feedbacks in the coupled human-natural system undermine identification in a treatment effects framework
  - True for any spatial-dynamic system
  - Severity of contamination is an empirical question
- Market-based counterfactual is immune to this problem
- Hypoxia causes deviations from stable long-run price relationships

Discussion

- For market goods, prices may be better judge of whether a consequential ecological disturbance has occurred than quantities
- We still do not know the welfare impacts of hypoxia
- Next step: structural bioeconometric model with synoptic spatio-temporal DO data
- When ecological disturbance worse for economic outcomes (no price compensation), it may be more difficult to detect
- Examples of spatial-dynamic treatment-control contamination
  - marine reserves
  - oil spills
  - Hurricanes
  - terrestrial protected areas and deforestation
- Examples of price-based identification of ecological disturbance
  - Hard and soft blue crabs, molting, and hypoxia
  - ENSO and soybean meal / fishmeal markets
  - Ocean acidification and calcifying organisms