# **Supporting Information**

# *Further Details on Figure 1*

This stylized figure depicts baseline long-run market equilibria. Because shrimp life history (e.g. the annual growth cycle) imposes strong seasonal patterns on supplies of different size classes of shrimp,  $S_0$ can be interpreted as a typical supply for small or large shrimp in a given month. Each month has a corresponding demand (D) that reflects seasonal demand for small and large shrimp and prices of competing small and large shrimp from other sources, including imported frozen shrimp. A weak recruitment year is then a short-run deviation from the typical long-run supply in each month (supply shifts to  $S_1$ ). And a bad hypoxia year (more than average hypoxia) is a short-run deviation from the typical long-run supply in each month (again, supply shifts to  $S_1$ ). In the same manner, a strong recruitment year would correspond to outward shifts in supplies for small and large shrimp, whereas a mild hypoxia year would correspond to an inward shift in supply of small shrimp and an outward shift in supply of large shrimp. In all cases, the typical level of hypoxia is embedded into the baseline long-run market relationships, and it is inter-annual variation in hypoxia (good and bad years relative to the typical year) that allow us to identify effects on economic outcomes.

### **Naïve Treatment Effects**

### *Details on Hypoxia Data*

Based on the SEAMAP data, if the polygon does not have a reading of dissolved oxygen level (DO) below 2 mg/l in either the summer or the fall, then the polygon is coded as non-hypoxic for the entire year. If the polygon has a reading below 2 mg/l in the summer but not in the fall, the polygon is coded as hypoxic from May to August. If the polygon has a reading below 2 mg/l in the fall, but not in the summer, the polygon is coded as hypoxic from September to December. Finally, if the polygon has a

reading below 2 mg/l in both the summer and the fall the polygon is coded as hypoxic from May to December. All polygons are assumed to be non-hypoxic in January through April of every year.

# *Descriptive Statistics and Correlations*

Table S1a contains descriptive statistics for the variables used in the treatment effects models and in the discrete choice model of fishing participation. Table S1b contains descriptive statistics for variables used in the time series analysis.

We first examine raw correlations in the data between hypoxia and catches. Previous work has shown that the areal extent of hypoxia is negatively correlated with shrimp landings, suggesting the possibility of negative impacts on the fishery [\(1,](#page-14-0) [2\)](#page-14-1). We correlate four measures of hypoxia with shrimp landings from our subarea-depth zone polygons. The first hypoxia measure is the annual estimate of areal extent from 1990 to 2009 [\(3\)](#page-14-2). This measure is used below in the time series modeling. The remaining three measures are from SEAMAP and are used in our treatment effects modeling. There are separate summer (June-July) and fall (October-November) measures based on averaging dissolved oxygen observations within the polygons from summer and fall SEAMAP cruises. Unlike previous work that uses Gulf-wide landings to calculate the correlation [\(2,](#page-14-1) [4\)](#page-14-3), here there is no statistically significant relationship between total landings and hypoxia (table S2). However, for the SEAMAP data hypoxia is negatively correlated with large shrimp landings and positively correlated with small shrimp landings (table S2).

# *Details on Naïve Treatment Effects Estimation*

There are important confounding factors in fisheries that modify the standard approach to difference-indifferences. We estimate the effect of treatment on the treated group by differencing outcomes conditional on fishing effort before and after treatment in the treatment group and subtracting the

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difference in outcomes before and after treatment in a control group. This approach resembles Before-After-Control-Impact (BACI) design [\(5\)](#page-14-4) but uses multiple treated and control sites with observations in multiple time periods before and after treatment, making it is more similar to an asymmetric BACI sampling design [\(6\)](#page-14-5). Previous empirical bioeconomic work on hypoxia suggests important modifications to the standard difference-in-differences model; because the effects of hypoxia on fisheries unfold over time, [\(7\)](#page-14-6) one must include lags of hypoxia in the analysis.

Here we develop Equation [5] from the main text. Because we define the dependent variable as catch, it is also important to condition on fishing effort. Fisheries scientists often use catch-per-uniteffort (CPUE) as a dependent variable in both stock assessments and policy evaluations. However, an implicit assumption in doing so is that the production technology that relates catch to effort is of a particular form:

$$
C_t = qE_t S_t, \tag{S1}
$$

where *t* is the time period,  $q$  is catchability,  $E$  is fishing effort, and  $S$  is the fish stock. This assumption is restrictive and empirically fails to hold in some settings [\(8\)](#page-15-0). If there is curvature in the production function such that there are potentially increasing or decreasing returns to stock or effort, the CPUE specification leads to biased measurements of policy impacts [\(9\)](#page-15-1), fish stocks [\(8\)](#page-15-0), and effects of environmental shocks such as hypoxia [\(7\)](#page-14-6). A more general model is:

$$
C_t = q E_t{}^{\beta} S_t{}^{\varphi}, \tag{S2}
$$

Taking the natural logarithm of both sides leads to a linear specification:

$$
lnC_t = ln(q) + \beta lnE_t + \varphi lnS_t
$$
 (S3)

Following [\(7-9\)](#page-14-6), an alternative to the CPUE specification is simply to regress catch on effort and the other relevant covariates, where  $ln(q)$  is then a part of the constant. Combining these insights, our regression generalization of the differences-in-differences model can be expressed as:

$$
lnC_{jmy} = \alpha + \beta lnE_{jmy} + d_j + d_y + d_m + d_{jy} + d_{jm} + \gamma_0 H_{jmy} + \sum_{\tau=1}^{T^{max}} \gamma_{\tau} H_{j(m-\tau)y} + \varepsilon_{jmy} \quad \text{[S4]}
$$

where *j* indexes the spatial location (combination of sub-area and depth zone), *m* is month, *y* is year, d's are fixed effects that capture different combination of location and time, and *H* is a binary variable to indicate whether the location is hypoxic in month *m* and year *y*,  $\tau$  is the lag length,  $\tau^{max}$  is the maximum lag length considered, and  $\varepsilon$  is a random shock. The dummy variables capture seasonal patterns of shrimp abundance that are similar across years (owing to the annual life cycle of shrimp), annual differences that reflect overall recruitment strength, spatial differences that reflect quality and type of habitat, and various combinations of these features. Although stock is not directly observed, the combinations of zone, year, and month dummy variables control for its influence [\(7-9\)](#page-14-6). Equation [S4] matches Equation [4] from the main text. If the model were properly identified, including the requirement that the Stable Unit Treatment Value Assumption holds, the coefficients on the hypoxia indicator variables would be the estimates of the causal effects of hypoxia on fishing outcomes.

There are four different definitions of the dependent variable: all shrimp, large shrimp, medium shrimp, and small shrimp. The size-based variables combine three size classes each into large and small shrimp and two size classes into medium shrimp. Large includes < 15, 15-20, and 20-25 shrimp per pound. Medium includes  $25-30$  and  $30-40$  shrimp per pound. Small includes  $40-50$ ,  $50-67$ , and  $> 67$ shrimp per pound. There are thirty zones in our model (10 sub-areas by 3 depth zones). We interact the zone dummies with year dummies, and we interact zone dummies with monthly dummies. As discussed above, a key covariate to control for is fishing effort; more effort generally translates into more catch. This approach addresses the curvature problem in the CPUE approach described above but raises the possibility of endogeneity through correlated unobservable variables. That is, when fishermen expect to catch more shrimp, they are more likely to fish. We address endogeneity below using an instrumental variables approach based on discrete choice model results.

The SHRCOM database contains all recorded landings, but not every record has complete information in every field. Many records are missing the days-at-sea variable, which we use as a measure of shrimping effort. Others are missing information on the vessel size. Hence, we summarize the data for the treatment effects in two ways: 1) all records and 2) records that contain complete trip information.

# *Discrete Choice Model Details and Results*

There are several thousand active vessels fishing for brown shrimp during our study period. A daily model would have over 25 million observations. Including all vessels for all days in a 31-choice conditional logit model with alternative-specific constants would quickly become computationally problematic. To address computational problems, we draw a stratified random sample of 337 active vessels  $(i= 1, 2, ..., 337)$  and estimate the model over the entire time horizon. To ensure spatial coverage throughout the Gulf and spatial coverage across depths, which may reflect underlying vessel heterogeneity, we stratify in two dimensions. We assign vessels to a home state category based on the location of the port where they have landed the most catch: Texas, Louisiana, or Other. The Other category includes Mississippi, Alabama, and Florida. We allocate shares of our 337 vessels to these three categories based on total catch shares in our sample period. We assign each vessel to a depth bin based on the bin where it has historically landed the most shrimp and compute catch shares for each depth bin within each state category, using the results to arrive at shares within each state category. We draw vessels randomly according to state-depth shares. We include discrete choices for each of these vessels in all 8,875 time periods for a total of 2,990,875 observations.

Covariates in the model include distance, daily price, expected catch, expected revenue, wave height, and diesel price. [\(10-13\)](#page-15-2). Distance is the travel distance from a vessel's home port to the centroid of the statistical zone bin. Price is an index that we create for medium-sized shrimp that does not vary

over space to capture the background market dynamics. Expected catch is a moving average based on the previous year's catches in the zone-depth bin 15 days ahead and 15 days prior. This captures zonespecific aspects of stock dynamics that may influence behavior from one year to the next (i.e. long-lived information). Expected revenue is a 30-day backward moving average based on the current year's revenues in the zone bin. This form captures short-lived information that contains both catch and price, the latter being a proxy for size structure of the population. For both expected catch and expected revenue, we adjust the weights in the moving average to account for data sparseness (not all days in all zones have landings). Weather data are from the National Data Buoy Center, which provides time series data from many locations in the Gulf of Mexico with fine temporal resolution (typically every fifteen minutes) (http://www.ndbc.noaa.gov/). To generate covariates for wave height, we selected buoys with consistent observations throughout our sample period and aggregated wave heights to the daily level (by averaging finer scale observations). We standardized each daily wave height series (subtracting the series mean and dividing by the series standard deviation) and constructed distance-weighted averages for our individual zone-depth bins. Diesel prices are from the Energy Information Agency and converted to daily observations through linear extrapolation of monthly (early part of the time series) and weekly (later part of the time series) prices (http://www.eia.gov/).

We estimated the discrete choice model with alternative-specific constants by nesting a contraction mapping algorithm within a maximum likelihood routine [\(14,](#page-15-3) [15\)](#page-15-4). Table S3 contains results of the discrete choice model. Although the model is not intended to be structural, all of the parameter signs conform to expectations and are consistent with previous discrete choice modeling studies of commercial fishing across a wide range of fisheries, model types, and choice structures [\(11,](#page-15-5) [15-20\)](#page-15-4) (table S3). Covariates that increase revenues are correlated with more effort (price, expected catch, expected revenues), and covariates that increase costs are correlated with less effort (distance, wave

height, and diesel price). The expected catch and expected revenue variables suggest that fleet behavior is responsive to economic opportunities over space that could be influenced by hypoxia. Daily predicted choice probabilities are vessel-specific only to the extent that different vessels are located in different ports and hence face different travel distances to each site. We evaluate all vessel-specific choice probabilities for each day, sum across vessels, and then sum across days to arrive at 30 depth-andstatistical-area-specific predicted effort levels for each month in our data set.

The results from the discrete choice model are used in two ways. First, in the next section, the discrete choice model is used to form predicted probabilities to serve as instruments for fishing effort. These instruments are necessary to control for potential endogeneity of fishing effort in the treatment effects models. Second, the discrete choice model provides evidence for spatial sorting. This mechanism is the feature that leads to contamination of control sites in the spatial-dynamic bioeconomic model.

# *Treatment Effects Model Results*

Although numerous studies establish ecological effects of hypoxia that are consistent with the theoretical supply shifts depicted in Fig. 1, causal economic effects have not been established. Experimental and observational studies specifically demonstrate lethal and sublethal metabolic consequences of hypoxia for a wide range of marine fauna, including a variety of shrimp species [\(21-](#page-16-0) [33\)](#page-16-0).

Tables S4-S7 report results from the treatment effects models. We estimated treatment effects models separately for each of data sets: one that includes catch records for which all vessel and effort information is available and a second that includes all catch records regardless of whether there is missing vessel or effort information. We report only the results for the treatment variables and the predicted effort variable. Each model contains a contemporaneous treatment variable (the instantaneous causal effect of hypoxia on landings) and lagged treatment variables (the causal effects of hypoxia on

future landings). The number of monthly lags tested are 0, 3, 6, and 12. Each table contains separate results for different size groups of brown shrimp: all brown shrimp combined (table S4), large brown shrimp only (table S5), medium brown shrimp only (table S6), and small brown shrimp only (table S7), as described above. Standard errors are clustered by zone. All regressions include dummy variables for zone, month, year, and interactions (zone\*year and zone\*month), which are not shown in the tables. All effort coefficients are positive and significant at the 1% level. As expected, increased effort results in increased catch.

Importantly, none of the lagged hypoxia variables are statistically significant in any of the models (tables S4-S7). There is no evidence in these models that suggests hypoxia causes any lasting effect on shrimp landings despite theoretical reasons that strongly suggest deleterious impacts through bioenergetic pathways and empirical evidence of dynamic effects in other settings [\(7,](#page-14-6) [21-24,](#page-16-0) [26,](#page-16-1) [28,](#page-17-0) [34\)](#page-17-1). We explore possible explanations for these null results in the next section of the supplemental materials. For contemporaneous effects, the models provide evidence of positive effects of hypoxia for large brown shrimp (table S5) and mixed evidence for positive effects on medium brown shrimp, but no evidence for positive effects in aggregate or for small shrimp (tables S4 and S7). The positive contemporaneous effects of hypoxia are consistent with observational studies of aggregation along the edges of hypoxic areas [\(22\)](#page-16-2).

### *Panel Models of Fishing Effort and the Potential for Treatment-Control Contamination*

The discrete choice model provides evidence of potential SUTVA violations. Because the fishing fleet sorts over space in response to economic opportunities, control areas that are not directly affected by hypoxia may experience different levels of effort relative to the counterfactual. A complementary approach to testing for potential SUTVA violations is to specify a panel data model of fishing effort.

The model includes two-way fixed effects based on the fishing zone-depth combination (the same spatial units used in the treatment effects model) and month-year combinations. We measure hypoxia in six different ways. We use the standard cutoff of DO<2.0 mg/l and also include cutoffs of DO<1.5 mg/l and DO<2.5 mg/l. For threshold models, a zone-depth combination is coded as hypoxic if at least one observation in the SEAMAP data is below the cutoff. This follows the methodology used in the treatment effects models. We also run models based on whether the mean DO is below the cutoff.

The null hypotheses under SUTVA are that the presence of hypoxia has no effect on contemporaneous fishing effort in a zone, the presence of hypoxia has no effect on fishing effort in subsequent periods, and the presence of hypoxia has no effect on fishing effort in other zones. The first two of these hypotheses (contemporaneous effects on effort and temporally lagged effects on effort) are indirect tests of SUTVA violations. When effort increases (or decreases) in the hypoxic zone, some of that effort will be drawn from candidate control sites (positive effects) or will redistribute to candidate control sites (negative effects). This process is consistent with sorting behavior revealed by the discrete choice model (table S3) as well as other models of fishing spatial behavior [\(12,](#page-15-6) [15,](#page-15-4) [19\)](#page-16-3). The spatial lag variable is a more direct test of SUTVA violations. A significant coefficient on the spatial lag means that hypoxia in an adjacent area influences effort in an area that otherwise could serve as a control site.

Across model specifications, we reject each of the null hypotheses (tables S8-S13). In the effort panel models, the evidence is strongest for the standard cutoff for hypoxia of 2.0 mg/l using a threshold rather than average measure. There is also some indication of cycling behavior in the temporal pattern of effort response to hypoxia (a sequence of positive and negative responses). This behavior is consistent with the dynamic open access model used in modeling hypoxia's effects on fisheries [\(35\)](#page-17-2). Cycling behavior is a general feature of spatial-dynamic bioeconomic fishery models, both models in discrete and in continuous time, when access to specific fishing grounds is not limited [\(4,](#page-14-3) [35-37\)](#page-17-2). Essentially, the

process of free entry to dissipate economic rents under open access overshoots the bioeconomic equilibrium when there is sluggish adjustment, inducing a boom and bust pattern in stocks, harvests, and fishing effort [\(38\)](#page-18-0). Mathematically, the eigenvalues of the system are a conjugate pair associated with a focus. The associated cycling behavior is a qualitative result, but the cycling frequency depends on parameter values. This pattern unfolds across fishing grounds in the spatial generalizations of the model [\(36,](#page-17-3) [37\)](#page-17-4). In our case, hypoxia increases effort instantaneously relative to the counterfactual (a positive contemporaneous effect). Over time, that increased effort would reduce stocks in an area relative to the counterfactual, encouraging effort to redistribute to other areas (negative lagged effects). However, the exit of effort from the once hypoxic area would lead to a rebounding of stocks relative to the counterfactual, so as time continues effort is drawn back in (positive effects on higher order lags).

# *Spatial-dynamic Bioeconomic Model Results*

The spatial-dynamic bioeconomic model also provides important context for our empirical work. First (and most obvious), when the true counterfactual is known, hypoxia affects the shrimp fishery exactly as theory predicts. The growth and mortality effects both reduce catches and associated revenues. The catchability effect increases catches instantaneously but reduces catches later in the season because fewer shrimp survive to larger size classes [\(4\)](#page-14-3) (Figs. S3 and S4). The net effect of the catchability effect can theoretically be positive or negative, but it tends to be positive because the shortrun profitability increase draws more effort into the fishery, and overall catches increase. When hypoxia effects are combined in model runs, the net effect on the fishery depends on the strength of each effect. Although the net effect tends to be negative such that the catchability effect at best tends to attenuate losses due to hypoxia (Figs. S3 and S4), the countervailing forces suggest it is an empirical question.

Second, even when the true counterfactual is known, the treatment effect of hypoxia can be subtle, vary dynamically, be sensitive to the mixture of structural biological effects, and often be nonmonotonic [\(4\)](#page-14-3) (Figs. S3 and S4). All of these features suggest that identifying the effects of hypoxia from perfect data would still be challenging. Nevertheless, by including lags of hypoxia in the treatment effects models, we would expect to identify these dynamic and non-monotonic effects if they are large in magnitude.

Third, the effects of hypoxia may interact with growth overfishing [\(4\)](#page-14-3). For example, a strong recruitment year makes a shrimp fishery more profitable and draws more effort into the fishery early in the season [\(4,](#page-14-3) [39\)](#page-18-1). This effect increases the amount of small shrimp landings and, at the annual scale, bioeconomically tends to skew the size distribution of landings toward smaller shrimp [\(4\)](#page-14-3). Fuel prices, weather conditions, global seafood markets, and changing regulations can also influence the profitability of shrimp fisheries and hence the level of fishing effort [\(4,](#page-14-3) [39-41\)](#page-18-1) (table S3). Prior research in general shows that within-season behavior of fishing fleets can influence aggregate fishery outcomes [\(39,](#page-18-1) [42-](#page-18-2) [44\)](#page-18-2). In the GoM shrimp fishery, increased profitability will tend to reduce the average size of shrimp that are landed, and decreased profitability will tend to increase the average size. Indeed, the weighted average shrimp size is trending upward in recent years, which likely reflects higher fuel prices, increased competition from imported shrimp, and increased costs of regulation [\(4\)](#page-14-3). On the other hand, we expect that the ecological effects of hypoxia will reduce shrimp size on average; holding other things constant, hypoxia should reduce the landings of larger shrimp. So, isolating the effects of hypoxia requires a model that controls for the confounding effects of economic behavior because the economics and the ecology contribute potentially countervailing forces.

With this context in mind, the primary purpose of the spatial-dynamic bioeconomic model is to diagnose the severity of potential SUTVA violations. The model demonstrates explicitly how spatial sorting of the fishing fleet creates the possibility of contaminating statistical control sites with treated sites [\(4\)](#page-14-3). We explore the robustness of this finding to a more general life history model of brown shrimp

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that incorporates 25 recruitment cohorts. Specifically, shrimp recruitment is distributed uniformly across 100 days (a new cohort every 4 days), and each cohort is followed throughout the year. Fig. S3 illustrates the treatment/control contamination result, highlighting three zones of the simulation that includes a zone that never experiences hypoxia. The blue line "Never Hypoxic" should always track zero if it were a valid counterfactual. The behavioral response to hypoxia reverberates through the spatial-dynamic system. Despite the fact that some zones never go hypoxic, they are unavoidably influenced by the environmental disturbance in other zones. This result helps to explain our null results above and suggests that treatment effects approaches based on spatio-temporal identification strategies are problematic in spatial-dynamic systems. Nevertheless, the contamination of the control appears modest at the onset of hypoxia and worsens over time as behavioral responses feedback on the natural system. As such, the contemporaneous treatment effect results (coefficients on contemporaneous hypoxia) may not be as biased as the estimates of dynamic treatment effects (coefficients on lagged hypoxia) (tables S4-S7). Thus, despite some bias, the results may signal some of the effect from shrimp aggregating behavior around hypoxic areas.

Although qualitatively the contamination of control sites with treatment sites persists for any positive level of economic responsiveness to revenue changes over space, quantitatively the effect is negligible at low levels of responsiveness. For example, reducing the fleet responsiveness to 10% of what was assumed in Fig. S3 produces contamination of the control group that is substantially less problematic (Fig. S4). Thus, the treatment effects results could be true null results with mild contamination bias due to spatial sorting, or they could reflect severe control site contamination through spatial sorting that introduces substantial bias.

We can use the spatial-dynamic simulation model in combination with the discrete choice model to determine whether SUTVA violations are severe. The comparison is based on the Marginal Rate of

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Substitution (MRS) of travel distance for expected revenue. In conditional logit models like the one estimated above and embedded into our simulation model, coefficients are only estimated up to scale [\(45\)](#page-18-3). That is, estimates for two parameters  $\theta_1$  and  $\theta_2$  are actually estimates of  $\frac{\theta_1}{\theta_2}$  $\eta$ and  $\frac{\theta_2}{\theta_1}$  $\eta$ where  $\eta$  is an unknown scale parameter. However, by taking a ratio of two estimated parameters, the unknown scale parameter differences out. Thus, the MRS can be used to make comparisons across models.

We specifically compare the MRS of distance for expected revenue in the simulation model to the MRS of distance for expected revenue in the empirical model of GoM shrimp fishing. The empirical model provides evidence for a high degree of responsiveness to expected revenues over space. This degree of responsiveness exceeds the level that is implied by the severe contamination simulation (Fig. S3). As such, the empirical estimates strongly support the likelihood of severe treatment-control contamination. These findings motivate the use of alternative approaches to examine the causal effects of hypoxia on the Gulf shrimp fishery.

# *Time Series Results*

Here we present the full results for our main findings: hypoxia causes changes in the relationship between small and large shrimp prices, and these changes are consistent with theoretical predictions based on how hypoxia is expected to affect small and large shrimp abundance and landings.

We first find that individual shrimp price series are non-stationary in levels but stationary in first differences (table S14) [\(46,](#page-18-4) [47\)](#page-18-5). The implication for our analysis is that spurious correlations could be induced by regressing levels of shrimp prices on covariates such as hypoxia.

We next find that pairwise small and large shrimp prices are cointegrated, and the hypothesis that size-based prices are proportional to each other cannot be rejected (table S15) [\(48,](#page-18-6) [49\)](#page-19-0). These results provide empirical evidence for what we see visually in Figures 2 and S5. Statistically, the implication is

that by regressing a large shrimp price on a small shrimp price, the residuals are stationary, and spurious correlation is not an issue. Economically, these results indicate that there are stable long-run price relationships between small and large shrimp. The fact that we fail to reject proportional prices supports the hypothesis that the Law of One Price (LOP) holds. However, the evidence for LOP is not as strong as the evidence that there is some cointegrating relationship and thus some stability in the long-run price relationships. We test our main hypotheses about hypoxia under both the more restrictive assumption of LOP and the less restrictive one, that the prices are simply cointegrated. In either case, we can use stable long-run relationships as a market counterfactual. Regressing large shrimp price on small shrimp price and hypoxia then becomes a test of whether hypoxia causes a short-run departure from this stable longrun relationship.

Tables S16-S23 contain full results from all of the time series models. Each one of tables S16- S23 contains results for all of the pairwise small-to-large shrimp price comparisons  $(3x3=9)$  and two different definitions of the dependent variable (logarithm of price level and logarithm of relative price), and two different interpolation schemes for a total of  $9x2x2=36$  models. We estimate models using Weighted Least Squares, and we also estimate models using Newey-West standard errors with four lags to account for potential heteroscedasticity and autocorrelation [\(50\)](#page-19-1). We report results using the standard measure of hypoxia (areal extent of  $DO < 2.0$  mg/l). As robustness checks, we run models using three alternative definitions of hypoxia in addition to the standard measure: areal extent of  $DO < 1.5$  mg/l, areal extent of  $DO < 2.5$  mg/l, and volumetric extent of  $DO < 2.0$  mg/l. Both areal extent and volumetric extent measures are based on geo-statistical modeling of hypoxia [\(3\)](#page-14-2). The results strongly support the causal effect of hypoxia on the large shrimp market (Fig. 1); nearly all hypoxia coefficients are positive, most are statistically significant, and only one hypoxia coefficient is negative and statistically significant. Positive and statistically significant hypoxia coefficients occur in a variety of model

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specifications that include many of the different pairwise price comparisons, models with both types of hypoxia interpolation, models with both types of dependent variable, different measures of hypoxia, and different approaches to computing standard errors (Eq. S8 and Eq. S9). Negative and statistically significant coefficients on fuel prices provide indirect supporting evidence.

# **Supplemental References**

- <span id="page-14-0"></span>1. O'Connor T & Whitall D (2007) Linking hypoxia to shrimp catch in the northern Gulf of Mexico. *Marine Pollution Bulletin* 54(4):460-463.
- <span id="page-14-1"></span>2. Zimmerman RJ & Nance JM (2001) Effects of hypoxia on the shrimp fishery of Louisiana and Texas. *Coastal hypoxia: Consequences for living resources and ecosystems*:293-310.
- <span id="page-14-2"></span>3. Obenour DR, Scavia D, Rabalais NN, Turner RE, & Michalak AM (2013) Retrospective analysis of midsummer hypoxic area and volume in the northern Gulf of Mexico, 1985–2011. *Environmental Science & Technology* 47(17):9808-9815.
- <span id="page-14-3"></span>4. Smith MD, Asche F, Bennear LS, & Oglend A (2014) Spatial-dynamics of Hypoxia and Fisheries: The Case of Gulf of Mexico Brown Shrimp. *Marine Resource Economics* 29(2):111- 131.
- <span id="page-14-4"></span>5. Green RH (1979) *Sampling design and statistical methods for environmental biologists* (John Wiley & Sons).
- <span id="page-14-5"></span>6. Underwood A (1994) On beyond BACI: sampling designs that might reliably detect environmental disturbances. *Ecological Applications* 4(1):3-15.
- <span id="page-14-6"></span>7. Huang L, Smith MD, & Craig JK (2010) Quantifying the Economic Effects of Hypoxia on a Fishery for Brown Shrimp Farfantepenaeus aztecus. *Marine and Coastal Fisheries: Dynamics, Management, and Ecosystem Science* 2:232-248.
- <span id="page-15-0"></span>8. Zhang J & Smith MD (2011) Estimation of a Generalized Fishery Model: A Two-Stage Approach. *Review of Economics and Statistics* 93(2):690-699.
- <span id="page-15-1"></span>9. Smith MD, Zhang J, & Coleman FC (2006) Effectiveness of Marine Reserves for Large-Scale Fisheries Management. *Canadian Journal of Fisheries and Aquatic Sciences* 63:153-164.
- <span id="page-15-2"></span>10. Abbott JK & Wilen J (2011) Dissecting the tragedy: A spatial model of behavior in the commons. *J.Environ.Econ.Manage.* 62:386-401.
- <span id="page-15-5"></span>11. Haynie A & Layton DF (2010) An expected profit model for monetizing fishing location choices. *J.Environ.Econ.Manage.* 59(2):165-176.
- <span id="page-15-6"></span>12. Holland D & Sutinen JG (2000) Location Choice in the New England trawl fisheries: old habits die hard. *Land Economics* 76:133-149.
- 13. Smith MD (2000) Spatial search and fishing location choice: methodological challenges of empirical modeling. *American Journal of Agricultural Economics*:1198-1206.
- <span id="page-15-3"></span>14. Timmins C & Murdock J (2007) A revealed preference approach to the measurement of congestion in travel cost models. *J.Environ.Econ.Manage.* 53(2):230-249.
- <span id="page-15-4"></span>15. Zhang J & Smith MD (2011) Heterogeneous Response to Marine Reserve Formation: A Sorting Model approach. *Environmental & Resource Economics* 49(3):311-325.
- 16. Curtis R & Hicks RL (2000) The cost of sea turtle preservation: The case of Hawaii's pelagic longliners. *American Journal of Agricultural Economics* 82(5):1191-1197.
- 17. Eales J & Wilen JE (1986) An examination of fishing location choice in the pink shrimp fishery. *Marine Resource Economics* 2:331-351.
- 18. Hicks RL & Schnier KE (2008) Eco-labeling and dolphin avoidance: A dynamic model of tuna fishing in the Eastern Tropical Pacific. *Journal of Environmental Economics and Management* 56(2):103-116.
- <span id="page-16-3"></span>19. Smith MD (2002) Two econometric approaches for predicting the spatial behavior of renewable resource harvesters. *Land Economics* 78(4):522-538.
- 20. Ward JM & Sutinen JG (1994) Vessel entry-exit behavior in the Gulf of Mexico shrimp fishery. *American Journal of Agricultural Economics* 76(4):916-923.
- <span id="page-16-0"></span>21. Charmantier G & Soyez C (1994) Effect of molt stage and hypoxia on osmoregulatory capacity in the peneid shrimp Penaeus vannamei. *Journal of Experimental Marine Biology and Ecology* 178(2):233-246.
- <span id="page-16-2"></span>22. Craig JK (2011) Aggregation on the edge: Effects of hypoxia avoidance on the spatial distribution of brown shrimp and demersal fishes in the northern Gulf of Mexico. *Marine Ecology Progress Series* 445:75-95.
- 23. Craig JK & Crowder LB (2005) Hypoxia-induced habitat shifts and energetic consequences in Atlantic croaker and brown shrimp on the Gulf of Mexico shelf. *Marine Ecology Progress Series* 294:79-94.
- 24. Craig JK, Crowder LB, & Henwood TA (2005) Spatial distribution of brown shrimp (Farfantepenaeus aztecus) on the northwestern Gulf of Mexico shelf: effects of abundance and hypoxia. *Canadian Journal of Fisheries and Aquatic Sciences* 62(6):1295-1308.
- 25. Diaz RJ & Rosenberg R (2008) Spreading dead zones and consequences for marine ecosystems. *Science* 321(5891):926-929.
- <span id="page-16-1"></span>26. Le Moullac G*, et al.* (1998) Effect of hypoxic stress on the immune response and the resistance to vibriosis of the shrimp Penaeus stylirostris. *Fish & Shellfish Immunology* 8(8):621-629.
- 27. Pörtner HO, Langenbuch M, & Michaelidis B (2005) Synergistic effects of temperature extremes, hypoxia, and increases in CO2 on marine animals: From Earth history to global change. *Journal of Geophysical Research: Oceans* 110(C9).
- <span id="page-17-0"></span>28. Racotta IS, Palacios E, & Méndez L (2002) Metabolic responses to short and long-term exposure to hypoxia in white shrimp (Penaeus vannamei). *Marine and Freshwater Behaviour and Physiology* 35(4):269-275.
- 29. Rosas C*, et al.* (1998) Effect of dissolved oxygen on the energy balance and survival of Penaeus setiferus juveniles. *Marine Ecology Progress Series* 174:67-75.
- 30. Vaquer-Sunyer R & Duarte CM (2008) Thresholds of hypoxia for marine biodiversity. *Proceedings of the National Academy of Sciences* 105(40):15452-15457.
- 31. Wei L, Zhang X, Huang G, & Li J (2009) Effects of limited dissolved oxygen supply on the growth and energy allocation of Juvenile Chinese Shrimp, Fenneropenaeus chinensis. *Journal of the World Aquaculture Society* 40(4):483-492.
- 32. Wu RS (2002) Hypoxia: from molecular responses to ecosystem responses. *Marine Pollution Bulletin* 45(1):35-45.
- 33. Zou E (2009) Effects of Hypoxia and Sedimentary Naphthalene on the Activity of N-acetyl-β-Glucosaminidase in the Epidermis of the Brown Shrimp, Penaeus aztecus. *Bulletin of Environmental Contamination and Toxicology* 82(5):579-582.
- <span id="page-17-1"></span>34. Huang L, Nichols LAB, Craig JK, & Smith MD (2012) Measuring Welfare Losses from Hypoxia: The Case of North Carolina Brown Shrimp. *Marine Resource Economics* 27(1):3-23.
- <span id="page-17-2"></span>35. Smith MD (2007) Generating value in habitat-dependent fisheries: The importance of fishery management institutions. *Land Economics* 83(1):59-73.
- <span id="page-17-3"></span>36. Sanchirico JN & Wilen JE (1999) Bioeconomics of spatial exploitation in a patchy environment. *J.Environ.Econ.Manage.* 37(2):129-150.
- <span id="page-17-4"></span>37. Smith MD, Sanchirico JN, & Wilen JE (2009) The economics of spatial-dynamic processes: Applications to renewable resources. *J.Environ.Econ.Manage.* 57(1):104-121.
- <span id="page-18-0"></span>38. Smith VL (1969) On models of commercial fishing. *The Journal of Political Economy*:181-198.
- <span id="page-18-1"></span>39. Huang L & Smith MD (2014) The dynamic efficiency costs of common-pool resource exploitation. *American Economic Review* 104(12):4071-4103.
- 40. Keithly WR & Poudel. P (2008) The Southeast U.S. Shrimp Industry: Issues Related to Trade and Antidumping Duties. *Marine Resource Economics* 23:459-483.
- 41. Mukherjee Z & Segerson. K (2011) Turtle Excluder Device Regulation and Shrimp Harvest: The Role of Behavioral and Market Responses. *Marine Resource Economics* 26:173-189.
- <span id="page-18-2"></span>42. Abbott JK & Wilen JE (2009) Regulation of fisheries bycatch with common-pool output quotas. *Journal of Environmental Economics and Management* 57(2):195-204.
- 43. Homans FR & Wilen JE (1997) A model of regulated open access resource use. *Journal of Environmental Economics and Management* 32(1):1-21.
- 44. Smith MD, Zhang JJ, & Coleman FC (2008) Econometric modeling of fisheries with complex life histories: Avoiding biological management failures. *Journal of Environmental Economics and Management* 55(3):265-280.
- <span id="page-18-3"></span>45. McFadden D ed (1974) *Conditional Logit Analysis of Qualititative Choice Behavior* (Academic Press., New York).
- <span id="page-18-4"></span>46. Dickey DA & Fuller WA (1981) Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica* 49:1057-1072.
- <span id="page-18-5"></span>47. Kwiatkowski D, Phillips PC, Schmidt P, & Shin Y (1992) Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics* 54(1):159-178.
- <span id="page-18-6"></span>48. Engle RF & Granger CW (1987) Co-integration and error correction: representation, estimation, and testing. *Econometrica* 55:251-276.
- <span id="page-19-0"></span>49. Johansen S (1988) Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control* 12(2):231-254.
- <span id="page-19-1"></span>50. Newey WK & West KD (1987) A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55(3):703-708.



**Figure S1. Spatial resolution of the fisheries data.** Each vessel reports depth and subarea for each shrimp landing. Depth information is aggregated into three zones. Based on Gulf of Mexico bathymetry data, landings are assigned to one of three contour bins (left panel). The subareas are statistical reporting zones defined by National Marine Fisheries Service (right panel). Overlaying the two spatial measures provides a set of polygons with different shapes and sizes to which landings are assigned.







**Figure S2. Mapping summer hypoxic status into fisheries data polygons.** For each SEAMAP summer cruise (t), geocoded observations on bottom dissolved oxygen (DO) are assigned to fisheries data polygons (j) (overlaid left and right panels in Figure S1). The dissolved oxygen observations within each polygon averaged, and the polygon is coded as hypoxic if  $\overline{DO}_{jt}$  <2 mg/L. Otherwise, the zone is coded non-hypoxic. Each panel depicts the resulting summer hypoxia status for each year 1986-2009. The same procedure is used for coding fall hypoxia for each SEAMAP fall cruise. Polygons that are hypoxic in both summer and fall are assumed to be hypoxic for the months in between the cruises.



**Figure S3. Spatial sorting of the fishing fleet contaminates candidate control sites for isolating the treatment effect of hypoxia.** The lines depict percent differences in catches comparing simulated outcomes with and without hypoxia in three different locations using a spatial-dynamic bioeconomic simulation model of the shrimp fishery (11). Zones that are never hypoxic are candidates for estimating the statistical counterfactual of catches in moderately and severely hypoxic zones. Without spatial sorting, the percent change in catch with and without hypoxia would be zero in the never hypoxic zone (blue line), i.e. the blue line would track the straight dotted line. However, at the onset of hypoxia in late spring, catches in the never hypoxic zone begin to deviate as effort responds to shrimp aggregations in the severely hypoxic area and then reallocates to moderate (orange line) and never hypoxic zones as catches plummet in the severe hypoxic zone (red line). A similar pattern occurs in the summer when the moderate hypoxic zone begins to experience hypoxia. When hypoxia dissipates altogether in the fall, another more modest effort reallocation occurs that produces kinks in all three curves as the aggregation effect of hypoxia disappears.







**Fig. S5. Monthly natural logarithm of real (March 2010 \$) brown shrimp prices by market size.** Same as Fig. 2 with prices converted to real dollars and log-transformed.

# **Table S1a. Descriptive statistics for data used in the treatment effects and discrete choice models.**

The number of observations, N, reflects the amount of variation in the relevant model. For treatment effects, there are 30 sites and 291 months (for a total of 8730 observations), but some sites have missing hypoxia data in some periods. For discrete choice, there are 8875 unique days, so N=8875 for variables that vary across days but not across space. Wave height varies across subarea (10 total) and day, so N=88750.

Expected revenue and catch vary across day, subarea, and depth bin (3 distinct bins), so N=266750.

Distance varies across vessel (337 vessels), day, subarea, and depth, so N=89726250.



# **Discrete Choice Model**



**Table S1b. Descriptive statistics for data used in the time series analysis.** Brown shrimp are sold in size classes that reflect the number of shrimp per pound (smaller number per pound indicate larger shrimp). Nominal prices are total monthly value of brown shrimp landings within the size class divided by total monthly landings within the size class. Nominal prices are converted to real prices using the U.S. Consumer Price Index for all urban consumers. Diesel prices are real price per gallon from the Energy Information Agency. Sea surface temperature is the monthly simple average of daily simple average Gulf-wide sea surface temperature (SST) provided by NOAA

[http://www.aoml.noaa.gov/phod/regsatprod/gom/sst\\_ts.php.](http://www.aoml.noaa.gov/phod/regsatprod/gom/sst_ts.php) The mean SST for each day is uses satellite observations from<http://www.remss.com/> in areas of the Gulf of Mexico with depth > 200m. The monthly hypoxia (interpolation 1) is linearly interpolated annual snapshot of aerial extent of hypoxia in square kilometers from June to the following June (5). Hypoxia (interpolation 2) is linearly interpolated annual snapshot of aerial extent of hypoxia in square kilometers from June down to 0 in December and up to the next year's annual snapshot in the following June (5).



# **Table S2. Correlations of brown shrimp landings with measures of areal extent of hypoxia.**

Pearson's correlation coefficient with t-statistic reported below in parentheses.

\* and \*\* indicate statistically significant at the 10% and 5% levels respectively.

SEAMAP hypoxic areas calculated by summing the areas of all hypoxic subarea-depth polygons based on Summer and Fall surveys. Total landings include all size categories and unclassified landings. Small landings include pieces.



**Table S3. Conditional Logit Results with Alternative-Specific Constants.** The discrete choice model uses a stratified random sample of shrimp vessels (stratified on Gulf region and vessel size) and includes 31 choices (30 fishing locations that are subarea/depth zone combinations and the choice of not to fish) based on landings data in the SHRCOM database. Wave Height is from National Data Buoy Center and varies over space (j) and time (t). Shrimp price uses the SHRCOM data to create a Gulf-wide aggregate index that varies only over time (t). Diesel Price is from the Energy Information Agency and varies only over time. Expected Revenue and Expected Catch are constructed from the SHRCOM dataset and vary over space (j) and time (t). Distance is calculated from each vessel's primary port to each subarea/zone polygon centroid and varies over individual vessel (i) and space (j). All coefficients are statistically significant at the 1% level, and all parameter signs conform to theoretical expectations. Alternativespecific constants are solved for using contraction mapping and do not have associated standard errors (56). The constant for the choice of not fishing is normalized to zero.



### **Alternative-Specific Constants**



### **Table S4. Treatment effects results - the effects of hypoxia on natural logarithm of total brown shrimp landings.**

"Filtered" indicates data only includes records for which effort and vessel information is available. "All" indicates all records.

The t-statistc is reported below each coefficient in parentheses. All tests are based on clustered standard errors.



### **Table S5. Treatment effects results - the effects of hypoxia on natural logarithm of large brown shrimp landings.**

"Filtered" indicates data only includes records for which effort and vessel information is available. "All" indicates all records.

The t-statistc is reported below each coefficient in parentheses. All tests are based on clustered standard errors.



### **Table S6. Treatment effects results - the effects of hypoxia on natural logarithm of medium brown shrimp landings.**

"Filtered" indicates data only includes records for which effort and vessel information is available. "All" indicates all records.

The t-statistc is reported below each coefficient in parentheses. All tests are based on clustered standard errors.



### **Table S7. Treatment effects results - the effects of hypoxia on natural logarithm of small brown shrimp landings.**

"Filtered" indicates data only includes records for which effort and vessel information is available. "All" indicates all records.

The t-statistc is reported below each coefficient in parentheses. All tests are based on clustered standard errors.



**Table S8. Panel data models of fishing effort with low mean hypoxia measure.** Hypoxia measure is mean DO < 1.5 mg/l in the month-zone-depth unit of observation. Standard errors are in parentheses.





**Table S9. Panel data models of fishing effort with typical mean hypoxia measure.** Hypoxia measure is mean DO < 2.0 mg/l in the month-zone-depth unit of observation. Standard errors are in parentheses.





**Table S10. Panel data models of fishing effort with high mean hypoxia measure.** Hypoxia measure is mean DO < 2.5 mg/l in the month-zone-depth unit of observation. Standard errors are in parentheses.





**Table S11. Panel data models of fishing effort with low threshold hypoxia measure.** Hypoxia measure is minimum DO < 1.5 mg/l in the month-zone-depth unit of observation. Standard errors are in parentheses.





**Table S12. Panel data models of fishing effort with typical threshold hypoxia measure.** Hypoxia measure is minimum DO < 2.0 mg/l in the month-zone-depth unit of observation. Standard errors are in parentheses.







**Table S13. Panel data models of fishing effort with high threshold hypoxia measure.** Hypoxia measure is minimum DO < 2.5 mg/l in the month-zone-depth unit of observation. Standard errors are in parentheses.



**Table S14. Stationarity tests of shrimp prices.** A data series with a stable probability distribution is said to be stationary. Stationarity is a requirement for ordinary statistical inference. All tests indicate that times series of the natural logarithm of price for each shrimp size class are non-stationary in levels but are stationary after first differencing. The \*\* indicates significance at the 1% level. In the Augmented Dickey Fuller test (45) (top), the null hypothesis is that the distribution of the data series is non-stationary. Testing the natural logarithm of each brown shrimp monthly price time series, we fail to reject the null of non-stationarity in all cases. After first differencing, we reject the null in all cases. In the KPSS (46) test (bottom), the null hypothesis is that the data series is stationary. In levels, we reject the null hypothesis in all cases. After differencing, we fail to reject the null in all cases. These results are consistent with previously published results for a different window of time (26).





**Table S15. Bivariate Johanssen cointegration tests.** Nonstationary data series will have the same distribution at each observation if there is an equilibrating force that makes them move together over the long run. Such data series are said to be cointegrated (47). Johansen tests indicate that all pairs of large (L) and small (S) shrimp prices (in natural logarithms) are cointegrated, i.e. have stable long-run relationships (27). (A) reports the L and S price size classes for which each cointegration test is conducted. (B) is the number of lags used in the test selected by the Akaike's Information Criterion (AIC). (C) and (D) are the test statistics and corresponding P-values for whether the bivariate systems have rank 0, i.e. no cointegration vectors. (E) and (F) are the test statistics and corresponding P-values for whether the bivariate systems have rank 1, i.e. one cointegration vector. (G) is the P-value for a test of whether the relative prices are stable, i.e. Law of One Price holds. The results indicate one cointegration vector in all relationships; an equilibrium relationship exist between the prices for all sizes. The null hypothesis that the prices are proportional cannot be rejected.



# **Table S16. Time series results using natural logarithm of shrimp prices**

**Areal extent of hypoxia (bottom DO < 2.0 mg/l), weighted least squares based on landed quantity of large shrimp size class**



# **Table S17. Time series results using natural logarithm of shrimp prices**

**Areal extent of hypoxia (bottom DO < 2.0 mg/l), Newey-West standard errors**



# **Table S18. Time series results using natural logarithm of shrimp prices**

**Areal extent of hypoxia (bottom DO < 1.5 mg/l), weighted least squares based on landed quantity of large shrimp size class**



# **Table S19. Time series results using natural logarithm of shrimp prices**

**Areal extent of hypoxia (bottom DO < 1.5 mg/l), Newey-West standard errors**



# **Table S20. Time series results using natural logarithm of shrimp prices**

**Areal extent of hypoxia (bottom DO < 2.5 mg/l), weighted least squares based on landed quantity of large shrimp size class**



# **Table S21. Time series results using natural logarithm of shrimp prices**

**Areal extent of hypoxia (bottom DO < 2.5 mg/l), Newey-West standard errors**



# **Table S22. Time series results using natural logarithm of shrimp prices**

**Volumetric extent of hypoxia (DO < 2.0 mg/l), weighted least squares based on landed quantity of large shrimp size class**



# **Table S23. Time series results using natural logarithm of shrimp prices Volumetric extent of hypoxia (DO < 2.0 mg/l), Newey-West standard errors**

